# Demand Modeling and Relocation Strategies for Free-Floating Bicycle Sharing Systems

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**In memory of my beloved Grandfather Alfred (1928-2017).**

Thank you for your unconditional love, your wisdom, your cordiality and generosity, and simply - everything.

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# Abstract

This dissertation comprises an innovative Relocation Model for free-floating Bicycle Sharing Systems. In such flexible systems, one-way trips can cause fleet imbalances which imply an insufficient demand satisfaction of potentially requested trips.
This research grounds on real trip data of a free-floating Bicycle Sharing System in Munich, Germany. With the help of a detailed empirical data analysis, potential gaps between supply – i.e. current fleet distributions – and demand are identified. Based on this analysis, a demand model is developed, which predicts detailed spatial-temporal demand patterns within the operating area and recommends optimal fleet distributions for specific days and time frames.
In order to to realize the favored fleet distributions, so called relocation strategies are required. Such strategies enable an efficient redistribution of the fleet. Therefore different strategies are designed and investigated.
Firstly, an operator-based relocation strategy is developed: within an optimal relocation route, the operator relocates the unfavorably distributed part of the fleet by visiting under-supplied and over-saturated zones of the operating area in the most cost-efficient way.
Secondly, a user-based strategy is designed: in order to incentivize users to relocate parts of the fleet by themselves, discount offers apply to trips with certain origins and destinations.
Thirdly, a combination of previous strategies builds up the hybrid relocation strategy: the highly imbalanced zones of the operating area are relocated by a compact operator-based relocation route. Concerning the remaining moderate imbalances, specific discount offers for certain trips make the users redistribute the fleet by themselves.

In order to capture the impact and value of such relocations, the different strategies are validated and tested by means of a real time simulation case study. Within a testing period of three months, the different strategies are evaluated referring to efficiency, cost and benefit and optimal relocation intervals.
As a conclusion, the hybrid relocation strategy generates the best results. While keeping the cost low, an optimal fleet distribution is mostly maintained so that the demand can be satisfied comprehensively.

# Kurzfassung

Diese Dissertation beinhaltet ein innovatives Relokationsmodell für flexible, sogenannte free-floating Fahrradverleihsysteme. In solchen Systemen können durch Einwegfahrten Ungleichgewichte der Flotte entstehen, die dazu führen, dass die Nachfrage nach potenziellen Fahrten nicht mehr ausreichend befriedigt wird.
Als Basis dienen reale Fahrdaten eines flexiblen Fahrradverleihsystems in München, Deutschland. Durch eine detaillierte empirische Datenanalyse werden mögliche Ungleichgewichte zwischen Angebot – d.h. aktuelle Flottenverteilungen - und Nachfrage identifiziert.
Darauf aufbauend wird ein Nachfragemodell entwickelt, welches detaillierte räumlich-zeitliche Nachfragemuster innerhalb des Geschäftsgebiets des Systems prognostiziert und optimale Flottenverteilungen für bestimmte Wochentage bzw. Zeitfenster vorhersagt.
Um diese Flottenverteilungen zu realisieren bedarf es sogenannten Relokationsstrategien, welche eine effiziente Umverteilung der Flotte ermöglichen. Hierfür werden verschiedene Strategien entworfen und beleuchtet.
Zuerst wird eine betreiberbasierte Relokationsstrategie entwickelt: innerhalb einer optimalen Relokationsroute verteilt der Betreiber den unausgeglichenen Flottenanteil um, indem er die unterversorgten und überfüllten Zonen des Geschäftsgebiets nach und nach anfährt.
Weiter wird eine nutzerbasierte Relokationsstrategie erarbeitet: um Anreize zu schaffen, damit Nutzer selbst Teile der Flotte umverteilen, werden für bestimmte Start- und Zielorte einer Fahrt Preisrabatte gewährt.
Die hybride Relokationsstrategie kombiniert beide zuvor beschriebenen Strategien: durch eine kompakte Route werden nur die größten Flottenungleichgewichte innerhalb des Geschäftsgebiets ausgeglichen. Für die verbleibenden, mäßigen Ungleichgewichte werden wiederum die Nutzer durch Preisnachlässe motiviert, selbst Relokationsfahrten durchzuführen.

Um den Einfluss und Mehrwert solcher Relokationen auszuwerten werden die verschiedenen Relokationsstrategien mithilfe einer Simulation getestet. Innerhalb des Testzeitraums von drei Monaten können die einzelnen Strategien bezüglich Effizienz, Kosten/Nutzen und optimaler Relokationsintervalle bewertet werden.
Abschließend stellt sich heraus, dass die hybride Reloaktionsstrategie mit Abstand die besten Ergebnisse erzielt. Bei vergleichsweise geringen Kosten kann eine optimale Flottenverteilung nahezu immer gewährleistet werden und somit die Nachfrage flächendeckend befriedigt werden.

# Contents

# Abbreviations

| | |
|---|---|
| **BS** | Bicycle Sharing |
| **CS** | Car Sharing |
| **DS** | Demand Satisfaction |
| **FD** | Fleet Distribution |
| **GIS** | Geographic Information System |
| **GPS** | Geographic Positioning System |
| **ILP** | Integer Linear Program |
| **lat.** | Latitude |
| **long.** | Longitude |
| **MILP** | Mixed Integer Linear Program |
| **MIP** | Mixed Integer Program |
| **NIP** | Nonlinear Integer Program |
| **PDP** | Pickup and Delivery Problem |
| **PT** | Public Transit |
| **RQ** | Research Question |
| **RS** | Relocation Strategy |
| **TSP** | Travelling Salesman Problem |
| **VRP** | Vehicle Routing Problem |
| **VS** | Vehicle Sharing |

# Chapter 1

# Introduction

Mobility and transport systems are essential to modern societies, as they serve as the key to economic and social activities [104]. Transport systems empower individuals' mobility in the first place, enable interaction with other members of a network and thus meet their practical, productive and hedonistic needs [2, 114]. Individual motorized traffic is one of the most popular means of transportation, but it is also the most unsustainable. Automobile traffic contributes strongly to climate change and causes harmful environmental effects and health issues [139]. This leads to environmental challenges, especially in metropolitan areas. The World Health Organization (WHO) stated in 2016 that more than 80% of people living in urban areas that monitor air pollution are exposed to air quality levels that exceed their acceptable limits [121, 140]. Consequently, there is an urgent need for change in urban transportation.

Fortunately, human mobility behavior has changed over the last decades, primarily because of an evolution in the attitudes to private car ownership. Up to the 1990s, the car was considered as a status symbol, whereas for the last decade, smart phones and other mobile devices have substituted this symbolism [60, 62]. Especially younger people are more willing to use other means of traffic nowadays - a trend predicted to continue to rise [61].

Riding a bicycle is very popular nowadays, it is trendy not only because of low emissions that are associated with this traffic mode, but also due to technical innovations and ongoing development: since 2009, sales figures of e-bikes have been booming in

Germany and worldwide [143]. Bicycles equipped with a supporting electric motor allow longer travel distances to be covered by bicycle and boost cycling in general [49]. Furthermore, cargo bicycles are a suitable substitute for an automobile, especially in urban areas: on the one hand they are used for private purposes e.g., to transport children or groceries, and on the other hand, they are used for courier services [53]. Integrating such specific bicycle types into Bicycle Sharing (BS) Systems creates a holistic transportation option for several user groups and serves diverse needs.

BS Systems form an important module in today's urban transportation - they offer additional flexibility to users, close the first and last mile problem especially in combination with public transit (PT) and create added value even for cyclists owning private bicycles. Such systems boost cycle traffic and reduce traffic congestion and thus air pollution. By extension, BS Systems can help to improve public health [105] and even contribute to economic benefits, i.e. BS Systems have a positive impact on sales [20].

Well designed BS Systems enable quick, convenient and cheap trips for users. However, systems lacking an appropriate design are doomed to failure and dissuade potential users e.g., due to insufficient availability of bicycles. As a consequence, systems collapse and have to be decommissioned as announced recently for the BS System in Seattle [98, 119]. Therefore thorough planning and management are crucial to maintaining such systems as an important component of urban traffic.

## 1.1 Research Objectives and Design

Contemporary existing BS Systems are mostly station-based. Such systems typically allow one-way trips, i.e. users can return bicycles at stations different from the pickup station. An even more user-friendly system type is provided by so-called free-floating BS Systems, where pickup and drop-off is not bound by docking stations, but rather is possible in a predefined operating area. Different BS System types are explained in detail in section 2.1.

On the one hand, free-floating BS Systems stand out from station-based systems, as the free-floating feature offers major flexibility to users. On the other hand, this flexibility bears a certain risk for the operator, as unfavorable fleet distributions (FDs) are no longer confined to stations. Station-based BS Systems are frequently subject to

heavy imbalances, resulting in empty and overcrowded stations. Exceeding a certain imbalance threshold makes the system unusable, as users are either unable to rent a bicycle because the station is empty or unable to return a bicycle because the station is full. For free-floating systems, at least the latter case is negligible. However, the occurrence and frequency of imbalances between bicycle supply and demand in free-floating BS Systems requires examination, as such systems have not been considered comprehensively as yet.

This gap leads to the first research question (RQ) in this dissertation:

**Research Question 1:**
*What particular dynamics can be found in free-floating BS Systems?*

The initial RQ strives to understand this special type of BS System. An empirical data analysis of the system's usage should capture the dynamics and characteristics. For this purpose, a detailed analysis of free-floating BS Systems is required. As a consequence, a potential fleet skewness can be detected, which gives rise to RQ 2:

**Research Question 2:**
*Do fleet imbalances occur in free-floating BS Systems?*

On that point, the empirical data analysis builds the foundation and is crucial for identification of occurring imbalances. Based on booking data, demand estimations can be carried out to reveal the gaps between bicycle supply and demand. A well balanced FD within the operating area might enhance the system's performance and operation. In order to quantify this, the third RQ seeks further investigations:

**Research Question 3a:**
*How can the utility-level of a BS System be increased at best?*

This question comprises a thorough consideration of strategies in order to redistribute the fleet, of so-called *relocation strategies*. Long idle times or clustering of bicycles in certain parts of the operating area can cut down the system's utility and indicate a potential for enhancements of the system's efficiency.
That issue transfers directly to users and is formulated as part b of RQ 3:

**Research Question 3b:**
*Which strategies are suitable and qualified to reach the desired fleet status?*

Answers to this questions concern the system's imbalances from the user's point of view rather than from the operator's. Therefore measures like demand satisfaction outweigh the (in the short term) increased cost for potential relocation trips. Assuming no relocation intervention at all, this could result in a massive under-supply of bicycles. Furthermore, if users repeatedly do not succeed in finding an available bicycle, they might lose confidence in the entire system and hence the operator could lose customers. Further examinations consider different strategies in order to relocate parts of the fleet in an optimal, time- and cost-efficient way.

RQs 4a and b refer to an overall performance evaluation:

**Research Question 4a:**
*Which effects and impacts on the system's performance can be achieved by relocation strategies?*

Different strategies have to be designed and applied to an existent free-floating BS System. Diverse evaluations are required to show the degree of fleet imbalances to which a strategy is suitable. Further, smart combinations of different relocation strategies (RSs) might be feasible.
Part b addresses further the regularity of potential RSs and is formulated as the follows:

**Research Question 4b:**
*How often does the BS System need support from such strategies in order to maintain the desired fleet status?*

Answers to this final RQ shall reveal efficient application frequencies as well as the optimal combination of developed RSs. This gain in knowledge would increase the performance quality of realized relocation trips and therefore the effectiveness of the entire BS System - for the operator **and** the user.

This dissertation aims to give answers to the defined RQs, which frame the research objectives. Therefore an appropriate research methodology is required. The relevant research design is expounded in the following and depicted in figure 1.1.

| Research Question | | Examined in | | Approach |
|---|---|---|---|---|
| RQ 1 | → | Chapter 3 | → | Empirical Data Analysis |
| RQ 2 | → | Chapter 5 | → | Demand Forecasting |
| RQs 3a,b | → | Chapter 6 | → | Relocation Strategies |
| RQs 4a,b | → | Chapter 7 | → | Validation & Simulation |

FIGURE 1.1: Research Design

**Literature review**

A comprehensive literature review provides the basis for this research. In consequence, different types of BS Systems are introduced. Further, the actual motivation of this thesis is resolved: a vehicle relocation problem. Existing approaches for similar systems and problems are presented in detail and the possible transferability is discussed. However, free-floating BS Systems have distinctive requirements in order to prevent or eliminate occurring imbalances. This work is intended to close any identified research gaps.

**Empirical Data Analysis**

As already indicated by RQ 1, the system's dynamics and fleet imbalances have to be revealed and identified. This is carried out by a detailed empirical analysis of booking data, arising from the free-floating BS System in Munich. Further, this is the foundation of subsequent approaches, as real booking data play a crucial role for consideration of a real-world system.

**Development of a Demand Model**

In order to estimate and forecast upcoming demand for a free-floating BS System, an appropriate model is developed. Demand satisfaction is not bound by a discrete set of locations (as in station-based BS Systems); thus, the demand patterns evolve structures that are more complex. These patterns need to be derived from different components in a spatial and temporal sense. As a result, current utility levels can be read out by comparing occurring demand to the current FD. Unmet demand is hereby identified and RQ 2 is answered in the affirmative.

**Design of Relocation Strategies**

The core objective of this work is the efficient fleet rebalancing of a free-floating BS System. For this purpose, different RSs are designed. Required input parameters like predictions of occurring demand are provided by the precedent demand model. An answer to RQ 3a is obtained by evaluating the ensuing utility level after respective strategies. As a result, remaining unmet demand is identified. In order to eliminate this undesirable state, a comparison and combination of the designed strategies strives to answer RQ 3b.

**Validation and Simulation**

The final objective of this thesis seeks evidence for the developed models and strategies. Within a simulation case study, the potential effects and enhancement of the overall system's performance are simulated and evaluated. This validation eventually reveals answers to RQ 4a. Further, relocation scenarios for different time frames are carried out. As a result, recommendations for fleet relocation operations concerning regularity and required time intervals are given. These recommendations eventually answer the final RQ 4b.

## 1.2 Outline of the Dissertation

The structure of this work is outlined in the following and illustrated in figure 1.2.

Chapter 2 provides an overview of existing BS Systems. Further, a comprehensive literature review is given: studies treating the vehicle routing problem are presented. Firstly, applied to BS Systems and secondly, applied to generalized Vehicle Sharing (VS) and Car Sharing (CS) systems. Different strategies in order to rebalance BS fleets are expounded: operator-based and user-based strategies. The limitation to mostly station-based systems defines the research gaps.

In chapter 3, a detailed spatial and temporal booking data analysis is conducted. This empirical analysis reveals occurring fleet imbalances for free-floating BS Systems by identifying distinct usage flow patterns for different time frames. In consequence, the need for fleet relocations is proven.

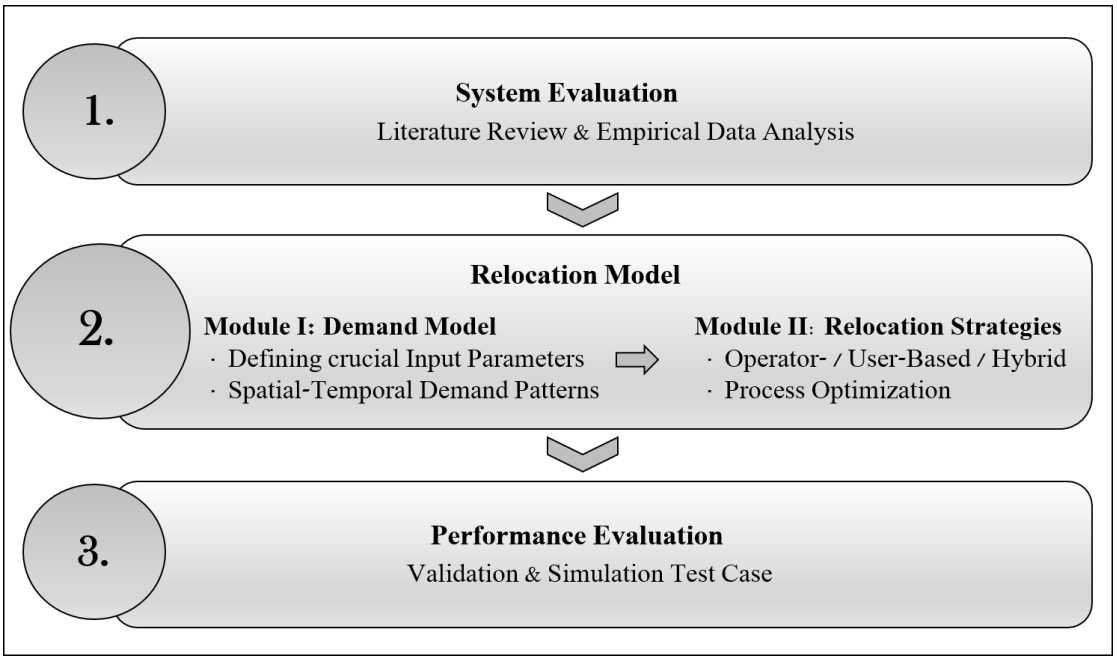


FIGURE 1.2: Outline of the dissertation

In chapter 4 the overall approach of the Relocation Model is given. It consists of two interdependent modules: a demand model and corresponding RSs. Both components are developed in separate chapters subsequently.

Chapter 5 elaborates module I of the Relocation Model: the Demand Model. It forecasts upcoming demand in a spatial and temporal sense. For this purpose, different demand model components are designed and a final saturation pattern provides required bicycle stocks in dependence on time and location.

In chapter 6, module II of the Relocation Model is designed: Relocation Strategies. Different strategies are elaborated in order to reach a balanced FD in a free-floating BS System. First, an operator-based RS is developed and applied. Second, a user-based strategy and a respective incentive pattern is elaborated and tested. By combining both strategies, the overall relocation scheme is optimized.

Chapter 7 evaluates the strategies' performance by carrying out a validation methodology referring to booking data. Further, a simulation case study is set up and reveals the effects and impact of the relocation performance.

Chapter 8 presents a summary of the main results and contributions. Finally, the transferability to other BS Systems is discussed and an outlook on future research is given.

# Chapter 2

# State of the Art

This chapter provides a theoretical basis and tools in order to give answers to the research questions defined in chapter 1.
An introduction of Bicycle Sharing (BS) Systems in general is given as well as their development history. Diverse types of BS Systems are presented and their various operating modes and dynamics are examined in detail. As a result of this, fleets in most BS Systems feature a skewness of distribution, which bears the actual problem formulation: a vehicle relocation problem. A comprehensive literature review provides various approaches for station-based BS Systems and also studies, which are applicable to the present problem e.g., the vehicle imbalance problem of Car Sharing (CS) Systems. Only few approaches concern the free-floating case, i.e. they mostly address station-based Vehicle Sharing (VS) Systems.
Further, different strategies for fleet relocations are expounded in detail. Operator-based methods and incentive-regulated, so-called user-based methods are presented. Concerning the latter, studies can be scarcely found especially dealing with free-floating systems. Based on this limitation, the research gaps are framed.

## 2.1 Bicycle Sharing Systems: an Overview

### 2.1.1 Evolution of Bicycle Traffic in the last decades

Until the 50s of the last century, the bicycle was regarded as one of the most important means of transportation in Germany. Due to the *Wirtschaftswunder* (the German economic miracle) in 1955, a sharp increase in motorization proceeded and bicycle traffic slid into obscurity. Owning a car and its usage was a status symbol until the late 90s of last century. Since then however, this trend has been declining and bicycle traffic is gaining importance once again, especially in urban areas. This is supported by modal split data. In Munich for instance, in 1998 8% of all trips were realized by bicycle. This percentage evolved to 17.4% in 2011 [45, 82]. In Vienna, car traffic was reduced from 40% in 1993 to 27% in 2014 due to policies making car use slower and less convenient while creating better conditions for public transit (PT) and bicycle traffic at the same time [22].

Nowadays, a significant proportion of citizens particularly in metropolitan areas are loath to be stuck in congested traffic every day or be dependent on PT. Cycling is a time-efficient mode of transportation - especially in urban areas for distances up to 5 km [43]. Besides that, cycling is a sustainable and environmentally-friendly traffic mode. Concerning safety for cyclists, studies in several cities and countries have shown that the higher the bicycle modal share, the fewer bicycle accidents occur in relation to overall bicycle trips. This is mainly caused by an increased appearance and perception of cyclists on the road [3, 54, 99, 120].

In keeping with the *sharing economy* [55], a major component for cycling promotion in urban areas - besides the extension of cycling infrastructure [21, 144] - is provided by implementing BS Systems. Such systems create additional upswing for cycle traffic overall (e.g., in Paris [85]) as they increase the perception of the bicycle as a transportation mode and appeal to different user groups: commuter trips as well as trips for leisure are made by shared bicycles (see also [26]). Conventional BS Systems allow one-way-trips, i.e. the vehicles can be dropped off at a station close to the desired destination (at best) and users do not have to return them at the point of origin [77]. This attribute promotes trips that would not be feasible by private bicycles.

In consequence, BS Systems turn out to be a flexible and convenient mode of transportation [23]. Further, BS Systems close the *last mile* and allow a convenient approach to the nearest PT stop. Martens even characterizes the bicycle as a *feedering mode* [71] and states that this multi-modal behavior is prevailing for distances between 2 and 5km to a PT stop.

### 2.1.2 Four generations of Bicycle Sharing Systems

Within the past 50 years, BS Systems literally reinvented the wheel over and over again. The evolution from plain, low-tech BS Systems to systems well-provided with innovative and groundbreaking technology can be categorized into four generations. The corresponding timeline is illustrated in figure 2.1.

In 1965, the **first generation** of BS Systems kicked-off in Amsterdam. The so-called *Witte Fietsen* ("white bicycles") were simple, white painted bicycles for public use. No registration or prior identification was needed, as the unlocked bicycles were spread among the city for everybody's usage. This idealistic and non-materially motivated system collapsed within days because bicycles were vandalized or turned into private bicycles by using a private lock [34].

It took almost 30 years for the **second generation** of BS Systems to arise. In a few small towns in Denmark in 1991 (see [91, 112]) and in 1995 in Copenhagen under the name of *Bycykler København*. The bicycles were more rugged (solid tires and a stable frame) and hence a bit more vandalism-proof. Pick up and drop-off was possible only at specific locations within the city center and was controlled by a coin deposit. These enhanced features prolonged the operating period and the system's persistence, but since customers could use the system anonymously, the fleet got more and more depleted.

This unresolved issue led to **third generation** of BS Systems with improved customer tracking: launched in 1995 at Portsmouth University in England, *Bikeabout* was the first BS System that required a prior registration before usage [15, 33, 131]. The registered customers received a magnetic stripe card that allowed to rent a bicycle and identified the respective user at the same time. Such systems continue to operate in various cities around the globe up to today [18, 27, 125] and have been modernized by

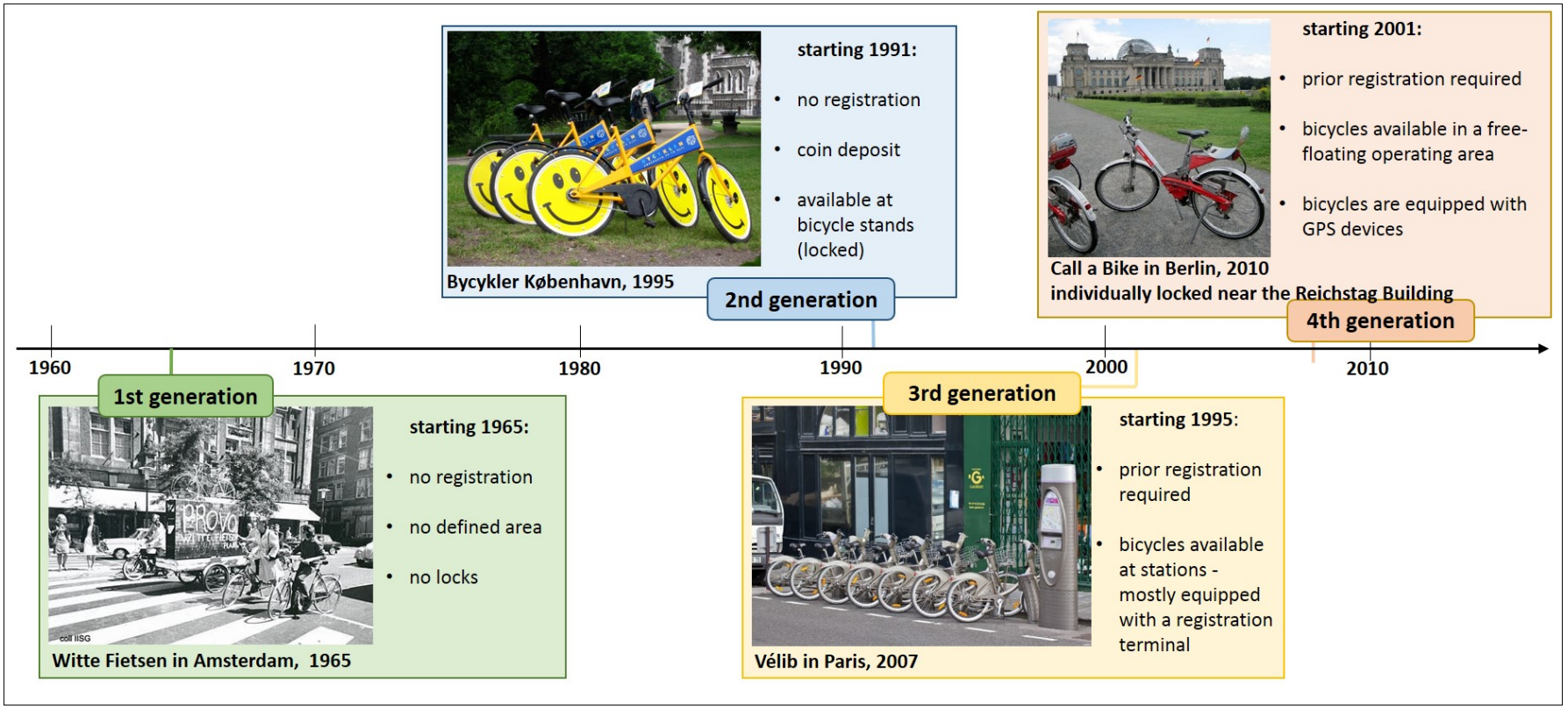


FIGURE 2.1: Timeline and development history: four generations of BS Systems, picture sources [14, 38, 89, 129]

mobile phone access, on-board computers and integration of e-bikes e.g., the BS System *gobike* in Copenhagen that solely supplies e-bikes [52].

Within the three generations the systems evolved from flexible programs to station-based systems. Thereafter, a more user-friendly and convenient system design revived and builds up the **fourth generation**, the so-called *free-floating* BS Systems.

In 2001, the German Rail launched this new type of BS System *Call a Bike* [24]. Unlike a station-based system, the bicycles are free-floating, meaning that the user can rent and return a rental bicycle everywhere within a clearly defined operating area, with contemporary constraints though:
back in 2001, rental and return was only possible at public phone boxes, where the user literally had to "call a bike". Dialing the number on the favored bicycle, the computer voice on the phone provided a code for the electronic lock to open [128].

The entire process improved significantly over time by cell phones and especially by the usage of smart phones nowadays. Since 2013, the bicycles have been equipped with GPS devices, which makes this system very user-friendly: finding the nearest bicycle and renting it is possible via a smart phone application, as well as the billing after payment verification. Users can even return bicycles outside the operating area, though this is subject to a service charge as the operator has to collect the dispersed bicycles eventually.

This special type of BS System is not (yet) very common. In Berlin for instance, such a free-floating BS System was shut down in 2011, because of high cost in operation and maintenance [93]. In Munich, an additional *hybrid* BS System *MVG Rad* (see also figure 2.3 in the subsequent section) was launched in fall 2015 by the Munich Transport Corporation [84]. This system allows rentals and returns not only at the stations, but also has a free-floating operating area, where users can rent and return the bicycles flexibly. In China, the free-floating BS Systems *Mobike* [81] have been launched in nine cities since April 2016 and are considered to be a technical innovation in BS Systems.

### 2.1.3 Bicycle Sharing Systems nowadays and their impact

Numerous cities all over the globe have followed the trend to promote cycling and implemented public BS Systems over the last few years [112], and new systems are added each year, as illustrated in figure 2.2 (top). At the end of 2016, almost 1200 BS Systems were spread around the globe and this number is increasing each year.
The continents to have implemented the most BS Systems are Europe and Asia, followed by North and South America, Oceania and Africa as illustrated in figure 2.2 (bottom left).
According to [35], at the end of 2015 China's fleet of bicycles in public BS Systems was greater than the entire world's fleet at the end of 2014. This fact is visible in figure 2.2 (bottom right) as well: in 2016, 83% of all public bicycles worldwide were operated in a BS System in China.

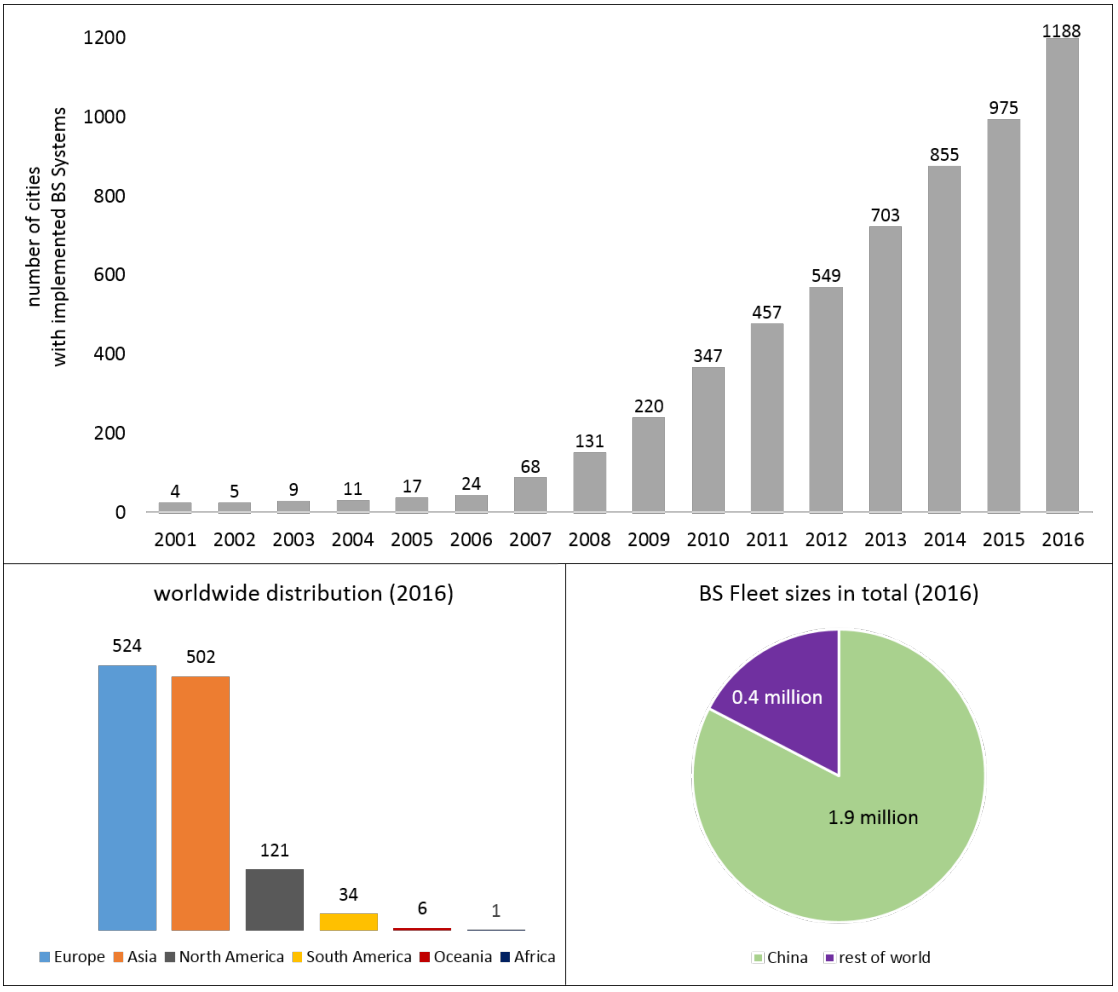


FIGURE 2.2: Growth of BS Systems in cities (top), their distribution worldwide (bottom left) and total fleet sizes (bottom right), sources: [35, 103]

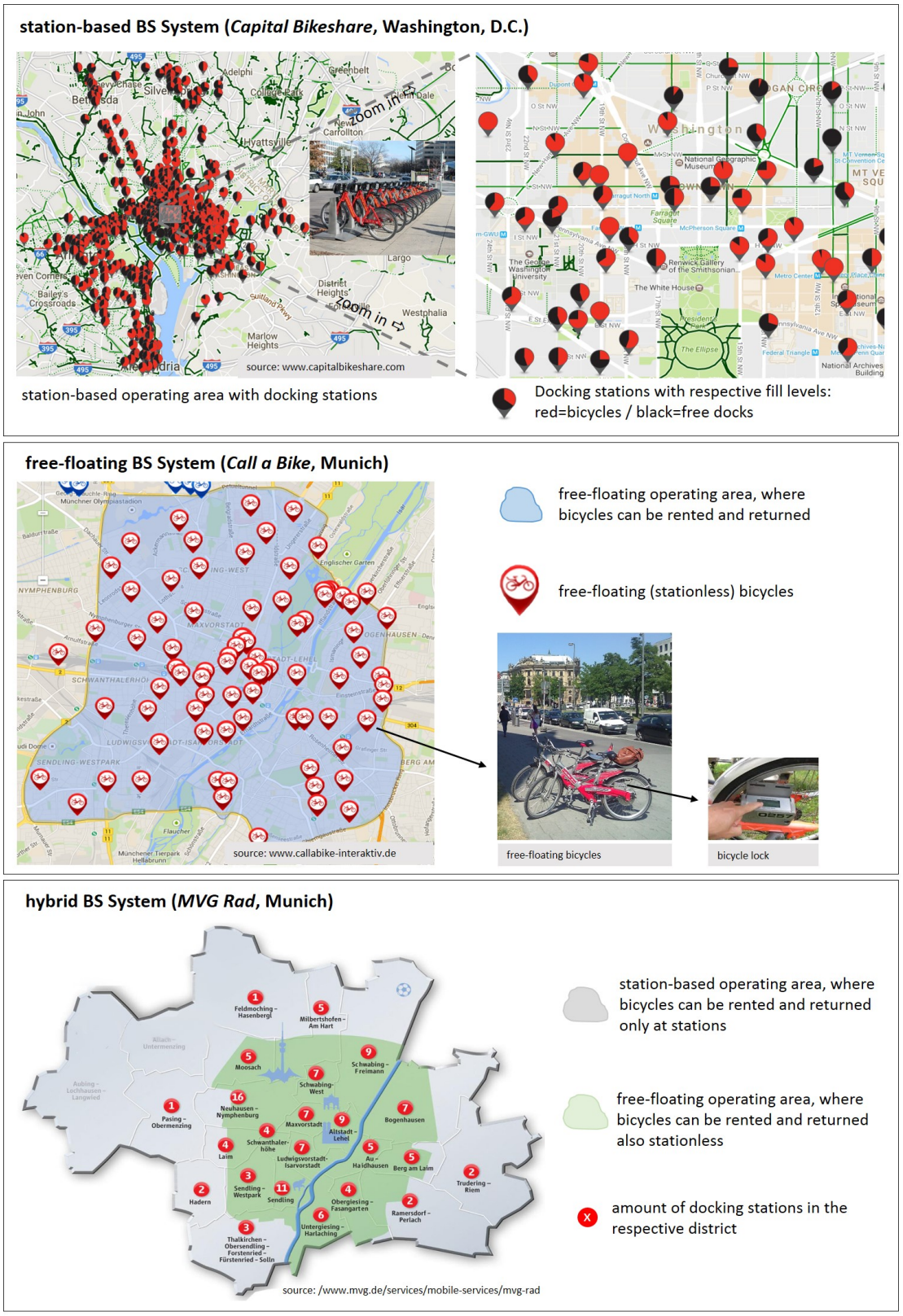


FIGURE 2.3: Illustration of different BS System types: station-based (top), free-floating (center) and hybrid (bottom)

Nowadays, the majority of existing BS Systems are **station-based**, i.e. they are assigned to the third generation. As illustrated in figure 2.3 (top), showing *Capital Bikeshare* in Washington D.C., station-based BS Systems comprise a set of docking stations within a certain surrounding, the city boundary for instance. Users can rent and return bicycles only at these docking stations.

In **free-floating BS Systems**, no docking stations are required, as depicted in figure 2.3 (center), showing the free-floating BS System *Call a Bike* in Munich. There is a predefined operating area (blue area) within which the free-floating bicycles can be rented and returned. The bicycles are equipped with GPS devices so that they can be found and rented by users and also be retrieved by the operator.

The third system type is a fusion of both stated system types: the **hybrid BS System** *MVG Rad* in Munich, illustrated in in figure 2.3 (bottom). There is a free-floating area (green area) and additional docking stations, within and also outside the free-floating area. That means: if users want to ride beyond the free-floating boundary (gray area), they have to return the bicycles to a docking station. Within the free-floating area, they can decide whether to return the bicycles to a station (a discount may apply) or to lock them individually at the desired destination.

An overview of selected BS Systems and their respective fleet size, system type and pricing scheme is given in table 2.1.

Concerning station-based BS Systems, three well-known systems among a variety have

| System | launched in | fleet size | system type | # of stations | pricing |
|---|---|---|---|---|---|
| *Vélib*, Paris | 2007 | 20 000 | station-based | 1 800 | 1.70€/day → 30min free/trip [125] |
| *Santander Cycles*, London | 2010 | 11 500 | station-based | 750 | 2£/day → 30min free/trip [107] |
| *Capital Bikeshare*, Washington D.C. | 2010 | 3 700 | station-based | 440 | 2$/trip up to 30min [27] |
| *Call a Bike*, Munich | 2001 | 1 400 [142] | free-floating | - | 1€/30min (+3€/year) [24] |
| *Mobike*, Shanghai | 2016 | 80 000 [115] | free-floating | - | 1CYN/30min [116] ≙ 0.14€/30min |
| *MVG Rad*, Munich | 2015 | 1 200 [142] | hybrid | 84 | 0.08€/min [84] |

TABLE 2.1: Overview of selected BS Systems operating in different system types

been selected in the cities Paris, London and Washington, D.C. As free-floating BS Systems are rather unusual, table 2.1 presents two known systems of this kind, namely in Munich and Shanghai. The second BS System in Munich features a unique characteristic: a hybrid system type, which is also listed in the table.
The pricing systems vary, especially if users subscribe to annual memberships for instance. The pricing listed in table 2.1 refers to single trips without any subscription. In case of annual memberships each trip up to 30 minutes is for free, which is a good bargain for frequent users. Such annual passes cost 29€ for *Vélib*, 90£ for *Santander Cycles* and 85$ for *Capital Bikeshare*.

*Vélib'*, Europe's biggest BS System was established in Paris in 2007. By now, more than 20 000 bicycles are available at 1 800 stations, users can typically access a station within a 300 meters distance [125].
One of the main goals of implementing *Vélib* was the reduction of motorized private transport. As stated in [97], 10% of the 25 million bicycle trips substituted a former car trip in the first year of operation. Especially in urban areas, the implementation of such systems can help to reduce congestion and emissions [46, 105].
In Washington D.C. 55% of respondents in a 2014 survey said they used a car less frequently since joining the local BS System *Capital Bikeshare* [26, 27].
Furthermore, such systems can shift trips from an overloaded PT system. In London, a survey of customers revealed that 54% of the realized rental bicycle trips would have been done by PT without an existing BS System [123]. Martin et al. conclude in [72] that
*"shifts away from public transit are most prominent in core urban environments with high population density. Shifts toward public transit in response to bikesharing appear most prevalent in lower density regions on the urban periphery."*
The former statement refers to trips that were previously realized by PT and now by shared bicycle, whereas the latter refers to BS as a feedering mode (see [71]).
There is a certain impact of BS Systems on other modes of transportation. On the one hand BS Systems reduce private motorized traffic and thus reduce emissions [4] and on the other hand they help to relieve PT overloads. Either way, such systems evidently increase bicycle traffic.
In summary, BS Systems can contribute to CO2 avoidance and hence increase the level of livability of a city (see also [141]).

## 2.2 Bicycle Sharing System Setup

The success of a BS System hinges on reasonable planning: multiple studies address the optimal fleet size, station-to-station distance as well as the optimal station allocation [50, 73] dependent on a spatial and temporal demand distribution. In case of a free-floating BS System this question is reduced to an initial FD within the operating area. In station-based systems however, the stations' implementation requires careful consideration. The following sections provide approaches for treating RQs 3a and b. If a low utility level is caused by a disadvantageous FD, appropriate strategies can help to reach a more balanced fleet status.
A summary of existing studies referring to a priori planning of BS Systems is outlined in table 2.2 and discussed in the following sections.

### 2.2.1 Bicycle Sharing System design

In station-based BS Systems, docking stations are mostly linked to public transport. By providing additional stations, the users benefit from closing the first and last mile by bicycle, unlike walking to a public transport station. To minimize the walking distance to the next public bicycle station, the system has to be quite dense. The higher the number of available stations, the more convenient the usage and, consequently, the greater the willingness to travel by bicycle instead of by car or PT [112].
This feature is perfectly resolved in free-floating BS Systems for users - on condition that the fleet is well distributed. In a worse case, users have to walk a certain distance to approach the nearest available bicycle, but at least they can return it directly at their desired destination (assuming it is still within the operating area). In a station-based system though, the stations' allocation needs thorough planning. The *Bike Sharing Planning Guide* [63] provides diverse guidelines that should be considered in the process of planning with a practical orientation:

1. minimum system coverage area: 10 $km^2$
2. station density: 10 – 16 stations per $km^2$
3. bicycles/resident: 10 – 30 bicycles for every 1 000 residents (within coverage area)
4. docks per bicycle ratio: 2 – 2.5 docking spaces for every bicycle

| Study | Focus | Approach | Objective | System Type |
|---|---|---|---|---|
| García-Palomares et al. [50] | Optimal station locations | Geographic information system | Maximizing covered demand | BS |
| Krykewycz et al. [68] | Defining operating area | Geographic information system | Maximizing covered demand | BS |
| Lin and Yang [70] | Optimal station numbers / locations; Optimal network structure of bicycle paths / travel paths between stations | Optimization | Maximizing covered demand | BS |
| Romero et al. [106] | Optimal station locations | Optimization | Maximizing efficiency and covered demand | BS |
| Martinez et al. [73] | Optimal station locations / fleet size | Optimization; Simulation case study | Maximizing operator's profit | BS |
| Sayarshad et al. [108] | Minimal fleet size; Relocation | Optimization | Minimizing unmet demand / number of bicycles / relocations | BS |
| Shu et al. [113] | Optimal station sizes; Relocation | Estimation of bicycle flows; Simulation | - | BS |
| Barth and Todd [7] | Measures of effectiveness; Optimal fleet size | Simulation | Minimizing wait times / number of relocations | VS |
| Cepolina and Farina [29] | Optimal fleet size / vehicle distribution | Optimization | Minimizing vehicle costs and wait times | CS |

TABLE 2.2: Optimal System Design of Station-Based VS Systems

These quantities are rough indications and dependent on the specific city, land use, population density etc.
There are several studies and design models from a more theoretical point of view [83, 92]. Morency et al. stated in [83] that the optimal system design, i.e. fleet size and station allocation, can reduce the system's fleet imbalances. Ergo: if the initial setup of a BS System is *optimal*, fleet imbalances can be kept within a limit and cost for extra relocation trips can be saved. In order to find these measures, further empirical values or models are required.

To determine the optimal fleet size of a BS System, Sayarshad et al. [108] created a mathematical model by determining the minimum required fleet size that minimizes simultaneously unmet demand, unutilized bicycles and necessary relocation trips. Shu et al. [113] captured bicycle movements by network flow modeling. They determined the total trip numbers the system can supply with an initial FD and the required station size. As a result, they stated that a previously computed and realized bicycle allocation enhances the overall system's performance compared to a random bicycle allocation. Lin and Yang optimized the strategic planning of station-based BS Systems with a Nonlinear Integer Program (NIP) formulation [56, 70]. On the one hand, operator's interests are considered by suggesting optimal station allocation and respective station sizes. On the other hand, this model represents the user's needs by maximizing covered demand and optimizing the network structure of bicycle paths and travel paths between stations. Another approach is given by Romero et al. in [106]. The authors simultaneously modeled private car and BS transport modes by using modal split data and the assignment of each mode's trip to the network. The objective was to find optimal station locations in order to design the entire transport system to be as efficient and sustainable as possible in an economic and social context.

All existing studies address the optimal BS System design from different points of view. However, a crucial input variable - if not the most important one - is the prevailing demand at the stations or in different locations of the operating area. This demand is very likely to change during the day and cannot be set as a static measure. Therefore a review of studies on demand forecasting is given in the following section (also listed in table 2.2).

### 2.2.2 Approaches to demand predictions

Current, location-dependent demand patterns help to assemble the data inputs for the system design and are also usable for further strategies to keep the BS System balanced. Demand predictions arise from various perspectives: traffic counts, surveys, PT usage numbers and booking data of VS Systems can provide the basis for this.
Jones and Buckland estimated bicycle and pedestrian demand in [64]. The authors therefore counted bicycle and pedestrian traffic and merged the results with social factors and land use data. Krykewycz et al. used a GIS analysis to obtain a potential market area in [68]. The authors identified two different market areas with respective prevailing demand potential for a BS in Philadelphia. The demand was scaled by knowledge transferred from other BS Systems. Data analyses from peer European cities, i.e. the daily BS trip diversion rates, were applied to these market areas. Borgnat et al. [17] and Kaltenbrunner et al. [66] derived the demand from booking data as well for the existing station-based BS Systems in Lyon [126] and Barcelona [12]. Firstly they visualized the bicycle trips and studied rental numbers for each station separately. Secondly, they determined the flow of the entire system by taking into account all stations and their interdependencies. The authors thus revealed a dynamic spatial demand distribution.
Nair et al. [88] created different short-term demand scenarios computed on a stochastic basis and scaled by historical booking data. As a result, the authors present flow patterns for the BS System in Paris.
More general studies concerning Vehicle Sharing (VS) Systems were carried out by Barth and Todd [7]. The authors estimated the optimal fleet size with the help of a simulation model, including different scenarios for current demand. Results provided optimal fleet size recommendations with respect to minimize customers' waiting times and required relocations. Similar studies concerning Car Sharing (CS) can be found. In [29], Cepolina and Farina designed an optimization problem that minimizes cost and waiting times in order to determine the optimal fleet size for a CS System.
Once the demand is estimated, the grade of imbalances can be evaluated, assuming the current FD is known. The resulting problem - lack of bicycles and surplus bicycles respectively at several stations/in different parts of the operating area - requires an approach to resolve it; therefore the vehicle routing problem is discussed in the following sections.

## 2.3 The Vehicle Relocation Problem

In many VS Systems vehicle imbalances occur from time to time. For station-based BS Systems, this hypothesis has been proven by many studies (see also [109, 113]). Such systems allow one-way trips e.g., users may return bicycles at different stations.

Additionally, temporal demand oscillations can occur [132], leaving some of the stations empty and others overcrowded at the same time. These states are depicted in figure 2.4. The left part shows a full station of *Capital Bikeshare*, where potential users cannot return their bicycles anymore. The right part of figure 2.4 illustrates the opposed case: the station is empty and consequently no rentals are possible right now.

FIGURE 2.4: Full station (left) [5] vs. empty station (right) [76] in the BS System *Capital Bikeshare* in Washington D.C. [103]

Some station-based BS Systems allow returning bicycles even at full stations, i.e. next to the docking station, provided that the bicycles are lockable individually. In figure 2.5, a docking station of the station-based BS System *StadtRAD* in Hamburg [117] is shown: this docking station is surrounded by additional 150 returned bicycles and the station and nearby areas are clearly over-saturated.

In general, some stations are rather origins of trips (e.g., at the central station after a train ride) and hence tend to empty out. Accordingly, other stations are rather destinations of trips and thus are given to filling up. These imbalances can constrain the entire performance of the BS Systems, as both rentals and returns are only possible at a limited set of stations and thus the short-term demand might be unmet [87].

FIGURE 2.5: Overcrowded docking station in the BS System *StadtRAD* in Hamburg [24, 117]

In free-floating BS Systems, the problem of full stations cannot occur, as there is no capacity limitation in public space to return bicycles. At times though, parts of the fleet can cluster in some areas. Besides the *Call a Bike flex* BS Systems in Germany [24] (currently in Munich, Cologne and Frankfurt) and *Mobike* in China (since 2016), no further sheer free-floating BS Systems are existent and consequently existing literature does not cover such systems' dynamics thoroughly. However, it is assumed that bicycle imbalances also occur in the free-floating case, i.e. some areas are under-supplied and show a lack of bicycles (comparable to an empty station). Further, the prediction of potential imbalances might be more complex, as more spontaneous usage is a feature of free-floating VS Systems.

Moreover, it is known of free-floating CS Systems that the Origin/Destination-relations are asymmetric, as stated in [134]. This is additionally caused by a variation of trip purposes on different days. In studies referring to a free-floating CS System in Munich [69, 80], the authors found different major trip purposes on Sundays ("driving home", "leisure activity" and "picking someone up") and weekdays ("shopping trip" and "trip to work"). In consequence, vehicle imbalances are rather likely to occur in turns between weekends and weekdays.

In terms of a potential rebalancing process, relocating bicycles is a lot easier compared to cars, as up to 25 bicycles (concerning *Capital Bikeshare* in Washington D. C. [25])


FIGURE 2.6: A relocation vehicle in Verona [13], picture: Klaus Bogenberger, 2012

can be transported by an appropriate relocation vehicle. Figure 2.6 shows a relocation vehicle belonging to the *Verona Bike* BS System. This vehicle can carry up to 24 bicycles and conveys them on two platforms.

Comparing station-based and free-floating BS Systems, the relocation process for the free-floating case is aggravated, as specific surplus bicycles (spread in the operating area) have to be chosen and dropped off at optimal locations, which have to be found or defined. The dispatchers of *Call a Bike* in Munich figured out certain *hot spots* where they usually put surplus bicycles e.g., near the central station or close to the university. Further, as mentioned in an interview [118], realized relocations are based on gut feeling, do not follow a specific strategy and are carried out a few times per week.

Smart relocation strategies (RS) can make the relocation process more efficient and also enhance the performance and utility level of the entire BS System. Therefore the vehicle relocation problem (VRP) has to be solved and tailored to the specific needs of the considered system.
In general, the VRP can be categorized into three classes for all types of BS Systems:

1. optimizing the system design in advance to prevent major imbalances
2. elimination of occurred imbalances by a conventional relocation route
3. incentivize users to make them relocate the fleet

Class 1 defines proactive and rather static steps which are already discussed in section 2.2. This is rather an a priori method in order to implement the (future) BS System best

possible. An efficient system design (i.e. appropriate location and number of stations, fleet size) can help stem the degree of occurring imbalances. In the free-floating case, these prior implementing options are limited to defining the fleet size and operating area.
Classes 2 and 3 comprise reactive steps, i.e. they work on the running system and are dynamic. The former represents the operator-based RSs and the latter refers to so-called user-based RSs. Both schemes are expounded in detail in the following sections.

### 2.3.1 Operator-based strategies

In most operator-based RSs, one or more routes for relocation vehicles are determined by computation. From a theoretical point of view, a mathematical optimization problem has to be solved.
A summary of the presented operator-based RSs is outlined in table 2.3.

Most studies (see [1, 100]) define the resulting VRP as a MILP, a Mixed Integer Linear Program. Angeloudis, Hu and Bell referred to a multiple Travelling Salesman Problem (TSP) approach in [1], which finds the optimal route between all stations that need to be rebalanced. This TSP formulation can be solved by diverse exact and approximate approaches (see also [9, 57, 137]). Within this TSP formulation, different objectives can be defined, such as "minimizing relocation cost" or "maximizing operator's profit". Additional side conditions are provided by constraints like capacity limitation of the relocation vehicle or timeout for the relocation process.

Another problem classification is often used in order to solve a VRP: so-called Pickup and Delivery Problems (PDPs). Dell'Amico et al. [32] specified this by a one-commodity PDP with additional capacity constraints. Their objective was to minimize relocation cost, similar to Benchimol et al.'s study in [10]. Vogel et al. set up a MIP formulation for a station-based BS System in [127]. The optimization problem was formulated in order to obtain optimal fill levels at all stations and minimal cost at the same time. Brinkmann et al. [19] proceeded similarly. For an efficient execution of the relocation routing, the authors used a variable neighborhood search in order to divide the set of stations into appropriate subsets which single relocation vehicles are assigned to.

Chemla et al. [30] and Schuijbroek et al. [109] focus on efficient relocation performances as well, by planning different, simultaneous relocation routes in order to obtain routes and schedules for staff operation planning. For this purpose, Schuijbroek et al. designed a heuristic that combines a Clustering Problem (station-to-station routing) with service level feasibility constraints.

Miller-Hooks and Nair [87] formulated a stochastic MILP with joint chance constraints to detect efficient operator-based relocation routes with minimal costs for VS Systems in general. Different demand constraints have to be satisfied while minimizing cost was the prior objective. In [88] the authors applied this model to the BS System *Vélib* in Paris, resulting in routing plans for several relocation vehicles. This strategy ensures that available surplus bicycles and concurrently free or empty docking stations get rebalanced and most short-term demand scenarios are met.

Further studies exist for CS Systems. The respective methods are similar to previously described strategies for BS Systems and therefore are applicable for diverse system types. The main difference appears in performing the relocation: in CS Systems, vehicle relocations have to be realized for each automobile separately and hence are more time-consuming and cost-intensive.

Jorge et al. designed a relocation model that maximizes the operator's profit in [65]. The authors subsequently compared the results to a simulation model that represented the relocation scenario of CS System in Lisbon, Portugal.

Weikl developed a mesoscopic relocation model for free-floating CS Systems [134]. In order to maximize the operator's profit and concurrently to minimize unmet demand, Weikl solved an optimization problem, which yielded optimal vehicle distributions and also staff operation planning for performing the relocation steps. This strategy was validated within several real-world field tests. As a result, conducted relocation trips led to higher booking numbers in the subsequent time period due to a better vehicle distribution.

| Study | Focus | Approach | Objective | System Type |
|---|---|---|---|---|
| Angeloudis et al. [1], Raviv et al. [100] | Relocation | Optimization | Minimizing unmet demand | BS |
| Benchimol et al. [10], Dell'Amico et al. [32] | Relocation | Optimization | Minimizing cost | BS |
| Brinkmann et al. [19], Vogel et al. [127] | Relocation; Station allocation | Optimization | Optimal fill levels/ minimizing cost | BS |
| Chemla et al.[30] | Staff operation planning | Optimization | Minimizing relocation costs | BS |
| Schuijbroek et al.[109] | Optimal vehicle routing; Service level requirements | Optimization; Clustering Problem | Minimizing relocation costs | BS |
| Nair et al. [88] | Relocation | Optimization; Simulation | Minimizing unmet short-term demand / Deriving vehicle redistribution plans | BS |
| Nair and Miller-Hooks [87] | Relocation | Optimization; Simulation case study | Minimizing relocation costs | VS |
| Jorge et al. [65] | Relocation; Optimal station locations | Optimization vs. Simulation | Maximizing operator's profit | CS |
| Weikl [134] | Relocation; Staff operation planning | Optimization; Simulation | Maximizing operator's profit / Minimizing unmet demand | CS |

TABLE 2.3: Solving the Vehicle Imbalance Problem Of Station Based VS Systems - Operator-Based Relocation Strategies

### 2.3.2 User-based strategies

Besides the proactive intervention by the operator, some BS Systems implemented so-called *user-based* RSs. Such schemes mostly ground on incentives for users to make them take certain trips at a reduced fare. In a short-term sense, this might decline the operator's profit. Taking into account a better fleet distribution due to user-based relocation trips, such RSs can even lead to a long-term profit increase.

In most BS Systems, such price reductions are addressed to users without a subscription. Frequent users with annual pass, for example, can ride for free for up to 30 minutes per trip, hence there is no additional value for this user group.

In general, there are different options to grant incentives: some BS Systems offer extra minutes or free rides for following trips. Other pricing schemes credit via bonus points, reduced fares or directly in the form of cash.

The BS System *Vélib'* in Paris launched a dicount pricing scheme in 2008. Before then, the stations located uphill e.g., in Montmartre were always empty and a persistent station balance could not be preserved by operator-based relocations. Consequently, the operator offers a simple and transparent discount scheme if users return bicycles to "*one of 100 stations perched over 60 meters above the rest of the city*" [16]. In this case, users get a credit of 15 minutes of free riding.

In London the *Barclays Cycle Hire* (as of March 2015 *Santander Cycles* [107]) incentivizes or rather compensates their users reversely: if users approach a full station, they get an extra 15 minutes of free time to cycle to the next one [59]. Additionally, the operator runs complementary redistributions daily on weekdays between 8 a.m and 10 p.m. with sometimes nearly 30 repositioning vehicles.

These real-world strategies are usually derived from theoretical approaches. All presented studies are listed in table 2.4.

Pfrommer et al.[94] designed a user-based relocation scheme and applied it to London's *Barclays Cycle Hire*. The authors stated that appropriate price incentives could keep the service level above 87% on weekends. During the week, such strategies are

| Study | Focus | Approach | Objective | Incentives | System Type |
|---|---|---|---|---|---|
| Pfrommer et al. [94] | Relocation | Monte Carlo method; Simulation | Balancing supply / demand; Minimizing operator-based relocations | pricing incentives | BS |
| Fricker and Gast [48] | Relocation | "power-of-two-choices"-modeling | Balancing supply / demand; reduction of empty stations | advice for return station | BS |
| Waserhole et al. [132, 133] | Relocation | Markovian formulation of a closed queuing network; Fluid approximation; Case study | Maximizing operator's profit | pricing incentives | VS |
| Di Febbraro et al. [37] | Relocation | Discrete event systems; Optimization; Simulation case study | Maximizing operator's profit | pricing incentives | CS |
| Barth et al. [8] | Relocation | Simulation; Real-world university setting | Minimizing relocations | trip splitting / joining | CS |
| Uesugi et al. [124] | Relocation; Optimal fleet size | Optimization; Simulation case study | Minimizing unmet demand | trip splitting / joining | CS |

TABLE 2.4: Solving the Vehicle Imbalance Problem Of Station Based VS Systems - User-Based Relocation Strategies

not sufficient and have to be supplemented by the operator. The results rest on a Monte-Carlo method based on historical booking data. Similar models and simulations can be found referring to different objectives.

Fricker and Gast built up a stochastic relocation model in order to reduce empty and full stations in [48]. By suggesting users return to the least loaded of two stations, the authors obtained significant improvements of the overall fleet balance.

Waserhole et al. [133] set up a user-based RS through pricing incentives for VS Systems. With the help of a Markovian formulation of a closed queuing network the authors aim for self-regulation of the VS System by maximizing the operator's profit.

For user-based RSs in BS Systems mathematical approaches, formulations and objectives may remain the same as for CS Systems. Di Febbraro et al. [37] for instance carried out a simulation case study based on discrete event systems for station based CS Systems. The authors determined an optimal pricing incentive pattern in order to maximize the operator's profit. Barth et al. [8] evaluated a real-world implementation on campus by simulating the effects of trip splitting and and trip joining. The former refers to the case if users want to travel from a station with too many vehicles to one with a shortage. Then they were incentivized to drive separate vehicles. The latter refers to the opposed case: if users want to travel from a station with a shortage of vehicles to one with surplus, ride sharing was promoted.

A similar approach of pricing incentives through trip splitting and joining is examined by Uesugi et al. in [124]. The model itself can be easily applied to the BS System case. The incentive strategy however, has to be transformed into pricing incentives, as neither trip splitting nor trip joining is feasible on a conventional bicycle.

This section presented various approaches of different RSs and their according performance. An overview of evaluation methods in order to quantify the impact of such performed relocations is given in the following.

### 2.3.3 Impact and value of relocations

As known for existing BS Systems such as *Capital Bikeshare* and *Vélib*, relocation trips have to be performed in order to keep the system running (see [16, 25]). In consequence, these relocations have a significant impact on the utility level of the entire BS System.

However, clear statements on performance values are hard to determine, not least because it is almost impossible to compare the same system under identical circumstances simultaneously without any relocation interventions and by applying RSs to it respectively.

In previous sections, different models and tools for such RSs were examined. In order to rebalance bicycle stocks at stations or in the operating area in general, various methods following different objectives were outlined. To quantify the success of such methods, i.e. the grade of fulfilling these objectives after performing the respective strategies, appropriate evaluation and testing is required. Different evaluation approaches are found and outlined in this section.

Barth et al. carried out a performance analysis of their RS, by applying it to a real-word testbed in [6]. This testbed was the station-based VS System operating on the University of California, Riverside campus. The overall efficiency is evaluated by previously defined performance measures that indicate required vehicle relocations to comply with the required stock distribution. Weikl and Bogenberger performed a real-world field test for the free-floating CS System in Munich in [135]. The authors revealed that due to the operator-based relocation method at night, the overall system's performance during the following day was increased concerning measures like idle times of the fleet, more generated trips and thus additional profit.

If a real field test is not feasible, alternative validation schemes have to be designed. Hence Jorge et al. carried out a simulation model to study different real time relocation policies in [65]. As a result the authors stated that the operator's profit can be enhanced, even with increased costs due to relocation trips. Preisler et al. designed

a simulation architecture based on a multi agent system (see [95, 96]). Hereby a user-based strategy was evaluated. The simulations were run for different test cases in dependence on the users' cooperativeness. This approach provides a data-adaptive simulation, where real data can be filled on demand and suitable microscopic simulations are implemented.

## 2.4 Research Gaps

This chapter mainly presented approaches and tools for station-based VS Systems, especially for station-based BS Systems. The free-floating case of VS Systems is rarely covered by literature, relevant literature for BS Systems is not existent. Some analyses are applicable to the present case, namely a free-floating BS System - however, the **transferability is limited**. By dividing the free-floating operating area into zones, artificial bicycle docking stations can be created. Nevertheless, the systems' dynamics may differ highly.

Referring to the system design in section 2.2, the suggested prior station allocation ibidem is not suitable for the free-floating case. As there is only the operating area limitation without any stations, an initial FD cannot be orientated by static docking stations and needs further considerations. In addition, this is compounded by lacking knowledge of dynamics of free-floating BS Systems. Ergo an **empirical data analysis** is required.

Methods for demand estimations are scarce. They exclusively cover demand predictions on a station-based level. Demand patterns can vary and evolve if there are no spatial restrictions by docking stations. Further, the main approaches only take into account booking data, with no respect to *invisible demand*, i.e. potential **unfulfilled demand** in case of empty stations. Referring to a free-floating CS System, Niels and Bogenberger [90] investigated app requests of users in order to find the nearest available vehicle. The study revealed that a good spatial vehicle distribution is crucial for trip accomplishment. If the distance to the nearest vehicle is greater than 500 meters, the probability for a booking is significantly decreased. Within that, the unmet demand could be captured.

Existing demand predictions at BS System stations are mostly static and not time-dependent during one day. For a well-balanced fleet at all times, **demand patterns for shorter time periods** have to be predicted.

For RSs in general, various approaches can be found. The methods on station-based VS Systems are only partly applicable to the free-floating systems, as the vehicle routing comprises not only a finite set of stations but requires pick-ups and drop-offs within the entire operating area. For the free-floating case though, only studies of CS Systems exist. This gap is hard to overcome as the relocation process for automobiles is entirely different from that for bicycles: whereas the redistribution can be carried out for a multitude of bicycles within one single relocation route, all vehicles have to be moved separately in CS Systems. A specific **operator-based RS** tailored to the needs of a **free-floating BS System** is required.

The literature review listed some user-based RSs. Again, for the present free-floating case, the range is not comprehensive. Referring to CS Systems, such incentive strategies are not entirely transformable or applicable (for instance trip splitting and joining). Further, incentive patterns for BS Systems only exist at a station-level. The potential for **user-based relocations** may vary if applied to a **free-floating BS System** and therefore new **incentive approaches** have to be specifically designed. The return of a bicycle is not confined to a station, in consequence trip incentive schemes are even more challenging as the user's destination is unknown. Therefore a predictive approach is deployed in order to estimate the user's willingness for relocation trips.

# Chapter 3

# Empirical Data Analysis

In this chapter of the dissertation, booking data from the free-floating BS System *Call a Bike* in Munich are analyzed in detail. As a result, fleet imbalances are identified and in consequence, a need for bicycle relocations is proven.
First, the considered system and the available data set are introduced. Second, booking data are analyzed temporally and the impact of weather conditions is validated. Different time slots and day types which provide similar booking patterns are identified and defined. In a next step, a spatial data analysis is conducted by partitioning the operating area into zones. This makes it possible to identify highly attractive spots in the operating area from less popular ones.
Finally a spatial and temporal fleet evolution can be read out during different time periods at a zone level and builds the foundation for further steps regarding a potential fleet redistribution.

## 3.1 Description of the Data

This section provides information about the available data sets and presents the basic tools for filtering and exploitation of the data.

### 3.1.1 Booking data

The basis of this work is the booking data from the free-floating BS System *Call a Bike* in Munich (see also section 2.1.3). Within the files, following data for each trip have been recorded:

1. bicycle number
2. customer ID (anonymous)
3. start date and time of booking
4. end date and time of booking
5. start coordinates of booking (long./lat.)
6. end coordinates of booking (long./lat.)

In figure 3.1, an excerpt of the raw data is shown. The data set comprises the time period of the entire year 2014. The first entry is relevant to calculate the idle times at

| AUTO_ID | KUNDE_II | ANFANG | ENDE | KREUZUNG_X | KREUZUNG_Y | KREUZUNG | KREUZUNG |
|---|---|---|---|---|---|---|---|
| 116301 | xxx | 22.03.2014 16:57 | 22.03.2014 17:08 | 11,58222222 | 48,13555556 | 11,57211111 | 48,12872222 |
| 116445 | xxx | 22.03.2014 16:58 | 22.03.2014 17:11 | 11,54666667 | 48,14972222 | 11,57640052 | 48,15091559 |
| 120231 | xxx | 22.03.2014 16:59 | 22.03.2014 17:11 | 11,53583333 | 48,11944444 | 11,57222222 | 48,13527778 |
| 143694 | xxx | 22.03.2014 17:01 | 22.03.2014 17:20 | 11,56361111 | 48,14583333 | 11,56611111 | 48,15388889 |
| 120151 | xxx | 22.03.2014 17:01 | 22.03.2014 18:45 | 11,55899 | 48,16049 | 11,57777778 | 48,16972222 |
| 113492 | xxx | 22.03.2014 17:02 | 22.03.2014 17:07 | 11,56721955 | 48,13370924 | 11,55027778 | 48,11944444 |
| 120199 | xxx | 22.03.2014 17:03 | 22.03.2014 17:22 | 11,5725 | 48,12055556 | 11,57660269 | 48,12789178 |
| 120226 | xxx | 22.03.2014 17:06 | 22.03.2014 17:38 | 11,57269007 | 48,19486797 | 11,57583333 | 48,15777778 |
| 120608 | xxx | 22.03.2014 17:06 | 22.03.2014 17:18 | 11,575 | 48,13444444 | 11,57416667 | 48,13305556 |
| 119727 | xxx | 22.03.2014 17:08 | 22.03.2014 17:20 | 11,58 | 48,13222222 | 11,58444444 | 48,15722222 |
| 109354 | xxx | 22.03.2014 17:11 | 22.03.2014 17:44 | 11,59944444 | 48,15333333 | 11,57222222 | 48,11444444 |
| 120522 | xxx | 22.03.2014 17:15 | 22.03.2014 17:37 | 11,5918029 | 48,181907 | 11,575868 | 48,147708 |
| 120449 | xxx | 22.03.2014 17:15 | 22.03.2014 17:34 | 11,57533 | 48,19223 | 11,57711 | 48,19213 |
| 119172 | xxx | 22.03.2014 17:15 | 22.03.2014 17:30 | 11,570082 | 48,185552 | 11,581125 | 48,1588516 |
| 143788 | xxx | 22.03.2014 17:18 | 22.03.2014 17:21 | 11,57797032 | 48,142614 | 11,57166667 | 48,14388889 |
| 120686 | xxx | 22.03.2014 17:19 | 22.03.2014 21:47 | 11,5713995 | 48,1378035 | 11,576594 | 48,13549672 |

FIGURE 3.1: Excerpt from raw booking data 2014, processed by Excel

a vehicle level. For the initial data analysis, the exact time and location of every trip is crucial. The start and end locations respectively are provided by GPS coordinates. The GPS device on the bicycle does not track the entire trip, only the start and end position. Therefore it is hard to estimate the trip purpose, especially if it was a round trip for instance. In section 3.2, trip purposes are derived from trip durations and time. Further, time-depending booking patterns are identified.
In section 3.3, a spatial booking analysis is carried out, based on the start and end coordinates respectively.

### 3.1.2 Weather data

In general, the usage of Sharing Systems is very sensitive to weather conditions. This fact seems rather obvious, but a definition and distinction of certain weather conditions has to be made in order to find evidence. To investigate this impact on bicycle traffic, especially on the free-floating BS System in Munich, historical weather data from DWD (Deutscher Wetterdienst, German Weather Service, [36]) was evaluated in the relevant time period. This data set provides temperature, wind and precipitation in hourly intervals, measured in Munich's city center. These data are free and accessible on the referenced website.

## 3.2 Temporal Analysis

To get a first overview of the annual booking behavior, figure 3.2 illustrates the booking numbers for each day in the booking period of the year 2014, i.e. from March 17 to December 15, as well as a smoothed booking trend curve (dashed line).

At first sight, the booking behavior looks quite unsettled: there are many highs and lows, presumably caused by various weather conditions and public events.

The purple marks in figure 3.2 indicate good weather conditions: between May 20 and May 22, there was a first longer period of warm weather (more than 20° Celsius) and this is reflected in the booking numbers.

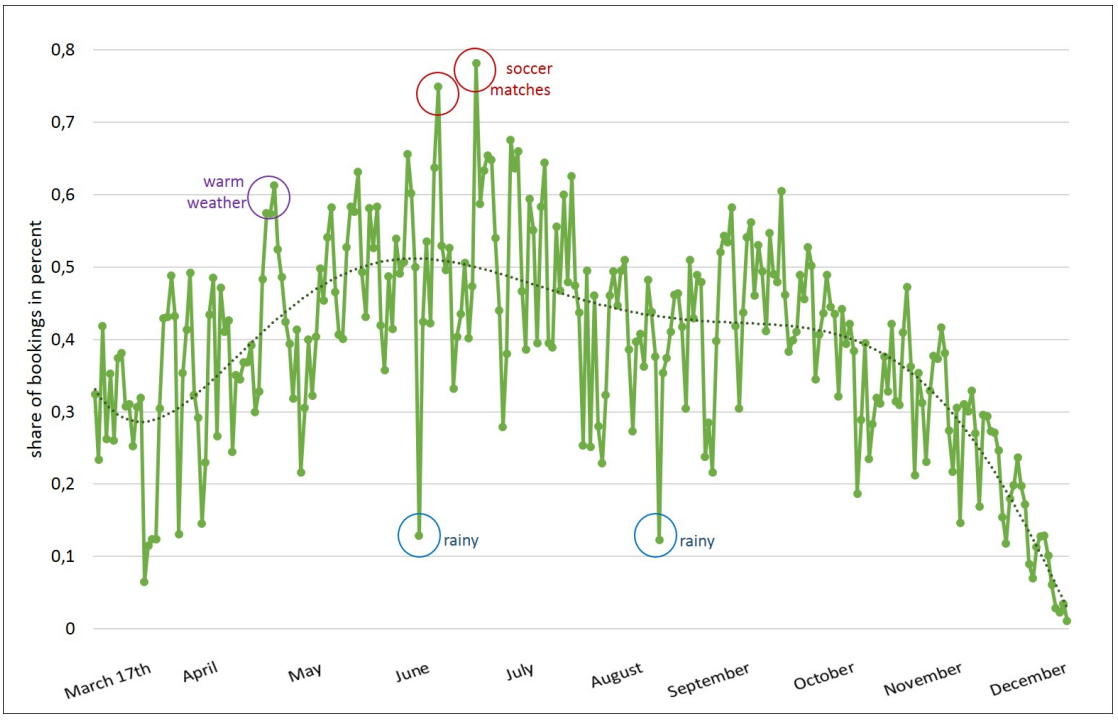


FIGURE 3.2: Booking behavior on a daily basis and according annual trend curve 2014

Drops in booking numbers are in most cases caused by precipitation, as indicated in blue in figure 3.2. On these two exemplary days, precipitation was prevailing during the entire day.

During the FIFA World Cup in the summer of 2014, there were many events for people to watch the soccer, for example at the Olympic stadium, leading to huge crowds and therefore heavy traffic before and after matches. Public transportation was temporarily overloaded, and so more people decided to use rental bicycles. This is most likely the case on the red marked days in figure 3.2, as the German team was playing then.

Taking a look at the dashed trend curve, booking numbers are highest and most stable in early summer months, whereas in spring and fall the booking level is significantly lower. Further details about correlations between bicycle usage and weather conditions are outlined in 3.2.3.

In summary, it can be stated that every outlier resulted from either good or bad weather conditions or public events, i.e. from *non-recurrent* incidents. The effects of *recurrent* incidents - daily traffic peaks for instance - are examined in the following section.

### 3.2.1 Detection of temporal differences in usage behavior

In order to analyze how much the booking numbers vary over the course of single days, trend curves have been plotted. Therefore all trips were filtered by specific days and counted per hour, to get the rental profile of the daytime course. Figure 3.3 illustrates the averaged trend over all individual days in 2014.

The most significant discrepancy in usage of the BS System was detected between weekdays and weekends/public holidays. The differences between individual weekdays are mostly marginal, as figure 3.3 illustrates: every weekday, there is a usage peak in the morning between 7 a.m. and 10 a.m. and in the late afternoon/evening between 5 p.m. and 8 p.m. The shape is similar, but on Thursdays and Fridays, the morning peak is lower whereas especially on Fridays, the afternoon peak starts earlier and the maximum share of trips between 6 p.m. and 7 p.m. is less than 8%, compared to around 9% on the other weekdays. Comparing Saturdays and Sundays, the trend shows many similarities, with one exception: after 11 p.m. on Saturdays, the booking numbers are rising again, whereas on Sundays, they are steadily decreasing. The reason for this is obvious: on Saturday night, more potential users are out compared

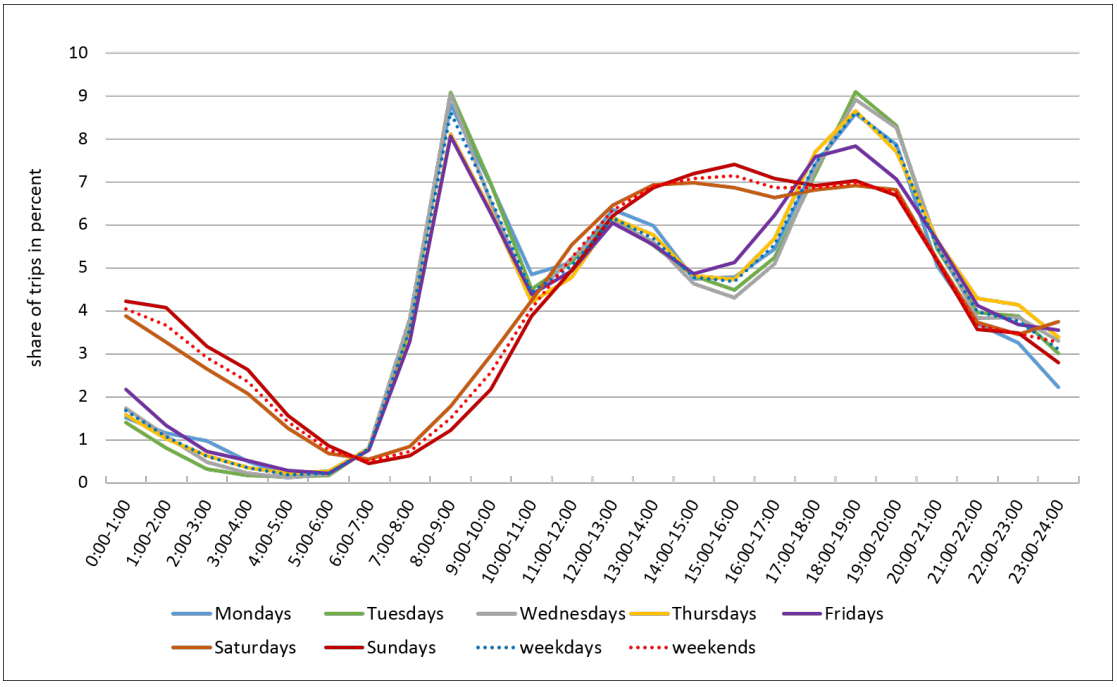


FIGURE 3.3: Rental profiles for all day types, based on average daily trip distributions in one-hour-intervals

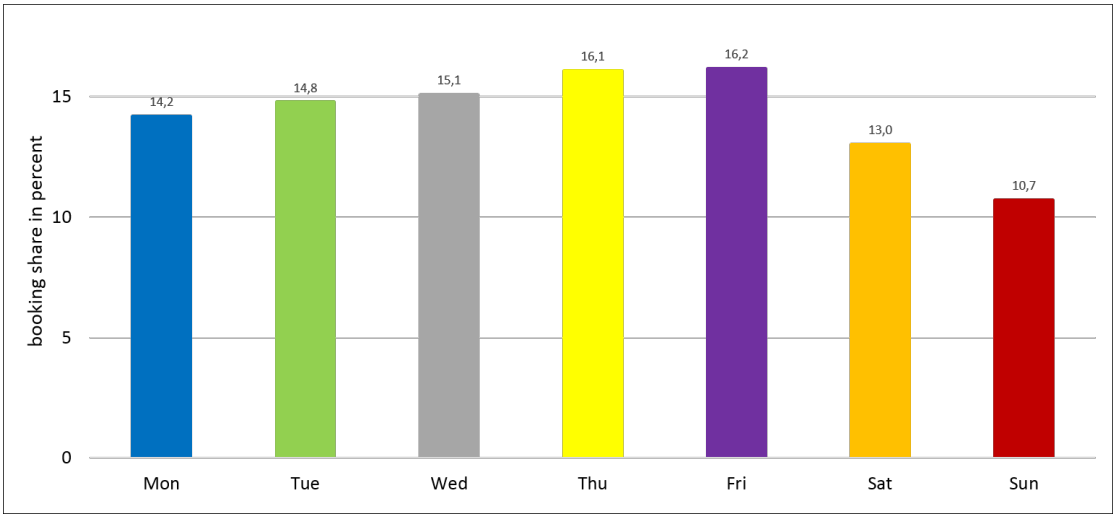


FIGURE 3.4: Number of bookings (percentage) aggregated by weekdays

to Sunday night, where the booking behavior and therefore the trend curve is more similar to the one on weekdays.

Figure 3.4 illustrates the overall booking share per day: the share on weekdays increases between Monday (14.2%) and Friday (16.2%), but together with the rental profiles in figure 3.3 it can be stated that the weekdays do not vary significantly. On weekends, as already indicated in figure 3.3, not only the daily patterns differ but also the overall booking share only comes to 13.0% on Saturdays and 10.7% on Sundays.
As a result of this, it can be stated that there is only a subtle difference between the individual weekdays and weekend days. Hence, the following analyses distinguish between weekdays (from Monday to Friday) and weekends (Saturday, Sunday and public holidays).

In figure 3.5, the average rental profiles for weekdays (Monday to Friday) and weekends (Saturday and Sunday) are depicted. The deviation between weekdays and weekends is significant: on weekdays (blue line), the total number of trips decreases from midnight till 6 a.m. In the next two hours the rise depicts the rush-hour traffic until 10 a.m. During afternoon there is only a marginal increase but the curve eventually reaches the top at 6 p.m., when most commuters are on their way home or off to leisure activities.
The trends on weekends show a completely different pattern (red line): it is much smoother without clear commuter peaks. The usage during midnight and 6 a.m. is significantly higher, mainly because of more people having a night out on weekends.

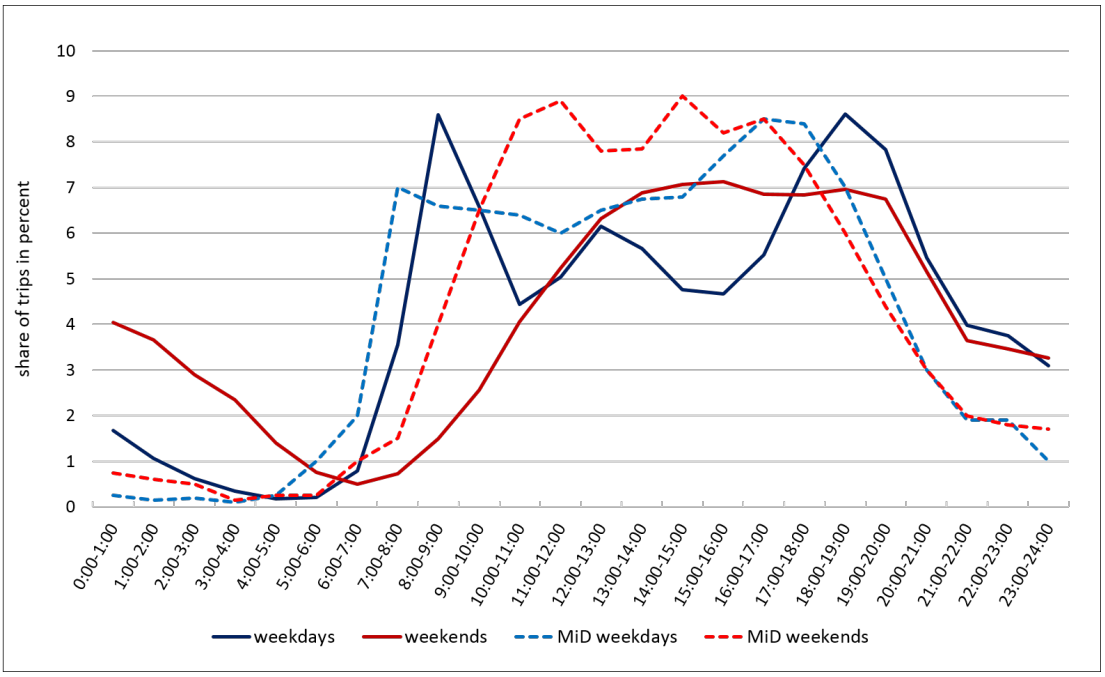


FIGURE 3.5: Rental profiles on weekdays and weekends, compared to MiD [44]

After 6 a.m. the bicycle usage increases constantly until late afternoon, when the usage decreases again.
The dashed lines in respective colors show the average number of trips for all traffic modes in Germany. This data arise from MiD (Mobilität in Deutschland [44]), a comprehensive study on traffic behavior in Germany carried out in 2008.
On weekdays, the BS traffic peaks around one hour later and significantly higher, whereas the overall traffic seems more stable in the afternoon. The evening peak starts again earlier and is already quite low when the BS evening peak is highest.
On weekends, the average traffic curve does reflect the BS usage patterns better, although main overall traffic occurs between 9 a.m. and 8 p.m., and the BS traffic is again shifted around two hours backwards.

These differences can be explained by a different user's mentality. Among other shared mobility services such as CS, similar results were found: Müller and Bogenberger investigated rental profiles for CS Systems in Munich and Berlin [79]. The resulting profiles for a CS System in Munich are plotted together with the BS rental profiles on weekdays (Monday to Friday) and on weekends (Saturday and Sunday) in figure 3.6.

There is one main difference, referring to the morning peak hour on weekdays: BS (blue line) peaks with a booking share of 8.5%, whereas booking numbers in CS (blue

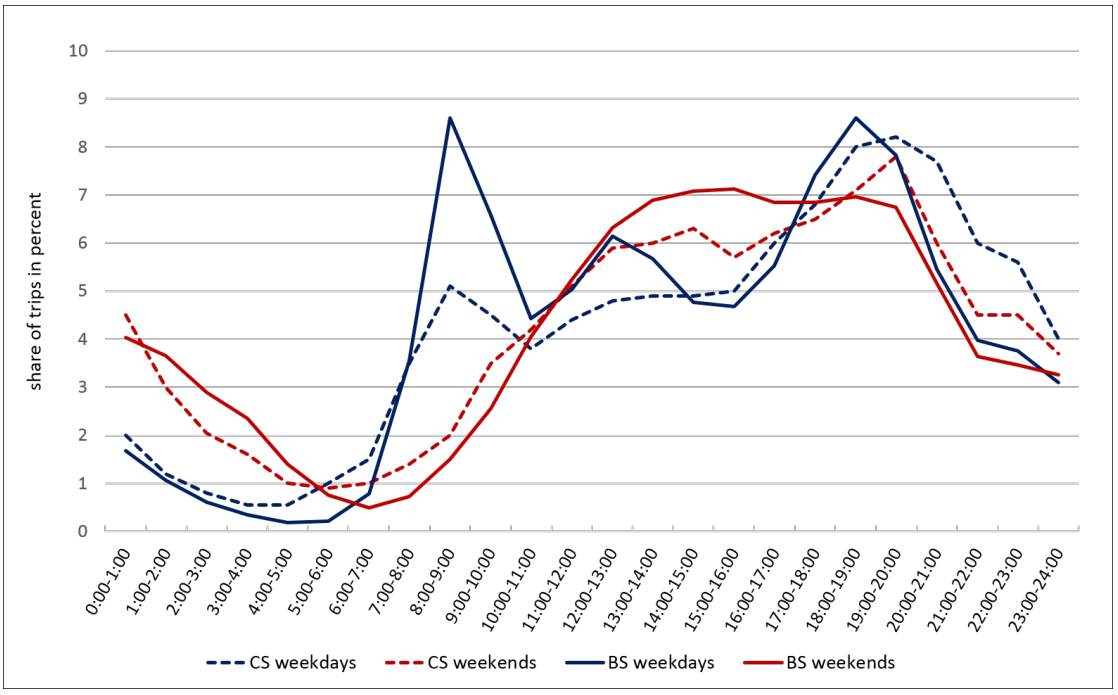


FIGURE 3.6: Rental profiles for BS and CS Systems in Munich on weekdays and weekends

dashed line) with around 5% are significantly lower. In remaining time intervals, the differences are rather marginal.

The authors stated in [79] that shared mobility usage differs from overall traffic and the usage peaks are temporally shifted. A major part of shared mobility trips are taken spontaneously and that might cause a shift to regular traffic options as well, as Kopp stated in [67]. According to figure 3.6, BS users seem to rent bicycles on a more regular basis during morning peak hours compared to CS users.

Further, Müller proved a correlation between bad weather and higher booking numbers in Munich's and Berlin's free-floating CS System in [78].
This sounds paradoxical at first: trend curves show similarities for CS and BS Systems compared to overall number of trips, but the reasons to use them are entirely different.

Unsurprisingly, section 3.2.3 reveals that almost no BS trips are made if it is rainy. In case of bad weather, the actual BS user might switch to the more convenient option of a shared car.

### 3.2.2 Definition of daily time intervals

For a detailed analysis on a daily basis, different time intervals are defined for each day. According to the rental profiles in the previous section, the following five time intervals are defined:

1. 00:00-06:00, the night time interval
2. 06:00-10:00, the morning time interval
3. 10:00-16:00, the afternoon time interval
4. 16:00-20:00, the evening time interval
5. 20:00-24:00, the late-night time interval

Note that these time slots are ranges between four and six hours, as based on the daily booking trends, this partition covers the usage patterns at best.
With this division, weekdays and weekends can be examined further. At first, the respective trip durations and booking shares per day and time slot were analyzed.

As illustrated in figure 3.7, there is a certain discrepancy between the average trip duration on weekdays (about 18 minutes) and weekends (about 29 minutes). This result

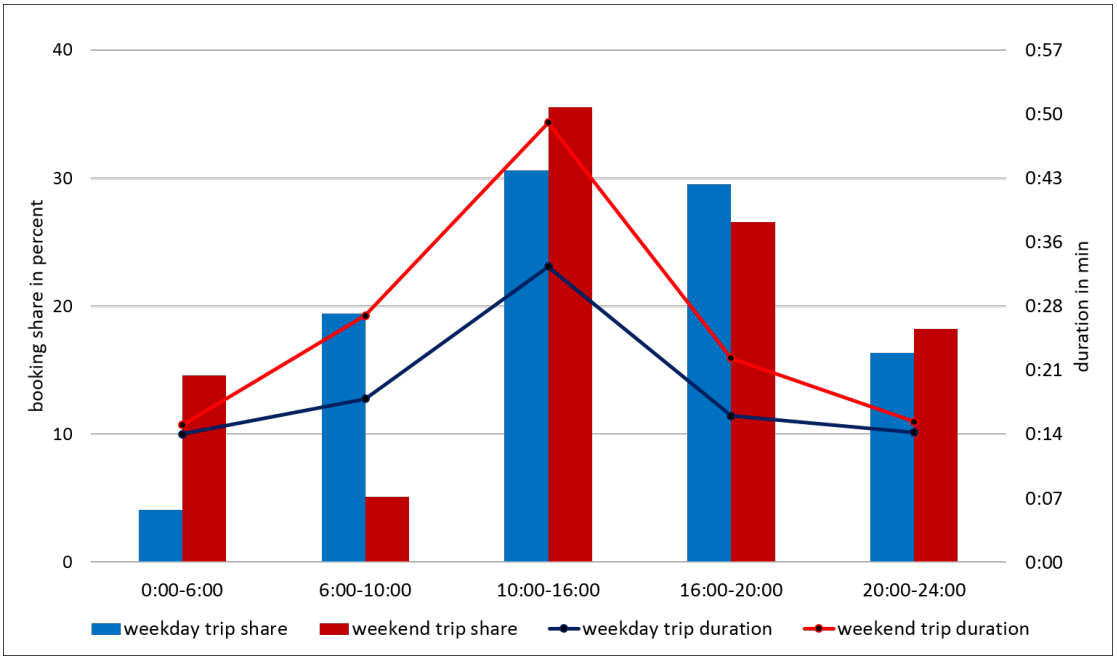


FIGURE 3.7: Comparison between average daily trip distribution and trip duration on weekdays (in blue) and on weekends (in red)

can be explained by more spare time trips on weekends, as there are day saver fares which are only economical if the bicycle usage exceeds 3 hours. For commuting trips and/or after work leisure trips it is more profitable to pay per minute as the total trip duration per day and user most likely does not exceed 3 hours.

On weekdays, the weakest time slot is between midnight and 6 a.m., with less than 5% of the trips. In comparison to that, most of the trips are made between 4 p.m. and 8 p.m. (scaled by booking share per hour), which can also be read out in the rental profile on weekdays. Assuming that most commuting trips are made between 6 a.m. and 10 a.m. and after 4 p.m., one can conclude that the trip duration is shorter when the user is riding to work/home. Instead, if the bicycle is used for a leisure trip, which is more likely to take place in the afternoon, the trip duration is longer.

The pattern entirely changes on weekends: in the first time slot, the trip share is about 10% higher compared to weekdays. This is mainly caused by home trips after a night out on weekends. The weakest trip share is between 6 a.m. and 10 a.m. with less than 5% of trips made in this time slot. Most trips take place in the afternoon between 10 a.m. and 4 p.m. Taking into account the trip durations, one can deduce: the longer the average trip duration, the more trips in this time slot are most likely day trips, i.e. recreational cycling tours. Hence, many trips in the time slot between 10 a.m. and 4 p.m might be day trips, where users get a rental bicycle for the entire day.

For the purpose of a better understanding of the frequency of certain trip durations,

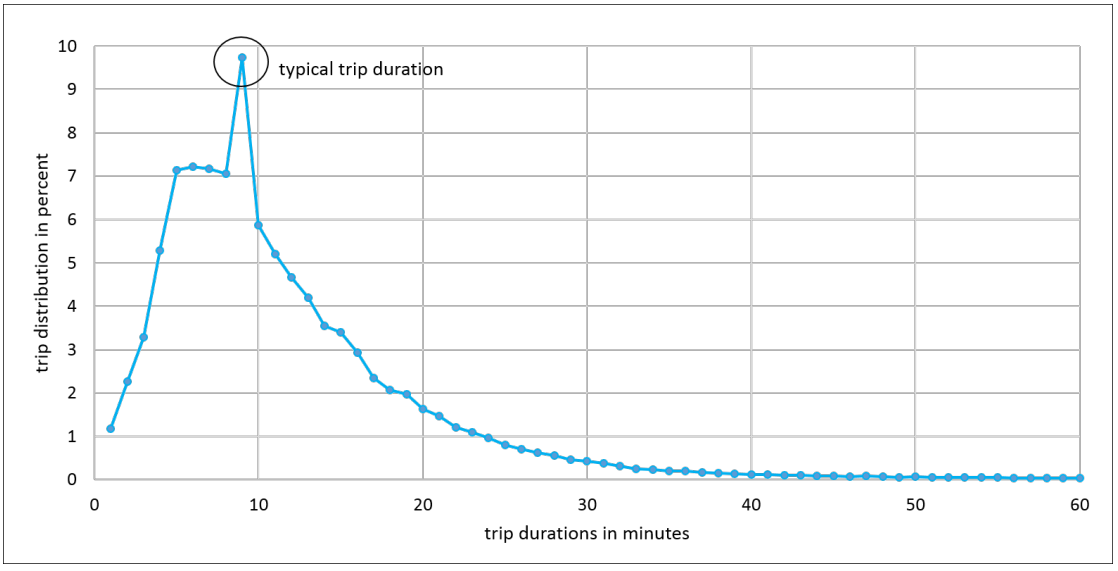


FIGURE 3.8: Frequencies of trip durations, taking into account all trip durations up to 60 minutes

the trip durations were clustered into one-minute-intervals. Taking a look at the according frequencies (in percent) of all trip durations up to 60 minutes, figure 3.8 reveals that almost 10% of these trips take between 8 and 9 minutes. This frequency is significantly higher compared to trips taking a little more/less time. A trip duration taking between 8 and 9 minutes is therefore considered to be the typical trip duration (as labeled in figure 3.8).
In this figure, all trips longer than 60 minutes are omitted: trip durations up to 48 hours were detected in the data set - the according occurrences are (relatively) little though. This is also visible in figure 3.8: trip durations of 40 minutes are almost on the same (low) trip distribution level as durations of 60 minutes. However, longer trips take place - for instance day trips as mentioned earlier - which cause higher overall trip durations depicted in figure 3.7.

### 3.2.3 Weather effects

At first, the data set was divided into 3 seasons by dividing the booking period from March 17 to December 15 into 3 equal time intervals:

1. Spring 2014: March 17 - June 16
2. Summer 2014: June 17 - September 16
3. Fall 2014: September 17 - December 15

During winter, the fleet is collected for maintenance as the BS System is not operating. Therefore the data set comprises only 3 seasons.

In [51] Gebhart and Noland examined the impact of weather conditions on bicycle trips for the BS System *Capital Bikeshare* in Washington D.C. They found that users still go by rental bicycle (albeit less) even if it is rainy, cold, hot or dark. This behaviour might be different for every single city and therefore an analysis with the booking data and an according weather data set was conducted.

The weather data base arises from the German Meteorological Service as already described in section 3.1.2. This data set provides hourly measured data for Munich, i.e.

precipitation, sunshine and temperature, online for free [36]. By filtering the trip data in hourly intervals as well, it is possible to read out correlations directly.

At first, the terms fair and bad weather have to be defined, as there is no universal definition. A reasonable approach is given by Müller (see [78]):
in spring and fall, the weather in one time interval is called fair weather if the temperature is warmer than 5° Celsius and if there is less than 0.5 mm precipitation. In summer, the temperature threshold is increased, i.e. a higher temperature than 15° Celsius and less than 0.5 mm precipitation is called a fair weather interval. If there is either more precipitation or the temperature is lower than the fixed temperature threshold for spring, fall and summer respectively, it is called a bad weather interval. Excluding the night hours between 12 midnight and 6 a.m., a day of the year 2014 is defined as a fair weather day if it was warmer than 5° C (15° C respectively, depending on the season) and if there was less precipitation than 0.5 mm in two consecutive hours. Otherwise it is denoted as a bad weather day. Referring to this scheme, the weather in the year 2014 was distributed as follows: in spring, this classification leads to 74 fair weather days and 18 bad weather days. In summer, weather conditions are uniformly distributed, i.e. there were 49 fair weather days and 43 bad weather days. In fall, the fair weather days were predominant, with 57 days compared to 33 bad weather days.

In order to compare the fair and bad weather days to the according booking behavior, days with high booking numbers were defined as follows: if the overall booking share per day in spring and fall was higher than 0.3 (0.4 in summer respectively), the regarded day was a day with relatively high booking numbers, otherwise low booking numbers accordingly.
On the season-level, this correlation has the highest variance of 18 days in spring. This is caused by predominantly fair weather in spring and (yet) low booking numbers. In summer and fall this correlation is higher with few non-matching days: four in summer and six in fall. The overall correlation for the entire operating period is illustrated in figure 3.9. On more than 70% of the days in the operating period 2014, high booking numbers were observed in fair weather conditions or low booking numbers were observed in bad weather conditions. The remaining cases (around 30%) do not show a correlation, whereas the case of low bookings despite good weather conditions is predominant with 18%. This fact implies that the case of high booking numbers in times of bad weather is indeed very rare (11%).

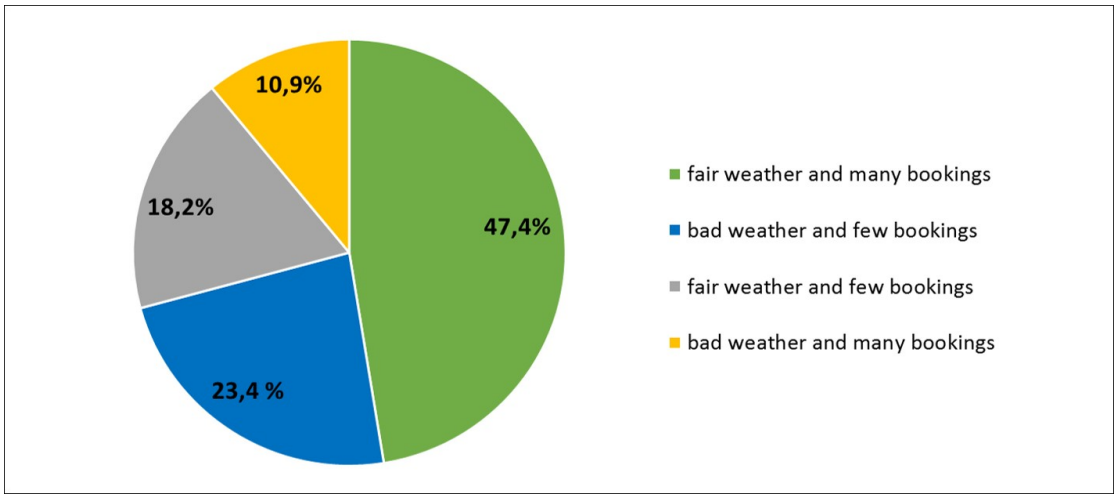


FIGURE 3.9: Correlation of weather conditions and booking numbers in 2014

This classification is quite coarse and only serves as a first overview of weather impacts on the usage of the BS System in Munich. For the purpose of a detailed weather analysis, daily usage patterns are examined on an hourly basis as follows.

Figure 3.10 shows the annual trend curve of bookings on a daily basis, as well as the corresponding weather conditions, i.e. temperature and precipitation. At first sight, the temperature (orange curve) seems to correlate with the actual booking numbers

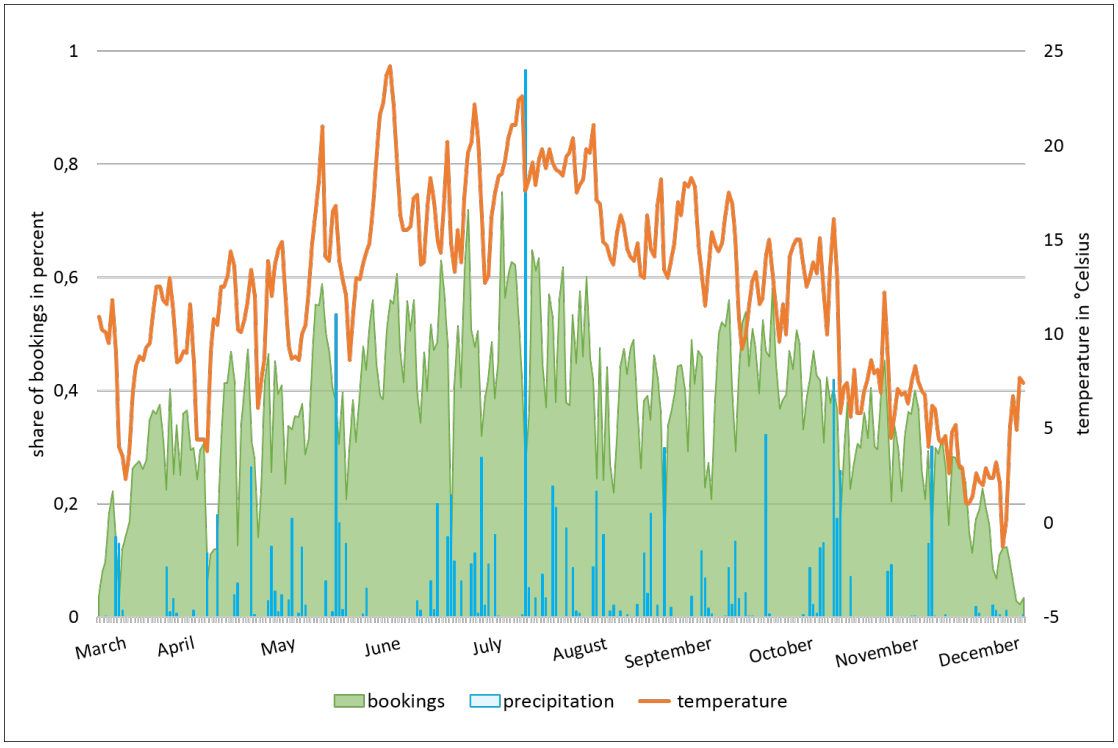


FIGURE 3.10: Annual trend of bookings on a daily basis vs. weather conditions in 2014

(green surface). Comparing the daily precipitation (blue bars) to the bookings, a direct correlation can be read out, for instance in mid/end of July, when the precipitation is highest in 2014 and the booking numbers drop in synchronism.

To get a more detailed analysis of the short-term weather impact on shared bicycle trips, the following methodology has been chosen.
All trips were investigated by month and filtered between weekdays and weekends. In figures 3.11 to 3.13 the relationship between the diverse measures is investigated for one entire week from Monday to Sunday: the average trip chart per day type i.e. weekday or weekend (blue dotted line) and the actual trips for one single considered day, i.e. the booking share per hour (depicted in the green surface). To read out the direct influence of precipitation, the hourly rainfall got embedded into the plot (blue bars).

Figure 3.11 shows these four measures for one week in June 2014 from Monday to Sunday. A direct impact of precipitation on booking numbers can be read out not only on weekends (in this case Sunday), but also on weekdays, as observed on Tuesdays: the precipitation at night/in the early morning leads to a sharp decline in booking numbers. Although it already stopped raining, the lack of bookings lasts for hours and the average bookings are only achieved for the evening peak again. The subsequent Sunday is rainy until late afternoon and the booking numbers do not seem to recover the

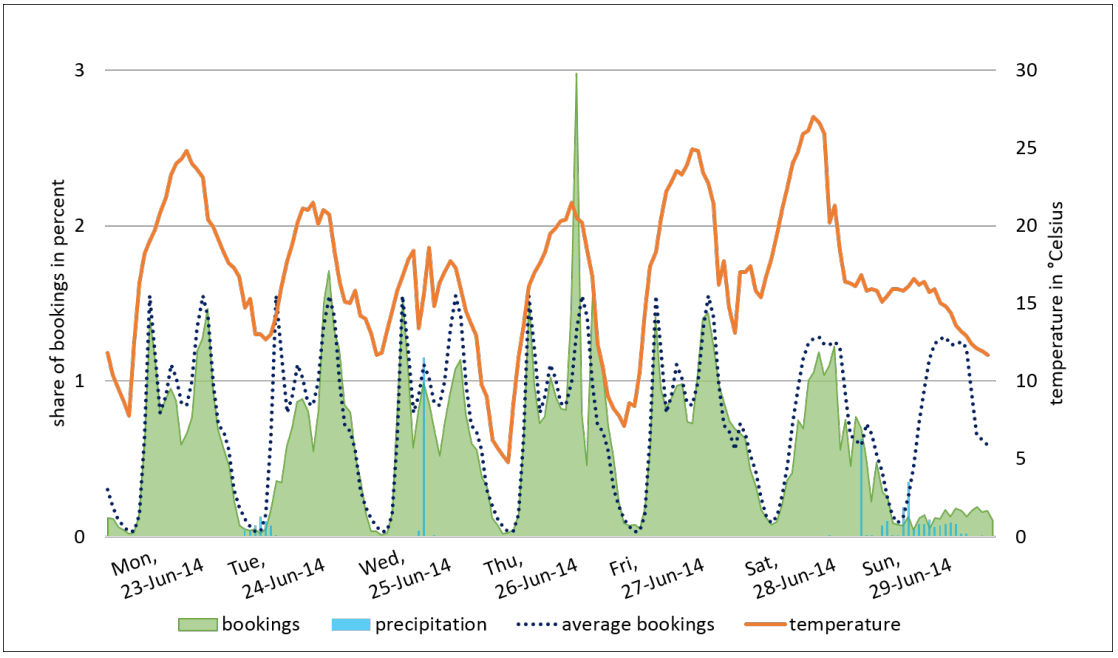


FIGURE 3.11: Booking numbers vs. weather conditions during one week of June 2014

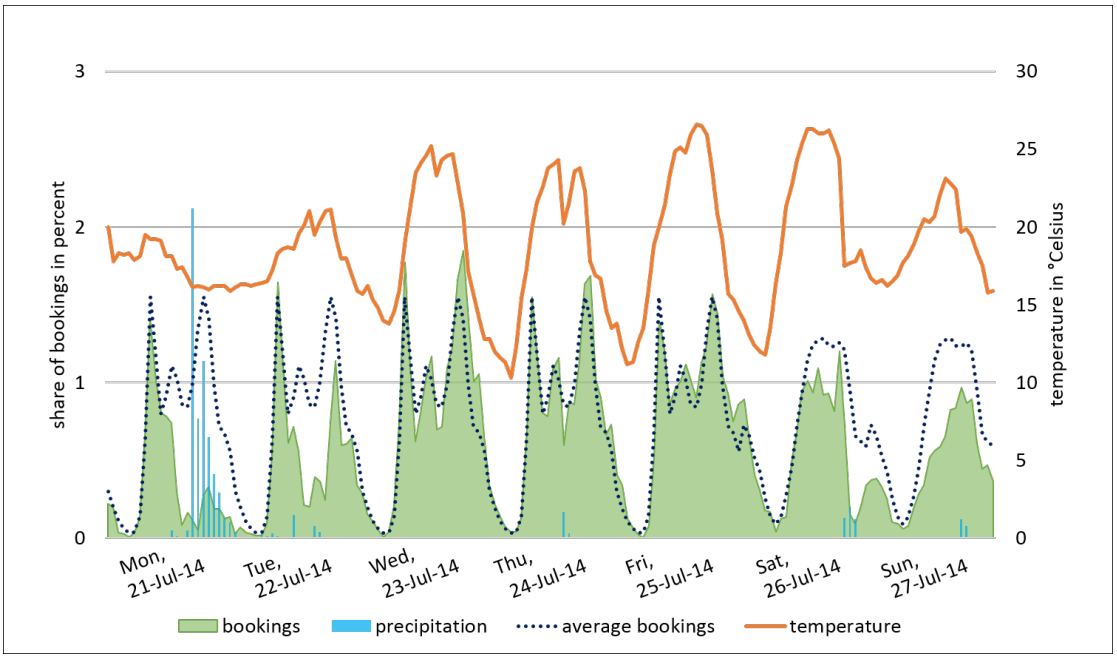


FIGURE 3.12: Booking numbers vs. weather conditions during one week of July 2014

whole day. A reason for this might be that people are more suspicious of the weather if it rained shortly before and are more likely to go by public transport for instance to avoid potential showers on the bicycle.

This effect for weekdays is even sharper in figure 3.12, considering a week in July. On Monday, the booking numbers are heavily diminished apparently by rainfalls. On the next day, there is less precipitation, which still leads to a decrease of BS trips - at least the booking level almost recovers until the evening peak. In case of only a short time of precipitation as on Thursday, July 24th, booking numbers are not that much affected as the average booking share level is covered. The subsequent weekend also illustrates the direct impact of precipitation on BS trips: on both days moderate rainfalls lead to a significant drop in booking numbers.

Further, the examples show that temperature by itself does not influence the booking behavior as much as precipitation does: figure 3.13 illustrates the trip numbers in one week of late October, without any precipitation at all. Despite the temperatures ranging between 5 and 17° Celsius during day time, the booking numbers are stable, i.e. they are congruent to their daily average.

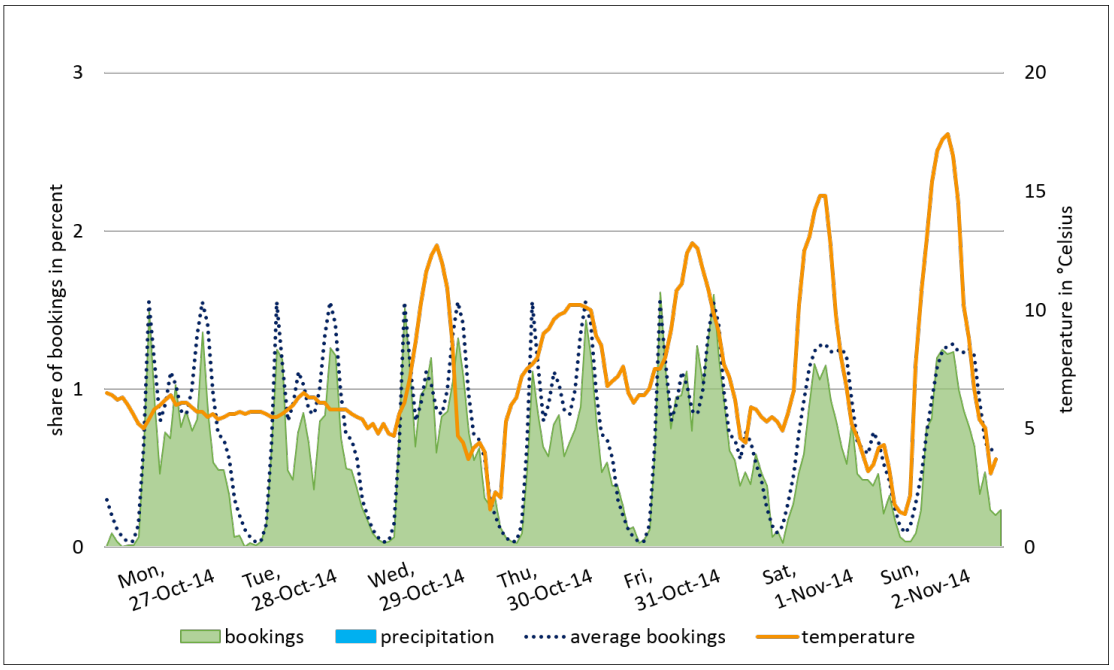


FIGURE 3.13: Booking numbers vs. weather conditions during one week of October 2014

In summary it can be stated that especially precipitation has a significant impact on BS System's usage and not only in a short-term sense. After a rainfall, the bicycle trip numbers reach the average level only after three hours (on average). Temperature by itself (too high or low) does not prevent most users from taking a rental bicycle.

For the operating period in 2013, a qualitative weather correlation analysis was carried out as well, (see also [102]). The main results remain the same: heavy rain stems the systems' usage, whereas other weather conditions like wind and temperature do not feature a high impact on booking numbers.

## 3.3 Spatial and Temporal Analysis

Spatial distribution of rentals and returns within the operating area are another important factor examined. Compared to a conventional station-based BS System, the distribution of the fleet is much more complex in a free-floating system like this. Especially when it comes to relocation trips, the fact that the fleet is spread not only at over a set number of stations complicates this process.

The top part of figure 3.14 gives a (schematic) overview of rentals and returns. It already indicates opposed fleet movements in the morning and evening: between 6 a.m. and

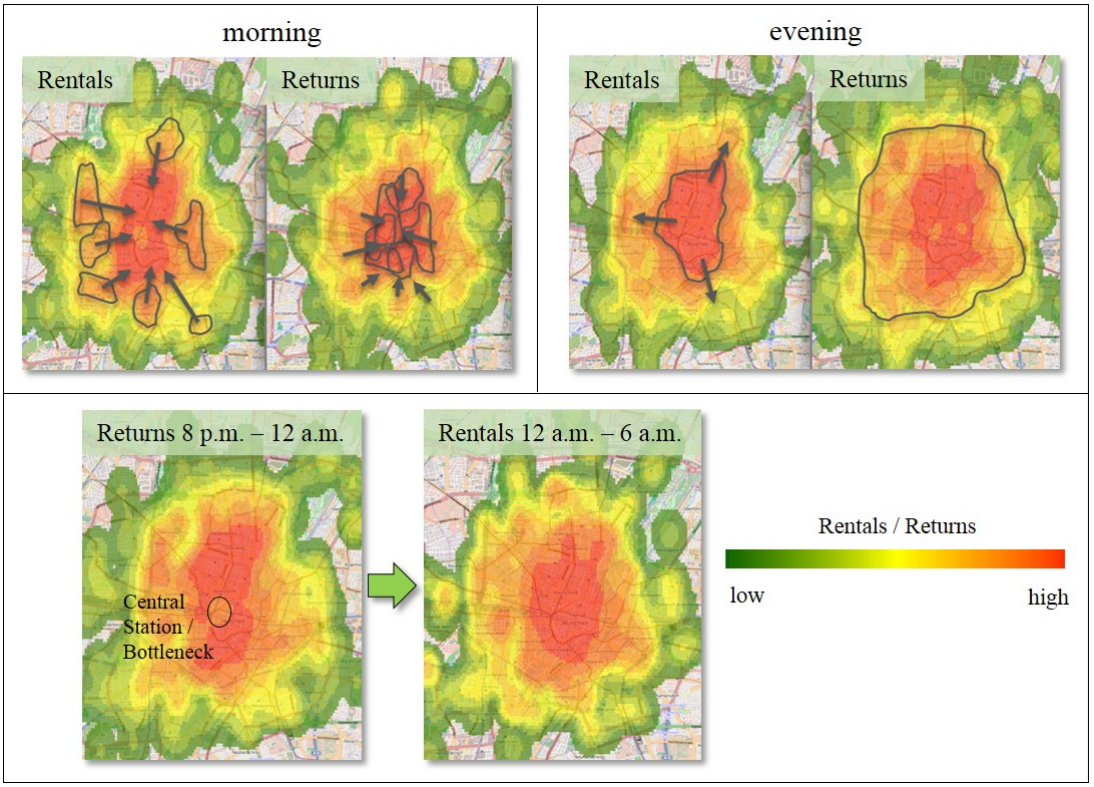


FIGURE 3.14: Differences between rental and return patterns in different day times (top) and returns vs. subsequent rentals (bottom)

10 a.m. the fleet moves from outside to inside, meaning that most users start their trip from their home, which is most likely located in residential areas, i.e. more towards the city boundary. The end of trips, however, is quite likely more central, as many offices are spread around the city center. In the afternoon, an opposed process begins: most users are around the city center and hence the fleet moves reversely, i.e. from a compact pattern to a broader spread around the operating area.

For an initial check, the returns were compared to the subsequent rentals, as illustrated in the bottom part of figure 3.14. This example shows a possible lack of bicycles near the central station, because only a few bicycles get returned there. In the next time slice, potential users might want to rent a bicycle there. At first sight, the fleet seems to self-regulate during one day, but taking a closer look, some bottlenecks in some areas will rise at a certain time.

To analyze this spatial and temporal behavior of the fleet in detail, the operating area is divided in disjoint zones in the following section. These zones can be seen as fictitious stations, which makes the method comparable to conventional, station-based BS Systems.

### 3.3.1 Definition of zones

At first, all booking starts and ends were plotted with ArcGIS 10.2 Advanced Desktop [40] to get an overview of the fleet movements in general. To yield a more detailed analysis, the operating area was divided in disjoint zones by the following methodology, based on a similar approach using ArcGIS by Weikl (see [134]).

The booking starts of four weeks are imported into ArcGIS to represent the main locations where bicycles get rented by users. These positions are illustrated on the top left in figure 3.15. The idea is to find a set number of artificial stations in order to define several disjoint zones within the operating area. To minimize the total travel time of all customers, i.e. the walking time to reach a bicycle, a street network based on *OpenStreetMap* is generated.

The initial problem needs facility suggestions and therefore a so-called fishnet is created within the operating area, as depicted on the top right in figure 3.15. A fishnet is a grid containing rectangular cells with a selected edge length which is set to 500 meters in the present case. This edge length corresponds to the maximal distance a potential user is willing to walk to the nearest bicycle. There are different studies concerning the accepted walking distance for different walking groups. Seign and Bogenberger stated in [111] that the maximal distance which a free-floating CS user is willing to walk to the next vehicle is 500 meters. In a more recent study concerning such a CS System in Munich [90], Niels and Bogenberger stated a walkability threshold of only 200 meters. For the nearest public transit station, Walker [130] sets this distance to 400 meters (for North America) with a remark that the willingness to walk in Europe is higher and this distance might be longer there.

Following this, the facility location problem - i.e. finding the optimal placement of facilities to minimize transportation costs (see [31]), is solved with the help of a *location-allocation analysis* which can be found in the toolbox *network analyst* in ArcGIS [42]. Within this tool, solving the *p-median problem* finds optimum locations of $p$ facilities such that the sum of the (weighted) distance between each demand location and the nearest facility is minimized. The operating area should be divided into an appropriate amount of zones. Various trials have figured out that the amount of 40 zones is

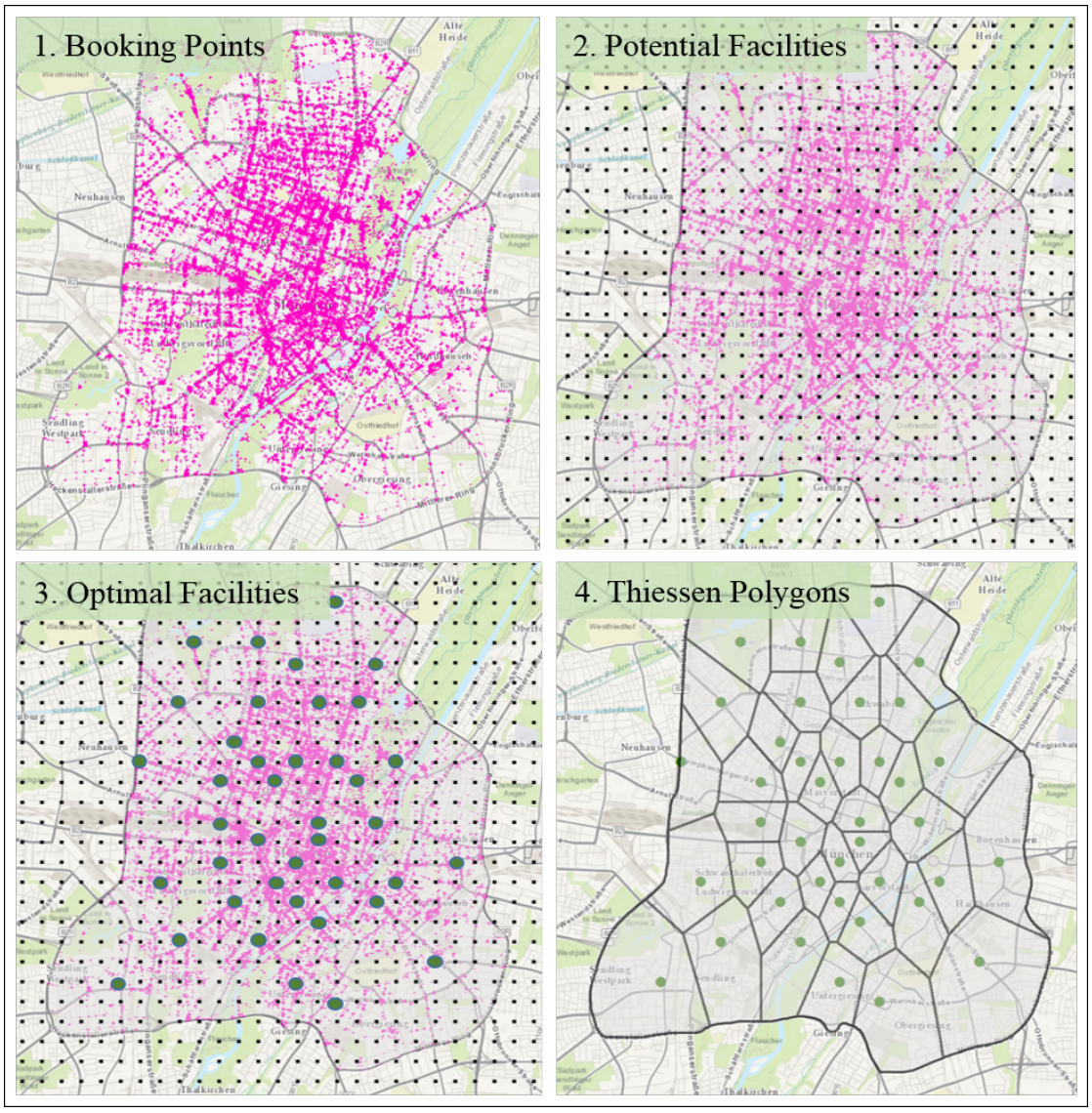


FIGURE 3.15: Dividing the operating area in 40 zones in four steps

most reasonable: fewer zones would make the division too coarse and nuanced information would be lost. In case of many more zones, some areas turn out very small and zones with same properties cluster next to each other anyway. Ergo, the number of optimum locations is set to 40. ArcGIS then finds the 40 most appropriate points of the fishnet, see on the bottom left in figure 3.15, from where every bicycle is reached the fastest way (i.e. the sum of all travel times to reach every bicycle from this 40 points is minimal).

By solving the empty container problem (see Daganzo [31]), these 40 facilities are the base grid of the resulting zones of the operating area, i.e. are their respective centers. The zones are defined by the so-called Thiessen Polygons which have the intrinsic

feature that every location within one polygon is closer to its center than to any of the other polygons' center [41]. These polygons yield the required 40 disjoint zones of the operating area, as illustrated on the bottom right in figure 3.15.

The division of the operating area is the basis for the spatial analysis. In the following section, the different usage behavior per zone is extracted and analyzed.

### 3.3.2 Usage patterns at a zone level

On the basis of dividing the operating area into 40 zones, the spatial and temporal behavior of the fleet can be investigated in more detail. In order to do so, the rentals and returns per zone are examined for every day, for every time slot (as defined in section 3.2) separately.

The following figures 3.16 to 3.19 illustrate the spatial (i.e. in all zones) rental and returning behavior for different time slots. The brightness of the color indicates the level of rentals and returns respectively. Ergo: the darker the green, the more bicycles have been rented or returned in a respective zone. The rentals are plotted in the first row and the returns in the second. Note that the colors in each plot only represent the percentage of bookings per zone in relation to the according time slot. A comparison to other time slots is thus not possible. On the one hand, the confidentiality agreement does not allow showing of absolute trip numbers and, on the other hand, each time slot features every coloring, i.e. if there were only a few trips per se, the plot still shows zones with relatively high bookings in dark green.

Figure 3.16 represents the rental and returning behavior for all weekdays from Monday to Friday: in the fist time slot from midnight to 6 a.m. most rentals occur in the city center and spread a bit up north, moderate rentals are found westerly. In the southeastern part, almost no rentals occur. Regarding the returns for this time slot, the pattern changes entirely: in the city center, almost no returns occur as well as in the southeastern edge of the operating area.

The second time slot from 6 a.m to 10 a.m features no rentals in the city center at all and neither in most fringe areas. Most rentals are prevalent in a few zones up north, a moderate renting behavior is detected in the southwestern part of the operating area. Referring to the contemporaneous returns, the city center is covered well and only

northern and southern parts do not receive any returns of bicycles. The rental pattern here is exactly the same as the return pattern, which is an interesting observation.

Moving to the following time slot from 4 p.m. to 8 p.m., the rental pattern changes only slightly. The returning behavior shows more returns in the southwestern and eastern part though.

The last time slot from 8 p.m. until midnight features moderate rentals in the main parts of the operating area, apart from a few high rental zones up north and low rental zones in the most fringe areas. Referring to the returns, the zones in the city center as well as some fringe areas get lighter, whereas the eastern and southern parts get darker, i.e. there are relatively more returns at that time.

For a comparison, the same analyses have been conducted for each single day. The results for all Wednesdays in the operating period 2014 are depicted in figure 3.17. The only slight differences are visible in the first time slot. Apart from that, the results are the same and a distinction between single weekdays is not significant. Therefore it is sufficient to consider the overall weekdays result in the following analyses and to denote them as *weekdays*.

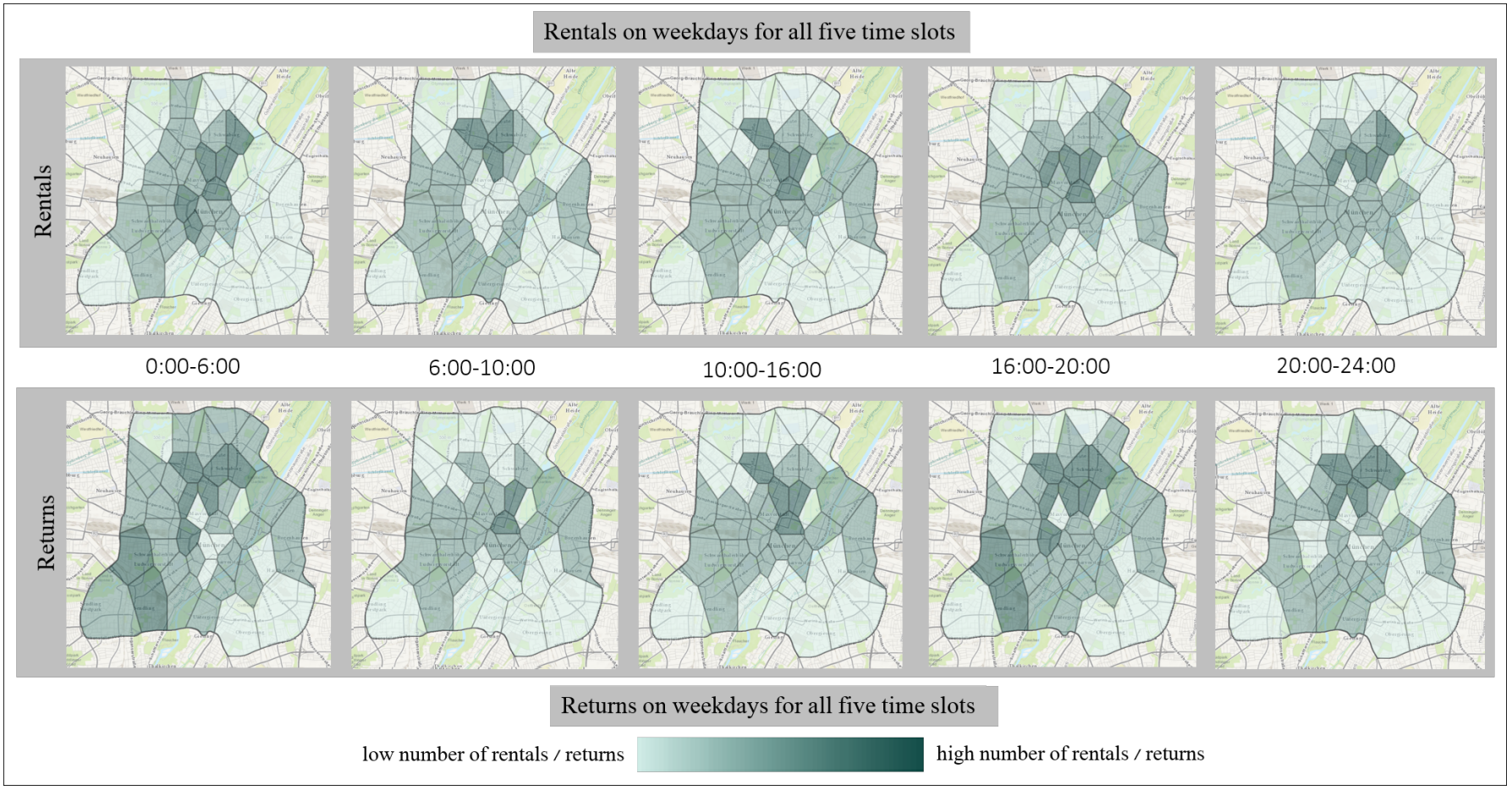


FIGURE 3.16: Spatial analysis for all weekdays in 2014

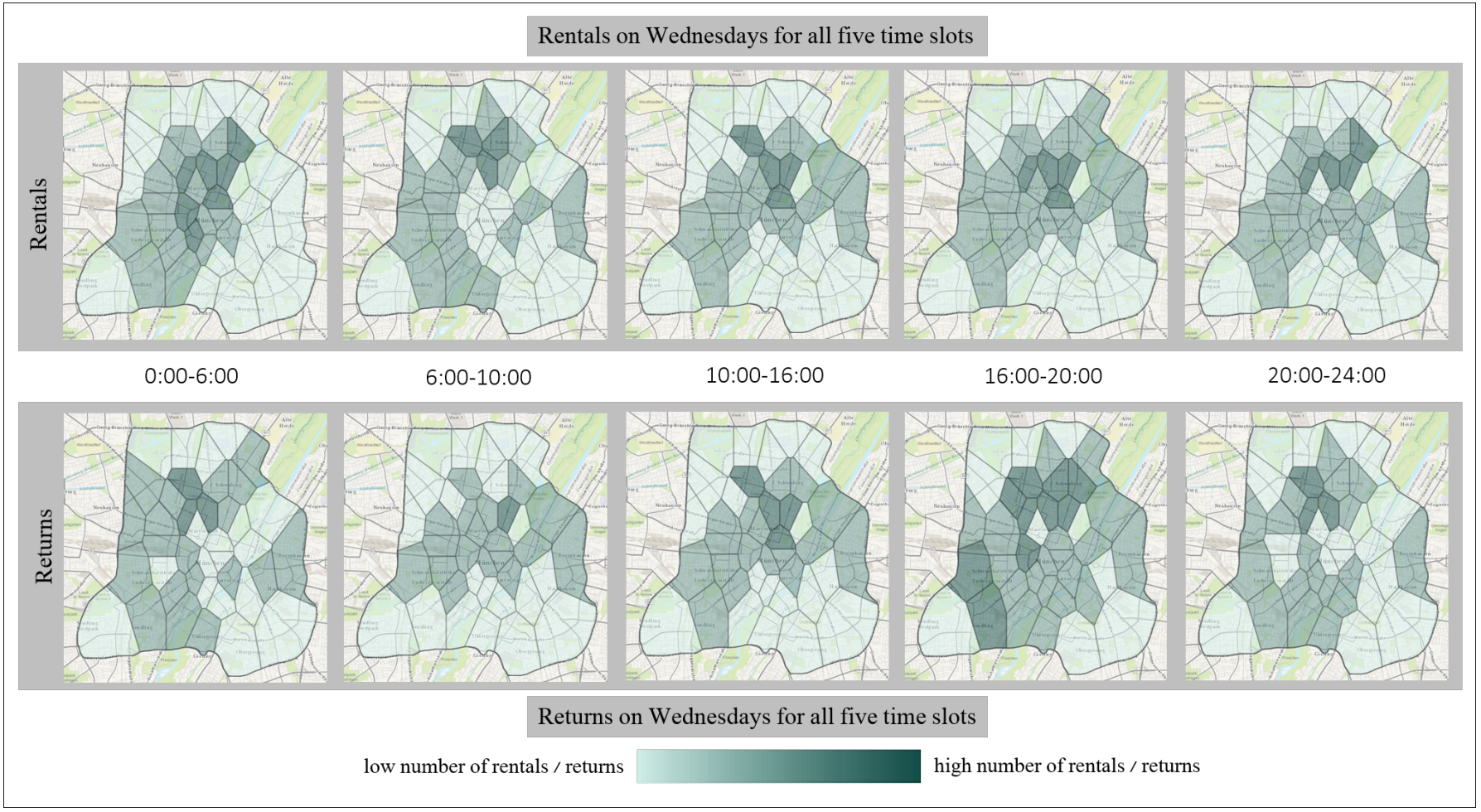


FIGURE 3.17: Spatial analysis for all Wednesdays in 2014

Figure 3.18 shows the rental and returning behavior for weekends, i.e. for all Saturdays, Sundays and public holidays in the operating period 2014 on average. In the first time slot, the zones with high rental numbers are rare and in the city center. A few more moderate zones can be found in the center as well and in the southwestern part of the operating area. The remaining zones - the major part - feature only low rentals. Concerning the returns, high return numbers are more spread across the operating area and the low return zones are not so extensive.

In the next time slot from 6 a.m to 10 a.m., the rentals in the northern city center as well as in the western part of the operating area are high. In the southeastern part, not only the rentals are low, but also the contemporaneous returns in this area are marginal. Additionally, the returns in the fringe areas are low, too. The city center and western part shows moderate/high return numbers though.

Between 10 a.m. and 4 p.m. the rental and return patterns are quite similar: low rentals and returns can be found in the same zones in the northwestern and southeastern fringe areas. The remaining zones have moderate and high rentals and returns, whereas the returns are shifted a bit to the south, compared to the high rentals in that time slot.

From 4 p.m. to 8 p.m. both the rental and returning behavior is quite resembling: the same low booking areas can be detected as in the previous time slot and there are a few more zones with high rental and returning behavior. A difference can be found in two zones in the city center, where more bicycles get rented than returned.

The last time slot from 8 p.m. to midnight shows high rentals in the southwestern and northern part of the operating area. Almost the entire fringe area features low rentals and the remaining, the zones in the center and northwest, have moderate rentals. Referring to the returns in that time slot, they are a bit more spread and the sparse fringe area has a few more moderate return zones, too.

In figure 3.19 the same analysis for only Saturdays is illustrated. The results are almost the same with one marginal difference though: taking a look at the time slot between 8 p.m. and midnight, there is only one zone on Saturdays that features high rentals and high returns. Compared to the averaged weekend plots, this property is shown by many more zones.

The difference in this time slot is easy to explain: the booking behavior on Sunday evening is more similar to an evening during the week in terms of leisure time activities, as most people have to work on Monday again and thus the weekend is over. The same argument applies to Friday (and all days before public holidays) night, which time slot is rather a weekend time slot.

Besides these exceptions, the rental and return patterns can be consolidated to the two day types, namely *weekdays* and *weekends*, and the five time slots. The single outlier evening time slots are added to the respective other day type, i.e. Friday from 8 p.m. to midnight is defined as weekend time slot (although Friday is a weekday by definition) and Sunday evening vice versa.

Finally, a spatial evaluation of the weather impact was carried out. For this purpose, the trip distribution at a zone level was compared between different weather conditions, namely average, fair and bad weather. As no specific pattern could be detected, the weather impact on shared bicycle trips has no spatial dependency, i.e. if trip numbers drop in case of bad weather conditions, this happens uniformly distributed within the entire operating area. Besides that, spatial rental and return patterns were evaluated for each season in 2014 separately for singular weekdays. The respective patterns in spring, summer and fall for all Wednesdays (exemplarily) are are attached to Appendix A.

In summary of the spatial analysis, it can be stated that the usage behavior changes not only during single days, but also depending on the day type. Whereas during a week, the same booking behavior applies for each single day, the patterns differ on weekends but are again similar for this day type. Within one day type, a clear usage pattern is detected for each time slot in the 40 different zones of the operating area. Comparing previous return patterns with the following rental patterns, the needed bicycles might have been returned in other areas than where they are actually demanded. These analyses only show the rental and return pattern of real bookings, i.e. it is not clear if a lack of bicycles occurred at a certain time and place. But this is highly likely to be the case, as the rentals do not match the previous returns, and therefore these dynamics lead to a skewness of the fleet. This fact will be discussed further in chapter 5, where the *real* demand is estimated, which obviously cannot be directly derived from the booking data only.

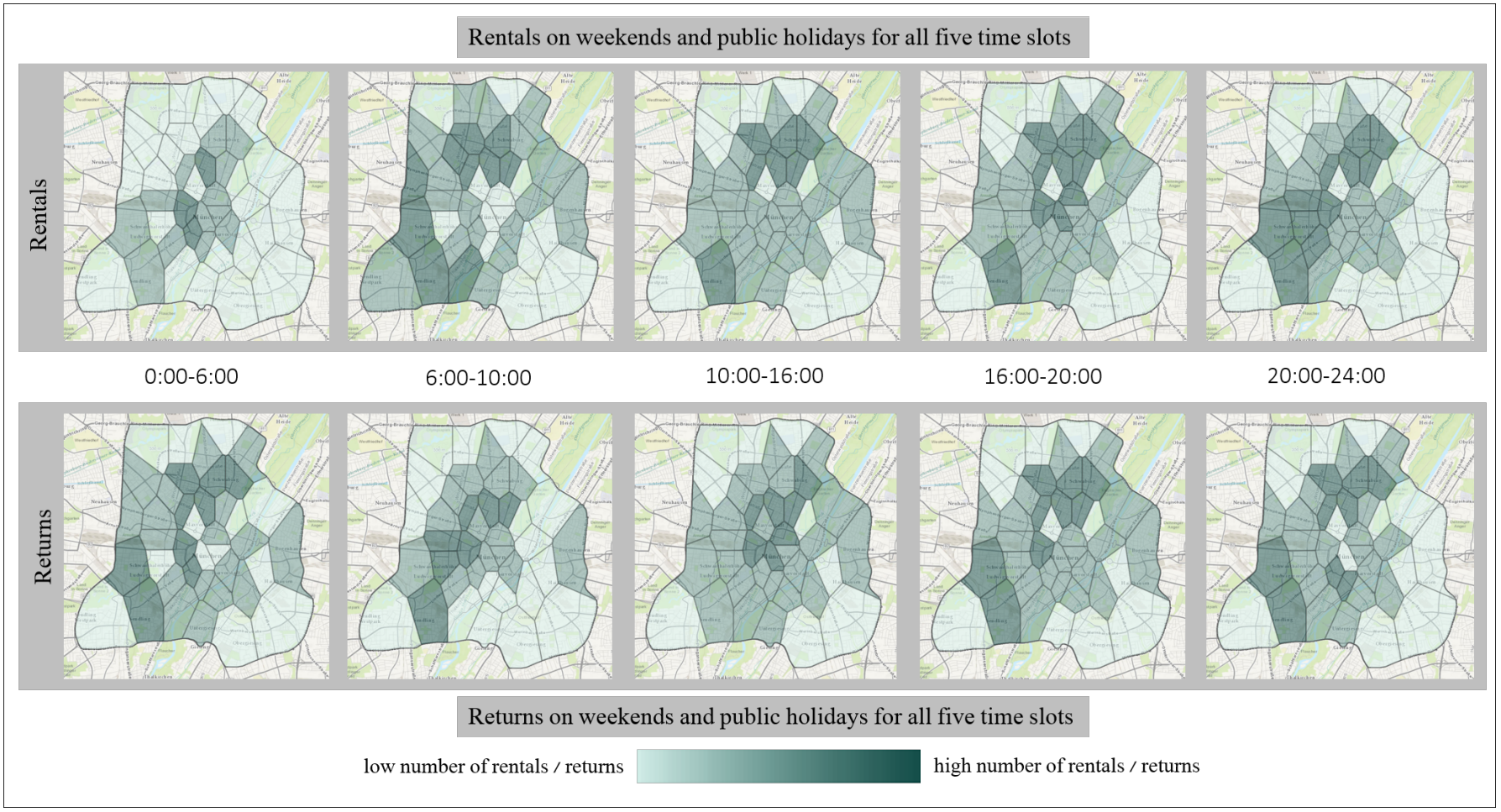


FIGURE 3.18: Spatial analysis for all weekends and public holidays in 2014

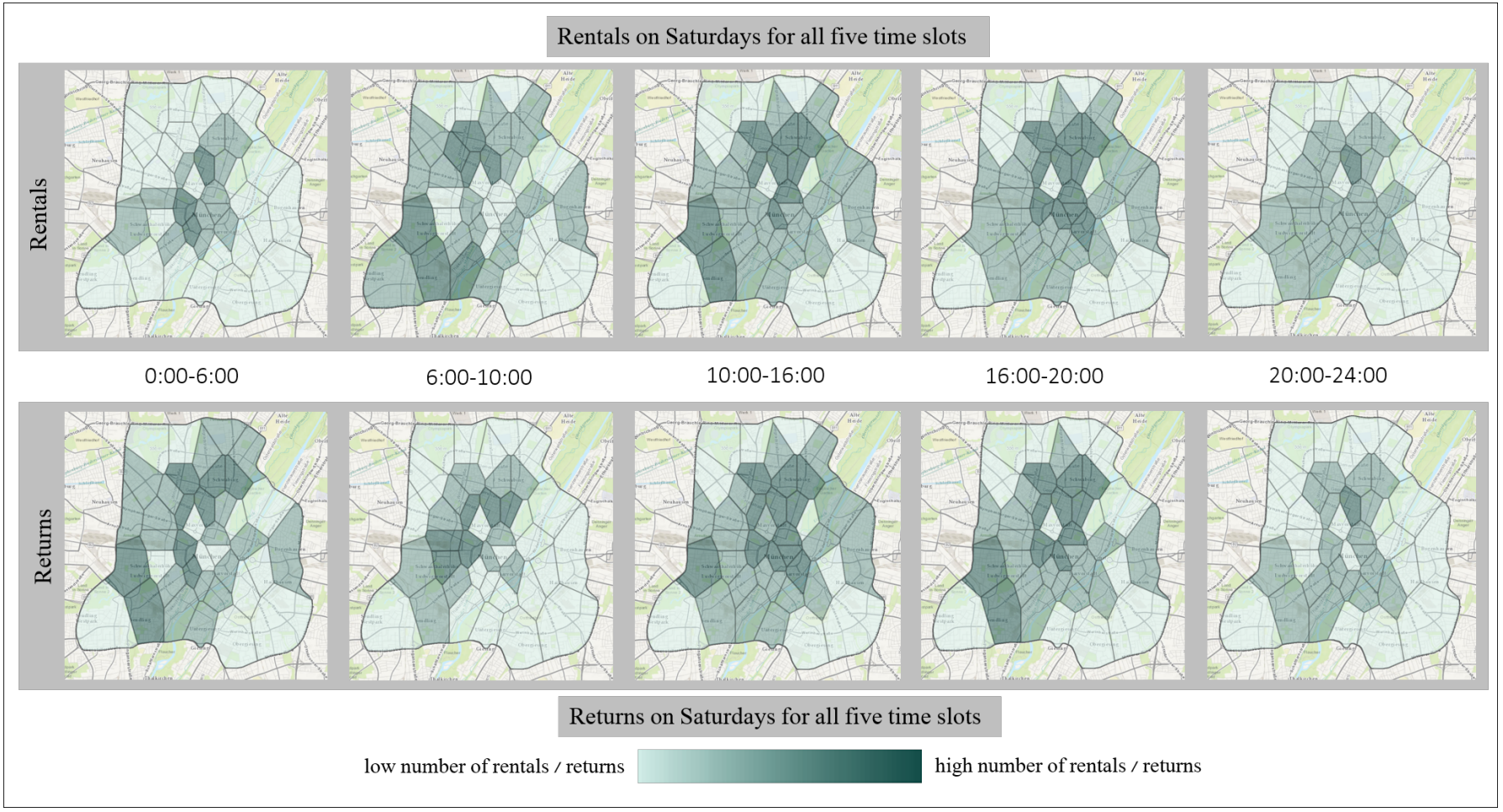


FIGURE 3.19: Spatial analysis for all Saturdays in 2014

### 3.3.3 Idle times

A further quantity that can be read out of the booking data are the idle times. The idle time is defined as the time between the return of a bicycle and the subsequent rental by the next user. This measure can be taken as evidence if a zone is currently a *hotspot* for instance. If a zone features short idle times, one can conclude that many bicycles are currently requested. In case of long idle times, however, a zone does not seem to be very attractive currently or is simply over-saturated with vehicles. This section examines the idle times for each trip in the operating period 2014.

At first, all idle times were sorted by their duration and aggregated by different time intervals. The results are depicted in figure 3.20. The highest cluster of idle times in 2014 is found for idle times less than one hour, which add up to almost 25%. The one-hour-classification shows a steep decline for every added hour, so that idle times between five and six hours are only represented by 3%. Between eight and eleven hours of idle time, the percentage is increasing again, which seems paradoxical at first. This can be explained by the night time effect (as labeled in figure 3.20): the system is not used to capacity during night hours and most of the fleet is idling. Referring to the rental profiles in section 3.2.1, the booking shares between 9 p.m. and 7 a.m. are less than 4%, i.e. most part of the fleet idles during that time. This leads to the rise in idle times around ten hours, when bicycles get rented in the morning again. Apart from that outlier, the

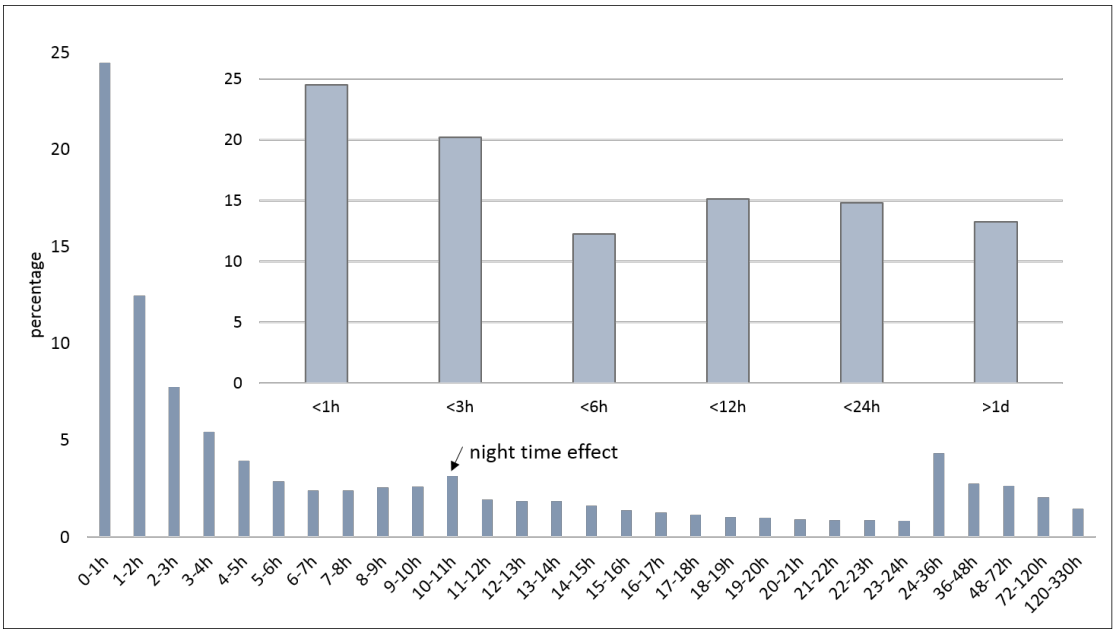


FIGURE 3.20: Averaged Idle Times in 2014 on different time scalings

hourly intervals steadily decrease. For longer idle times than 24 hours, the idle times are accumulated to 12-hours, 24-hours etc. intervals up to several day intervals. All idle times longer than 330 hours (around 14 days) were excluded, since such long idle times are most probably caused by technical issues.

The more coarse classification of the idle times reveals that 45% of the idle times were less than three hours, whereas almost 30% percent were idling more than 12 hours, 13% of these more than one day in fact. This distribution calls for improvement. Such long idle times are firstly not profitable for the operator and secondly, it is a sign that the bicycles are idling in the *wrong* spots and hence are lacking in the current hotspots.

Figure 3.21 divides the idle times in the previously defined time slots and day types. For weekdays, highest idle times are detected in the time slot between 6 a.m. and 10 a.m. This covers the assumption of long idle times at night, as an idle time is counted, when the bicycle gets rented again, which most likely happens in this time slot then. The idle times on weekends are a bit more *balanced*, i.e. the idle times at night are lower and by contrast, a bit higher during day time, as there is no typical commuter peak in the morning on weekends.

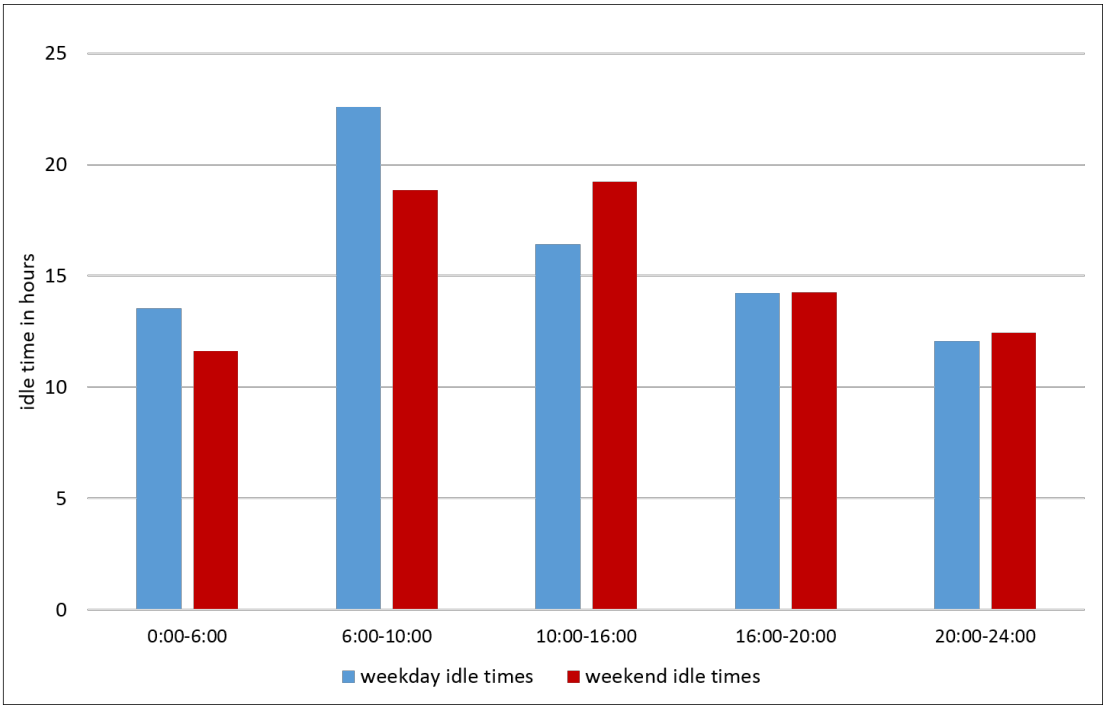


FIGURE 3.21: Averaged Idle Times in 2014 per time slot on weekdays and weekends

In general, the conducted analyses are all based on averaged idle times. This is reasonable, as single idle times are not reliable because of following issues:

- technical issues can cause long idle times (e.g., a broken bicycle or GPS failure)
- previous return in a hidden area (e.g., a private backyard) makes it harder for a potential following user to find it and leads to a high idle time.

Besides the temporal analysis of the idle times, a spatial examination for each of the 40 zones of the operating area was conducted. Figure 3.22 shows the spatial behavior for weekdays and weekends in all time slots concerning the idle times.

First, the shortest idle times are detected in the city center or north of that for all time slots without exception. This shows that the fleet that was returned over there has a quick fluctuation at all times. In most other parts of the operating area, this behavior changes for each time slot. In the northwestern part for instance, there are variations from short idle times to very long idle times. One zone there comprises the Olympic Park, especially on weekends rental bicycles are used in this zone and presumably cause short idle time there between 8 p.m. and midnight, when public events like concerts etc. end and a rental bicycle offers a good option compared to an overcrowded subway. One zone in the southwest though provides consistently long idle times. Firstly, this hints that a presumably high amount of bicycles is idling there (over-saturation) and secondly if a bicycle gets rented there now and then, it was idling a certain amount of time there before.

In summary it can be stated that the idle times analysis reveals certain dynamics: some zones are *performing* pretty well as there are short idle times consistently. Other zones are moderate and only get requested at some time slots, whereas the remaining zones have a high amount of time slots with high idle times. This is again a sign of skewness of the fleet, as the idling part is redundant in the current spots, although bikes might be needed in other parts of the operating area.

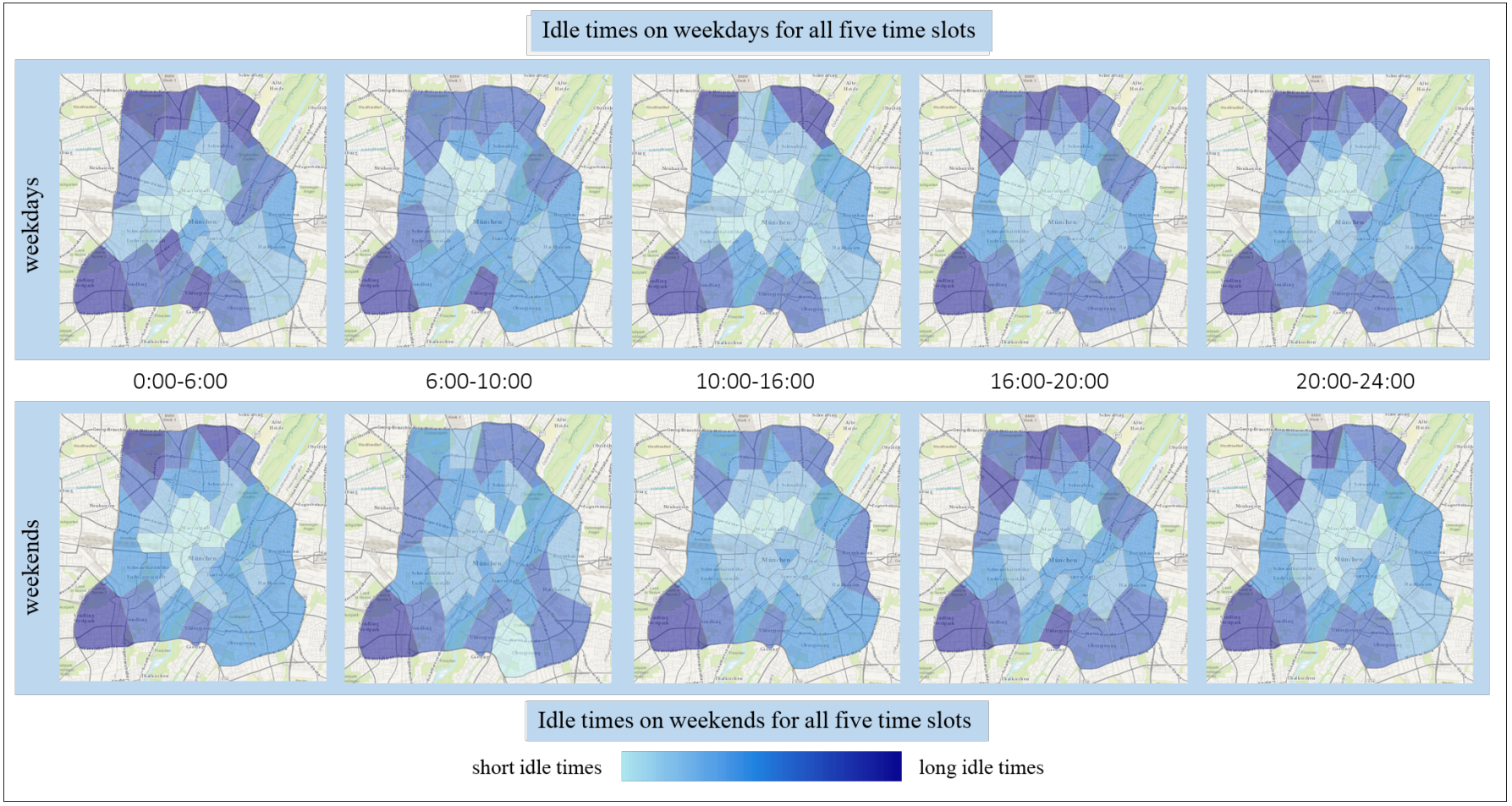


FIGURE 3.22: Spatial distribution for idle times on weekdays and weekends in 2014

This chapter provided a detailed empirical data analysis of a free-floating BS System in Munich. Within a temporal analysis, usage peaks were detected on weekday mornings and evenings, and general usage patterns were found for two day types, namely weekdays and weekends. For each day, trips were clustered and matching time slots were defined. The resulting five time slots combined with the concurrent day type allows conclusions about the usage behavior in a time-discrete grid. The weather analysis proved that mostly precipitation impedes the usage of a BS System, but no spatial sensitivity was found (bookings were similarly low all over the operating area). For the spatial analysis, the operating area was divided into 40 zones and the booking behavior was examined on zone level. Hereby, temporary imbalances were detected, as bicycles get returned in other areas than they will be rented again. In a last step, the idle time analysis underpins this hypothesis as well: long idle times were detected not only in fringe area zones but also in zones closer to the city center which indicates a bad fleet distribution (FD) at a certain time. Within this chapter, RQ 1 was treated thoroughly as the system's dynamics are captured. Further, RQ 2 was approached. Fleet imbalances occur; however, for a precise quantification of these imbalances further measures and tools are required: in order to capture the *real* demand that is actually prevailing, a demand model is created in the next chapter. Based on that, it is possible to judge if the FD was sufficient or if it led to some under-supplied zones.

# Chapter 4

# The Relocation Model

In the previous chapter, usage patterns of a free-floating BS System were identified and analyzed. There are spots where bicycles are more likely to be booked in the morning hours, while other areas seem to be most attractive by early evening. The empirical analysis of the real booking data lead to the assumptions that the fleet is not always optimally distributed and a certain skewness is prevailing. This rather unfavorable fleet status is ought to be overcome by the Relocation Model introduced in this chapter.

## 4.1 Overall Approach

In figure 4.1 the schematic overall approach is illustrated. The Relocation Model consists of two inter-dependent modules : the Demand Model and therefrom derived Relocation Strategies.

These modules are outlined in subsequent sections and form the autonomous chapters 5 and 6 respectively.

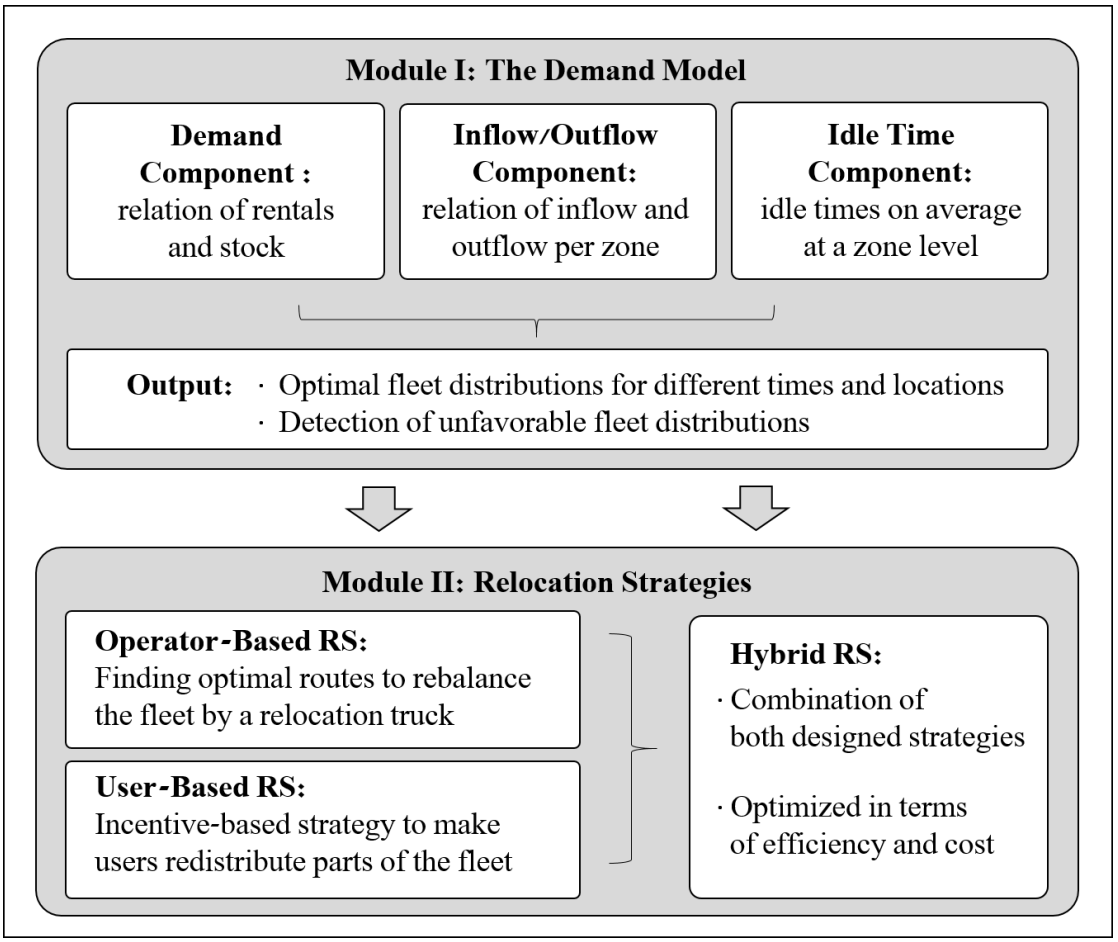


FIGURE 4.1: Structure of the Relocation Model

## 4.2 Module I: The Demand Model

Module I comprises a prediction model, which yields different demand patterns in a temporal and spatial dependency. Hereby, three different components are taken into account.

The first component investigates the occupancy rate of the bicycles at a zone level. Comparing the rentals per zone to the according available stock yields an indicator for current utilization of the fleet in singular zones.

Within the second component, the rentals are compared to the returns in each each zone: if a bicycle is rented, the present zone records and *outflow*, whereas each return in a zone causes an *inflow* in equal measure. As a result, time dependent flow rates for each zone are determined which are considered to be an important factor of the currently prevailing demand.

In the third component, idle times at a zone level are investigated in order to draw conclusions, where bicycles are frequently in use. Short idle times might be an indicator for high demand, whereas long idle times point to rather low demand.

These three different components are concatenated appropriately and this fusion finally results in a spatial and temporal demand pattern. This pattern yields optimal fleet distributions for all zones in different time intervals and can be seen as a saturation matrix, i.e. it yields a time dependent stock threshold for each zone that should not be undercut. If this is the case, however, an *unfavorable fleet status* is detected that ought to be eliminated. At this stage, module II - the Relocation Strategies come into effect.

## 4.3 Module II: Relocation Strategies

Within this module, various Relocation Strategies (RSs) are designed and applied. Most important input parameters are provided by module I, namely recommendations on fleet distributions (FDs) for different time intervals. Comparing these optimal FDs to current FDs, the deviation at a zone level forms the required relocation steps. Different approaches deal with this issue.

First, an operator-based RS is designed by solving a Vehicle Routing Problem (VRP). This optimization formulation yields a shortest route while accomplishing maximum bicycle relocations. In case of heavy imbalances, these relocation trips can take several hours though.

For the purpose of saving time and cost for the operator but still maintaining the BS System convenient for users, an incentive-based strategy is developed: the user-based RS. The main idea is to offer price discounts for bicycles idling in unfavorable zones and also incentivize users to return bicycles in such zones featuring a current lack of bicycles. The resulting RS - pricing schemes depending on the current FD - is applied for different test cases. If the FD is poor, this user-based RS might not work sufficiently, precisely because the users' behavior is hard to predict and influence. Therefore a third RS is designed.

Both previously described RSs bear their assets and drawbacks: while the operator-based RS performs precisely it might be time-consuming, whereas the user-based RS performs without any operator's effort but might be hard to regulate. The hybrid RS - a combination of both RS - provides a remedy. Within this strategy, the advantages of the respective RS are combined and performed concurrently. In consequence, the operator-based RS eliminates heavy imbalances in a marked-out route, while the user-based RS eliminates smaller imbalances, especially in fringe areas or far from the operator-based relocation route. This prevents the operator to approve detours in order to redistribute a few bicycles only for instance.

# Chapter 5

# The Demand Model

In the previous chapter, the Relocation Model was introduced, consisting of two interdependent modules. Module I - the Demand Model - strives to predict upcoming demand in a spatial and temporal dependency and is the subject of this chapter.
In chapter 3, fleet imbalances were already suspected. In order to qualify this hypothesis, the upcoming demand is estimated based on different perspectives. Considering that, booking data analyses are crucial, but this evaluation on its own does not necessarily reflect the actual demand. As a result, the demand model ought to provide recommendations on fleet distributions (FDs) for different times and locations. By implication, RQ 2 will be answered, as the deviation of an optimal FD and the actual FD reveals potential fleet imbalances.

There are two initial questions the demand model started out with:

1. In case of more available bicycles in specific areas: would there have been even more bookings? Or in other words: was the actual demand completely satisfied?
2. How does the fleet move and does the demand evolve correspondingly?

In order to answer these questions, this chapter builds up a model that forecasts the upcoming demand by three components. The combination of these leads to the actual occurring demand and thus makes it possible to identify when and where undersupplied areas occur.

## 5.1 Demand Model Components

The overall goal of this chapter is to determine the demand in a spatial and temporal dependency. The *actual demand* - which is highly likely to differ from the current bookings - needs to be derived from different perspectives. First of all, the term *actual demand* is defined: the actual, real demand is equal to the amount of bicycles that would be rented if every single zone was over-saturated by far, i.e. if the fleet size was super-sized. This implies that the demand is satisfied every time and everywhere, hence there is no unmet demand. As a result from this reasoning, the bookings would directly reflect the occurring demand then.

A typical BS System is not equipped with a super-sized fleet, as this would not be in no way economical. Thus, the booking data of a BS System with realistic fleet size do not necessarily give information about the actual demand. Nevertheless, historical booking data play a crucial role - but furthermore, the relation between bookings and the concurrent amount of available bicycles indicates whether low bookings correspond to low demand, or rather the bicycle supply was not sufficient and the actual need was higher.
Additionally, an Inflow/Outflow analysis is taken into account. Zones where users rent bicycles during a certain time slot but where only few trips end evolve into possibly under-supplied areas; at least they provide a first clue as to whether the demand/supply flow is self-regulating.
Further, idle times also have an impact on the demand model: a zone with low idle times might show a higher demand than one with long idle times; although this component itself does not necessarily correlate with demand.

Summing up, there are three main components which build up the demand model:

1. Demand Component $D_z$
2. Inflow / Outflow Component $O_z$
3. Idle Time Component $I_z$

Every component is calculated separately for the zones $z = 1, \ldots, 40$.
Ergo for every zone $z$ the calculations result in matrices of size $w \times k$, where $w = 1, 2$

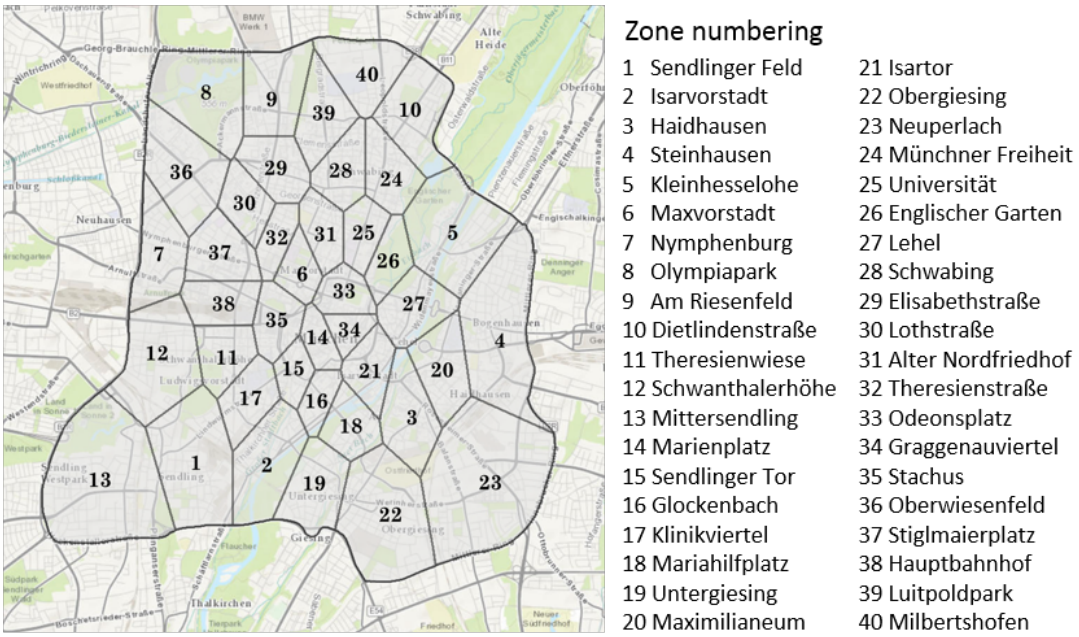


FIGURE 5.1: Operating area with zone numbering

displays the day type (1 = weekday and 2 = weekend), $t_k$ the time and $T_k$ the corresponding time slot $T = [t_k, t_{k+1}[$ with $k = 1, \ldots, 5$ for each of the five time slots during one day, as previously defined in chapter 3.

For reasons of clarity the zone indication $z$ is omitted in the following model definition of the model components. With this in mind, all calculations were run for every zone $z = 1, \ldots, 40$ separately. The zone number assignment can be read out in figure 5.1.

Within the analyzed booking period, there were 274 days in total, consisting of 188 weekdays from Monday to Friday and 86 weekend days, consisting of Saturdays, Sundays and public holidays.

### 5.1.1 The Demand Component

The demand component $D$ is based on the relation between the rentals $r^{T_k}$ during the time slot $T_k$ and the corresponding available stock $s^{t_k}$ at time $t_k$ for each day $n = 1, .., N$ in the operating period in 2014:

$$d_n^{T_k} = \frac{r_n^{T_k}}{s_n^{t_k}} \tag{5.1}$$

| Demand model variables | | | |
|---|---|---|---|
| $s^{t_k}$ | stock at time $t_k$ | $t_k$ | $t_1$ =12a.m., $t_2$ =6a.m., $t_3$ =10a.m., $t_4$ =4p.m., $t_5$ =8p.m. |
| $r^{T_k}$ | rentals in time interval $T_k$ | | |
| $x^{T_k}$ | returns in time interval $T_k$ | $T_k$ | time interval $T = [t_k, t_{k+1}[$ |
| $n$ | index for days in operating period | $N$ | # of days in operating period |
| $w$ | day type | $i^{t_k}$ | sum of all idle times at time $t_k$ |

TABLE 5.1: Input variables for the demand model

For each time slot, each day and each zone such a ratio is calculated and therefore this initial computation outputs $5 \times 274 \times 40 = 54\,800$ values for $d$. All demand model variables are outlined in table 5.1.

The ratio $d$ decides, in which measure the rentals in one zone during one time interval exploited its stock. The final result $D_w^{T_k}$ is a matrix of size $40 \times 5$, so for every of the 40 zones, $D^{T_k}$ provides the demand component for all time slots on weekdays ($w = 1$) and weekends ($w = 2$). In order to obtain such a matrix, the calculated values have to be consolidated appropriately.

A schematic overview for time (intervals), rentals, returns and stock at a zone level is given in figure 5.2: at time $t_k$, 12 bicycles are idling in zone $z$, i.e. the stock is $s^{t_k} = 12$. In the subsequent time interval $T_k$, 8 bicycles are returned in zone $z$, hence the inflow is $x^{T_k} = 8$. In the same time interval, 4 bicycles are rented and consequently exit zone $z$. Thus the outflow is $r^{T_k} = 4$. The stock at time $t_{k+1}$ is calculated by the previous stock and the acoording outflow and inflow rates, namely $s^{t_k+1} = s^{t_k} + x^{T_k} - r^{T_k}$.

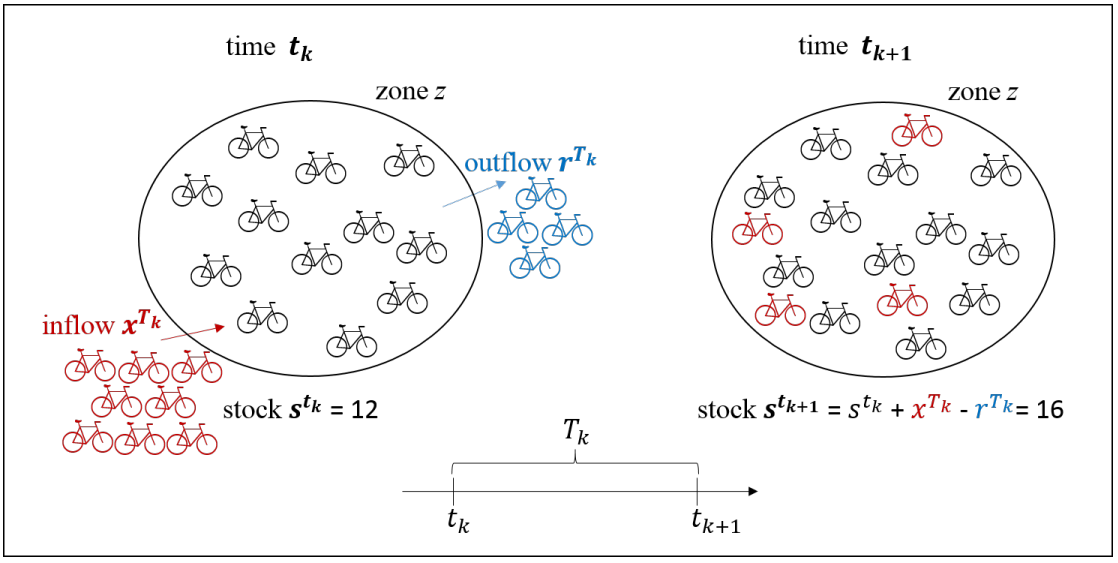


FIGURE 5.2: Schematic illustration of returns (inflow), rentals (outflow) per time interval $T_k$ and stock at time $t_k$

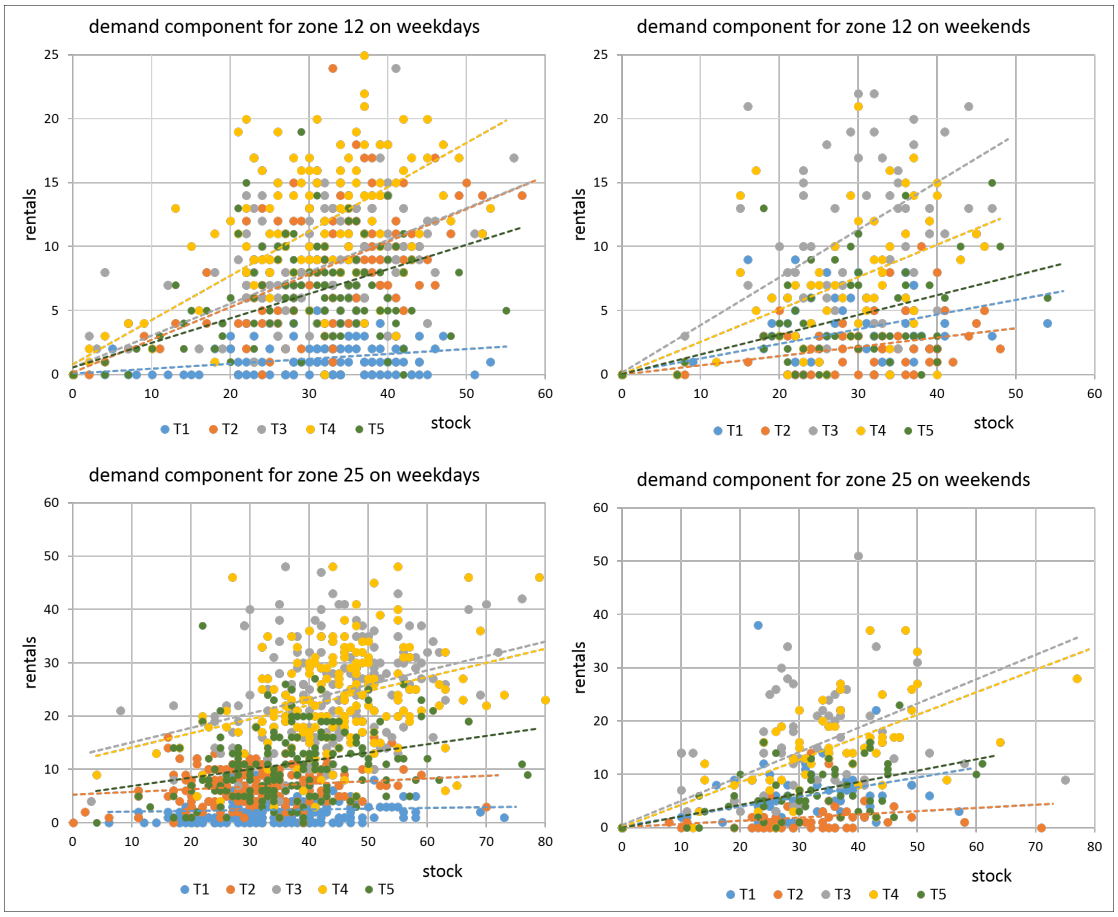


FIGURE 5.3: The initial demand components for selected zones 12 *Schwanthalerhöhe* and 25 *Universität*

The initial values of the demand component for two selected zones are depicted in 5.3. This shows only a small part of the calculations and serves as an example. For weekdays, 188 values per time slot are depicted and for weekends 86 values per time slot respectively.

In the top figure 5.3, the single components $s$ and $r$ of the demand component $d$ are plotted for weekdays and weekends in zone 12 *Schwanthalerhöhe*. On weekdays, the respective time slots build their own distinct cluster. Time interval $T_1$, i.e. between midnight and 6 a.m., features mostly data points with high stocks and low related bookings. In the next time interval $T_2$, the bookings are comparatively higher with a similar stock distribution. The data point clusters for $T_3$ and $T_4$ are widely spread but mostly show high bookings (if possible due to stock limitations). The last time interval is the most centric and compact cluster, with only a few outliers. On weekends, this clustering is more diffuse in zone 12. This is mainly caused by the lower sample of days

on weekends in 2014. However, a high distinction in comparison to weekdays is detected for $T_1$ and $T_2$, as they show the opposed behavior respectively: higher bookings in $T_1$ are common, whereas bookings in $T_2$ are rather low comparatively. This behavior can be read out by the respective dashed line, which shows the line of best fit for each time slot. The gradient of this line can be interpreted as the mean demand component with a certain variance of respective data points. This variance is lowest for $T_1$ on weekdays and highest for $T_4$ on weekends.

In zone 25 *Universität*, this clustering is even more distinct, see bottom figure 5.3. Here, the line of best fit sorts the different time interval by gradient: $T_1$ is the weakest time slot, followed by $T_2$, $T_5$ and $T_3$. The highest ratio can be read out for time interval $T_4$. Again, this pattern on weekends significantly changes: the weakest time slot then is $T_2$, followed by $T_1$, $T_5$ and $T_4$. The sharpest ratio here is provided by time interval $T_3$. Evaluating these results, there are identifiable clusters with certain variances for all different time slots. The lines of best fits form thresholds, where the current demand/supply relations change: underneath this line, it is likely that the zone was currently rather over-saturated and therefore the *real* demand was not limited by stock restrictions. Above this line, a lack of bicycles is more likely and stock limitations may have caused low rental numbers. Among that, the entire rental/stock relation analysis features outliers as well, which influence the result. These outliers have to be interpreted well, as a data point including a low stock can cause low bookings, whereas high stocks not always show high bookings respectively.

In order to sort out the meaning of the single components a case differentiation is given in the following chapter.

#### 5.1.1.1 Interpretation of the Demand Component

The component $d^{T_k}$ is a ratio, i.e. both stock $s^{t_k}$ and number of rentals $r^{T_k}$ are included in the particular result. There are different cases or reasons, why $d^{T_k}$ can be low or high respectively. This classification depends on the overall average of ratios $\overline{d}^{T_k}$ in respective time slots and the corresponding deviation of the current data point $d^{T_k}$.

The current, relative deviation is defined as

$$dev_{T_k} = \frac{d^{T_k} - \overline{d}^{T_k}}{\overline{d}^{T_k}} \tag{5.2}$$

If $dev_{T_k}$ is higher than 0.2 (upward outlier), the calculated demand component is denoted as *high*, compared to the other calculations in the same zone and time slot. If this deviation is lower than −0.2 (downward outlier), the current demand component is denoted as *low*.
An overview of the case differentiation scheme is given in figure 5.4.

In case of a **high demand component**, either

1. the bookings $r^{T_k}$ are high, or
2. the stock $s^{t_k}$ is low

or both at an extreme. In the first case, a high demand component always sets a right signal. For the second case, it is not obvious if the stock was too low in order to serve all the potentially requested bookings or if there is no demand anyway so that the low stock does not cause low bookings. For a checkup, an algorithm searches for more booking numbers related to the same low stock. If the other booking numbers are similar, the demand component is high with justification; otherwise the demand has

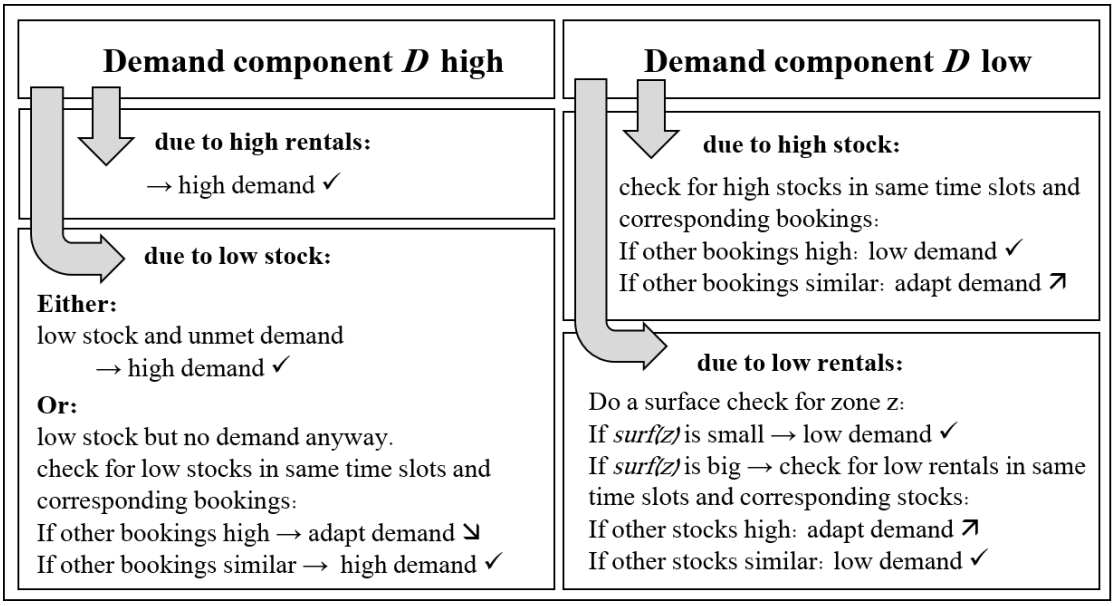


FIGURE 5.4: Interpretation scheme for the demand component $D$

to be adapted, i.e. revised downwards according to higher bookings with same stocks. This scheme is outlined in the left part of figure 5.4.

The other way around needs more reflections: in case of a **low demand component**, either

1. the bookings $r^{T_k}$ are low, or
2. the stock $s^{t_k}$ is high

or both at an extreme. The first case - if there are only a few bookings - can be caused by a (relatively) low stock. For instance, if a zone is large in terms of the surface area, the same stock of bicycles has more impact in smaller zones concerning visibility and perception. Therefore a second checkup is needed, which relates to the surface area of the respective zone. The demand in a big zone would be underrated otherwise and the demand component of a zone with low bookings due to current low stock would result in a false trail.

In the second case - if the stock is high - the demand component output works not reliable either. Of course, the demand component signalizes that no more bicycles are needed there. This would cause a stock-depending demand, or in other words, this measure would imply a low demand because of a high stock. For the purpose of estimating the *real* demand - the demand without any outer impact as the stocks in all zones were always over-saturated - a distinction is needed: if a high stock causes a low demand component, the algorithm searches for similar stock numbers in the present zone at different times and compares the related bookings. If the related bookings are higher, then the demand component is correct. Otherwise, if the other bookings are similar, the demand was underrated by the demand component and has to be revised upwards. The right part of figure 5.4 sketches the interpretation scheme in this case.

Due to the case differentiations, it is ensured further that the demand component is not stock-dependent, i.e. if a zone's stock was increasing over the course of the operating period, the demand component would not be affected by that. This is the case e.g., in zone 4 *Steinhausen* and is discussed in section 7.2.

In order to capture a universally-valid demand component for each zone and time slot, the results were clustered and examined, which day types feature similar demand

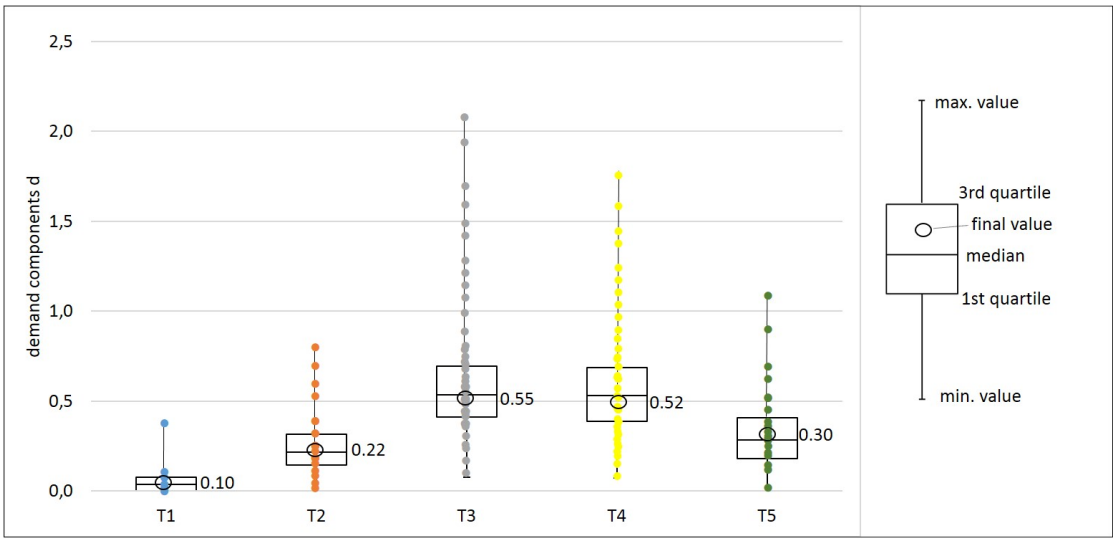


FIGURE 5.5: Box plot for zone 25 *Universität* containing values of each weekday 2014

component results. The precedent case differentiation of outliers allows a static, generally valid and stock-independent demand patterns for all 40 zones, distinguishing between the five different time slots $T_k$ and respective day type.

In figure 5.5, a box plot illustrates the value distribution of $d$ in each time interval $T_k$, exemplarily for zone 25 *Universität*. According to the prior case differentiation, 188 values (one for each weekday in 2014) were consolidated to the final demand component per time slot. The depicted measures of median and quartiles serve as indication of the overall value (and outlier) distribution. Time interval $T_3$ features the highest spread of values, whereas in $T_1$ only few outliers occur and $d$ has a low range. The curl depicts the final adjustment of $d$ per time interval.

The following plots show the the final adjusted demand component for selected zones exemplarily in order to derive information about the concurrent booking behavior in the respective zone. Figure 5.6 depicts the demand component for seven selected zones on both day types, weekdays and weekends. In zone 4 *Steinhausen*, which is location at the eastern edge of the operating area, the demand component is very low for all time slots. The maximal value is reached on weekdays between 10 a.m. and 4 p.m., however $d^{T_3} = 0.06$ is quite low and reflects a high stock and respective low booking numbers. Zone 8 *Olympiapark* features similar demand component patterns on weekdays, except for time slot 1 and 5, where $d^{T_1} = 0.50$ and $d^{T_5} = 0.36$ respectively is significantly higher in zone 8. That implies that between 8 p.m. and 6 a.m. considerably more rentals are made in relation to the current amount of available bicycles.

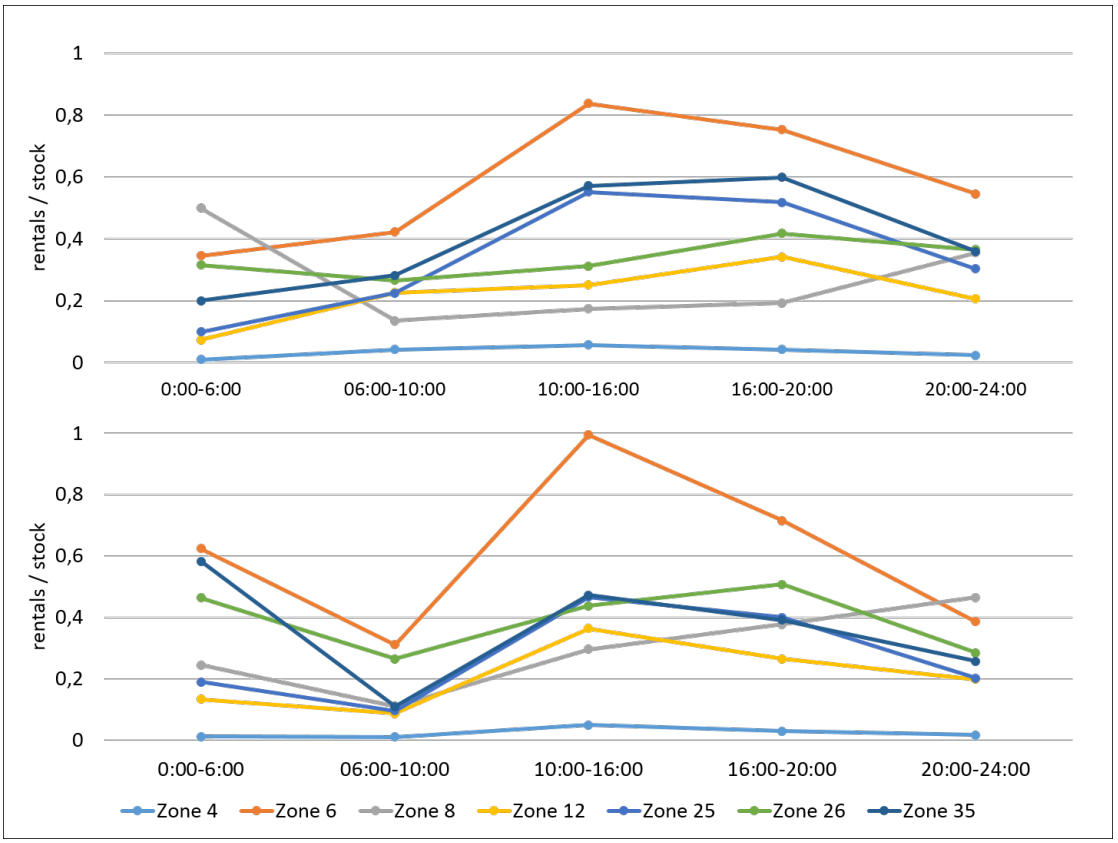


FIGURE 5.6: The demand component $d$ for selected zones on weekdays (top) and on weekends (bottom)

Zone 6 *Maxvorstadt* shows a constantly high demand component - the highest for all zones apart for one time slot - whereas it reaches its top with $d^{T_3} = 0.84$ on weekdays and $d^{T_3} = 0.99$ on weekends. The latter is a broad hint that this zone provides not enough bicycles to satisfy the demand, as almost every available bicycle will be booked in the following time slot.

The overall result $D^{T_k}_{w,z}$ is a matrix of size 40×10 and is displayed in Table 5.2. The entries of $D$ range between $d \in [0.01, 0.99]$.

This first demand model component gives hints about the grade of demand satisfaction in a spatial and temporal sense. The closer to 1 this value is, the higher is the need for bicycles and - apart from bicycles that were returned in the upcoming time slot in that zone - the more the bicycle stock there was emptied out. However, if this value is close to zero, which is often the case in $T_1$, i.e. between midnight and 6 a.m., the relatively high stock was idling and concurrently not many rentals were made.

| Demand component output | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 0.03 | 0.14 | 0.16 | 0.19 | 0.11 | 0.07 | 0.05 | 0.22 | 0.16 | 0.10 |
| 2 | 0.07 | 0.25 | 0.23 | 0.28 | 0.19 | 0.15 | 0.10 | 0.41 | 0.31 | 0.18 |
| 3 | 0.10 | 0.21 | 0.23 | 0.33 | 0.26 | 0.16 | 0.08 | 0.40 | 0.32 | 0.23 |
| 4 | 0.01 | 0.04 | 0.06 | 0.04 | 0.02 | 0.01 | 0.01 | 0.05 | 0.03 | 0.02 |
| 5 | 0.05 | 0.14 | 0.27 | 0.31 | 0.13 | 0.05 | 0.05 | 0.24 | 0.25 | 0.10 |
| 6 | 0.34 | 0.42 | 0.84 | 0.75 | 0.54 | 0.62 | 0.31 | 0.99 | 0.71 | 0.39 |
| 7 | 0.06 | 0.25 | 0.25 | 0.34 | 0.19 | 0.10 | 0.08 | 0.36 | 0.24 | 0.13 |
| 8 | 0.50 | 0.13 | 0.17 | 0.19 | 0.36 | 0.24 | 0.11 | 0.30 | 0.38 | 0.46 |
| 9 | 0.06 | 0.12 | 0.13 | 0.18 | 0.11 | 0.07 | 0.06 | 0.20 | 0.18 | 0.09 |
| 10 | 0.06 | 0.13 | 0.16 | 0.23 | 0.11 | 0.07 | 0.05 | 0.25 | 0.17 | 0.09 |
| 11 | 0.12 | 0.27 | 0.39 | 0.44 | 0.29 | 0.17 | 0.10 | 0.38 | 0.30 | 0.30 |
| 12 | 0.07 | 0.23 | 0.25 | 0.34 | 0.21 | 0.13 | 0.09 | 0.36 | 0.27 | 0.20 |
| 13 | 0.04 | 0.13 | 0.12 | 0.15 | 0.10 | 0.06 | 0.05 | 0.18 | 0.13 | 0.08 |
| 14 | 0.12 | 0.17 | 0.44 | 0.44 | 0.25 | 0.24 | 0.08 | 0.47 | 0.37 | 0.17 |
| 15 | 0.16 | 0.25 | 0.41 | 0.49 | 0.34 | 0.51 | 0.10 | 0.48 | 0.36 | 0.29 |
| 16 | 0.13 | 0.21 | 0.29 | 0.37 | 0.30 | 0.36 | 0.10 | 0.53 | 0.37 | 0.25 |
| 17 | 0.10 | 0.24 | 0.37 | 0.38 | 0.25 | 0.20 | 0.10 | 0.40 | 0.30 | 0.24 |
| 18 | 0.10 | 0.25 | 0.23 | 0.30 | 0.25 | 0.19 | 0.09 | 0.45 | 0.35 | 0.20 |
| 19 | 0.04 | 0.23 | 0.17 | 0.21 | 0.12 | 0.07 | 0.07 | 0.25 | 0.17 | 0.10 |
| 20 | 0.14 | 0.37 | 0.38 | 0.49 | 0.37 | 0.20 | 0.15 | 0.53 | 0.37 | 0.25 |
| 21 | 0.08 | 0.23 | 0.30 | 0.34 | 0.23 | 0.19 | 0.07 | 0.37 | 0.28 | 0.18 |
| 22 | 0.09 | 0.19 | 0.20 | 0.27 | 0.19 | 0.11 | 0.10 | 0.29 | 0.24 | 0.15 |
| 23 | 0.09 | 0.23 | 0.19 | 0.31 | 0.15 | 0.12 | 0.11 | 0.27 | 0.18 | 0.11 |
| 24 | 0.11 | 0.19 | 0.32 | 0.38 | 0.28 | 0.19 | 0.05 | 0.39 | 0.32 | 0.18 |
| 25 | 0.10 | 0.22 | 0.55 | 0.52 | 0.30 | 0.19 | 0.10 | 0.47 | 0.40 | 0.20 |
| 26 | 0.31 | 0.27 | 0.31 | 0.42 | 0.36 | 0.46 | 0.26 | 0.44 | 0.51 | 0.28 |
| 27 | 0.08 | 0.31 | 0.35 | 0.44 | 0.24 | 0.13 | 0.09 | 0.39 | 0.33 | 0.18 |
| 28 | 0.08 | 0.34 | 0.37 | 0.37 | 0.28 | 0.14 | 0.10 | 0.51 | 0.35 | 0.21 |
| 29 | 0.02 | 0.12 | 0.14 | 0.09 | 0.06 | 0.03 | 0.03 | 0.12 | 0.08 | 0.04 |
| 30 | 0.12 | 0.43 | 0.39 | 0.57 | 0.36 | 0.20 | 0.15 | 0.53 | 0.44 | 0.27 |
| 31 | 0.14 | 0.37 | 0.56 | 0.61 | 0.47 | 0.40 | 0.13 | 0.71 | 0.51 | 0.35 |
| 32 | 0.12 | 0.38 | 0.53 | 0.65 | 0.43 | 0.23 | 0.14 | 0.67 | 0.50 | 0.32 |
| 33 | 0.17 | 0.20 | 0.52 | 0.60 | 0.31 | 0.33 | 0.10 | 0.57 | 0.41 | 0.22 |
| 34 | 0.12 | 0.15 | 0.38 | 0.42 | 0.24 | 0.23 | 0.07 | 0.38 | 0.30 | 0.16 |
| 35 | 0.20 | 0.28 | 0.57 | 0.60 | 0.36 | 0.58 | 0.11 | 0.47 | 0.39 | 0.26 |
| 36 | 0.07 | 0.19 | 0.18 | 0.21 | 0.11 | 0.07 | 0.08 | 0.23 | 0.17 | 0.11 |
| 37 | 0.10 | 0.29 | 0.37 | 0.51 | 0.30 | 0.19 | 0.11 | 0.44 | 0.36 | 0.22 |
| 38 | 0.11 | 0.33 | 0.40 | 0.52 | 0.34 | 0.25 | 0.09 | 0.35 | 0.30 | 0.27 |
| 39 | 0.07 | 0.22 | 0.19 | 0.26 | 0.15 | 0.11 | 0.09 | 0.34 | 0.27 | 0.14 |
| 40 | 0.06 | 0.14 | 0.15 | 0.18 | 0.10 | 0.09 | 0.06 | 0.24 | 0.16 | 0.09 |

TABLE 5.2: The demand component $D$ for all zones

### 5.1.2 The Inflow / Outflow Component

The Inflow / Outflow component $O$ describes the difference between outflow, i.e. the bicycles that were rented $r^{T_k}$ – and inflow, i.e. the bicycles that were returned $x^{T^k}$ in zone $z$ in time interval $T_k$. This component $O_z$ shows whether a zone is more attractive to rent bicycles at a specific time interval or if it is rather a zone where people return bicycles at that time of the day. Again for reasons of clarity, the zone index $z$ is omitted in the following definition.

$$O^{T_k} = \frac{1}{N_w} \sum_{n=1}^{N_w} \left( r_n^{T_k} - x_n^{T_k} \right) \tag{5.3}$$

This component calculates the average difference between outflow and inflow, i.e. the time intervals of all $N_w$ days within the booking period have been taken into account. Note that the set $N$ of days in the operating period was divided into two subsets: $N_1$ for all weekdays and $N_2$ for all weekdays and public holidays.

The result shows absolute bicycle numbers, and therefore illustrates the fleet movements during entire days. Figure 5.7 captures the I/O relations for all time slots on weekdays and weekends: the I/O patterns highly differ for both day types and the five different time slots. The typical movements, as already described in 3.3 can be read out here directly: on weekdays, beginning at 6 a.m., the fleet moves from the outskirts to the city center until 4 p.m. when this behavior gets inverse until the following morning at 6a.m. Roughly the same fluctuation is observed on weekends, whereas the flow seems to be less self-balanced, as there are a lot more blue respective red areas.

In general, this I/O component gives not only information about the current demand per zone, but also if the zone gets self-regulated by the users already. For instance, in case of a predicted high demand component $D$ (see section 5.1.1), a high inflow (red areas) indicates that the upcoming demand will be satisfied by the bicycles that will be most likely be returned there in the next time interval.

Besides the spatial evaluation of the I/O outcome, table 5.3 shows the corresponding calculated values. The values for $O$ range between $[-11.4, 7.9]$. Both values are detected in the same zone 25 *Universität*. In this zone, there is a high throughput. Especially in $T_2$ and $T_4$, i.e. between 6a.m. and 10 a.m. and 4 p.m and 8 p.m., both day types show a large magnitude, indicating more inflow for the former and more outflow for the latter respectively.

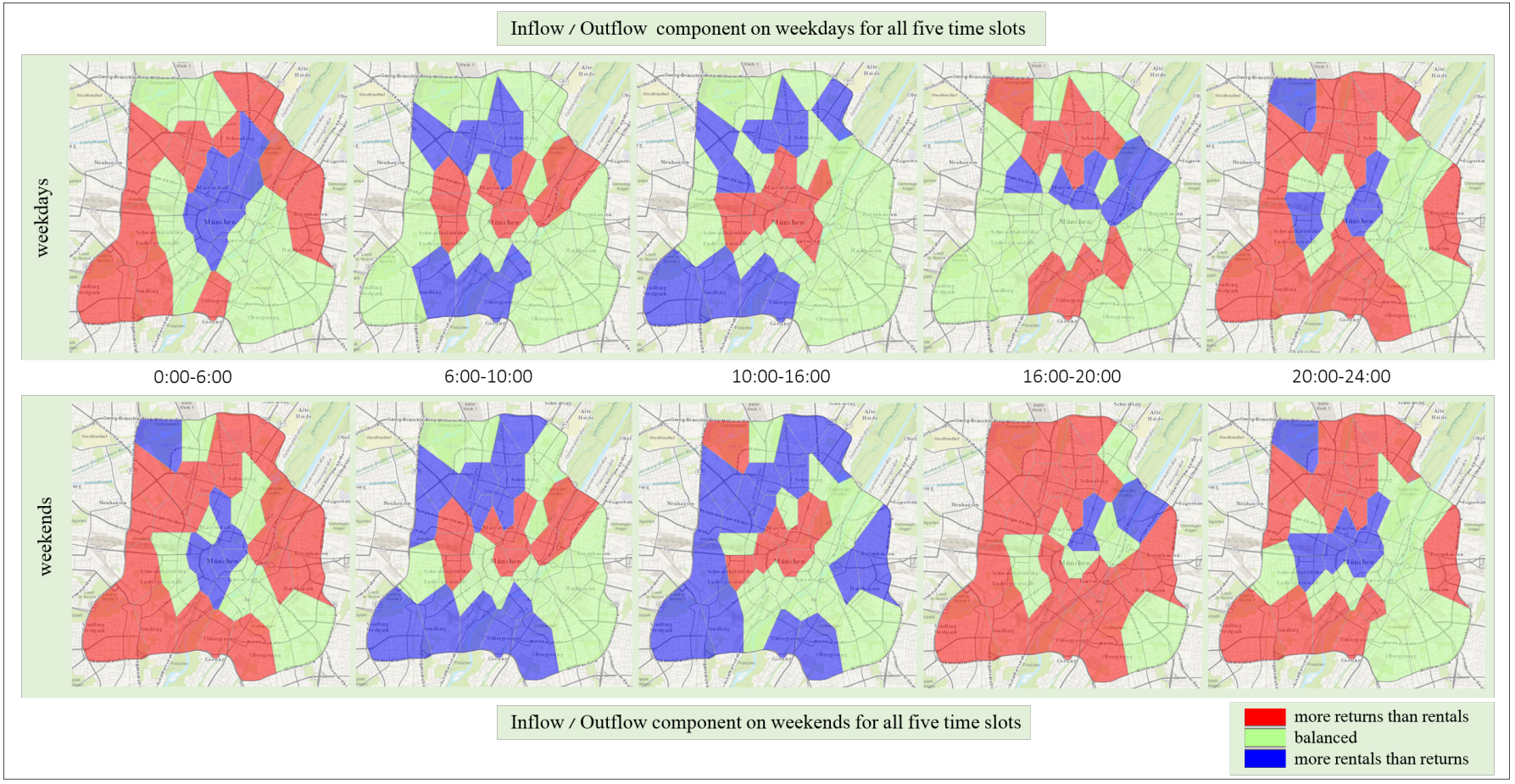


FIGURE 5.7: I/O component for all time slots on weekdays and weekends

| I/O component output in absolute numbers | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | -2.03 | 2.50 | 1.52 | -0.96 | -1.16 | -2.32 | 2.27 | 2.19 | -1.99 | -2.52 |
| 2 | -0.54 | 3.75 | 1.51 | -2.01 | -2.53 | -1.50 | 2.70 | 1.01 | -1.19 | -2.19 |
| 3 | -0.39 | 1.62 | 0.34 | -1.65 | 0.19 | -0.39 | 1.04 | 0.74 | -1.32 | 0.58 |
| 4 | -1.81 | 1.22 | 1.06 | 0.33 | -0.95 | -1.97 | 1.09 | 1.88 | -1.46 | -1.72 |
| 5 | -1.61 | -3.79 | 0.85 | 4.32 | 0.06 | -1.28 | -2.27 | 0.05 | 3.61 | -0.07 |
| 6 | 1.52 | -4.17 | -0.74 | 3.35 | 0.94 | 1.36 | -2.93 | -2.66 | 2.07 | 1.81 |
| 7 | -1.98 | 2.10 | 1.04 | -0.14 | -1.22 | -3.17 | 2.41 | 1.99 | -1.15 | -2.50 |
| 8 | 0.33 | 0.13 | -0.33 | -2.16 | 2.48 | 5.43 | -1.00 | -1.16 | -0.94 | 2.09 |
| 9 | -0.23 | 1.20 | 0.84 | -0.60 | -0.97 | -0.57 | 1.14 | 0.68 | -1.05 | -1.31 |
| 10 | -1.80 | 0.45 | 1.26 | 0.81 | -1.28 | -0.93 | 0.42 | 1.49 | -0.19 | -1.62 |
| 11 | 0.48 | -1.98 | -1.45 | 0.58 | 2.61 | 0.68 | -1.83 | -1.51 | 0.11 | 2.75 |
| 12 | -1.16 | 1.66 | 0.75 | -0.46 | -1.00 | -2.47 | 0.79 | 1.71 | -1.57 | -0.15 |
| 13 | -1.35 | 1.94 | 1.29 | -1.04 | -0.94 | -1.95 | 1.84 | 1.40 | -0.47 | -1.51 |
| 14 | 1.71 | -3.06 | -2.27 | 1.86 | 2.01 | 2.29 | -2.65 | -1.11 | 1.24 | 1.21 |
| 15 | 2.24 | -0.08 | 0.28 | -0.53 | -1.80 | 2.48 | 0.11 | 0.03 | -1.05 | -0.82 |
| 16 | 1.98 | 0.40 | -0.12 | -0.57 | -1.83 | 2.10 | 0.27 | 0.77 | -1.06 | -0.86 |
| 17 | -0.42 | -0.59 | 0.56 | 0.34 | 0.27 | 0.24 | -0.46 | 0.51 | 1.06 | -0.15 |
| 18 | -0.46 | 3.35 | 1.08 | -2.03 | -1.93 | -0.21 | 2.81 | 0.19 | -1.48 | -1.43 |
| 19 | -2.19 | 4.57 | 1.66 | -1.88 | -2.22 | -3.06 | 3.62 | 2.24 | -1.73 | -2.51 |
| 20 | -0.44 | 0.95 | 0.67 | -0.94 | -0.26 | -0.81 | 0.86 | 1.43 | -1.56 | 0.14 |
| 21 | 0.13 | 0.44 | -0.72 | -0.76 | 0.43 | 0.77 | -0.11 | 0.86 | -0.55 | -0.13 |
| 22 | -0.86 | 2.04 | 0.88 | -0.90 | -1.14 | -1.91 | 1.60 | 1.54 | -0.95 | -1.00 |
| 23 | -0.23 | -0.13 | 0.47 | 0.24 | -0.54 | 0.11 | -0.13 | 0.81 | 0.36 | -0.39 |
| 24 | 1.42 | -0.75 | 0.23 | -1.77 | 0.55 | 1.32 | 0.14 | 0.56 | -0.75 | 0.13 |
| 25 | 1.82 | -11.42 | 0.48 | 7.88 | 2.47 | 1.23 | -7.56 | -2.11 | 6.21 | 2.56 |
| 26 | 1.51 | -0.76 | -0.45 | 0.36 | -0.57 | 1.06 | -0.71 | -1.39 | 1.76 | 0.44 |
| 27 | -0.78 | -2.03 | -0.06 | 2.93 | -0.20 | -1.57 | -1.56 | 0.27 | 1.64 | -0.64 |
| 28 | -1.49 | 5.93 | 1.53 | -4.07 | -1.28 | -1.61 | 4.27 | 2.68 | -4.14 | -2.51 |
| 29 | -2.95 | 5.41 | 4.03 | -2.12 | -2.89 | -2.58 | 2.97 | 4.06 | -1.74 | -3.26 |
| 30 | -1.18 | 4.00 | 0.59 | -2.23 | -1.62 | -1.23 | 2.91 | 1.28 | -1.57 | -2.07 |
| 31 | 1.44 | 4.26 | -1.13 | -2.15 | -2.58 | 2.26 | 2.89 | 0.41 | -2.06 | -2.36 |
| 32 | -2.27 | 2.05 | 0.77 | 0.47 | -0.55 | -2.25 | 1.55 | 1.93 | -0.51 | -1.65 |
| 33 | 2.40 | -7.48 | -1.14 | 4.65 | 1.54 | 3.70 | -4.60 | -3.00 | 3.39 | 1.62 |
| 34 | 2.36 | -3.55 | -2.15 | 1.11 | 1.77 | 2.68 | -3.08 | -1.56 | 0.75 | 1.72 |
| 35 | 3.38 | -1.37 | -2.80 | -0.60 | 0.74 | 4.93 | -0.58 | -1.81 | -1.09 | 1.99 |
| 36 | -1.87 | 2.78 | 1.43 | -0.65 | -2.04 | -2.18 | 1.55 | 2.28 | -1.39 | -1.82 |
| 37 | -0.51 | -3.45 | 1.51 | 2.23 | 0.39 | -0.80 | -2.08 | 1.86 | -0.65 | 0.21 |
| 38 | 0.63 | -2.92 | -0.96 | 0.24 | 2.30 | 0.76 | -1.72 | -0.02 | -0.14 | 3.46 |
| 39 | -0.94 | 3.09 | 1.24 | -1.44 | -1.87 | -0.82 | 1.75 | 1.79 | -1.08 | -1.90 |
| 40 | -1.38 | 2.06 | 1.04 | -0.39 | -1.38 | -1.52 | 1.39 | 1.81 | -1.18 | -1.42 |

TABLE 5.3: The I/O component $O$ for all zones

### 5.1.3 The Idle Time Component

The third component $I$ ranks the 40 different zones according to their idle times. For each zone, the averaged idle times were calculated in all time slots and for all day types. To make this component comparable among the zones, the idle times were scaled by the amount of bicycles that were idling. This number corresponds to the stock $s^{t_k}$ at time $t_k$. Hence, for each zone an idle time per bicycle is obtained.
Let $\overline{I}_w$ be the average of all scaled idle times for all $N_w$ days in the operating period, calculated for each zone separately:

$$\overline{I}_w = \frac{1}{N_w} \sum_{n=1}^{N_w} \frac{i_n^{t_k}}{s_n^{t_k}} \tag{5.4}$$

$\overline{I}_w$ consists of 5 different time slots on 2 different day types, ergo yields 10 values for each of the 40 zones. The idle time component for each zone $z$ is calculated by

$$I_{w,z} = \frac{\overline{I}_{w,z}}{\sum_{l=1}^{40} \overline{I}_l} \times 100 \tag{5.5}$$

and results in the respective percentage, how much every single zone contributes to the total idle time.
The component $I$ describes how long each bicycle has not been used and hence indicates the attractiveness of a zone at a certain time. The longer bicycles are idling the lower is the demand in this zone, whereas if a zone has short idle time in a specific interval, the demand might be significant higher.
Table 5.4 shows the calculated percentage for each time slot, zone and day type. These values range from [0.60, 11.31]. The interpretation of the values is opposed to the prior components though: the higher this value is, the longer was the averaged idle time and therefore the demand is supposedly lower. There are some zones that feature quite low idle times for all time intervals. In zone 6 *Maxvorstadt* for instance, the contribution to the total idle time is around 1% only for all time slots. On the opposite side, zone 13 *Mittersendling* features very long idle times in all time slots, with percentages up to 11%. There are also zones where the idle times vary during the day e.g., in zone 9 *Am Riesenfeld*, similar to the demand and I/O component.

| Idle time component $I$ output in percent | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 2.85 | 2.90 | 3.47 | 3.32 | 3.32 | 3.96 | 3.96 | 3.65 | 4.01 | 3.67 |
| 2 | 2.75 | 2.44 | 2.78 | 2.74 | 2.36 | 3.03 | 2.44 | 2.25 | 2.33 | 2.84 |
| 3 | 1.72 | 1.77 | 1.54 | 1.51 | 1.82 | 2.12 | 1.98 | 1.54 | 1.57 | 1.41 |
| 4 | 1.81 | 2.26 | 2.95 | 2.48 | 2.23 | 2.14 | 1.08 | 3.80 | 1.94 | 2.63 |
| 5 | 2.99 | 3.13 | 2.86 | 3.57 | 2.90 | 2.43 | 2.13 | 2.88 | 3.36 | 2.48 |
| 6 | 0.92 | 1.13 | 1.10 | 0.80 | 0.78 | 0.89 | 1.17 | 0.72 | 1.00 | 0.98 |
| 7 | 2.59 | 2.49 | 2.99 | 2.87 | 2.69 | 2.25 | 4.00 | 2.65 | 3.22 | 2.38 |
| 8 | 6.20 | 4.43 | 6.58 | 3.02 | 6.59 | 5.95 | 1.69 | 3.04 | 3.39 | 2.02 |
| 9 | 5.18 | 3.70 | 2.20 | 4.98 | 4.98 | 4.93 | 1.13 | 5.85 | 5.33 | 6.37 |
| 10 | 4.27 | 4.41 | 4.83 | 4.32 | 3.66 | 4.19 | 3.97 | 3.81 | 3.54 | 3.60 |
| 11 | 1.38 | 1.44 | 1.57 | 1.62 | 1.51 | 2.30 | 1.27 | 1.77 | 1.57 | 1.97 |
| 12 | 1.43 | 3.16 | 2.18 | 2.28 | 2.44 | 2.59 | 3.02 | 2.14 | 2.08 | 2.96 |
| 13 | 6.80 | 7.23 | 5.69 | 7.60 | 6.10 | 7.37 | 11.31 | 9.94 | 6.30 | 6.76 |
| 14 | 2.28 | 2.01 | 1.89 | 1.90 | 1.63 | 1.52 | 1.91 | 2.01 | 2.35 | 1.84 |
| 15 | 1.93 | 1.55 | 1.52 | 1.59 | 1.50 | 0.99 | 1.33 | 1.87 | 1.98 | 1.38 |
| 16 | 1.68 | 2.25 | 1.76 | 2.19 | 1.46 | 1.54 | 1.92 | 1.63 | 1.69 | 2.00 |
| 17 | 4.64 | 2.09 | 2.69 | 2.04 | 1.93 | 1.93 | 1.43 | 1.32 | 1.67 | 1.70 |
| 18 | 2.36 | 2.05 | 2.61 | 2.63 | 2.22 | 1.94 | 3.97 | 2.29 | 2.15 | 2.53 |
| 19 | 4.71 | 6.05 | 4.16 | 4.17 | 4.16 | 4.23 | 6.58 | 4.56 | 5.00 | 3.34 |
| 20 | 1.47 | 1.41 | 1.84 | 1.69 | 1.65 | 1.54 | 3.22 | 1.65 | 1.69 | 1.99 |
| 21 | 1.65 | 1.96 | 1.96 | 2.01 | 2.08 | 2.68 | 1.83 | 1.87 | 2.06 | 2.90 |
| 22 | 3.91 | 2.73 | 3.54 | 3.04 | 3.49 | 2.70 | 0.69 | 2.81 | 3.13 | 4.17 |
| 23 | 1.71 | 2.20 | 2.36 | 3.13 | 2.59 | 2.31 | 4.48 | 2.83 | 2.91 | 1.77 |
| 24 | 2.98 | 2.21 | 2.14 | 2.23 | 1.90 | 1.91 | 1.28 | 2.02 | 2.17 | 2.53 |
| 25 | 1.74 | 1.54 | 1.50 | 1.27 | 1.52 | 1.37 | 2.52 | 1.11 | 1.04 | 1.75 |
| 26 | 1.36 | 2.40 | 2.04 | 1.35 | 1.38 | 1.09 | 0.60 | 1.61 | 1.06 | 1.34 |
| 27 | 2.88 | 2.10 | 1.85 | 1.89 | 2.04 | 2.29 | 1.96 | 1.49 | 2.13 | 1.82 |
| 28 | 1.61 | 1.94 | 2.29 | 1.94 | 1.74 | 2.22 | 2.08 | 1.98 | 1.89 | 1.72 |
| 29 | 1.91 | 2.11 | 2.01 | 2.06 | 2.01 | 2.27 | 1.75 | 2.04 | 2.09 | 2.41 |
| 30 | 1.92 | 1.19 | 1.45 | 1.60 | 1.62 | 1.63 | 1.83 | 1.35 | 1.75 | 1.68 |
| 31 | 0.96 | 1.15 | 1.14 | 1.09 | 1.08 | 1.06 | 0.94 | 0.97 | 1.40 | 1.52 |
| 32 | 1.08 | 0.75 | 0.88 | 0.96 | 1.14 | 1.18 | 1.24 | 0.84 | 0.98 | 1.22 |
| 33 | 1.01 | 1.51 | 1.26 | 1.04 | 0.90 | 0.61 | 1.60 | 1.44 | 1.50 | 1.18 |
| 34 | 1.62 | 2.06 | 1.77 | 1.73 | 3.58 | 1.96 | 1.23 | 2.13 | 2.52 | 1.88 |
| 35 | 0.88 | 1.29 | 1.30 | 1.08 | 0.92 | 0.93 | 1.11 | 1.56 | 1.08 | 1.14 |
| 36 | 3.06 | 3.92 | 3.89 | 4.80 | 4.73 | 4.96 | 3.57 | 4.67 | 4.49 | 6.20 |
| 37 | 1.51 | 1.55 | 1.46 | 1.15 | 1.54 | 1.86 | 2.11 | 1.15 | 1.32 | 1.77 |
| 38 | 0.96 | 1.84 | 1.89 | 1.23 | 1.24 | 0.98 | 1.13 | 1.38 | 1.54 | 1.56 |
| 39 | 1.94 | 3.92 | 2.79 | 3.25 | 3.17 | 2.49 | 5.12 | 2.65 | 2.99 | 2.48 |
| 40 | 5.36 | 3.73 | 5.25 | 5.87 | 5.39 | 5.68 | 3.44 | 4.75 | 5.79 | 4.11 |

TABLE 5.4: The Idle Time component $I$ for all zones

However, this component is not as reliable as $D$ and $O$, because of following issues concerning the idle time:

- due to the free-floating system it is possible (but not officially allowed) to return bicycles in hidden areas e.g., in private backyards where potential other users cannot enter. Some users seem to do that regularly and cannot be captured by the system. This circumstance may cause longer idle times even if the current demand in a zone is high.
- at some locations e.g., under bridges, bicycles cannot be GPS-located after returning. In this case, users do not find these bicycles on their smart phone app and therefore longer idle times are possible which does not necessarily corresponds to low demand.

According to these reasons, the idle time component $I$ must not be overrated if the other two components indicate high demand. There are some cases, where these components have to be interpreted well, for instance if components $D$ and $O$ result in different demand predictions. This case differentiation is carried out in the following section and leads to a reasonable combination of all three components.

## 5.2 Combination of the Demand Model Components

In previous sections, several components were defined and revealed indications of actual demand from different points of view. In order to set up an integrated demand model, these components have to be combined appropriately.

### 5.2.1 Case differentiation

The demand components $D_z$, $O_z$ and $I_z$ were calculated and evaluated in previous sections. Each of them indicate low, moderate or high demand, dependent on the respective value per zone and time slot. But so far, these components are independent, i.e. in some cases the components show opposing results.

In zone 25 *Universität* for instance, $D$ indicates a high demand whereas $O$ predicts a low demand in time slot $T_3$ on weekends. In this case, it is most likely that $O$ results in low demand, because even more bicycles are returned in this zone, but the demand is high nevertheless. Taking into account the according idle time component $I$, it approves a high demand in zone 25 as the available bicycles there have short idle times.

First of all, a case differentiation is necessary in order to merge the three demand components. For $D_z$, $O_z$ and $I_z$ there are three different ranges of values. These ranges were classified into three categories, i.e. the respective values are either "high","medium" or "low", as table 5.5 shows. The size of the intervals is not equally distributed, but such that every interval has around the same amount of entries, i.e. the values for $D_z$, $O_z$ and $I_z$ are uniformly distributed in the "high","medium" or "low" class. Table 5.6

| component | low | medium | high |
|---|---|---|---|
| $D_z$ | [0, 0.15] | ]0.15, 0.31[ | [0.31, 1] |
| $O_z$ | [−12, −5] | ] − 5, 2[ | [2, 8] |
| $I_z$ | [0, 1.7] | ]1.7, 2.6[ | [2.6, 12] |

TABLE 5.5: Interval classification for all components

depicts the correlation of the three single components and the actual meaning can be interpreted: in case of a high $D_z$, there are almost no low idle times $I_z$ if $O_z$ is high-/medium there are only 4 and 5 occurrences respectively. The other way around if $D_z$ is low, the occurrence of low idle times is little, but medium and high values for $I_z$ are prevalent. All in all, the demand component $D_z$ inversely correlates with the idle time component $I_z$, meaning that the higher $D_z$, the lower is $I_z$ and the other way around.

Taking a look at the I/O component $O_z$, a correlation with $D_z$ or $I_z$ is not visible at a glance. This is the case, because a low $O_z$ does not necessarily imply low demand. To

| $D_z \downarrow$ | $O_z \rightarrow$ | high | medium | low |
|---|---|---|---|---|
| high | $I_z$ low | 28 | 26 | 24 |
| | $I_z$ medium | 11 | 14 | 14 |
| | $I_z$ high | 4 | 5 | 0 |
| medium | $I_z$ low | 11 | 12 | 9 |
| | $I_z$ medium | 11 | 27 | 8 |
| | $I_z$ high | 23 | 18 | 16 |
| low | $I_z$ low | 8 | 9 | 8 |
| | $I_z$ medium | 11 | 14 | 24 |
| | $I_z$ high | 17 | 17 | 31 |

TABLE 5.6: Frequency distribution of all different cases

recapitulate, the I/O component describes the flow of the fleet, i.e. the difference of rentals and returns per zone, ergo "outflow" - "inflow". Therefore a low $O_z$ can be interpreted as *even more* bicycles get returned in the specific zone and a self-regulation works in this case. On the contrary, if in addition to a high $D_z$, $O_z$ is high, too, the respective zone has a severe lack of bicycles, because of a high amount of rentals compared to a relatively low amount of returns that are made in this zone.

### 5.2.2 Weighting of the single components

The demand component $D_z$ measures current demand with the help of available stocks. As stated in 5.1.1, the raw output of $D_z$ needs some interpretation and therefore was adjusted. Hence it results in a qualitative measure to estimate upcoming demand regardless of current stock and weights equally as the I/O component.

The I/O component $O_z$ provides information about the current fleet flow, which is a self-regulation of surpluses or lacks of bicycles in some cases. This measure carries great weight concerning user-based relocations, which are expounded in 6.2. For the demand model, it is helpful to compare the values of $O_z$ in between all zones for a specific time interval. The sum of these values should be equal to zero in theory, because it is a close system with no loss of bicycles.

In reality, there are two reasons which cause a higher overall inflow/outflow in single time intervals:

1. a considerable part of the fleet is rented or returned outside of the operating area. This is officially not allowed and users get fined if they do so. In the I/O - Analysis, additional bicycles appear (in case of prior renting outside of the operating area) or some bicycles just vanish (in case of returning them outside of the operating area).

2. the operator already did some relocation trips in the year 2014; some bicycles appear within a certain time interval with different GPS coordinates - these bicycles have been relocated or at least collected, maintained and redistributed and therefore cause inconsistencies.

The latter fact will be used in 7.2.2, in order to capture the relocation trips back then.

The value $O_z$ compared among the zones ranks the attractiveness to rent a bicycle there and hence is an essential component to determine the final demand prediction.

The idle time component $I_z$ is also an important indicator for demand, even though it is not that reliable as the other two components, because of technical issues that cannot be captured (see also section 5.1.3). Therefore this component only weighs half as much as $D_z$ and $O_z$.

The final saturation pattern then consists of the following:

$$S_z^{*T_k} = S_{min} + D_z^{'T_k} + O_z^{'T_k} + I_z^{'T_k} \tag{5.6}$$

whereas $S_{min}$ guarantees a minimum stock for all times and zones.
In order to establish a certain perception of the bicycles in a potential empty zone, this value is set to 5 and in consequence the optimal stock recommendation per zone is always greater or equal 5.

$D_z^{'T_k}$, $O_z^{'T_k}$ and $I_z^{'T_k}$ are functions which span the values of each component (see tables 5.2, 5.3 and 5.4) respectively and assign the number of needed bicycles to each zone and time slot.

$D_z^{'T_k}$ is a square root function that features a high gradient for values close to zero, as indicated in green in figure 5.8. This ensures that small values for $d_z$ have an impact, too, especially because of the cluster of values in between [0, 0.2]. Further, $D_z^{'T_k}$ returns a maximum value of 20, which reflects the maximum for a stock recommendation based on the demand component and the minimum value 0.

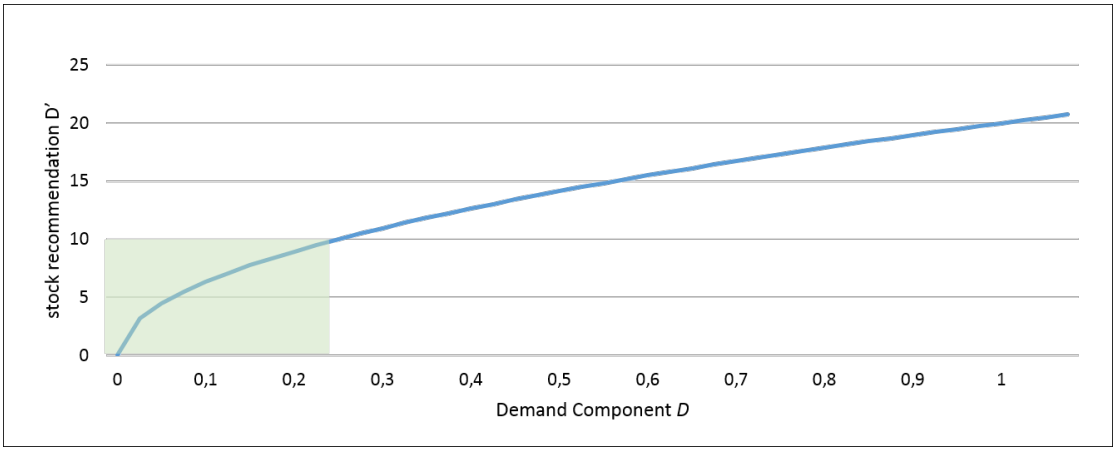


FIGURE 5.8: Conversion of the demand component $D$

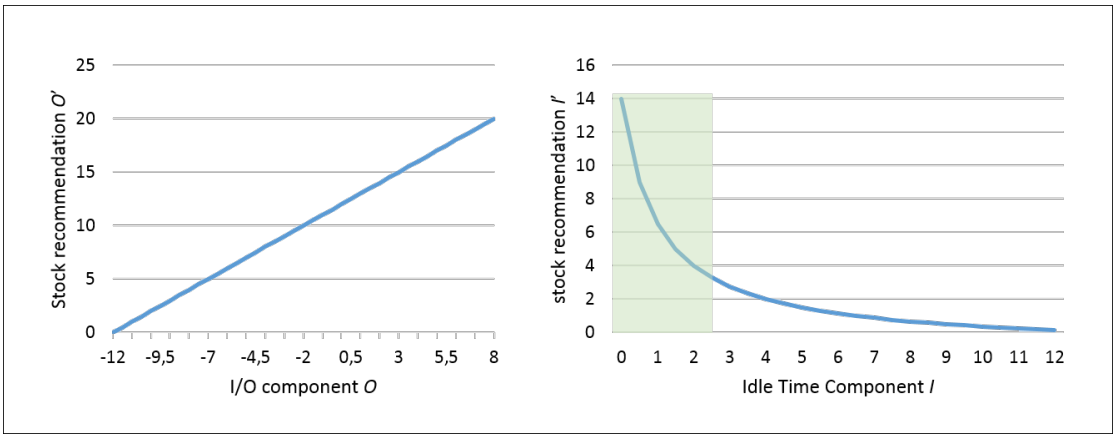


FIGURE 5.9: Conversion of the I/O component $O$ (left) and the idle time component $I$ (right)

$O_z^{'T_k}$ spans the values of table 5.3 linearly, as illustrated in the left part of figure 5.9.

$O_z^{'T_k}$ returns 0 in the case of *low demand* and also 20 for the maximum value of the I/O component. $I_z^{'T_k}$ follows a hyperbolic function, in order to push very short idle times (certain indicator for high demand) and not to overstate long idle times, as depicted within the green area in the right part of figure 5.9. The maximum of $I_z^{'T_k}$ is 10 (for the minimum value of $I_z^{T_k}$), which is only half as much compared to the other components - here the weighting comes into effect. The minimum of $I_z^{'T_k}$ is set to zero.

In consequence, a zone can have a maximum demand for 50 bicycles, only if all three components indicate maximum demand. In case of "zero demand indication" by all three components, the minimum stock remains and therefore a zone stock recommendation never undercuts the amount of five bicycles.

For each time slice per weekday and weekend, the demand model provides the upcoming demand for each of the 40 zones. For every zone and time slot, this model output represents a threshold, which should not be undercut, else the demand for rental bicycles is most likely not satisfied. Comparing the current FD with the calculated optimal distribution, we obtain the relocation steps, which are necessary to satisfy the occurring demand. The overall result of the demand model is the saturation matrix $S^*$ and resumed in table 5.7. This matrix is of size $40x10$ and contains the stock threshold for all 40 zones in respective 5 different time slots per weekday and per weekend. Hence it illustrates the optimal FD so that the demand can always - spatially and temporally - be satisfied.

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 8 | 21 | 18 | 24 | 14 | 10 | 8 | 22 | 20 | 14 |
| 2 | 8 | 25 | 20 | 26 | 16 | 11 | 9 | 26 | 25 | 16 |
| 3 | 9 | 25 | 22 | 30 | 18 | 12 | 8 | 27 | 28 | 21 |
| 4 | 8 | 19 | 17 | 22 | 14 | 10 | 9 | 18 | 20 | 13 |
| 5 | 8 | 18 | 20 | 28 | 15 | 10 | 8 | 22 | 25 | 16 |
| 6 | 12 | 27 | 29 | 43 | 24 | 16 | 10 | 35 | 37 | 24 |
| 7 | 8 | 24 | 20 | 27 | 16 | 11 | 8 | 25 | 23 | 16 |
| 8 | 10 | 19 | 16 | 23 | 17 | 12 | 9 | 22 | 25 | 22 |
| 9 | 8 | 19 | 19 | 22 | 13 | 10 | 9 | 19 | 20 | 13 |
| 10 | 8 | 19 | 17 | 24 | 14 | 10 | 8 | 21 | 22 | 14 |
| 11 | 10 | 25 | 23 | 33 | 20 | 12 | 9 | 25 | 28 | 21 |
| 12 | 9 | 22 | 21 | 29 | 16 | 11 | 8 | 26 | 25 | 17 |
| 13 | 7 | 18 | 16 | 19 | 13 | 9 | 7 | 18 | 18 | 13 |
| 14 | 9 | 21 | 22 | 33 | 19 | 14 | 8 | 26 | 27 | 19 |
| 15 | 10 | 25 | 24 | 33 | 19 | 16 | 9 | 27 | 27 | 21 |
| 16 | 10 | 23 | 22 | 29 | 19 | 14 | 8 | 28 | 28 | 19 |
| 17 | 8 | 23 | 21 | 30 | 18 | 12 | 9 | 28 | 28 | 20 |
| 18 | 9 | 25 | 20 | 26 | 17 | 12 | 8 | 26 | 26 | 17 |
| 19 | 7 | 21 | 18 | 22 | 13 | 9 | 8 | 21 | 19 | 15 |
| 20 | 10 | 28 | 23 | 32 | 20 | 13 | 8 | 29 | 28 | 19 |
| 21 | 9 | 24 | 21 | 29 | 18 | 12 | 8 | 26 | 26 | 17 |
| 22 | 8 | 22 | 18 | 26 | 15 | 11 | 10 | 23 | 23 | 15 |
| 23 | 9 | 23 | 20 | 27 | 16 | 11 | 8 | 23 | 23 | 18 |
| 24 | 9 | 22 | 22 | 29 | 18 | 13 | 9 | 26 | 26 | 18 |
| 25 | 10 | 19 | 26 | 40 | 20 | 13 | 7 | 28 | 35 | 20 |
| 26 | 11 | 23 | 21 | 34 | 20 | 15 | 10 | 26 | 34 | 21 |
| 27 | 8 | 23 | 22 | 33 | 18 | 11 | 8 | 27 | 28 | 19 |
| 28 | 9 | 28 | 22 | 28 | 18 | 11 | 9 | 28 | 26 | 18 |
| 29 | 8 | 24 | 21 | 23 | 14 | 10 | 8 | 23 | 21 | 14 |
| 30 | 9 | 31 | 24 | 33 | 19 | 13 | 9 | 30 | 28 | 19 |
| 31 | 11 | 30 | 26 | 36 | 21 | 15 | 10 | 33 | 30 | 21 |
| 32 | 10 | 32 | 28 | 39 | 21 | 13 | 9 | 34 | 33 | 21 |
| 33 | 11 | 21 | 25 | 40 | 22 | 16 | 8 | 28 | 32 | 22 |
| 34 | 10 | 20 | 22 | 32 | 17 | 13 | 8 | 24 | 26 | 19 |
| 35 | 11 | 26 | 25 | 37 | 22 | 17 | 9 | 27 | 31 | 22 |
| 36 | 8 | 21 | 18 | 22 | 13 | 9 | 8 | 21 | 20 | 13 |
| 37 | 9 | 24 | 24 | 37 | 19 | 12 | 8 | 30 | 30 | 20 |
| 38 | 10 | 24 | 23 | 35 | 21 | 14 | 9 | 27 | 28 | 22 |
| 39 | 9 | 22 | 19 | 25 | 15 | 11 | 8 | 24 | 24 | 16 |
| 40 | 7 | 20 | 17 | 21 | 13 | 9 | 8 | 21 | 19 | 14 |
| sum | 362 | 927 | 855 | 1183 | 695 | 484 | 338 | 1017 | 1040 | 722 |

TABLE 5.7: Saturation pattern for each zone and time slot on weekdays and weekends

**Remark:** the final result of the demand model refers to the entire operating period, i.e. from mid March to mid December 2014. Nevertheless, this model is also applicable for shorter time periods (e.g., if booking data are only available for a period of a few weeks). Mainly for testing reasons, the demand model was applied to monthly booking data. The differences of calculated demand patterns were not significant as only marginal differences in an inter-zone comparison occurred. Higher differences (but still moderate) concerned the overall fleet size (hence the overall demand), which was lower in the months April and May and also in October and November. This is consistent, as overall booking numbers in summer months are highest and ergo the demand is higher. For further calculations, the saturation pattern depicted in 5.7 is used. The results for each Month in 2014 (April to November) are attached to Appendix B.

In conclusion, a model to estimate the demand in a free-floating BS System was created in this chapter. The model output results in different time- and space-dependent thresholds that guarantee to satisfy the respective upcoming demand.

In the following chapters, different relocation strategies are presented in order to reach the state of an optimal FD, i.e. any previously unmet demand vanishes, as all under-supplied areas get eliminated. Further, the needed time and general impact of regularly conducted relocation trips is estimated.

# Chapter 6

# Relocation Strategies

In previous chapters, a detailed empirical data analysis led to a demand model, which estimates the occurring demand for rental bicycles on a spatial and temporal level. This demand forecast tool builds module I of the Relocation Model outlined in chapter 4. It predicts the needed amount of bicycles at several locations in the operating area within the next few hours. Depending on the current flee distribution (FD), the relocation process may vary from a few bicycles that need to be shifted to a severe relocation intervention by the operator. In order to realize this process most efficiently, module II is required and subject of this chapter: adequate Relocation Strategies.
This chapter is the core part of the thesis, as it addresses RQs 3a and 3b and forms the basis in order to answer the remaining RQs. It deals with finding the optimal execution to reach the state of a most balanced fleet, i.e. the demand model recommendations are optimally satisfied, in order to distribute the rental bicycles where users need them and hence increase the utility level of the entire BS System.

## 6.1 Operator-based Strategy

A conventional method to rebalance the fleet of a BS System is to use an operator-based strategy. The approaches vary widely (see also section 2.3.1) from relocating by instinct or experience, shifting parts of the fleet from *cold* to *hot spots* or performing a time-efficient strategy in order to keep the system running at minimized cost.

In the present case, the optimal FD for the current time interval is known, and - in cooperation with the operator - the actual current FD in the operating area is known as well. Consequently, the required fleet movements are evident already. The challenge is rather to obtain this fleet state in a minimum amount of time and at minimum cost. The resulting optimization problem is defined and solved in the following sections.

### 6.1.1 Optimization problem of the relocation process

This section deals with the question of how relocation trips can be carried out in a most efficient way. Main factors in the present case are time for the relocation, the operator's expense and most importantly the grade of accomplished relocations and resulting fleet status. In a best case, this status will satisfy the demand forecast in every zone.

In general, a vehicle routing problem (VRP) - a combinatorial optimization and integer programming problem - has to be solved. A VRP is characterized by a given set of customers that have to be delivered by a fleet of vehicles and a set of possible routes that have to be optimized. While the customers correspond to the zones (where the delivery should be accomplished), the fleet of vehicles corresponds to one relocation truck. The objective is to minimize the total route cost.

In the present case, instead of a central storehouse, there are spots with a surplus of bicycles that need to be picked up, and other spots where bicycles are needed and hence have to be delivered there – a case of classical pick up and delivery problems (PDPs). PDPs build up an important class of the vehicle routing problem, where commodities need to be transported between origins and destinations. In this case, the problem reduces to a so-called one-commodity pickup and delivery traveling salesman problem (1-PDTSP) as there is only one commodity, namely the bicycles.

Hernández-Pérez and Salazar-González elaborated this specific case of a VRP in [57, 58]. A problem definition and framework is given in the following.

#### 6.1.1.1 Problem formulation

Let $G = (V, A)$ be a complete and directed graph with vertex set $V_z = \{1, .., M\}$ with $M$ denoting the amount of customers/locations that have to be visited and $z$ denoting the according location index.
The arc set is defined as $A = (i, j) : i, j \in V, i \neq j$. Each arc length is non-negative, follows the triangle inequality and corresponds to the travel time/cost $c_{ij}$. It is assumed that the travel time between two zones is equal in both directions, i.e. $c_{ij} = c_{ji}$.
All optimization problem variables and defined quantities are listed in table 6.1.
The need for bicycles in the zones is either positive - if there is a lack of bicycles - or negative - if there is a surplus - or equal to zero in case of an already balanced zone $z$ at time $t_{cur}$ and is denoted by $b_z$. This quantity results from following equation:

$$b_z = s_z^{*T_k} - s_{z,cur} \tag{6.1}$$

whereas $s_z^{*T_k}$ arises from the the saturation matrix $S^*$ of demand model, as described in chapter 5 and $s_{z,cur}$ denotes the current FD. In this respect, the target time slot $T_{tar}$ is the subsequent time frame $T_k$ after the current time $t_{cur}$, such that $t_{cur} \in T_{k-1}$, assuming that the relocation process can be accomplished until time $t_k$ and $t_{cur} \in T_{k-2}$ elsewise. Without loss of generality the depot, i.e. the initial amount of bicycles to drop in the first zone, is defined as

$$b_1 := -\sum_{z=2}^{M} b_z \tag{6.2}$$

| Optimization problem variables | | | |
|---|---|---|---|
| $V$ | set of zones | $t_{cur}$ | current time |
| $A$ | set of paths between zones | $T_{tar}$ | target time interval |
| $M$ | number of zones | $C$ | Capacity of relocation vehicle |
| $z$ | zone index | $b_z$ | # of bicycles to shift per zone |
| $V'$ | any subset of $V$ | $\delta$ | small neighborhood of current zone |
| $A'$ | any subset of $A$ | $x$ | decision variable |

TABLE 6.1: Input variables for the optimization problem

and the capacity of the relocation vehicle is denoted by $C$, which is certainly positive. For each subset $V' \subset V$ a $\delta$-neighborhood is defined such as:

$$\delta(V') := \{(i, j) \in A : i \in V', j \notin V'\} \tag{6.3}$$

and for each subset $A' \subset A$ one has

$$x(A') := \sum_{(i,j)\in A'} x_{ij} \tag{6.4}$$

The goal is to minimize the total trip length, meaning the total duration of the entire relocation trip. Then the optimization problem is formulated based on the following edge-decision variables:

$$x_{ij} = \begin{cases} 1 & \text{, path goes from } i \text{ to } j \\ 0 & \text{, otherwise} \end{cases} \tag{6.5}$$

$$\min \sum_{(i,j)\in A} c_{ij} x_{ij} \tag{6.6}$$

Subject to

$$x(\delta(\{z\})) = 2 \quad \forall \ z \in V \tag{6.7}$$

$$x\left(\delta\left(V'\right)\right) \geq 2 \quad \forall \ V' \subset V \tag{6.8}$$

$$x(\delta(V')) \geq \frac{2}{C}\left|\sum_{z\in V'} b_z\right| \quad \forall \ V' \subset V. \tag{6.9}$$

Equation (6.7) ensures that the routing is Hamiltonian, i.e. every zone is visited exactly once. Constraint (6.8) guarantees the 2-connectivity between each zone. And equation (6.9) is a capacity constraint so that the relocation truck can always carry the required amount of bicycles. This constraint is similar to a typical capacity constraint

in capacitated VRPs (e.g., see [86]), with the additional property that the amount of bicycles that need to be relocated $b_z$ is allowed to be negative in case of a surplus.

The resulting optimization problem is an Integer Linear Program (ILP) and can be solved with the help of the following method: a branch-and-cut algorithm finds exact solutions e.g., [11, 57], which is basically a combination of two different solving approaches: a branch-and-bound algorithm and a cutting plane method. This scheme calculates an optimal routing by relatively low computational cost. The next section presents the implementation of this solver.

### 6.1.2 Software implementation

The optimization problem is classified as an Integer Linear Problem (ILP) and is solved by implementing it in MATLAB [74]. The provided solver *intlinprog* (see also [75]) is able to solve even Mixed Integer Linear Problems (MILPs) in polynomial time. The solver passes through following steps.

1. Reduction of the problem size using Linear Program Preprocessing.
2. Solving an initial relaxed (noninteger) problem using Linear Programming.
3. Performing (Mixed-)Integer Program Preprocessing to tighten the LP relaxation of the (mixed-)integer problem.
4. Try Cut Generation to further tighten the LP relaxation of the (mixed-)integer problem.
5. Finding integer-feasible solutions using heuristics.
6. Using a Branch-and-Bound algorithm to search systematically for the optimal solution.

As the MILP is reduced to an ILP, steps 2 to 4 are adapted and reduced accordingly. Based on the previously defined problem formulation, the implementation requires

following input:

$$\min_x \; f^t x \quad \text{subject to} \quad \begin{cases} x \quad \text{are integers} \\ A * x \leq b \\ Aeq * x = beq \\ lb \leq x \leq ub \end{cases} \tag{6.10}$$

where $A$ and $Aeq$ are matrices and $b$ and $beq$ the corresponding vectors that comprise the linear (in-)equalities and thus represent the needed constraints. These linear constraints restrict the solution $x$ by $lb$ and $ub$ - lower and upper bound. The respective quantities are set as follows.

As **input** variables there are:

1. number of locations, i.e. zones are set to $M = 40$
2. the corresponding centers of the zones, defined by lat. and long. of the GPS-coordinates
3. the capacity of the relocation vehicle is set to $C = 35$
4. current FD and the absolute number of required relocations
5. all imbalanced zones and their amount of surplus and lack of bicycles respectively comprised in $b_z$

with subject to minimize the total trip length of the relocation trip. Further constraints in order to avoid detours exclude routes that cause an extra travel time of 10 minutes per bicycle (accumulated). Additionally, the time for loading and unloading a bicycle is taken into account with 5 minutes on top per visited zone.

Let $S_{cur} = \sum_z s_{z,cur}$ denote the current fleet size and $B = \sum |b_z|$ the amount of required relocations in total. Then the fleet imbalances before the relocation intervention can be written as

$$I_{before} = \frac{B}{S_{cur}} \cdot 100\% \tag{6.11}$$

Further, $R_{acc}$ denote all accomplished bicycle relocations. The remaining imbalances are consequently

$$I_{after} = \frac{B - R_{acc}}{S_{cur}} \cdot 100\% \tag{6.12}$$

Let $\Re$ denote the relocation route. The travel time is composed of two components, an inter-zone distance, adding the path length between zones and a covered intra-zone distance, which depends on the amount of bicycles that need relocation per zone:

$$d_{total} = \sum_{(i,j)\in\Re} c_{ij}x_{ij} + \sum_{z\in\Re} d(b_z) \tag{6.13}$$

In case of a relocation tour during rush hours, a higher traffic density is most likely and the travel time is scaled. According to the Tomtom Traffic Index (see [122]), travel times for motorized traffic in Munich increase by 50% during 8 a.m. and 9 a.m and 5 p.m. and 6 p.m. on weekdays (besides Fridays when it is shifted to 4 p.m. to 5 p.m.). The entire morning and evening rush hours extend to the time intervals 7 a.m. to 10 a.m. and 4 p.m. and 8 p.m., as stated in [47]. Within these time periods, travel times are still increased but only around 30%. In case of a requested relocation trip within rush hour times, the total travel time $tt_{total}$ is accordingly adjusted.

The final **output** of the optimization problem then yields

1. the initial fleet imbalance in percent $I_{before}$ and the remaining imbalance $I_{after}$,
2. visited zones $Z_{vis}$ and amount of relocated bicycles $R_{acc}$
3. covered distance by relocation truck $d_{total}$
4. total travel time of relocation route $tt_{total}$

and is illustrated for selected dates in table 6.2. The runtime is not listed as the calculation in MATLAB is fast for any case (less than 5 seconds) and thus does not play a decisive role.

### 6.1.3 Performance in real time and link to reality

Table 6.2 reveals the results of the operator-based relocation strategy (RS).

It depicts the efficiency of the method for several test cases. In order to keep the results comparable, seven consecutive days (Monday to Friday) have been chosen in May, June and September respectively and the relocation trips started at 1 a.m. on weekdays (in June, the relocation method is applied for 4 a.m as well) and 10 a.m. on weekdays; this time is denoted as $t_{cur}$.

The second column, the target time $t_{tar}$ is the time, when all relocation steps should be accomplished. That means, the recommended FD (calculated in chapter 5) refers to the target time.

| Date / $t_{cur}$ | $t_{tar}$ | $I_{before}$ | $R_{acc}$ | $I_{after}$ | $Z_{vis}$ | $d_{total}$ | $tt_{total}$ |
|---|---|---|---|---|---|---|---|
| May 12, 1 a.m. | 6 a.m. | 37.07% | 296 | 10.31% | 26 | 33.11 km | 6.04 h |
| May 13, 1 a.m. | 6 a.m. | 37.63% | 321 | 9.28% | 23 | 30.95 km | 6.38 h |
| May 14, 1 a.m. | 6 a.m. | 38.88% | 304 | 12.38% | 24 | 33.46 km | 6.18 h |
| May 15, 1 a.m. | 6 a.m. | 37.69% | 309 | 11.10% | 23 | 31.51 km | 6.20 h |
| May 16, 1 a.m. | 6 a.m. | 41.33% | 349 | 11.95% | 28 | 34.16 km | 6.96 h |
| May 17, 10 a.m. | 4 p.m. | 42.01% | 421 | 6.99% | 30 | 34.41 km | 8.16 h |
| May 18, 10 a.m. | 4 p.m. | 41.49% | 437 | 5.37% | 28 | 35.20 km | 8.46 h |
| June 16, 1 a.m. | 6 a.m. | 34.64% | 258 | 14.38% | 21 | 31.57 km | 5.35 h |
| June 17, 1 a.m. | 6 a.m. | 35.95% | 305 | 12.27% | 24 | 33.11 km | 6.19 h |
| June 18, 1 a.m. | 6 a.m. | 37.83% | 329 | 12.48% | 24 | 33.17 km | 6.59 h |
| June 19, 1 a.m. | 6 a.m. | 34.81% | 287 | 12.56% | 22 | 30.79 km | 5.81 h |
| June 20, 1 a.m. | 6 a.m. | 32.03% | 268 | 11.15% | 23 | 31.60 km | 5.52 h |
| June 21, 10 a.m. | 4 p.m. | 33.41% | 345 | 6.73% | 26 | 32.66 km | 6.84 h |
| June 22, 10 a.m. | 4 p.m. | 31.49% | 365 | 3.04% | 27 | 31.30 km | 7.13 h |
| June 16, 4 a.m. | 10 a.m. | 33.62% | 199 | 17.99% | 16 | 30.08 km | 4.62 h |
| June 17, 4 a.m. | 10 a.m. | 35.98% | 242 | 17.17% | 22 | 34.93 km | 5.55 h |
| June 18, 4 a.m. | 10 a.m. | 37.39% | 251 | 18.04% | 20 | 33.20 km | 5.62 h |
| June 19, 4 a.m. | 10 a.m. | 32.22% | 187 | 17.74% | 15 | 28.55 km | 4.35 h |
| June 20, 4 a.m. | 10 a.m. | 29.44% | 162 | 16.82% | 14 | 29.57 km | 3.98 h |
| Sep 15, 1 a.m. | 6 a.m. | 33.93% | 332 | 10.94% | 26 | 32.80 km | 6.63 h |
| Sep 16, 1 a.m. | 6 a.m. | 32.41% | 308 | 11.08% | 25 | 32.68 km | 6.22 h |
| Sep 17, 1 a.m. | 6 a.m. | 35.94% | 371 | 10.49% | 26 | 33.91 km | 7.31 h |
| Sep 18, 1 a.m. | 6 a.m. | 34.40% | 340 | 10.82% | 23 | 31.82 km | 6.73 h |
| Sep 19, 1 a.m. | 6 a.m. | 33.43% | 318 | 11.33% | 25 | 34.76 km | 6.46 h |
| Sep 20, 10 a.m. | 4 a.m. | 33.96% | 436 | 3.74% | 29 | 32.36 km | 8.35 h |
| Sep 21, 10 a.m. | 4 a.m. | 37.22% | 459 | 5.35% | 32 | 35.73 km | 8.84 h |

TABLE 6.2: Results of operator-based Relocation Strategy

The following columns contain the final amount of accomplished relocations $R_{acc}$ (either picked up or dropped off), the percentage of imbalances before $I_{before}$ and after $I_{after}$ the relocation trip, i.e. the amount of required bicycle relocations and the remaining imbalanced bicycles respectively compared to the current fleet size.
Further, the number of zones that were approached $Z_{vis}$, the total travel distance $d_{total}$ and the corresponding travel time $tt_{total}$ are displayed.

In a comparison by week, the imbalances on weekdays are highest on Wednesdays but similar for all weeks. This is different on weekends, as the imbalances vary from 30% to 40% on the chosen dates. Comparing the test cases for different target times (in the week of June for 6 a.m. and 10 a.m.), the efficiency for the target time 10 a.m. (i.e. start of relocation tour on 4 a.m.) is lower. First, this is caused by more traffic between 6 a.m. and 9 a.m. and thus the travel time is higher (in relation to visited zones and accomplished relocations). Second, the BS System is already in heavy use during the relocation trip and hence, the rentals can affect the currently running relocation.

The fleet imbalances afterwards range between 3% and 18%. In the latter case, the relocation trip seems quite ineffective, as a severe amount of bicycles still idles in wrong spots. Nevertheless, the fleet imbalances before were really high e.g., on June 18 with around 37%. If the relocation trip already starts at 1 a.m. though, only 12% of imbalances remain which is also indicative of relocating earlier.

In general, $I_{after}$ is always lower on weekends, when the demand pattern differs and additionally, the traffic density is not as high as on weekdays. The insistence of fleet imbalances after a relocation trip has several reasons: on the one hand, small imbalances in zones are ignored due to detours causing higher travel times. On the other hand, the capacity of the relocation vehicle forces that very high imbalances cannot entirely eliminated, ergo some visited zones may still feature a lack or a surplus of bicycles.

In summary, it can be stated that a single relocation trip can take up to 8 hours in total, depending on time of day and initial state of the fleet. This is confirmed by real-word relocation trip durations: the dispatchers of the BS System *Captial Bikeshare* accomplish 25 bicycle relocations in around 45 minutes (see [25]). Compared to this, the calculated trip durations might be slightly optimistic.

In any case, relocation trips call for various costs, namely for labor, a vehicle and its maintenance, fuel etc. and do not seem to be a very efficient or quick way to bring the BS fleet in a fully balanced state so that the system can satisfy upcoming demand.

In order to enhance and accelerate the depicted relocation performance, the next section presents an incentive-based strategy that substitutes and/or supplements relocation trips by users.

## 6.2 User-based Strategy

This section deals with substituting operator-based relocations with relocation trips made by the users themselves. In a best case scenario, the fleet would be relocated constantly without any interference, hence no extra trips would either cause environmental drawbacks or labor cost, vehicles, fuel etc. At the same time, the current FD would satisfy the demand at all times and locations.

In reality, there are some constraints though:

1. the relocation process might take longer than operator relocations
2. a change of travel plans is not an option for many users and their trips
3. current user's willingness to change their travel plans is hard to predict

The process of relocating the fleet by an incentive-based approach only is not as predictable as a prior planned relocation route. In most cases, the fleet adjustment takes longer and it is hard to forecast when the needed bicycles will have been relocated by the users. If a user has an appointment (which is most likely at a set time and location) for instance, there is only a small chance to incentivize and convince them to adapt their destination. But there might be a user group that will check trip mode options before actually taking a trip - and if there is an appropriate discount (if there is any for the current location and the destination), they might take a rental bicycle.

### 6.2.1 Estimation of user's willingness

There are different user groups and of course different trip purposes for using a BS System. In general, for all trips (all modes) that are made by registered users, there is a potential for an incentivized relocation trip. The following decision tree illustrates the user behavior and the possibility for trip changes or the potential for decisions to realize trips by rental bicycles because of an interesting discount offer.

The following estimations are based on different sources of information, as listed in table 6.3.

Niels and Bogenberger analyzed the booking behavior of CS users [90] and found out that only 13% of all smart phone app requests resulted in a car reservation and eventually in a performed trip. Further, a share of 21% featuring a spontaneous booking behavior was determined. Transferred to BS, it is assumed that BS trips occur even more spontaneously, namely 67% and accordingly 33% are *planned* BS trips.

In 2014 a survey was carried out among BS System users in Germany [101]. A part of this survey investigated the price sensitivity and walking distance, users are willing to walk. 40% of the respondents stated to use a BS Systems only if a rental bicycle is available around the corner and convenient for the trip purpose. It is assumed that

| **Study /Source** | **Results** | **Adjusted Decision Factor** |
|---|---|---|
| booking behavior of CS users [90], applies to **decision level 1** | 13% make a car reservation after app consultation / 21% bookings directly (spontaneously) at the car | **33% ride definitely** by rental bicycle / **67%** decide **spontaneously** |
| survey of BS users [101], applies to **decision level 3** | 40% of users claimed to use a rental bicycle only if "conveniently situated" | **20%** chose **another trip mode** |
| price sensitivities in PT usage [138], applies to **decision level 3** | 10% more PT trips in case of a flexible pricing scheme | **10%** share of a **definite relocation trip** |
| price sensitivities in CS usage [28, 110], applies to **decision level 3** | sharp price consciousness due to low *indifference-percentage* of 15% of CS users, i.e. the remaining users care for pricing | between **20%** and **30%** (in resp. decision branch) are potential, **price-dep. relocation trips** |

TABLE 6.3: Sources of information concerning single decision levels

half of these possible trips are made by rental bicycle, whereas the remaining part is accomplished by other trip modes.

In [138], Wirtz modeled the mobility behavior of PT users and their choice for traffic modes and also approves a certain price sensitivity of users. The author determined a plus of 10% in PT trips (accomplished by users without subscription) if a flexible pricing scheme applies. This percentage is transferred directly to BS Systems: 10% of trips are additionally induced in case of a price incentive.

In [110], Seign investigated the user's willingness to pay certain prices for a CS vehicle. Different scenarios investigated a price consciousness. As a result, only 15% of users are indifferent to pricing schemes. This amount is assumed to be higher concerning BS, e.g. only up to 30% of trips are supposed to be *incentivizable*. Further, the CS System Operator Drive Now (see [39]) established the pricing model *Driv'n Save* [28] in 2015, in order to increase the occupancy rate of CS vehicles. However, a performance quantification e.g., the gain in booking numbers is not known.

Figure 6.1 unravels the three different decision levels and their respective likelihood. There is a trip from A to B the user wants to realize. A* and B* denote any deviation from the original start and end location respectively. There is one main time dependent difference: on weekday mornings, most of registered users might have their commuting routine without using the BS System (see also the empirical data results in chapter 3). Hence user-based relocations are presumed to be most effective on weekdays between 10 a.m. and 8 p.m. (after 8 p.m. the usage rate is rather low) as well as on weekends during day time with no further time constraint. Therefore these time frames, especially (late) afternoon and weekends support the following approach.

On **decision level 1**, there are two options: either the user has already decided to go by rental bicycle or they check available alternatives such as public transport, taxi, private car etc. This probability relation is 1:2, i.e. a third of all trips are previously decided to be realized by rental bicycle (see also table 6.3). For both cases, the user gets discount rates for the initial trip A to B - if available - or the adapted route A* to B*, but for the latter case (no trip mode yet), the discount offer leads to a higher likelihood to opt for the rental bicycle and hence generates extra (relocation) trips by bicycle.

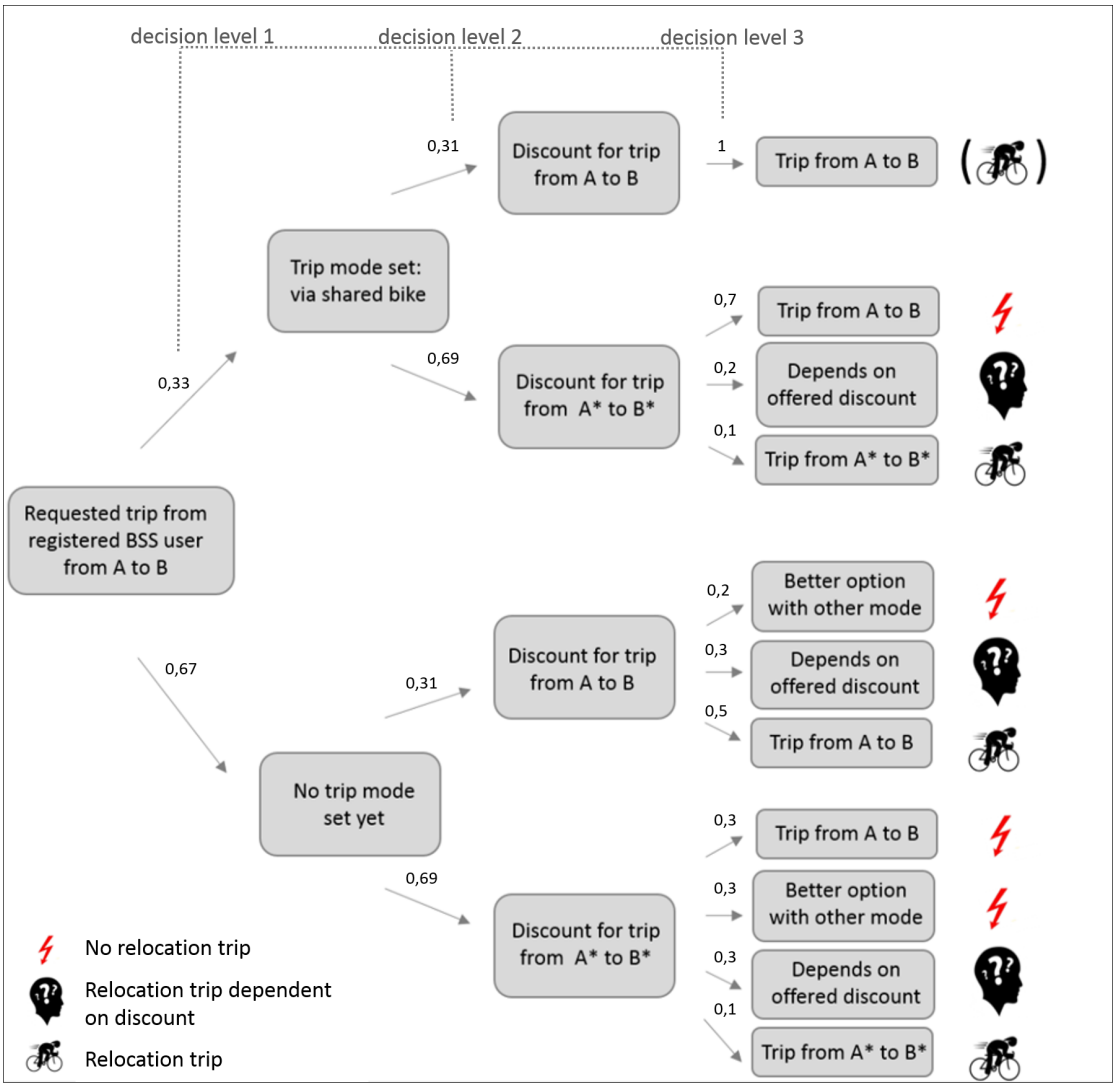


FIGURE 6.1: Decision tree of users's behaviour to trip changes

The likelihood in **decision level 2**, if the trip A to B is offered with discount, yields from following approach: a trip supports the needed relocation steps either if

1. A lies in a surplus zone and B lies in an under-supplied or balanced zone, or
2. A lies in a balanced zone and B lies in an under-supplied zone.

otherwise there is only a discount offer for an adjusted trip from A* to B*. Then the likelihood $P_z(x)$ of a discount offer for a trip from A to B dependent on the number of balanced zones can be written as

$$P_z(x) = \left(\frac{z-x}{2z}\right)^2 + \frac{x*(z-x)}{z^2} \tag{6.14}$$

where the variable $x$ denotes the number of balanced zones with the constraint that the amount of over- and under-supplied zones is equal and $z$ parametrizes the amount of zones, which is equal to 40 in the present case. This probability measure yields the following results: in case of low imbalances e.g., 30 zones feature a balanced distribution, $P_{40}(30) = 0.20$ and thus the likelihood for a discount trip from A to B is 20%. Analogously, $P_{40}(20) = 0.31$ in case of medium imbalances and $P_{40}(10) = 0.33$ in case of high imbalances. Ergo: the higher the imbalances, the more likely trip A to B will be discounted. Overall, the likelihood for discount of the initial trip ranges between 0.20 and 0.33, hence the likelihood for no discount, i.e. only for an adjusted trip A* to B*, ranges between 0.67 and 0.80, depending on the current FD state.

**Decision level 3** is the most complex one: the first case involves 'trip by BS System' and 'offered discount for A to B'. The resulting trip will be realized but would have been realized without the relocation incentive. Therefore these kind of trips are not *real* relocation trips and hence the symbol in figure 6.1 is in parentheses. The branch 'trip by BS System' and 'offered discount for A* to B*' results in three different scenarios. In 70% of the cases, the user realizes their trip from A to B regardless of the discount or route adjustment. The remainder splits in 10% that realizes the adjusted trip from A* to B* and 20% that weighs up the offer and decides dependent on that.
The branch 'no mode yet' and 'offered discount for A to B' also splits in three scenarios: either there is an alternate, better mode to realize the trip (20%) or the user weighs up (30%) or they accomplish the trip from A to B (50%) which then is a needed relocation trip. In case of only a discount offer for A* to B*, this share shrinks to only 10%, while 30% contemplate, find a better mode to travel or take the initial trip from A to B respectively.

To sum up, the decision tree scenario aims for time periods out off morning peak hours and is dependent on the current state of the fleet (decision level 2). Assuming medium imbalances, i.e. $P_{40}(20) = 0.31$ , the decision tree leads to following output:
10.41% are unintended relocation trips and go incidentally from A to B. In 47.71% the user will not conduct a relocation trip (either because of no trip adjustment or other mode). 17.29% of the trips turn assuredly into relocation trips and is denoted as $P_{as}$. Additional 24.59% have the potential to become relocation trips depending on the discount offer, which is denoted as $P_{dep}$. Besides the positive effect of relocating the fleet,

this user-based strategy might generate extra trips by rental bicycle up to almost 25% accordingly.

### 6.2.2 Urgency index

Previous sections show possibilities to counter imbalances from the operator view by a relocation route along the imbalanced zones.
The current grade of imbalances is taken into account, i.e. the amount of bicycles that have to be relocated. If those imbalances are high, these zones are prioritized as the optimal relocation route is determined.

For the incentive-based RS which is ideally self-regulating without any direct operator's relocations, a holistic view of the fleet dynamics is needed. Therefore the urgency to relocate in certain zones is not only dependent on the current imbalances, but also on the upcoming predicted fleet dynamics in these zones.

A reasonable urgency index most importantly points out under-supplied areas, as a persistence of unmet demand causes a deficit for the entire BS System.

The following components are included to set up the urgency index:

- current deficit/surplus of bicycles per zone
- forecasted inflow/outflow in the next time frame
- forecasted demand/needed stock in the next time frame.

In a worst-case scenario, there is a high fleet deficit in zone $z$, only a few bicycles will presumably be returned there in the next time frame (low inflow) and the demand model predicts an upcoming high demand there. In this case, there is an urgent need for action in zone $z$. Looking at it the other way around, the case of a surplus zone combined with a forecasted high inflow rate but only low demand in the next time frame does impair the BS System as well. In this zone, concerning bicycles will cluster and idle there redundantly while this part of the fleet might be lacking in other zones with temporarily high demand. However, the latter case is not that incisive for the BS System like the first named worst-case scenario, as bicycles there are actually needed to meet the demand and not only idling abundantly.

In order to create an urgency index, a function is set up by taking into account all three different components and mapping it to a natural number from 1 (low urgency) to 10 (ultimate urgency).

Assuming $t_{cur} \in T_k$ and denote $s^{T_k} := s_{cur}$, the current deviation can be written as

$$dev(T_k) = \frac{s^{*T_k} - s^{T_k}}{s^{*T_k}} \tag{6.15}$$

where $s^{T_K}$ is the current stock and $s^{*T_k}$ the current demand model recommendation calculated for each zone $z$ separately. Analogously, this deviation is calculated for the following time period $T_{k+1}$, however, the real stock (in future) $s^{T_{k+1}}$ is not known yet and therefore estimated by

$$s^{T_{k+1,est}} = s^{T_k} + o^{T_k} \tag{6.16}$$

with the flow component of the demand model $o_{T_k}$ (see section 5.3).

The next step compares the deviations for the current and following time step: is the deviation getting higher (both cases surplus zone with high inflow and deficit zone with high outflow) the urgency for relocation is highest.

$$U(|dev(T_k)|) = \begin{cases} 7-10 & |dev(T_{k+1})| > |dev(T_k)| \text{ and } |dev(T_k)| \geq 0.2 \\ 4-6 & |dev(T_{k+1})| \leq |dev(T_k)| \text{ and } 0,1 < |dev(T_k)| < 0.2 \\ 0-3 & |dev(T_{k+1})| < |dev(T_k)| \text{ and } |dev(T_k)| \leq 0.1 \end{cases} \tag{6.17}$$

where the refinement of the three urgency cases is dependent on the deviation in time period $T_{k+1}$. In case of $dev(T_k) < 0$, i.e. the zone is currently over-saturated, $U(dev(T_k))$ is denoted with a minus sign consequently.

This urgency index gives not only information about fleet imbalances at time $T_k$ but also includes potential worsening of the fleet state. For a set time in $T_{k+1}$, every zone features a corresponding urgency index and hence measures the importance of imminent relocations. To match this urgency to the user behavior, the incentive per user-based relocation trip is controlled by a pricing scheme.

### 6.2.3 Pricing

For a user-based relocation scenario - that should be accomplished in the fastest way possible - one could suggest to allow the users a free ride if their origin and destination match. Nevertheless, this scheme has a certain drawback - besides the fact that the operator would rent out the bicycles for free. There is no control over the user behavior and it is most likely that the fleet imbalances just shift after a short period of time, because currently 'attractive for returning' zones would get over-saturated and vice versa.

The scenario is very time-sensitive, as presumably many users take the offer, but the actual result is delayed in time: the accomplishment of a user-based relocation only gets detectable after the trip if the user really returned the bicycle at the stated destination. If not, the normal price is due.

A *predictive* approach is given by known regular trips and the estimation of potential user-based relocations in the precedent section. This is crucial to regulate the trip incentives in order to avoid a *relocation overflow*, which could possibly cause further relocations afterwards.

Ergo: the main questions for building up the incentive pricing are

1. how attractive is a zone for renting a bicycle?
2. how attractive is a zone for returning a bicycle?
3. how urgent is a relocation process in a zone?

The attractiveness for renting a shared bicycle is mapped by the stock recommendation $s*_{T_k}$ of the demand model, created in chapter 5. The higher the demand forecast, the higher the stock recommendation, hence the attractiveness for renting. To capture the attractiveness for returning, it is sufficient to use the inflow (returned bicycles) per zone and time slot $x_{T_k}$ that was calculated to determine the I/O component ibidem. The return of bicycles happens without any influence of external factors, there is no limitation like bicycle stations for instance. Returning a bicycle has no constraints and therefore the attractiveness for returning simply results in the current inflow. The urgency for relocation that prevails in the single zones is described by $U(dev(T_k))$ as

defined in the section 6.2.2 above.

To recapitulate: let A be the user's origin and B their requested destination. Then the trip from A to B gets incentivized if

1. A lies in a surplus or balanced zone and B lies in an under-supplied zone, or
2. A lies in a surplus zone and B lies in a balanced zone

whereas the cases in 1. weigh more because of the occurrence of under-supply. Hence, a trip from A to B requested in time interval $T_k$ will get most discount if A is in a surplus zone and currently not attractive for renting according to the stock recommendation $s^{*T_k}$ (40% off) and B lies in an under-supplied zone with a very low attractiveness for returning, based on the averaged inflow data per time interval (additionally 40% off). The user ergo gets an offer with 80% discount at the extreme. The remaining cases are scaled as listed in table 6.4. The discount cases for the start zone (whether balanced or surplus and its respective attractiveness) are added as well as the discount cases for the destination (whether balanced or deficit and its respective attractiveness) and result in a maximum discount of 80% as described above and 0% in case of both start and destination zone are balanced and hence excluded from the discount offer. In between the relocation incentives range between 10% and 70%.

Referring to the previous section 6.2.1, $P_{dep}$ = 25% of potential shared bicycle trips are influencable by offering an appropriate price. Hence in case of a high discount offer, more bicycle trips and hence relocation trips are generated.

Table 6.5 depicts the user-based relocation scenarios on different days in the operating period 2014. For each exemplary day, all five possible time slots are evaluated. The

| zone state | constraint | discount |
|---|---|---|
| A in surplus zone | $U(dev(T_k)) \in [-10, -5]$<br>$U(dev(T_k)) \in ]-5, 0]$ | 20%<br>10% |
| A in balanced zone | $U(dev(T_k)) \in ]-5, 5[$ | 0% |
| A in zone currently not attractive for renting | $s^{*T_k} < 10$<br>$s^{*T_k} < 15$ | 20%<br>10% |
| B in deficit zone | $U(dev(T_k)) \in [5, 10]$<br>$U(dev(T_k)) \in [0, 5[$ | 20%<br>10% |
| B in balanced zone | $U(dev(T_k)) \in ]-5, 5[$ | 0% |
| B in zone currently not attractive for returning | $x^{T_k} < 10$<br>$x^{T_k} < 15$ | 20%<br>10% |

TABLE 6.4: Pricing scheme for user-based relocation strategy

| Date / $t_{cur}$ | $t_{tar}$ | $M_{us,cur}$ | $R_{inc}$ | $M_{us,tar}$ | $\triangle M_{us}$ |
|---|---|---|---|---|---|
| Thu, May 15, 12 a.m. | 6 a.m. | 8 | 35 | 8 | $0 \rightarrow \ominus$ |
| Thu, May 15, 6 a.m. | 10 a.m. | 4 | 106 | 2 | $2 \rightarrow \oplus$ |
| Thu, May 15, 10 a.m. | 4 p.m. | 15 | 72 | 7 | $8 \rightarrow \oplus\oplus$ |
| Thu, May 15, 4 p.m. | 8 p.m. | 3 | 244 | 0 | $3 \rightarrow \oplus$ |
| Thu, May 15, 8 p.m. | 12 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Mon, June 16, 12 a.m. | 6 a.m. | 7 | 48 | 7 | $0 \rightarrow \ominus$ |
| Mon, June 16, 6 a.m. | 10 a.m. | 4 | 106 | 0 | $4 \rightarrow \oplus$ |
| Mon, June 16, 10 a.m. | 4 p.m. | 14 | 106 | 7 | $7 \rightarrow \oplus\oplus$ |
| Mon, June 16, 4 p.m. | 8 p.m. | 1 | 257 | 0 | $1 \rightarrow \oplus$ |
| Mon, June 16, 8 p.m. | 12 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Thu, June 19, 12 a.m. | 6 a.m. | 6 | 46 | 6 | $0 \rightarrow \ominus$ |
| Thu, June 19, 6 a.m. | 10 a.m. | 2 | 97 | 1 | $1 \rightarrow \oplus$ |
| Thu, June 19, 10 a.m. | 4 p.m. | 14 | 85 | 4 | $10 \rightarrow \oplus\oplus$ |
| Thu, June 19, 4 p.m. | 8 p.m. | 1 | 224 | 0 | $1 \rightarrow \oplus$ |
| Thu, June 19, 8 p.m. | 12 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Sat, June 21, 12 a.m. | 6 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Sat, June 21, 6 a.m. | 10 a.m. | 6 | 58 | 5 | $1 \rightarrow \oplus$ |
| Sat, June 21, 10 a.m. | 4 p.m. | 6 | 117 | 2 | $4 \rightarrow \oplus$ |
| Sat, June 21, 4 p.m. | 8 p.m. | 1 | 182 | 0 | $1 \rightarrow \oplus$ |
| Sat, June 21, 8 p.m. | 12 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Mon, Sep 15, 12 a.m. | 6 a.m. | 7 | 45 | 6 | $1 \rightarrow \oplus$ |
| Mon, Sep 15, 6 a.m. | 10 a.m. | 7 | 98 | 1 | $6 \rightarrow \oplus$ |
| Mon, Sep 15, 10 a.m. | 4 p.m. | 16 | 102 | 4 | $12 \rightarrow \oplus\oplus$ |
| Mon, Sep 15, 4 p.m. | 8 p.m. | 1 | 177 | 0 | $1 \rightarrow \oplus$ |
| Mon, Sep 15, 8 p.m. | 12 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Sat, Sep 20, 12 a.m. | 6 a.m. | 0 | 0 | 0 | $0 \rightarrow \ominus$ |
| Sat, Sep 20, 6 a.m. | 10 a.m. | 10 | 66 | 6 | $4 \rightarrow \oplus$ |
| Sat, Sep 20, 10 a.m. | 4 p.m. | 9 | 127 | 4 | $5 \rightarrow \oplus$ |
| Sat, Sep 20, 4 p.m. | 8 p.m. | 4 | 188 | 1 | $3 \rightarrow \oplus$ |
| Sat, Sep 20, 8 p.m. | 12 a.m. | 2 | 158 | 1 | $1 \rightarrow \oplus$ |

TABLE 6.5: Results of user-based Relocation Strategy

different columns show date and start time $t_{cur}$ and the target time $t_{tar}$, the number of under-supplied zones $M_{us,cur}$ at the start time referring to the target time, the amount of realized user-based relocation trips $R_{inc}$ and the number of under-supplied zones afterwards $M_{us,tar}$. The last column illustrates the effectiveness of the user-based RS: $\triangle M_{us}$ shows the amount of eliminated under-supplied zones and the performance is indicated by $\ominus$ (bad perfomance), $\oplus$ (good performance) and $\oplus\oplus$ (outstanding performance).

On the first day, Monday, June 16, the user-based strategy seems quite effective at first sight: under-supplied zones remain for only two target times - namely 6 a.m. and 4

p.m. - so this strategy rebalances the entire fleet for three time slots. At 6 a.m. though, the 48 realized relocation trips do not reduce the number of under-supplied zones. Comparing to other weekdays, this target time always works very poor. The main reason is simple: not many trips are taken between midnight and 6 a.m., therefore the potential to incentivize the users (meaning the current demand) is low. During weekdays, for target time 4 p.m. the user-based strategy is never sufficient: for all three test cases, at least 4 under-supplied zones remain.

On Saturdays, this pattern significantly differs: between midnight and 6 a.m. the strategy is not applicable due to low booking numbers in this time slot or in other words: the amount of needed bicycles at 6 a.m. on Saturdays is very low according to the demand model (see chapter 5) and therefore no under-supplied zones are detected. For the other target times, the strategy is not quite effective again because of lacking booking numbers. On June 21, 5 and 2 zones remain under-supplied and on September 20, 6 and 4 for the corresponding target times 4 p.m. and 8 p.m. respectively.

The table reveals that a user-based strategy might improve the fleet imbalances for some target times, especially on weekdays between 6 a.m. and 10 a.m. and between 4 p.m. and 8 p.m. For other target times however, this method is not sufficient in most cases, as the potential for incentivized trips is too low because of low booking numbers at this point. If the RS applies regularly though, the user-based scheme could perform better, as the imbalances might be lower. This scenario is covered in a long-term simulation in chapter 7.

To enhance the overall performance and the supply in a short-term sense, a combination of both presented strategies is carried out in the following section.

## 6.3 Hybrid Relocation Strategy

Previous sections showed results for different RSs: one operator-based and one user-based. In terms of efficiency both display optimal target times during which they work most effectively.

For the operator-based relocation route that is conducted by a relocation vehicle, the time frame between 1 a.m. and 6 a.m. (target time) works best. In case of the user-based scheme, the best results are achieved on weekdays between 6 a.m. and 10 a.m. and 4 p.m. and 8 p.m and on weekends between 6 a.m. and 4 p.m. Ergo: if the operator-based method is most efficient, the user-based method performs poorly and vice versa.

This section deals with finding an optimal combination of both strategies.

### 6.3.1 Decision variables for integration of both strategies

Previous sections have shown that both strategies, the operator-based and the user-based, have advantages, but also drawbacks as summarized in table 6.6.

Further, the best target times for a most efficient application of the respective strategy is given. With an optimal combination of both strategies, they can aid one another.

| relocation strategy | advantages | disadvantages | to apply |
|---|---|---|---|
| operator-based | fleet relocation is very predictable and reliable | cost for labor, relocation vehicles and extra trips | heavily dependent on traffic conditions |
| | combination with maintenance of bicycles is possible | not environmentally sustainable, because of vehicle support | at best accomplished weekdays before 6 a.m. |
| user-based | low cost because no staff is needed | strategy is maybe not efficient and reliable | weekdays in the morning and afternoon |
| | no generation of extra relocation vehicle trips, hence sustainable | willingness of users is hard to predict | weekends between 6 a.m. and 4 p.m. |

TABLE 6.6: Comparison of operator-based and user-based relocation method

The main goal hereby is to speed up the entire relocation process, followed by shorten the total trip length, the relocation vehicle has to cover.

The scheme works as follows and is sketched in figure 6.2:

1. search for heavy imbalances that only occur in a sub-part of the operating area
2. check for moderately imbalanced zones that cluster spatially round the detected imbalances in 1. and run the operator-based method for the detected sub-part
3. search for all remaining under-supplied zones and check if they will be eliminated by the user-based method
4. if under-supplied zones remain, rerun step 2. with remaining zones and check the generated extra cost: up to an extra travel time of 5 minutes per bicycle (accumulated) is accepted for one zone, otherwise only the user-based strategy applies here.

In a worst case, all heavily imbalanced zones are spread in the operating area, and the relocation route will result in a long trip. In other circumstances though, the algorithm finds a short route in order to approach all heavily imbalanced zones that are adjacent

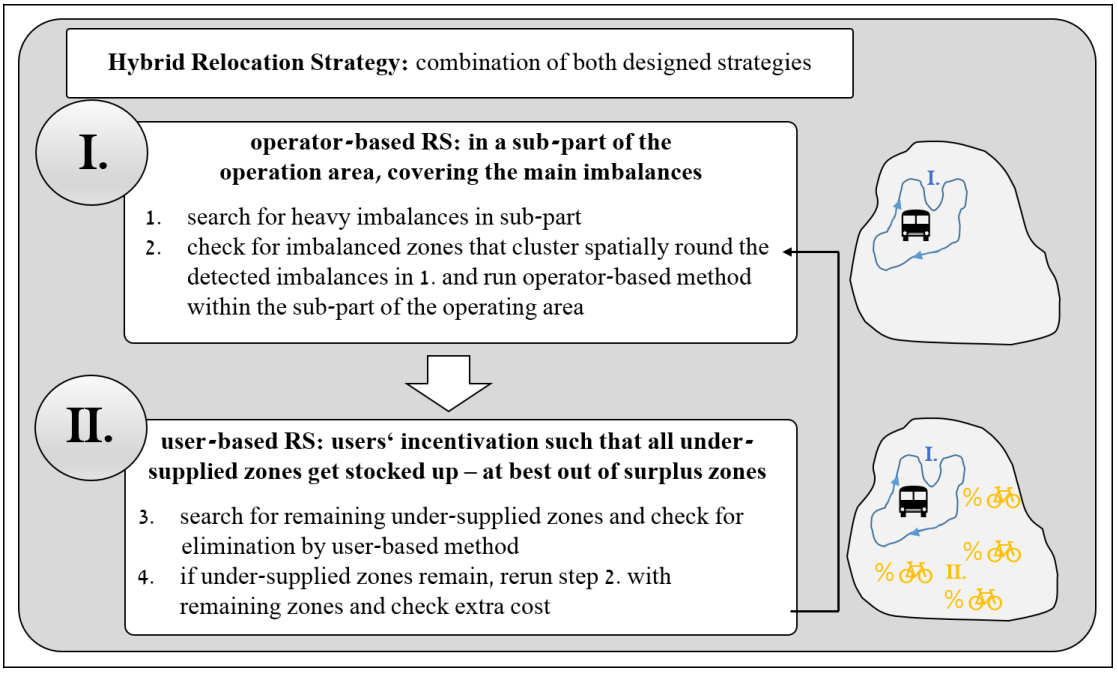


FIGURE 6.2: Scheme for the hybrid relocation method

and yields a matching incentive pattern for the remaining, moderately imbalanced zones.

In order to maintain the 'eliminating all under-supplied zones' constraint, the incentive pattern is adjusted, by calculating the needed discount to incentivize enough users for returning bicycles in the under-supplied zones.

As calculated in section 6.2.1, the potential for an assured user-based relocation trip is $P_{as} = 17.29\%$ with additional $P_{dep} = 24.59\%$ depending on the offered price.
Assuming that $P_{dep}$ is added in case of the maximum discount $Dis_{max} = 80\%$, this results in a total relocation trip share of $P_{total} = P_{as} + P_{dep} = 42\%$.
Accordingly, in case of 40% price reduction, the total relocation trip share yields $P_{total} = P_{as} + \frac{1}{2} \cdot P_{dep} = 30\%$ etc. and the needed discount $Dis$ can be formulated as a function of $P_{dep}$:

$$Dis(p_{dep}) = \frac{Dis_{max}}{P_{dep}} \cdot p_{dep} \tag{6.18}$$

This extrapolation helps to decide where to incentivize the users by what grade of discount. Or in other words: the amount of trips that will be made by the users are forecasted hereby and hence the contribution of the user-based RS is estimated.

In the initial step, the main imbalances are identified and their adjacent moderate imbalances are included in the operator-based scheme. In order to find the nearest zones with high imbalances, the algorithm searches for adjacent zones and their corresponding surplus or lack of bicycles (see also [19]).

The remaining part of the imbalanced fleet has to be relocated by applying the user-based strategy. Remaining bicycles mean not only those in the zones that were not covered by the relocation route, but also those that could not picked up or dropped off due to the capacity constraint of the relocation vehicle.

The entire relocation process starts at $t_{cur}$ and is planned to be accomplished at target time $t_{tar}$. During the relocation period (on average a few hours), the BS System is still running and thus the fleet moves. By assuming the booking numbers follow the average patterns (according to current day and time slot), one can include this to the stock prediction and determine, how many bicycles will be abundant or lacking in certain zones. This amount can be enlarged in case of surplus bicycles and a high inflow rate or in the even worse case: a lack of bicycles with a high outflow rate. In the best case,

those two measures complement each other, i.e. a surplus gets more balanced due to an high outflow and a lack gets compensated by a high inflow. These fleet evolutions, caused by regular customer trips are also considered for the hybrid scenario.

Under-supplied areas are very harmful for the BS System, currently - as the demand cannot be satisfied, but also in a long-term sense - because users might lose reliance on the system and will not use the system again. Hence, eliminating all lacks of bicycles in under-supplied areas has priority.

Let $L_z$ be the amount of bicycles that are currently lacking in an under-supplied zone $z$. Then the algorithm determines the discount for returning bicycles there in order to increase the current inflow $x_z^{T_k}$ to $x_{z,inc}^{T_k} = x_z^{T_k} + L_z$. The potential for relocation trips and adjusted trips were partly dependent on the discount rate. For adjusted trips, only trips in adjacent zones were taken in account.
Assuming a user plans a trip from A to B, whereas B $\in adj(z)$ and the user adjusts the trip from A to B*, whereas B* lies in the target zone $z$, i.e. $B^* \in z$.

Resulting from the I/O-Analysis, the forecasted fleet behavior, i.e. the inflow and outflow tell the lacking or surplus bicycles at target time $t_{tar}$ in all adjacent zones. In case of a total of returns $L_{adj(z)}$ in all adjacent zones of $z$, $P_{as} = 17.29\%$ of $L_{adj(z)}$ get additionally returned in target zone $z$ instead and encounter the lack of bicycles there with an only marginal incentivation of 10%. If this is not sufficient, i.e. zone $z$ is still under-supplied, the required discount rate gets calculated: let $L_{adj(z),10\%}$ denote the extra returns generated by 10% discount.
Then the remaining lack of bicycles is written as

$$L_{z,Dis} = L_z - L_{adj(z),10\%} \tag{6.19}$$

with the required discount rate $Dis$. Further, the required potential $p_{dep}$ is calculated by

$$p_{dep} = \frac{L_z}{x_{adj(z)}^{T_k}} \tag{6.20}$$

whereas $x_{adj(z)}^{T_k}$ is the amount of returns in $adj(z)$ in time period $T_k$. The required discount then is mapped by the function given in equation (6.18).

### 6.3.2 Test case for three different days

This section shows the performance of the hybrid RS - the combination of the operator-based and the user-based method. For the sake of comparability, three days have been chosen that were already considered for the evaluation of the both methods individually.

For reasons of practicability, the operator's headquarters are always included in the operator-based relocation route, as the truck starts there and obviously has its final destination again there. In the operator-based case, the most efficient time slot for relocation was weekdays between 1 a.m. and 6 a.m. However, the entire relocation process takes around seven hours on average though. As the route is significantly shortened now, the realization time (the time between the start of the relocation process $t_{cur}$ and the target time $t_{tar}$) is shorter, too and therefore is adjusted.

For the three hybrid RS test cases, following parameters were considered:

- start of operator-based RS referring to the current FD and aiming for the optimal FD at the target time
- fleet movements due to user-based relocations in the according time interval
- taking into account the regular fleet movements by users' trips within the relocation interval
- additional trips / fleet movements due to a better FD caused by prior relocations.

Following figures 6.3-6.5 show the hybrid relocation performances on different weekdays and target intervals respectively.

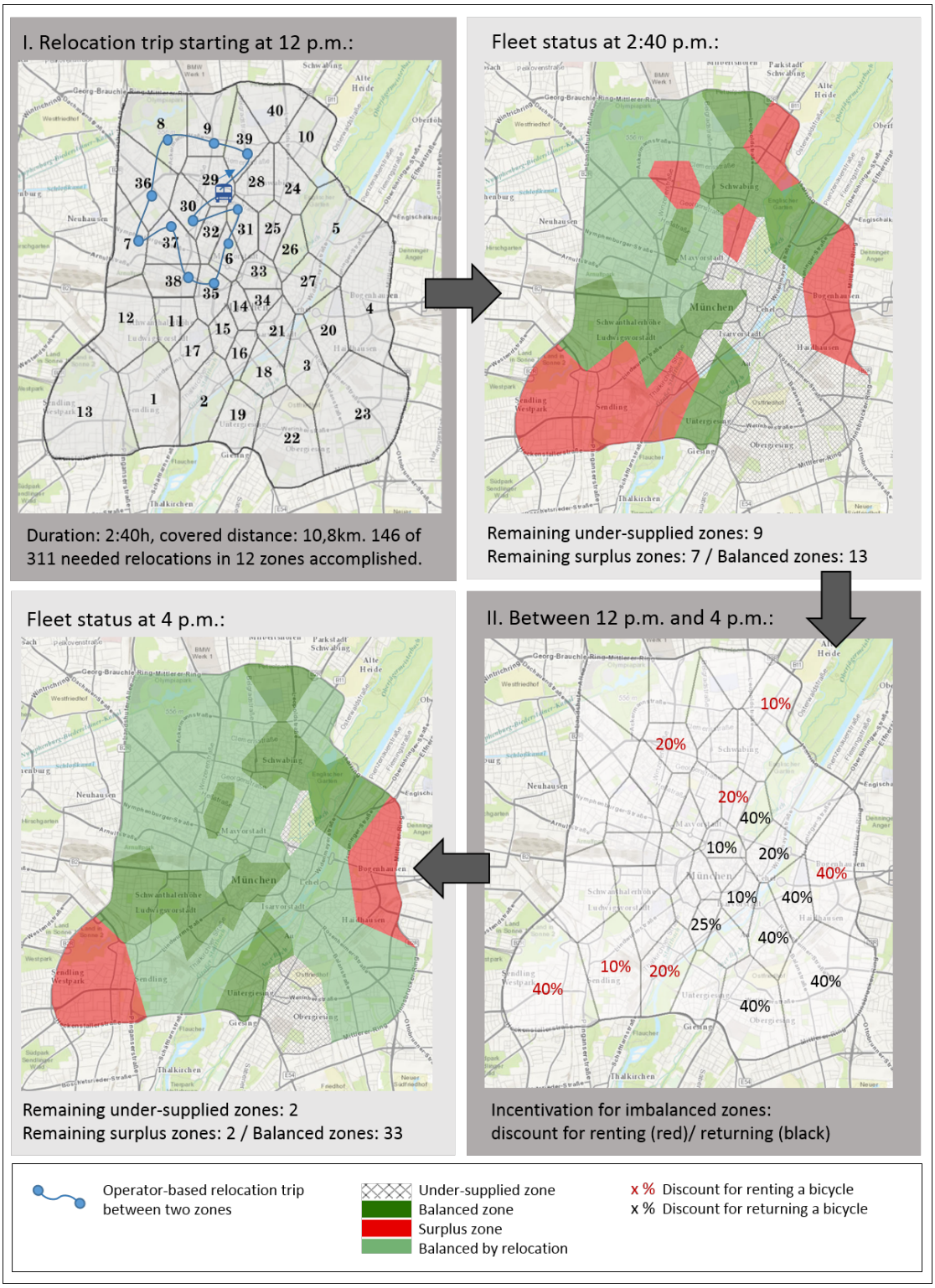


FIGURE 6.3: 1st test scenario on May 15 between 12 p.m. and 4 p.m.

The **first test case** was run for Thursday, May 15 between 12 p.m. and 4 p.m. Both strategies were evaluated singularly for this day as well in respective sections. The performance of the operator-based method is moderate, as even in the early morning (off-peak) the total trip duration is around 6 hours (listed in table 6.2).

The occurring imbalances in the course of this day get worse and hence a relocation trip by operator only would be even less efficient. If a major part of the needed relocations can be shifted to the users, the relocation trip travel time is significantly reduced and thus can be conducted in the afternoon (or when it is needed most). Taking a look at the results of the user-based strategy for May 15 (see table 6.5), the effectiveness (measured by reduction of under-supplied zones) is highest between 10 a.m. and 4 p.m.

As a consequence, the hybrid RS on May 15 starts at 12 p.m. noon and is accomplished four hours later at 4 p.m., as illustrated in figure 6.3. The partition algorithm picks 12 zones of which 6 are under-supplied and 6 are surplus zones. After step I. the sub-part of the operating area is rebalanced, besides zone 29 *Elisabethstraße* as depicted in the fleet status at 2:40 p.m. Due to the capacity constraint of the relocation vehicle, the surplus in this zone was only reduced, but not completely eliminated. Ergo, zone 29 is considered in the user-based scheme (step II.) as well.

Step II. starts simultaneously and offers a discount pattern: for trips starting in zones that feature a red percentage and not ending in such a zone, the users get the respective percentage off. If such a trip ends in a zone with a black percentage on top, the discount is added. For a trip starting in a balanced zone (no indication of a percentage sign), but ending in a zone with a black percentage, the trip fare is reduced as well. To give an example, if a trip starts in zone 13 *Mittersendling* and ends in zone 1 *Sendlinger Feld*, no reduction rate applies. If this trip ends in zone 12 *Schwanthalerhöhe* though, the user gets 40% off. If this trip ends in zone 22 *Obergiesing*, the discount adds up to 80%. In the present case, four zones remain imbalanced after both strategies have been carried out. The two under-supplied zones (22 *Obergiesing* and 26 *Englischer Garten*) however, show only minimal lacks of bicycles, namely 5 and 6 bicycles that are lacking compared to the available stock of 21 and 28 bicycles there respectively.

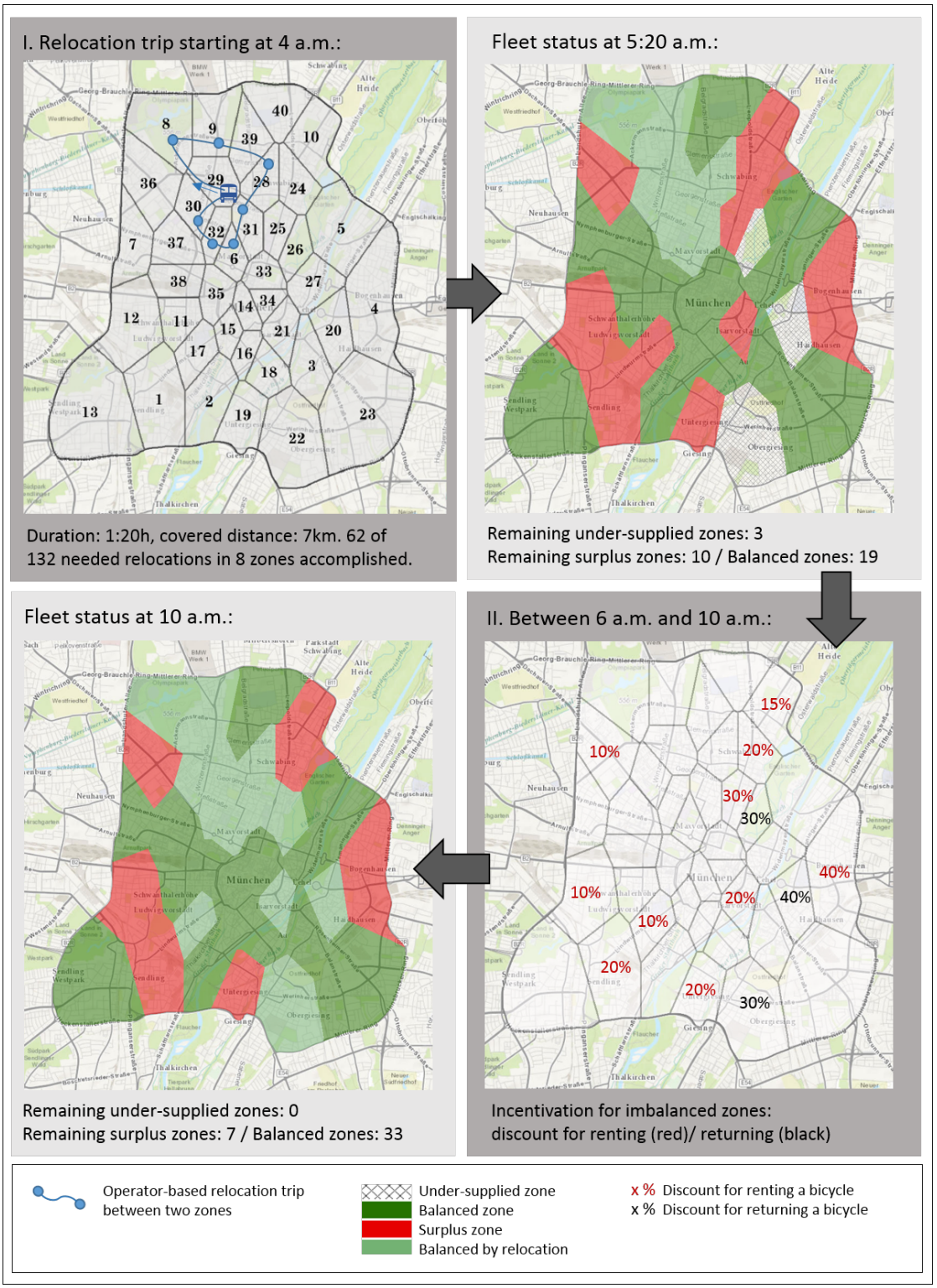


FIGURE 6.4: 2nd test scenario on June 19 between 4 a.m. and 9 a.m.

An extension of the operator-based route in order to include zone 26 would increase the travel time by more than 30 minutes and hence this small lack of bicycles is approved instead. The surplus zones 4 *Steinhausen* and 13 *Mittersendling* are heavily over-saturated, such that they could not be rebalanced by the operator-based method either.

The **second test case** addresses Thursday, June 19 between 4 a.m. and 9 a.m. and is illustrated in figure 6.4. The operator-based relocation route covers 8 zones and rebalances all of them by realizing 62 bicycle relocations in 80 minutes. This route omits surplus zone 36 *Oberwiesenfeld* due to capacity reasons or in other words: there are no close under-supplied zones and therefore the (heavy) surplus is approved.

After step I. all 8 visited zones are rebalanced, and the remaining part of the operating area yields three under-supplied zones. Again, the incentive pattern applies and eliminates all under-supplied zones within four hours. Seven zones remain surplus zones though: some zones (especially zone 4 *Steinhausen*) has an increasing surplus over the course of the operating period in 2014. In June, the available stock there is around 100 bicycles. A regularly conducted, step-by-step relocation is therefore highly recommended. For the present case though, it is not possible to diminish such surplus zones by onetime relocations.

A more positive aspect is that huge surpluses do not affect the demand satisfaction, as long as there are no under-supplied zones at the same time, or in other words: the clustering of surplus bicycles does not necessarily impair the dynamics of the BS System and can be ignored as long as no other zones experience a shortage of bicycles.

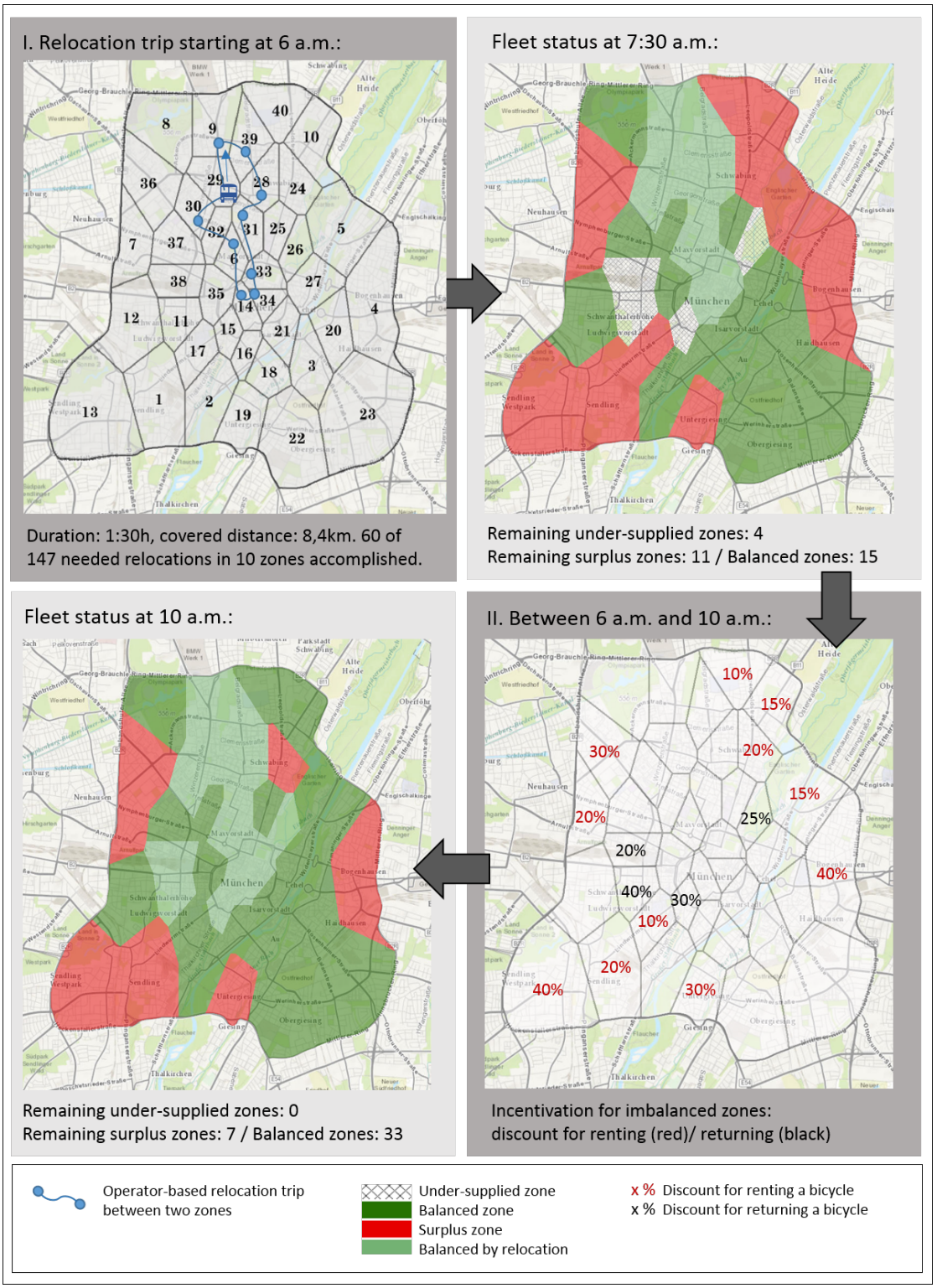


FIGURE 6.5: 3rd test scenario on September 15 between 6 a.m. and 10 a.m.

The **third test case** was applied to Monday, September 15 between 6 a.m. and 10 a.m. and is illustrated in 6.5.

In step I. ten zones get rebalanced in a relocation route that takes 1.5 hours and covers around 8 km. Almost adjacent zones that are under-supplied such as zone 38 *Hauptbahnhof* are not included in the operator-based relocation trip, as this would prolong the travel time about 30 minutes - the lack of bicycles there however, can be easily compensated via user-based relocation.

The user-based strategy has to deal with four under-supplied and eleven surplus zones. As mentioned before, over the course of the operating period in 2014, more and more bicycles cluster in certain zones as there was no intervention at all (further details are examined in section 7.2). The amount of surplus zones that cannot be rebalanced thus increases during 2014. That is the reason why seven surplus zones remain after the four-hour-relocation scenario.

This chapter presented different strategies for performing relocations in a BS System in order to redistribute and rebalance the fleet.

Firstly, a mathematical approach for a VRP was given, which provided the basis for the operator-based RS. The performance of this strategy works fine in some cases, but has a limited effectiveness in general. On the one hand, this is caused by the capacity constraint of the relocation vehicle and on the other hand, long distances per relocation route lead to high travel times i.e. times for the entire relocation performance, which matter gets even worse in times of peak hours of traffic.

Secondly, a user-based strategy was designed. Dependent on the urge for relocations an incentive pattern is given in order to make the users conduct relocation trips themselves and thereby eliminate existing imbalances, especially under-supplied zones.

Thirdly, a hybrid relocation strategy was designed, combining both precedent RSs. This strategy enhances the overall relocation performance by speeding up the entire relocation process and by eliminating more under-supplied zones than only one respective strategy can manage. With the help of the user-based strategy - i.e. shifting needed relocation trips to users via incentives - travel times for the operator-based strategy by relocation vehicle are diminished significantly and the operator saves cost due to lower labor cost, fuel etc.

The following chapter validates and evaluates the overall performance of the designed strategies. A validation methodology proves the increased demand satisfaction after relocations based on historical distributions and corresponding bookings. Further, a simulation case study shows the impact and long-term effects of relocations and finds optimal time periods for relocation iterations.

# Chapter 7

# Performance Evaluation

The previous chapters presented diverse strategies referring to fleet relocations both user-based and operator-based. A comprehensive performance evaluation of these strategies is required and given in this chapter. With the help of a validation methodology, well-balanced FDs captured from historical booking data are linked to related, subsequent booking numbers. Thereby, a quantification of higher booking numbers based on better FDs is derived.

Next a simulation case study is set up in order to analyze the fleet evolution in case of applying the different relocation strategies. As a result of this, answers to RQs 4a and 4b are found: the effects and impacts of bicycle fleet relocations are evaluated. Further, application time intervals are calculated in order to optimize the efficiency of these strategies by which the permanent overall BS System's performance is enhanced.

## 7.1 Potential Effects of Fleet Relocations

From previous chapters, especially as a result of the demand model in chapter 5, the optimal FD was calculated. In chapter 6 optimal relocation strategies (RSs) were determined in order to reach this FD state. This section strives to capture potential impacts of such relocations.

### 7.1.1 Validation methodology

The basic idea is to compare well-distributed fleet statuses and the subsequent booking numbers. Therefore the historical booking data is filtered and classified in clusters, where the distribution corresponds to recommendations of the model and where not. For the latter, there is the case where the saturation threshold is undercut, i.e. there is a lack of bicycles and where the saturation threshold is exceeded, i.e. the concerning zone is currently over-saturated and not all bicycles are needed there. The respective threshold is 20% and consequently results in the following classification:

- $s_{cur} < s^* - 20\% \rightarrow$ the current zone is under-supplied ("us")
- $s_{cur} > s^* + 20\% \rightarrow$ the current zone is over-saturated ("os")
- $s_{cur}$ in between $\rightarrow$ the current zone is well distributed ("bal")

At first, all time slots in the entire operating period 2014 were compared to the respective stock recommendation per zone. As a result, a percentage tells how often a zone was under-supplied, balanced or over-saturated in the respective time slot on the respective day type. Table 7.1 depicts the results for time slot $T_1$ exemplarily. The entire result tables are attached to Appendix C.

**Remark:** the highest percentage of each zone determines the respective zone status. For instance, table 7.1 yields that 98.4% of all regarded stocks were over-saturated in zone 1 *Sendlinger Feld* on weekends in time slot $T_1$. That means that almost all stocks in this specific time slot featured a bicycle surplus and this zone is therefore counted as an over-saturated zone. In zone 6 *Maxvorstadt*, the 84.9% indicate that this zone was mostly under-supplied during this time slot. Following this methodology, the highest percentage decides the stock status and is added to the overall result in figure 7.1.

| Zone status in $T_1$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | os | us | bal | ov |
| 1 | 1.1 | 0.5 | 98.4 | 2.3 | 0.0 | 97.7 |
| 2 | 1.6 | 1.6 | 96.8 | 1.1 | 9.2 | 89.7 |
| 3 | 3.2 | 4.3 | 92.5 | 3.4 | 12.6 | 83.9 |
| 4 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| 5 | 2.7 | 0.5 | 96.8 | 2.3 | 3.4 | 94.3 |
| 6 | 84.9 | 11.3 | 3.8 | 97.7 | 2.3 | 0.0 |
| 7 | 1.1 | 1.1 | 97.8 | 1.1 | 1.1 | 97.7 |
| 8 | 47.5 | 20.9 | 31.6 | 53.0 | 26.5 | 20.5 |
| 9 | 1.1 | 2.2 | 96.8 | 2.3 | 4.6 | 93.1 |
| 10 | 1.1 | 1.1 | 97.8 | 0.0 | 3.4 | 96.6 |
| 11 | 6.5 | 29.0 | 64.5 | 14.9 | 18.4 | 66.7 |
| 12 | 1.6 | 1.1 | 97.3 | 1.1 | 1.1 | 97.7 |
| 13 | 0.5 | 2.7 | 96.8 | 2.3 | 2.3 | 95.4 |
| 14 | 1.6 | 5.4 | 93.0 | 6.9 | 18.4 | 74.7 |
| 15 | 2.7 | 9.7 | 87.6 | 10.3 | 32.2 | 57.5 |
| 16 | 2.2 | 9.1 | 88.7 | 10.3 | 19.5 | 70.1 |
| 17 | 0.5 | 0.5 | 98.9 | 1.1 | 10.3 | 88.5 |
| 18 | 1.6 | 3.2 | 95.2 | 2.3 | 10.3 | 87.4 |
| 19 | 0.5 | 1.1 | 98.4 | 1.1 | 1.1 | 97.7 |
| 20 | 12.0 | 44.3 | 43.7 | 32.9 | 38.8 | 28.2 |
| 21 | 1.1 | 0.5 | 98.4 | 1.1 | 2.3 | 96.6 |
| 22 | 1.1 | 7.5 | 91.4 | 6.9 | 29.9 | 63.2 |
| 23 | 5.4 | 9.7 | 84.9 | 12.6 | 27.6 | 59.8 |
| 24 | 1.1 | 0.0 | 98.9 | 1.1 | 1.1 | 97.7 |
| 25 | 0.5 | 1.1 | 98.4 | 2.3 | 2.3 | 95.4 |
| 26 | 78.4 | 18.9 | 2.7 | 89.7 | 10.3 | 0.0 |
| 27 | 1.6 | 1.1 | 97.3 | 1.1 | 1.1 | 97.7 |
| 28 | 0.5 | 0.0 | 99.5 | 0.0 | 2.3 | 97.7 |
| 29 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| 30 | 4.3 | 5.4 | 90.3 | 12.6 | 36.8 | 50.6 |
| 31 | 1.6 | 0.5 | 97.8 | 0.0 | 3.4 | 96.6 |
| 32 | 2.2 | 10.8 | 87.1 | 3.4 | 11.5 | 85.1 |
| 33 | 2.7 | 16.1 | 81.2 | 13.8 | 27.6 | 58.6 |
| 34 | 0.5 | 5.9 | 93.5 | 0.0 | 5.7 | 94.3 |
| 35 | 1.6 | 10.8 | 87.6 | 6.9 | 26.4 | 66.7 |
| 36 | 0.5 | 2.7 | 96.8 | 0.0 | 2.3 | 97.7 |
| 37 | 1.1 | 2.2 | 96.8 | 4.6 | 18.4 | 77.0 |
| 38 | 4.3 | 14.0 | 81.7 | 10.3 | 21.8 | 67.8 |
| 39 | 1.1 | 1.1 | 97.8 | 0.0 | 8.0 | 92.0 |
| 40 | 3.8 | 1.1 | 95.1 | 3.4 | 4.6 | 92.0 |

TABLE 7.1: Zone statuses in time slot $T_1$ in percent for 2014

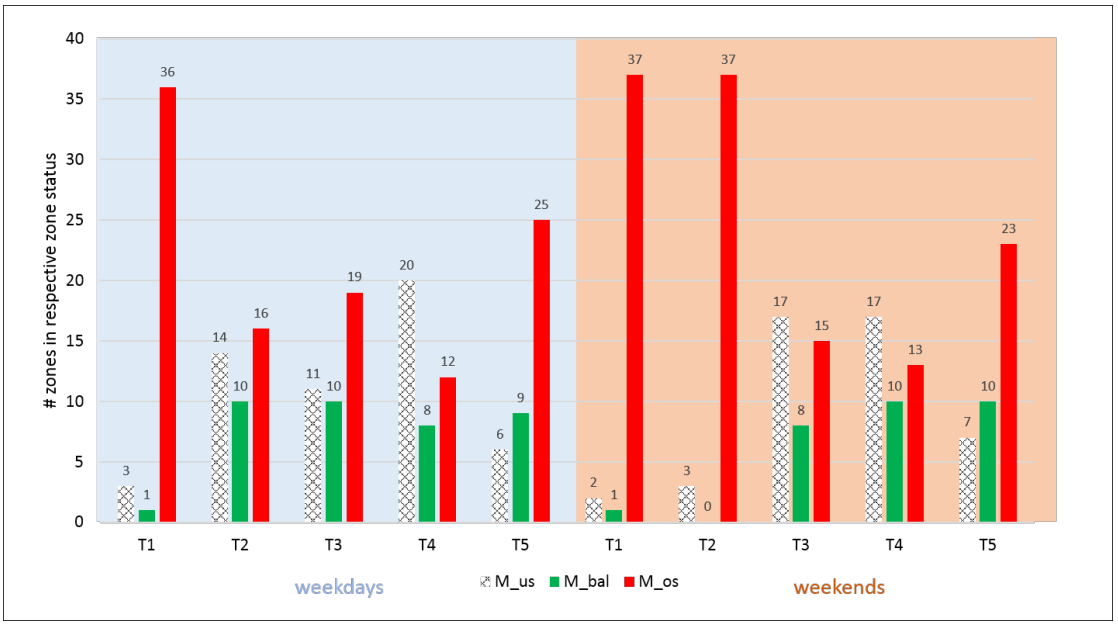


FIGURE 7.1: Classification of different distribution states per time slot

Figure 7.1 depicts the respective prevailing fleet statuses for all different time slots. Each zone is either labeled with "us", "bal" or "os". Altogehter they result in the total amount of zones $M$.

In time slot $T_1$ on weekdays, most of the zones were over-saturated, which is apparently caused by low demand in this slot. However, during daytime up to 20 zones get under-supplied (in time slot $T_4$).
On weekends, the fleet classification is different. Low demand in the first two time slots cause the over-saturation in most zones. For time slots $T_3$ and $T_4$, almost half of all zones are under-supplied though.

Building the overall average results in 25% under-supplied zones, 16.8% balanced zones and 58.3% over-saturated zones. Excluding the low demand time slots $T_1$ on weekdays and $T_1$ and $T_2$ on weekends - which are the respective reason for over-saturation there - the percentages yield 32.9% of under-supplied zones, 23.2% of balanced zones and 43.9% of over-saturated zones, which is still high, as this significant part of the fleet is idling in *wrong* zones and causes the under-supply in almost a third of all zones.

### 7.1.2 Potential gain for subsequent bookings

In this section, the related bookings in the subsequent time slot are analyzed to capture the effect of a well distributed fleet. Therefore the subsequent bookings within one classification are compared for each time slot: table 7.2 shows the results of this analysis exemplarily for time slot $T_2$ on weekdays. The entire analysis for each time slot on weekdays and weekends is attached to Appendix D.

Table 7.2 shows the measured data of under-supplied, balanced and over-saturated fleet statuses for all zones in time slot $T_2$ on weekdays in the entire operating period in 2014. Further, the corresponding averaged stocks and subsequent bookings are listed. For instance, zone 28 *Schwabing* was under-supplied on 29 weekdays. The subsequent bookings there result in $\emptyset r^{T_2} = 6.4$ rentals per time interval based on a stock of $\emptyset s^{t_2} = 18.7$ bicycles on average. In case of a balanced and over-saturated fleet status, this value increases to $\emptyset r^{T_2} = 10.4$ and even $\emptyset r^{T_2} = 12.7$ respectively.

Further, table 7.2 reveals the potential effect of a balanced fleet status in some zones. Taking a look at zone 25 *Universität* for instance, a lack of bicycles leads to only 2.7 subsequent bookings on average, whereas almost 7 bookings on average can be found for a balanced stock. Only marginal additional bookings appear in case of an over-saturation of zone 25, namely 0.1. In the respective first column of each fleet status, the number of data points is displayed. This is an important measure, as in case of only a few data points, the average of subsequent bookings may not be significant or informative. In zone 1 *Sendlinger Feld* for instance, the subsequent booking average based on a balanced fleet status is only $\emptyset r^{T_2} = 4.5$, whereas in case of an over-saturation, almost twice as much bookings were achieved. However, there were only 2 data points of a balanced fleet status in zone 1 in this time slot in 2014. Regarding such a small sample, random situations e.g., bad weather conditions causing exceptional low bookings, can come into effect and cause outliers. Therefore the averaged bookings (based on only two values) are not reliable here.

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ |
| 1 | 7 | 7.6 | 1.7 | 2 | 21.0 | 4.5 | 176 | 63.4 | 8.4 |
| 2 | 38 | 13.6 | 4.3 | 86 | 25.0 | 6.4 | 61 | 36.3 | 7.7 |
| 3 | 81 | 14.0 | 4.0 | 96 | 24.4 | 3.6 | 8 | 32.4 | 4.5 |
| 4 | 2 | 7.0 | 4.0 | 2 | 18.0 | 7.0 | 181 | 200.6 | 8.0 |
| 5 | 8 | 5.4 | 1.6 | 19 | 17.9 | 4.0 | 157 | 37.4 | 4.6 |
| 6 | 183 | 5.8 | 2.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 24 | 13.3 | 3.5 | 61 | 24.2 | 6.9 | 100 | 39.5 | 8.8 |
| 8 | 138 | 7.3 | 0.3 | 28 | 18.6 | 0.7 | 9 | 27.2 | 0.7 |
| 9 | 17 | 10.8 | 2.4 | 17 | 18.5 | 3.8 | 149 | 35.5 | 3.9 |
| 10 | 9 | 9.0 | 1.1 | 7 | 18.3 | 2.3 | 169 | 38.2 | 4.5 |
| 11 | 123 | 12.1 | 4.9 | 43 | 23.5 | 5.2 | 19 | 64.4 | 7.8 |
| 12 | 9 | 9.7 | 3.1 | 24 | 23.7 | 6.6 | 152 | 39.4 | 8.4 |
| 13 | 14 | 9.7 | 1.1 | 17 | 17.8 | 1.4 | 152 | 38.1 | 4.8 |
| 14 | 64 | 12.1 | 2.8 | 69 | 20.3 | 3.8 | 51 | 30.9 | 2.7 |
| 15 | 124 | 14.2 | 4.1 | 59 | 23.8 | 4.6 | 2 | 31.0 | 5.5 |
| 16 | 102 | 13.9 | 2.9 | 71 | 22.0 | 4.5 | 11 | 30.5 | 4.0 |
| 17 | 48 | 15.3 | 4.3 | 73 | 22.9 | 5.6 | 64 | 34.7 | 7.4 |
| 18 | 74 | 15.5 | 4.7 | 88 | 23.6 | 5.8 | 23 | 36.3 | 6.4 |
| 19 | 9 | 9.6 | 1.9 | 31 | 22.5 | 5.0 | 144 | 40.6 | 9.1 |
| 20 | 175 | 12.0 | 4.2 | 6 | 24.5 | 8.2 | 0 | 0.0 | 0.0 |
| 21 | 22 | 14.7 | 4.0 | 67 | 24.3 | 6.6 | 96 | 35.6 | 6.5 |
| 22 | 120 | 12.8 | 2.0 | 60 | 20.3 | 3.9 | 5 | 35.0 | 3.6 |
| 23 | 132 | 12.9 | 3.3 | 42 | 21.6 | 4.5 | 11 | 32.1 | 1.4 |
| 24 | 14 | 11.1 | 3.5 | 21 | 23.7 | 4.6 | 150 | 38.7 | 6.8 |
| 25 | 6 | 8.7 | 2.7 | 28 | 19.3 | 6.9 | 151 | 34.1 | 7.0 |
| 26 | 183 | 5.8 | 0.7 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 38 | 14.8 | 4.7 | 99 | 22.9 | 7.3 | 47 | 31.2 | 7.9 |
| 28 | 29 | 18.7 | 6.4 | 80 | 28.6 | 10.4 | 76 | 39.0 | 12.7 |
| 29 | 5 | 14.6 | 9.2 | 1 | 27.0 | 10.0 | 179 | 136.6 | 15.7 |
| 30 | 160 | 16.7 | 7.3 | 25 | 28.2 | 10.2 | 0 | 0.0 | 0.0 |
| 31 | 39 | 18.8 | 7.7 | 102 | 30.6 | 11.3 | 44 | 42.0 | 13.9 |
| 32 | 96 | 18.9 | 8.8 | 85 | 30.5 | 9.4 | 4 | 42.3 | 13.5 |
| 33 | 79 | 11.9 | 3.3 | 74 | 20.7 | 3.6 | 32 | 30.9 | 4.5 |
| 34 | 41 | 12.2 | 2.9 | 93 | 20.2 | 2.8 | 50 | 30.2 | 2.9 |
| 35 | 122 | 14.7 | 4.3 | 61 | 24.2 | 5.8 | 2 | 37.0 | 5.5 |
| 36 | 26 | 11.9 | 3.5 | 47 | 21.0 | 5.5 | 112 | 32.8 | 4.7 |
| 37 | 77 | 15.3 | 4.6 | 93 | 23.5 | 6.5 | 14 | 33.9 | 6.4 |
| 38 | 108 | 13.5 | 5.2 | 65 | 22.8 | 6.0 | 12 | 35.7 | 8.9 |
| 39 | 22 | 12.6 | 3.8 | 72 | 23.0 | 5.8 | 91 | 34.2 | 6.6 |
| 40 | 24 | 9.5 | 1.7 | 60 | 20.6 | 3.3 | 100 | 32.0 | 3.5 |

TABLE 7.2: Zone status and related bookings in time slot $T_2$ on weekdays

In general, this analysis is assumed to perform well only if all fleet statuses are represented by at least 10 data points per zone. In consequence, for an overall performance evaluation some zones in some time slots might not be considered. In time slot $T_2$ for instance, only 22 zones are taken into account, as the remaining 18 zones do not feature every fleet status at least 10 times and therefore the results are supposed to be skewed. In order to capture the average booking gain due to a sufficient bicycle stock per zone, the averaged bookings $\emptyset r^{T_k}$ in all regarded zones are compared between 'under-supplied' and 'balanced' statuses for each time slot separately. This results in a percentage of gain in bookings and is listed in table 7.3 for weekdays and weekends.

In combination with the booking share of the respective time slots, as calculated in section 3.2, the overall impact is deduced. On weekdays in time slot $T_5$ for instance, the gain of bookings is 73.1%. However, the trip share for weekends late-night is only about 18% - this downscales the overall impact for additional bookings to 28.0%. Some gains in bookings are in parentheses, as the amount of considered zones was too low and therefore the results are not reliable. Further, this refers to the time slots, when almost all zones are over-saturated due to low demand (see figure 7.1). Hence, a potential relocation could not enhance the current fleet status for target interval $T_1$ on weekdays and for $T_1$ and $T_2$ on weekends.

For all other time slots, the impact ranges between 20% and 40%. Time slot $T_4$ on weekends yields this maximum value. In this time slot, 50% more bookings can be achieved by a well distributed fleet. As the booking share for this time slot is relatively high with 32%, the corresponding impact with 40.3% is significantly higher as in the subsequent time slot, when the impact results in 26.2% due to a lower booking share of 20%.

| | weekdays | | | weekends | | |
|---|---|---|---|---|---|---|
| time slot | gain in $r^{T_k}$ | impact | # zones | gain in $r^{T_k}$ | impact | # zones |
| $T_1$ | (88.6%) | 5.7% | 4 | (−0.6%) | 0.0% | 5 |
| $T_2$ | 42.3% | 19.2% | 22 | (65.7%) | 9.9% | 1 |
| $T_3$ | 39.3% | 19.5% | 27 | 32.3% | 23.5% | 11 |
| $T_4$ | 38.4% | 27.6% | 20 | 49.3% | 40.3% | 14 |
| $T_5$ | 73.1% | 28.0% | 22 | 48.1% | 26.2% | 14 |

TABLE 7.3: Gain in bookings due to fleet balances and relative impact

The results of this section prove that more bookings can be generated if the fleet of the BS System is well distributed. As a consequence, the presence of under-supplied and over-saturated zones is prevented, there is no unmet demand at best and less bicycles feature long idle times. As a consequence, the utility level of the entire BS System is enhanced.

## 7.2 Real-Life Relocation Process

In order to capture the real effects and consequences of a desired relocation, a worst-case scenario shows the indispensable need for relocations. Furthermore, the realized relocations in the considered operating period in 2014 have to be revealed.

### 7.2.1 Fleet evolution without any interference

This scenario involves diverse required measures; on the one hand, an initial FD is needed for starting the scenario and on the other hand, flow measures of the fleet evolution are required.

For the initial state of the fleet, the distribution on May 1st on 6 a.m. is set. At that time, the BS System has been already running for six weeks, thus the FD was *warmed up* and users got aware of the reactivated BS System. Out of the I/O Analysis in chapter 3, there are inflow and outflow data, which represent the average inter-zone movements for singular time slices for both day types within the entire operating period 2014. These data are unaffected by any possible operator's intervention as they represent the real bookings. The flows for each zone are accumulated for the time period of one week and the stock in each zone gets adjusted by this weekly flow rate. If a zone runs empty, these average flows are obviously changing. Each zone needs a certain amount of bicycles, so that the outflow data is still valid. If this threshold gets undercut, the outflow also diminishes. Then, the outflow is less or equal to the inflow, as the only bicycle stock is provided by current inflow. In this case, the respective zones are labeled as empty.

For further examination all zones were classified in three groups.

In the **first group**, there are zones featuring a constantly **increasing** stock. In these zones, it is apparently more attractive to return bicycles there than to rent some.
The **second group** contains zones with opposed flow patterns. The respective stocks there are **decreasing** as more users rent bicycles from there than returning them.
Some zones - pooled in the **third group** - show only a slightly higher inflow than outflow (or the other way around) and are denoted as **self-balanced** zones. In these cases, the rentals adapt to the current supply, i.e. if there are less bicycles, they are less visible and the rentals will decrease accordingly and vice versa. This approach only works though if the inflow/outflow stays in tolerable bounds. This is the case if the average magnitude of inflow/outflow bicycles per zone and month is less than 10 (i.e. roughly less than two bicycles per week).

Table 7.4 lists all zones in the three described groups. For the first group of zones - with high inflow - the second last column indicates the time frame, until the stock size exceeded 50 bicycles, assumed there was no relocation/intervention by the operator. In the second group, zone stocks are decreasing and the second last column indicates the week from which the zone does not exhibit any bicycles anymore - again in case of no operator's intervention. The third, *balanced* group illustrates the zones with a quite self-regulated flow and the second last column there shows the calculated stock after 12 weeks without interference.

Table 7.4 reveals the intensity of a no-relocation scenario for the BS System: after just two weeks, three zones are already empty, whereas even more zones amass abundant bicycles. This excess is no small measure, as after four weeks, five zones are oversaturated and therefore contain a significant part of the fleet - and indeed, this part is missing in the previously mentioned zones.

The last column shows the real FD 12 weeks later, i.e. on July 24 on 6 a.m. For the first group of zones (high inflow), bicycles are most likely collected in some zones within a relocation (labeled with $\ominus$). For the remaining zones, it is is labeled with r.e. and denotes "random effects": for some reasons, the stocks are moderate; the higher perception of the bicycles could have led to a rental behavior above average. In zone 4 *Steinhausen*, the checkmark ($\checkmark$) indicates that the real stock corresponds to the calculated stock.

| zones with higher inflow | initial stock | I/O rate in one week | stock > 50 in week | real stock after 12 weeks |
|---|---|---|---|---|
| 1 Sendlinger Feld | 71 | 6.5 | 0 | 92 ✓ |
| 4 Steinhausen | 76 | 6.1 | 0 | 195 ✓ |
| 7 Nymphenburg | 20 | 7.0 | 5 | 41 ⊖ |
| 10 Dietlindenstraße | 34 | 4.9 | 4 | 30 ⊖ |
| 12 Schwanthalerhöhe | 30 | 5.2 | 4 | 40 ⊖ |
| 13 Mittersendling | 33 | 2.2 | 8 | 50 ✓ |
| 19 Untergiesing | 39 | 3.8 | 4 | 45 r.e. |
| 27 Lehel | 19 | 5.2 | 6 | 18 ⊖ |
| 30 Lothstraße | 20 | 4.0 | 8 | 18 ⊖ |
| 36 Oberwiesenfeld | 16 | 5.6 | 7 | 24 r.e. |
| 37 Stiglmaierplatz | 19 | 2.7 | 12 | 21 r.e. |
| 40 Milbertshofen | 25 | 2.5 | 11 | 23 r.e. |
| **zones with higher outflow** | **initial stock** | **I/O rate in one week** | **runs empty in week** | **real stock after 12 weeks** |
| 3 Haidhausen | 17 | −2.1 | 8 | 20 r.e. |
| 6 Maxvorstadt | 5 | −3.9 | 2 | 7 ⊕ |
| 8 Olympiapark | 2 | −13.1 | 1 | 11 ⊕ |
| 14 Marienplatz | 24 | −3.7 | 7 | 15 ⊕ |
| 15 Sendlinger Tor | 18 | −2.4 | 8 | 15 ⊕ |
| 16 Glockenbach | 17 | −2.2 | 8 | 16 r.e. |
| 17 Klinikviertel | 31 | −3.8 | 9 | 29 r.e. |
| 25 Universität | 34 | −7.2 | 5 | 44 ⊕ |
| 26 Englischer Garten | 3 | −3.3 | 1 | 10 ✓ |
| 29 Elisabethstraße | 73 | −6.3 | 12 | 136 n.a. |
| 31 Alter Nordfriedhof | 28 | −2.0 | 14 | 37 r.e. |
| 33 Odeonsplatz | 14 | −2.5 | 6 | 18 r.e. |
| 35 Stachus | 17 | −5.0 | 4 | 20 ⊕ |
| 38 Hauptbahnhof | 8 | −2.0 | 4 | 12 ⊕ |
| **balanced zones** | **initial stock** | **I/O rate in one week** | **calc. stock after 12 weeks** | **real stock after 12 weeks** |
| 2 Isarvorstadt | 36 | 1.8 | 58 | 18 r.e. |
| 5 Kleinhesselohe | 19 | 0.8 | 28 | 30 ✓ |
| 9 Am Riesenfeld | 18 | 1.5 | 36 | 26 ✓ |
| 11 Theresienwiese | 25 | −1.7 | 4 | 11 ✓ |
| 18 Mariahilfplatz | 24 | 0.4 | 28 | 17 ✓ |
| 20 Maximilianeum | 15 | 0.0 | 15 | 10 ✓ |
| 21 Isartor | 18 | 0.5 | 24 | 34 ✓ |
| 22 Obergiesing | 16 | 1.6 | 35 | 20 r.e. |
| 23 Neuperlach | 14 | −0.9 | 4 | 20 r.e. |
| 24 Münchner Freiheit | 34 | −1.7 | 13 | 26 r.e. |
| 28 Schwabing | 39 | −0.1 | 38 | 34 ✓ |
| 32 Theresienstraße | 23 | −0.3 | 20 | 21 ✓ |
| 34 Graggenauviertel | 15 | 1.2 | 29 | 24 ✓ |
| 39 Luitpoldpark | 27 | 0.2 | 29 | 22 ✓ |

TABLE 7.4: Evolution of stocks at a zone level without interference

In the second part of table 7.4, most of the zones with higher outflow most likely were supported by dropping off additional bicycles there, as indicated with ⊕. In some zones, there are still high stocks which are labeled with r.e., as possibly bicycles were hidden or damaged. But still, a few bicycles might be brought there in the regarded 12 weeks. Zone 29 *Elisabethstraße* contains 136 bicycles, this is not applicable "n.a.", as the BS System's headquarters (and garage) are located in zone 29. Many bicycles can be considered to be there for maintenance work.

Zones in the third part often yield similar calculated stocks compared to the real stocks (labeled with a ✓). Stocks in the remaining zones are again subject to random effects. As the flow magnitude is very low in this third group, the fleet movements can easily change.

The entire scenario calls for an appropriate visualization. Taking a look at the spatial distribution of the classified zones, figure 7.2 reveals the severity of "no interference" at all.

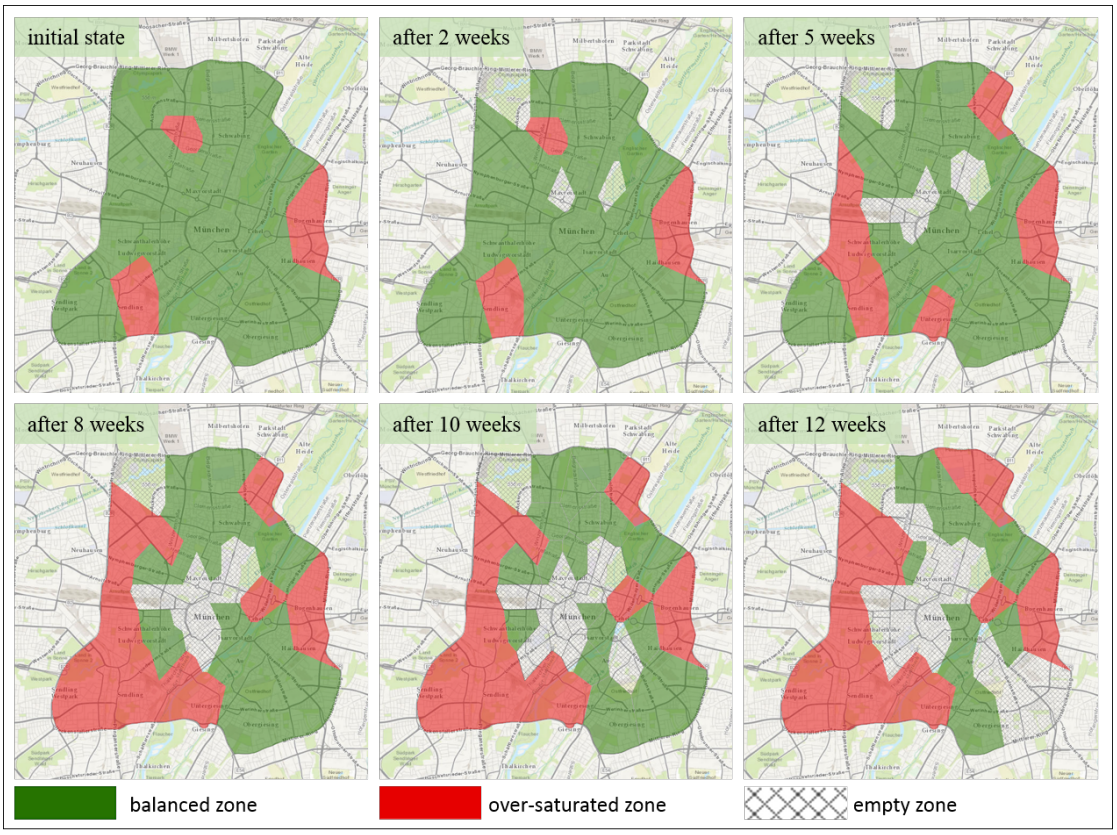


FIGURE 7.2: Fleet evolution for a 12-week time frame of "no interference"

In the beginning, almost all zones have a balanced stock of bicycles (less than 50) and are marked in green. Over-saturated zones (more or equal to 50) are marked in red. The FD is depicted in two- to three-week intervals. If a zone runs empty over time, it is marked with a checked pattern. After two weeks, two key zones run empty, followed by a concentric pattern during the course of the weeks. In the end, a crucial part of the fleet is located on the edge of the operating area, whereas 15 zones are completely empty.

The main outcome of this linear "no interference" - scenario is:

1. severe imbalances occur after only a few weeks
2. after 9 weeks, 11 zones (including 6 of the most attractive ones) are empty and as a consequence the system is condemned to failure
3. after 8 weeks, 10 zones are heavily over-supplied and the fleet there is redundant

This "no interference" - simulation is a worst-case scenario. As already hinted in table in 7.4, fleet relocations were performed in the considered operating period. However, this scenario shows the significance of keeping a BS System well distributed. Following section captures the real relocation performance in 2014.

### 7.2.2 Relocation process in 2014

According to the operator, there is no special strategy to redistribute the fleet so far (see [118]). Of course, there were redistribution trips - e.g., in case of damaged bicycles - but there was no methodology behind: bicycles at the edge of the operating area were monitored and eventually collected and brought to very attractive areas (measured by instinct), namely to *Universität* and *Stachus*, which correspond to zone 25 and 35. This approach can be tracked by the data set, as already hinted in 5.2.2. With the help of the I/O component $O$ that was determined for the demand model in chapter 5, the flow of the fleet is described. Theoretically, the sum of all inflows and outflows in one time slice should be equal to zero. Taking into account that some bicycles were returned outside of the operating area (and maybe rented there again eventually some time later), an artificial zone 0 was created in order to close this gap.

| zone | | 1-Apr-2014 | stock 1-Aug-2014 | 1-Dec-14 | flow cumulated for 8 month | calculated stock in dec | relocation numbers | avg. relocations per month |
|---|---|---|---|---|---|---|---|---|
| 1 | Sendlinger Feld | 26 | 87 | 58 | 207 | 233 | -175 | -21,9 |
| 4 | Steinhausen | 45 | 204 | 282 | 231 | 276 | 6 | 0,8 |
| 6 | Maxvorstadt | 4 | 6 | 2 | -124 | -120 | 122 | 15,3 |
| 7 | Nymphenburg | 19 | 22 | 20 | 223 | 242 | -222 | -27,8 |
| 8 | Olympiapark | 0 | 15 | 5 | -420 | -420 | 425 | 53,1 |
| 10 | Dietlindenstraße | 19 | 23 | 38 | 156 | 175 | -137 | -17,1 |
| 12 | Schwanthalerhöhe | 35 | 39 | 42 | 168 | 203 | -161 | -20,1 |
| 14 | Marienplatz | 11 | 20 | 32 | -118 | -107 | 139 | 17,4 |
| 25 | Universität | 19 | 35 | 35 | -230 | -211 | 246 | 30,8 |
| 29 | Elisabethstraße | 50 | 141 | 230 | -203 | -153 | 383 | 47,9 |
| 35 | Stachus | 9 | 15 | 14 | -161 | -152 | 166 | 20,8 |
| 36 | Oberwiesenfeld | 11 | 26 | 31 | 180 | 191 | -160 | -20,0 |

FIGURE 7.3: Extraction of realised relocations in 2014

Out of the data set, the current stock per zone at a given time can be read out. The I/O component $O$ gives the average difference of rented and returned bicycles per time interval, i.e. there is an inflow if $O$ is negative and and outflow if $O$ is positive. During the operating period from March to December 2014, the FD, i.e. the stock in every single zone evolved. Without any interference, the stock in April 1st in addition to the cumulated I/O component $O$ for 8 months, which corresponds to 166 weekdays and 78 weekend days, would result in the stock in December 1st. The results are outlined in figure 7.3 for the most significant zones.

Zones 1, 7, 10, 12 and 36 have a higher inflow than outflow so that the stock would be ever-expanding. As the stock in December there is significantly lower, bicycles must have been removed from there. The absolute amount of bicycles is depicted in red.

Zones 6, 8, 14, 25, 29 and 35 show the opposed situation. There, the outflow is higher and until December, the stock would have been negative. The magnitude of this lack plus the real stock in December yields the amount of bicycles (green numbers) that must have been brought there. In zone 29 *Elisabethstraße*, the headquarters and the garage for maintenance is located. This explains why during the course of the year more and more bicycles are brought there. The table also shows a special case in zone 4 *Steinhausen*: during 2014, the stock there was constantly rising. This behavior is also covered by the I/O analysis - in December this inflow results in 282 bicycles in this zone. Apparently, bicycles from there were never collected and redistributed, so that a substantial part of the entire fleet is idling in a zone with rather low demand (see also table 5.7).

Figure 7.3 shows only 12 of 40 zones. The remaining 28 zones do not show heavy clustering of bicycles as in zone 4 for instance, but only small shifts of bicycles with ±10 bicycles per month (not even 3 bicycles per week), which are negligible. In summary, the operator collected randomly single bicycles from different zones, and from 5 main zones which featured a high surplus (blue areas). According to the table there are five target zones, where bicycles seem to be always demanded (red areas, zone 29 excluded) and were dropped off there.

The corresponding zones are illustrated in figure 7.4. In the southeastern part of the operating area are no relocations at all, or at least only an insignificant number of broken bicycles were collected there from time to time. Taking into account that the operator's headquarters are in the northwestern part of the operating area (purple flag in figure 7.4), the conducted strategy is more pragmatically motivated: only a quarter of all zones are involved and most of them are adjacent and/or not far away from the headquarters. Although the operator's interference is quite low and spatially bounded, it keeps the BS System running compared to no relocations at all. Referring to figure

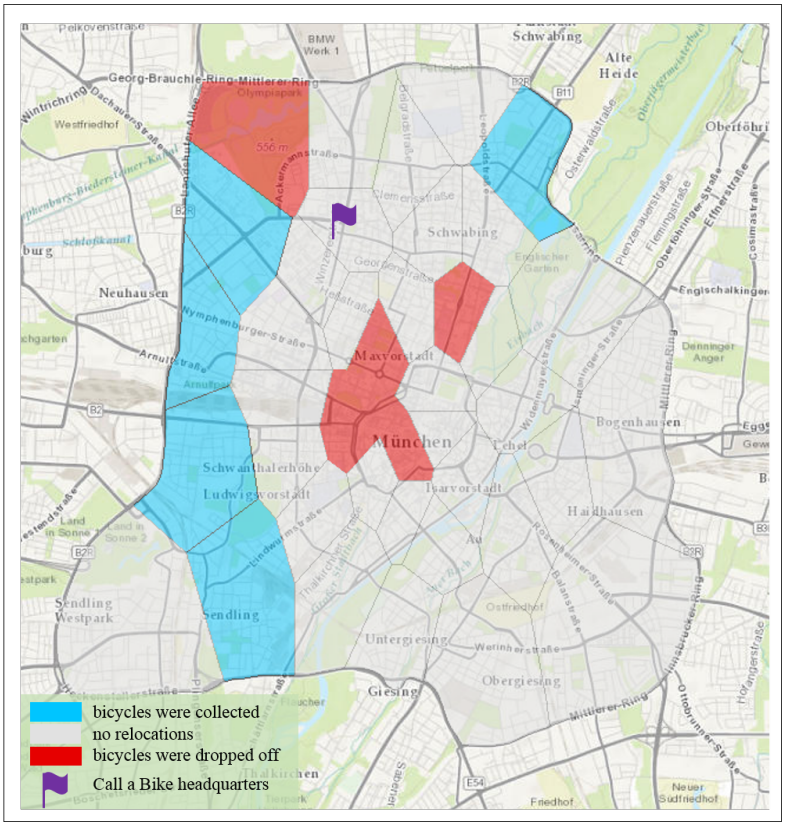


FIGURE 7.4: Zones with realised relocations in 2014

7.3, there are six zones (regarding positive relocation numbers colored in green) that would have been empty without any interference.

Compared to the previously discussed "no-interference" - scenario, the relocation performance in 2014 showed vastly less weak points. But still, there is room for improvement, e.g. expanding the relocation route to more zones, especially in southern parts of the operating area. Further, priorly planned relocation trips conducted on a regular basis can enhance the system while keeping the overall effort little, as the simulation case study in the following section will show.

## 7.3 Simulation Case Study

In order to estimate the real impact of a regularly conducted relocation strategy (RS) a real time simulation is required. This simulation framework applies the different RSs and captures the respective system's dynamics in a long-term scenario.

Based on the historical booking data, regular fleet movements by users and general demand patterns are known. By this simulation, the effects of performing RSs can also be captured on a long time scale. On the one hand there are direct effects, which lead immediately to more trips due to a better FD. On the other hand, the application of RSs can generate more trips not only in the subsequent time slot, but also in ongoing time slots, due to an enhanced overall performance of the system. This long-term evaluation represents an important extension to the developed methods. In consequence, the simulation helps to identify, avoid and/or eliminate fleet imbalances, optimize relocation results and improve the BS System service entirely. A similar approach of a simulation case study referring to CS Systems can be found in [136].

### 7.3.1 Simulation setup

In figure 7.5, the simulation framework is illustrated.

Similar to the "no interference" - scenario in section 7.2.1, the initial day $d_0$ for starting the simulation is set to May 1st, when the BS System was already operating for six weeks. Start time is 12 a.m., ergo $t_{cur} = t_1$ and the corresponding stock is $s^{t_{cur}}$, which is known from the booking data set. This is denoted as step 1.

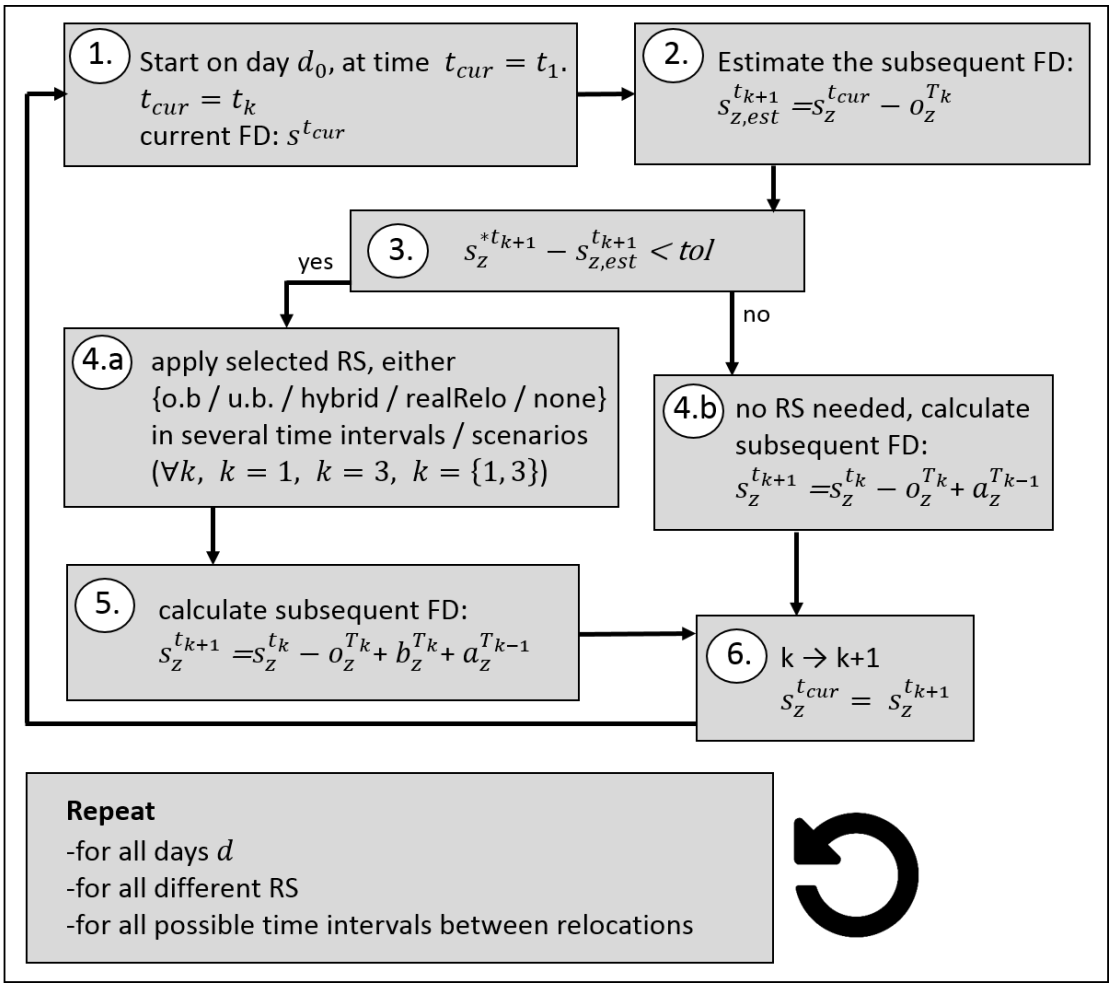


FIGURE 7.5: Simulation framework

Step 2. estimates the subsequent FDs. Therefore the I/O component $O^{T_k}$ listed in table 5.3 is utilized to calculate the FD in the next time slice:

$$s_{z,est}^{t_{k+1}} = s^{t_{cur}} - o_z^{T_k} \tag{7.1}$$

Note that $o_z^{T_k}$ represents "rentals - returns", i.e. an inflow per zone $z$ results in a negative $o^{T_k}$. Hence the minus sign is required in this equation.

Step 3. comprises a test if an application of a RS is required in the current time interval. As a result of the demand model in chapter 5, the saturation matrix $S^*$ was determined, providing a stock recommendation for each zone $z$ and every time $t_k$. A tolerance value $tol$ is set to a deviation of 20%, similar to section 7.1.1.

If the test reveals a higher deviation than $tol$, a RS is applied for the current time slice, see step 4.a. In this step, several options can be selected. At first, each RS is tested solely

for different application intervals. Per simulation test case, an application interval is set e.g., $k = 1$ applies a RS each day in time interval $T_1$, or $k = \{1, 3\}$ performs the selected RS in time slice $T_1$ and $T_3$. In further simulation runs, combinations of the RS are tested e.g., the operator-based and the user-based RS are combined, resulting in the hybrid strategy presented in section 6.3.

If the deviation of the recommended fleet status $s_z^{*t_{k+1}}$ and the estimated fleet status $s_{z,est}^{t_{k+1}}$ is less than $tol$, no RS is required in this time step and the subsequent FD receives another adjustment, see step 4.b:

$$s_z^{t_{k+1}} = s_z^{t_k} - o_z^{T_k} + a_z^{T_{k-1}} \tag{7.2}$$

The value $a_z^{T_{k-1}}$ represents additional fleet movements by users caused by a better FD in the previous time interval $T_{k-1}$, in case of an applied RS in time step $t_{k-1}$. In this case of applying no RS, the algorithm proceeds directly to step 6.

After the application of the selected RS (step 4.a), the resulting stock in each zone is calculated in step 5. and results in

$$s_z^{t_{k+1}} = s_z^{t_k} - o_z^{T_k} + b_z^{T_k} - a_z^{T_{k-1}} \tag{7.3}$$

Here $b_z^{T_k}$ represents the additional bookings caused by a better FD due to relocations in the current time slot $T_k$.

In summary, each simulation iteration comprises FD changes due to

1. current fleet movements because of usual bookings $o_z^{T_k}$ in time interval $T_k$
2. current additional bookings $b_z^{T_k}$ based on an improved FD due to relocations in $T_k$
3. current additional bookings $a_z^{T_{k-1}}$ based on an improved FD due to relocations in $T_{k-1}$

Once the subsequent stock $s_z^{t_{k+1}}$ is calculated, the simulation algorithm proceeds to the next time step $t_{k+1}$ (step 6.) and starts over in step 1.

This procedure is run through for all regarded days $d$ in the simulated time period - for three months in total, i.e. 92 days, consisting of 62 weekdays and 30 weekend days.

The simulation is carried out during May, June and July, in the main operating period featuring most trips (see also chapter 3).

For all different RSs, the simulation results in separate test cases, as well as for every different time interval combination.

In each iteration, output measures evaluating the quality of fleet dynamics are determined. Hereby the quantification of unmet demand is crucial. Two different approaches calculate the demand satisfaction (DS): on the one hand a quantitative DS that refers to satisfied demand per zone. On the other hand, a spatial DS is required in order to capture the degree of DS in the entire operating area. Both measures are calculated as follows.

Let $s_{z,av}^{t_k}$ the amount of available bicycles in zone $z$ at time $t_k$:

$$s_{z,av}^{t_k} = \min\ (s_z^{t_k}, s_z^{*t_k}) \tag{7.4}$$

Then, the ratio of $s_{z,av}^{t_k}$ and the fleet recommendation $s_z^{*t_k}$ - for each the sum over all zones $z$ is taken - yields the quantitative DS at time $t_k$:

$$DS_{quant}^{t_k} = \frac{\sum_z s_{z,av}^{t_k}}{\sum_z s_z^{*t_k}} \tag{7.5}$$

In order to obtain the daily average $DS_{quant}^{d}$ the average of $DS_{quant}^{t_k}$ for all five time slots is calculated. For the spatial DS, this factor is calculated at a zone level at first, for each zone $z$ separately:

$$DS_z^{t_k} = \frac{s_{z,av}^{t_k}}{s_z^{*t_k}} \tag{7.6}$$

Then, the average of $DS_z^{t_k}$ for all zones (in the present case $M = 40$) is determined and the calculation of the daily average yields the spatial DS $DS_{spat}^{d}$ eventually.

A high quantitative DS does not imply a high spatial DS: if $DS_{quant}^{d}$ results in a high percentage, it is still possible that a few zones in the operating area feature a poor FD and therefore $DS_{spat}^{d}$ is low. These distinct calculations guarantee that the DS takes into account singular (maybe under-supplied) zones as well, and hence builds up a holistic measure of DS.

The general utility level is represented by the current amount of under-supplied zones $M_{us}^{t_k}$ at time $t_k$ as this fleet status harms the utility of the BS System. The daily average of all five time slots is denoted as $M_{us}$.

The described simulation framework is carried out for different test cases, each simulated in the same time period of three months. An overview of all simulation test cases and scenarios is listed in table 7.5.

Regarding the operator-based RS, an additional variation is given by different time

| Relocation Strategy | scenario | applied for | initial FD | results in |
|---|---|---|---|---|
| operator-based | real data | −− | real | figure 7.7 |
| | economic | $k = 1$, $k = 3$ | real | figure 7.7 |
| | ambitious | $k = \{1, 3\}$ | real | figure 7.7 |
| | best-case | $\forall k$ | real | figure 7.7 |
| | no interference | $k = \{\}$ | optimal | figure 7.8 |
| | economic | $k = 1$, $k = 3$ | optimal | figure 7.8 |
| | ambitious | $k = \{1, 3\}$ | optimal | figure 7.8 |
| | best-case | $\forall k$ | optimal | figure 7.8 |
| user-based | worst-case | low user's willingness | real | figure 7.9 |
| | realistic | moderate user's willingness | real | figure 7.9 |
| | best-case | high user's willingness | real | figure 7.9 |
| | worst-case | low user's willingness | optimal | figure 7.10 |
| | realistic | moderate user's willingness | optimal | figure 7.10 |
| | best-case | high user's willingness | optimal | figure 7.10 |
| hybrid | economic | $k = 1$/moderate user's willingness $k = 3$ | real | figure 7.11 |
| | economic + | $k = 1$/moderate user's willingness $\forall k$ | real | figure 7.11 |

TABLE 7.5: Different test scenarios run separately within the simulation period

intervals, the respective RS is applied in. The "no interference" - scenario is obviously represented by $k = \{\}$, i.e. the RS is not applied in any time slot $T_k$. An economic scenario concerning the operator-based RS is carried out for a single value for $k$, i.e. once per day. Hereby, effects are tested and compared if the RS is applied at night/early morning, i.e. in $T_1$ (for the target interval $T_2$) or rather during the day, i.e. in $T_3$ (for the target interval $T_4$). Within the ambitious scenario, the effects of applying a RS twice per day, i.e. in $T_1$ and $T_3$ is tested. Further, a best-case-scenario is simulated by applying the RS in every time interval $T_k$, ergo five times a day, disregarding the high amount of labor cost etc. caused by such frequently performed RSs. As a consequence, the maximal impact and benefits of relocations are determined.

Applying the user-based RS, three different scenarios are simulated. Similar to the operator-based RS, there is also a best-case-scenario, which assumes a high users' willingness to adapt their route choice. Based on the results of section 6.2, the entire potential of user-based relocations is exhausted. In this case, the depending relocation potential is maximal, $P_{dep} = 24.6\%$.
In a second scenario, the user-based RS is assumed to perform moderately, caused by an according user's willingness for route adaption. Consequently, the depending relocation potential diminishes to $P_{dep} = 12.3\%$
The worst-case scenario for the user-based RS applies by setting the user's willingness to a minimum, i.e. $P_{dep} = 0\%$ and only the assured relocation potential $P_{as} = 17.3\%$ remains.

In order to analyze the impact of an initially well distributed fleet, the described scenarios are tested for two different initial conditions: the real FD on May 1st, and the optimal FD as calculated within the Demand Model in chapter 5. Consequently, the value of good initial FDs can be read out, as well as time thresholds until the BS system needs relocation interventions because of a constantly worsening FD.

The final part of the simulation test case captures the performance of the hybrid RS. The results build a fusion of precedent test cases. The *economic* scenario tests operator- and user-based interventions both for one time interval concurrently. The *economic+* case applies the operator-based RS again for one time interval. Additionally, the user-based RS is applied for each time interval, i.e. $\forall k$.

Regarding computation time, the simulation case study requires around one hour per test case. The relatively high computational cost is negligible though, as this test case is a static potential analysis and validation of the designed RSs, i.e. an execution is required only once and not recurrently.

### 7.3.2 Simulation results

The initial simulation run regarded the two different measures for demand satisfaction. In figure 7.6, $DS_{quant}$ and $DS_{spat}$ are plotted for three different scenarios.

Firstly, the fleet movements are simulated for the "no interference" - scenario, i.e. $k = \{\}$, depicted in red in figure 7.6. Both demand measures decrease from about 0.85 at day $d_0$ to only 0.6 at the end of the simulation period of three months. The spatial demand satisfaction $DS_{spat}$ (dashed) only slightly differs from the quantitative demand satisfaction $DS_{quant}$.

Secondly, the demand satisfaction for the real relocation performed in 2014 is displayed in black. These values are calculated by the historical FD per day (based on the existing booking data) within the simulation period. $DS_{quant}$ and $DS_{spat}$ are significantly higher compared to the "no-interference" - scenario. This is the first indicator that fleet redistributions are crucial to the overall system's performance: back in 2014,

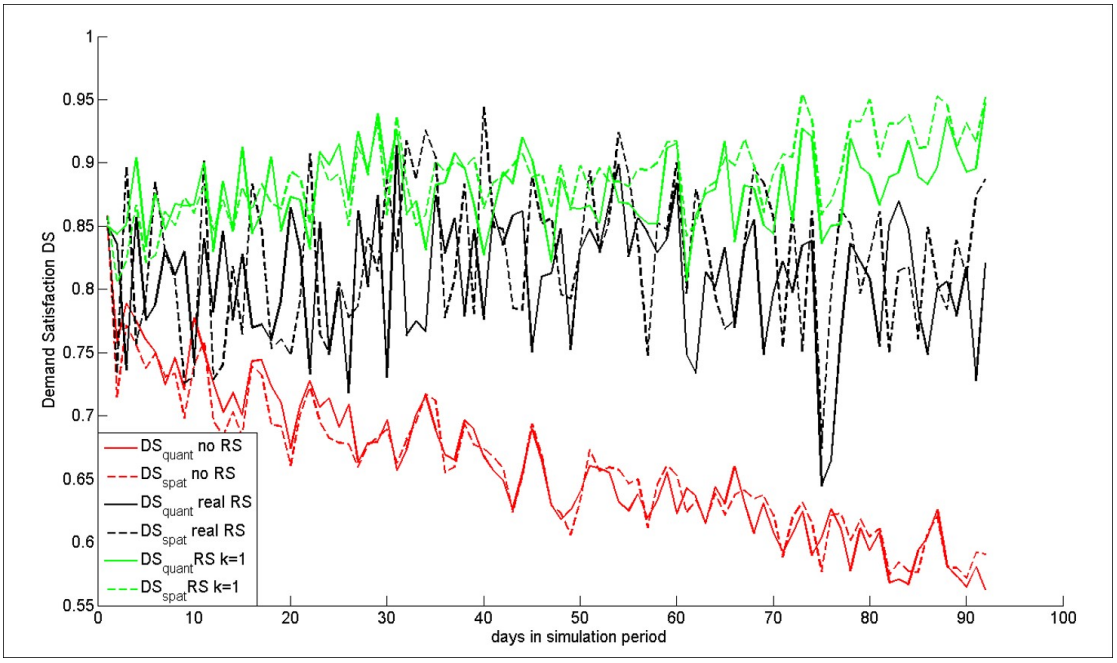


FIGURE 7.6: Quantitative and spatial DS during the simulation period

| | no RS | real RS | $k = 1$ |
|---|---|---|---|
| $\overline{DS}_{quant}$ | 0.66 | 0.81 | 0.88 |
| $\overline{DS}_{spat}$ | 0.66 | 0.82 | 0.89 |
| $\overline{DS}_{\emptyset}$ | 0.66 | 0.82 | 0.88 |
| $\overline{DS}_{conv}$ | 0.59 | 0.81 | 0.92 |

TABLE 7.6: Comparison of different DS measures for different RS

the demand satisfaction ranged between 0.8 and 0.94 with only marginal differences between $DS_{quant}$ and $DS_{spat}$ (dashed black line).

The third test case evaluated the DS for the operator-based RS, applied once per weekday for the target interval $T_1$ ("economic" scenario) depicted in green. Compared to the real RS, the respective values of the demand satisfaction are mostly higher, as they range between 0.85 and 0.96. As a consequence, the economic operator-based RS, applied once per weekday yields better results than the conventional RS back in 2014 regarding the spatial and quantitative DS, especially in the last third of the simulation period. This effect is quantified by the calculation of a *converged* demand satisfaction $\overline{DS}_{conv}$, i.e. the mean value of $\overline{DS}$ regarding only the last two weeks of the simulation period $d = \{79, ..., 92\}$. Like that, the long-term dynamics are captured. The respective values for the different scenarios, among the averaged values $\overline{DS}_{quant}$ and $\overline{DS}_{spat}$ and their average are listed in table 7.6. As a result, applying no RS leads to a poor $\overline{DS}_{conv} = 0.59$, whereas the economic scenario leads to a slightly enhanced DS at the end of the simulation period $\overline{DS}_{conv} = 0.92$.

In general, both DS measures do not feature high varieties. Therefore the average of both is displayed in the following simulation results and simply denoted as $DS$.

The next simulation test case treats the operator-based RS, applied for every weekday at different target intervals. The results regarding $DS$ and $M_{us}$ are depicted in figure 7.7 top and bottom respectively.

The value of $DS$ for the real RS (black line) serves as reference for comparison to the different relocation scenarios. The green line displays a daily application in time slot $T_1$, i.e. the target time is beginning of $T_2$ ergo 6 a.m. The line in magenta depicts the same scenario in time slot $T_3$, providing an optimal FD for 4 p.m. Both demand distributions show a similar trend, although the application in $T_1$ yields a slightly higher $DS$. The cyan line shows the DS if the operator-based RS is applied twice per weekday, i.e. for both time slots $T_1$ and $T_3$. Apparently, the values of $DS_{k=\{1,3\}}$ are higher than $DS_{k=1}$

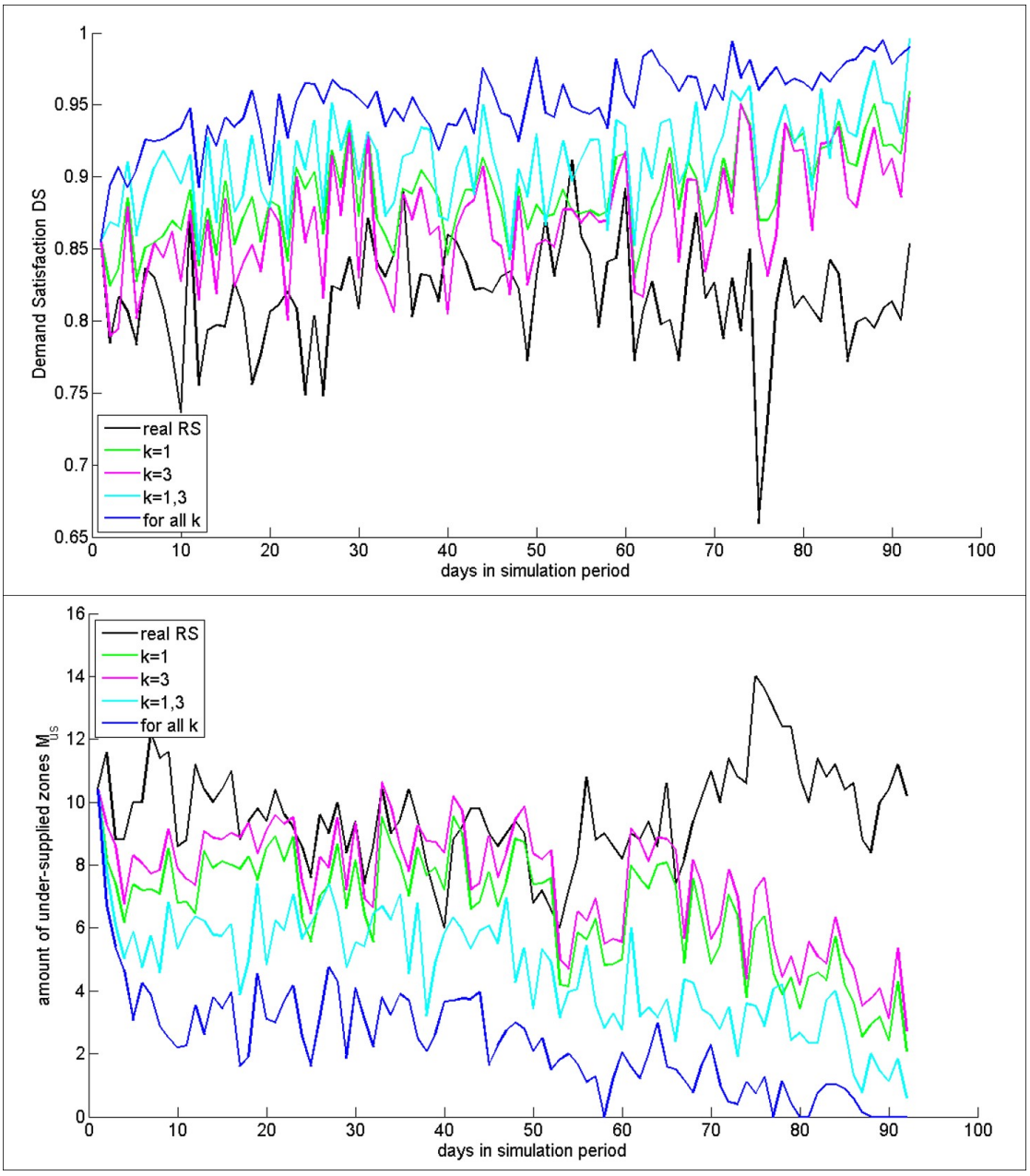


FIGURE 7.7: Results of the operator-based RS for different time interval applications: $DS$ (top) and $M_{us}$ (bottom), real initial FD

or $DS_{k=3}$ at all times, as now the RS is applied in both time intervals. The best-case-scenario is simulated by performing the operator-based RS in all time slots, i.e. five times per weekday. The blue line depicts the according values for $DS_{\forall k}$. This DS even exceeds $DS_{k=\{1,3\}}$, as a RS is nonstop applied. A further measure in order to evaluate the performance of the applied RS is defined by the number of currently under-supplied zones $M_{us}^{t_k}$. The operator-based RS is applied for different relocation intervals and $M_{us}^{t_k}$ is accordingly displayed as the average value $M_{us}$ of all five time slots per day. In figure

| | $k = 1$ | $k = 3$ | $k = \{1, 3\}$ | $\forall k$ | real RS |
|---|---|---|---|---|---|
| $\overline{DS}$ | 0.88 | 0.87 | 0.91 | 0.95 | 0.82 |
| $\overline{DS}_{conv}$ | 0.92 | 0.91 | 0.94 | 0.97 | 0.81 |
| $\overline{M}_{us}$ | 6.60 | 7.25 | 4.63 | 2.32 | 9.62 |
| $\overline{M}_{us,conv}$ | 3.78 | 4.97 | 2.10 | 0.35 | 10.47 |

TABLE 7.7: Comparison of $DS$ and $M_{us}$ for different RS application intervals, real initial FD

7.7 (bottom), $M_{us}$ of the real relocation performance is plotted in black: on a daily average basis, between 6 and 15 zones have been under-supplied during the simulation period. For the economic RS applied in $T_1$ (plotted in green), the performance measured in $M_{us}$ is slightly better in the beginning and significantly better at the end of the simulation period. Applied for two time slots, $M_{us}$ is further enhanced (plotted in cyan). In case of applying the RS in every time slot (plotted in blue), the number of $M_{us}$ is lower than 4 for the entire simulation period.

Altogether, both output measures $DS$ and $M_{us}$ yield similar results. The mean values of $DS$ and $M_{us}$ for all simulation days and the respective converged values are listed in table 7.7. As a result, performing an operator-based RS in $T_1$ has a marginal better effect ($\overline{DS} = 0.88$) on the DS than relocating in time slot $T_3$ ($\overline{DS} = 0.87$). The effect of relocating twice is more significant, and relocating in all five time slots results in the highest mean value $\overline{DS}$. In any case the RS performs better than the real RS. Regarding the converged values $\overline{DS}_{conv}$, each value is increased at the end of the simulation period, whereas $DS$ over the course of the simulation period is slightly worsened for the real RS. In a long term sense, the economic scenarios - conducting an optimized RS regularly every day once - pay off, as $\overline{M}_{us,conv} = 3.78$ and $\overline{M}_{us,conv} = 4.97$ respectively are significantly enhanced compared to the real RS performance featuring $\overline{M}_{us,conv} = 10.47$. By implication, two and five applications per day lead to a clearly improved performance, resulting in $\overline{M}_{us,conv} = 2.10$ and $\overline{M}_{us,conv} = 0.35$ respectively. Again, the converged values show that a regularly application enhances also the long-term performance, whereas $\overline{M}_{us} = 9.62$ in case of the real RS increases to $\overline{M}_{us,conv} = 10.47$.

The next test case investigates the importance of initial FDs. For this purpose, a simulation test case with an optimal FD at the initial day $d_0$ was run. That means, in the first iteration of the simulation period, $DS$ is set to 1 and no under-supplied zones occur. This scenario examines if a FD with optimal initial conditions requires relocation interventions and estimates the time, from which an interference is inevitable.

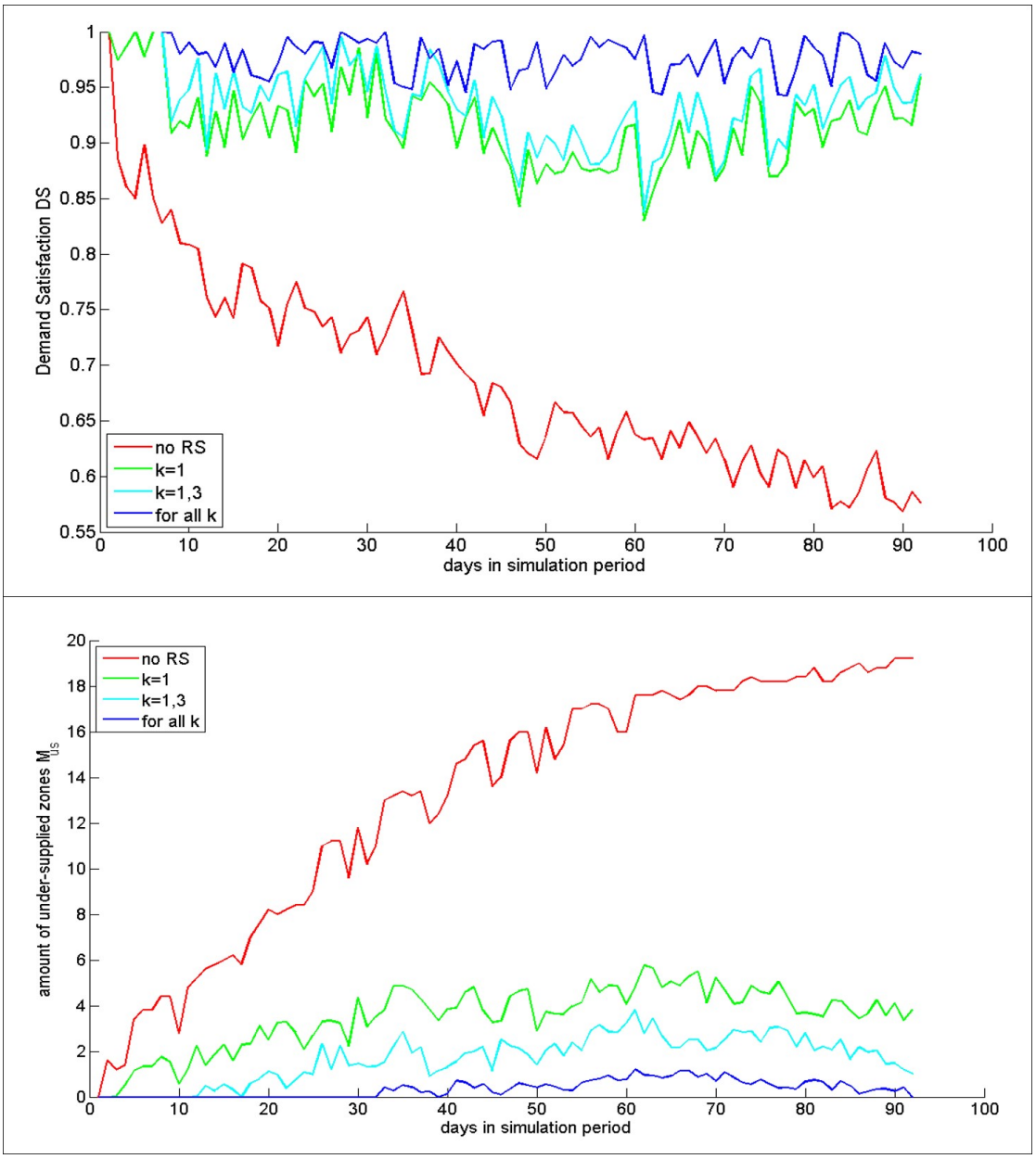


FIGURE 7.8: Results of the operator-based RS for different time interval applications: $DS$ (top) and $M_{us}$ (bottom), optimal initial FD

In figure 7.8, this scenario is illustrated for $DS$ (top) and $M_{us}$ (bottom). The test case comprises three different application intervals and the "no interference" - scenario as in the first test case. Regarding the "no interference" - scenario (red line), $DS$ decreases constantly from 1 in the beginning to only 0.6 at the end of the simulation period. The test case for application interval $k = 1$ (green) result in a significantly higher $DS$, followed by the test cases for $k = \{1, 3\}$ (cyan) and $\forall k$ (blue).

Similar results referring to the according number of under-supplied zones are obtained. Figure 7.8 (bottom) shows the respective values for $M_{us}$. In time slot $T_1$ (green

| | $k = 1$ | $k = \{1, 3\}$ | $\forall k$ | no RS |
|---|---|---|---|---|
| $\overline{DS}$ | 0.91 | 0.93 | 0.96 | 0.69 |
| $\overline{DS}_{conv}$ | 0.93 | 0.94 | 0.98 | 0.59 |
| $\overline{M}_{us}$ | 3.51 | 1.78 | 0.21 | 13.61 |
| $\overline{M}_{us,conv}$ | 3.73 | 2.05 | 0.34 | 19.37 |

TABLE 7.8: Comparison of $DS$ and $M_{us}$ for different RS application intervals, optimal initial FD

line), the first under-supplied zone appears after four days.This value is increasing and eventually settles down to around four under-supplied zones. If the RS is run twice per day, the first under-supplied zone occurs only after twelve days and $M^{d}_{us,k=\{1,3\}}$ ranges around two under-supplied zones on average. The longest period without any under-supplied zones is apparently established by five relocation intervals per weekday (blue line). In this case, it takes more than four weeks until the first under-supplied zone appears - further, within this dense relocation performance, not more than one under-supplied zone on average occurs during the entire simulation period. This pattern changes completely in case of no relocation at all (red line). After only one simulation day, there are already under-supplied zones, and the number is continuously rising. After the entire simulation period of three months, 20 zones, i.e. 50% of the zones in the operating area are under-supplied and the utility level hence is very low.
This scenario proves that it is crucial to perform a RS even if the FD is optimal in the beginning. Otherwise, the system collapses within a few weeks. Further it shows that applying an operator-based RS on a regular basis, the amount of under-supplied zones behaves asymptotically, i.e. for $k = 1$, $k = \{1, 3\}$ and $\forall k$ the value of $M_{us,conv}$ settles down at around 4, 2 and less than 1 respectively, as listed in table 7.8.

In the following, the simulation results of the user-based RS are described. Three different scenarios are simulated:

- a worst-case scenario, assuming a low willingness of the users to conduct relocation trips by adapting the desired route
- a modest scenario, taking into account a moderate users' willingness for a route adaption
- a best-case scenario, assuming the maximum potential of user-based relocations is exhausted by assuming a high users' willingness.

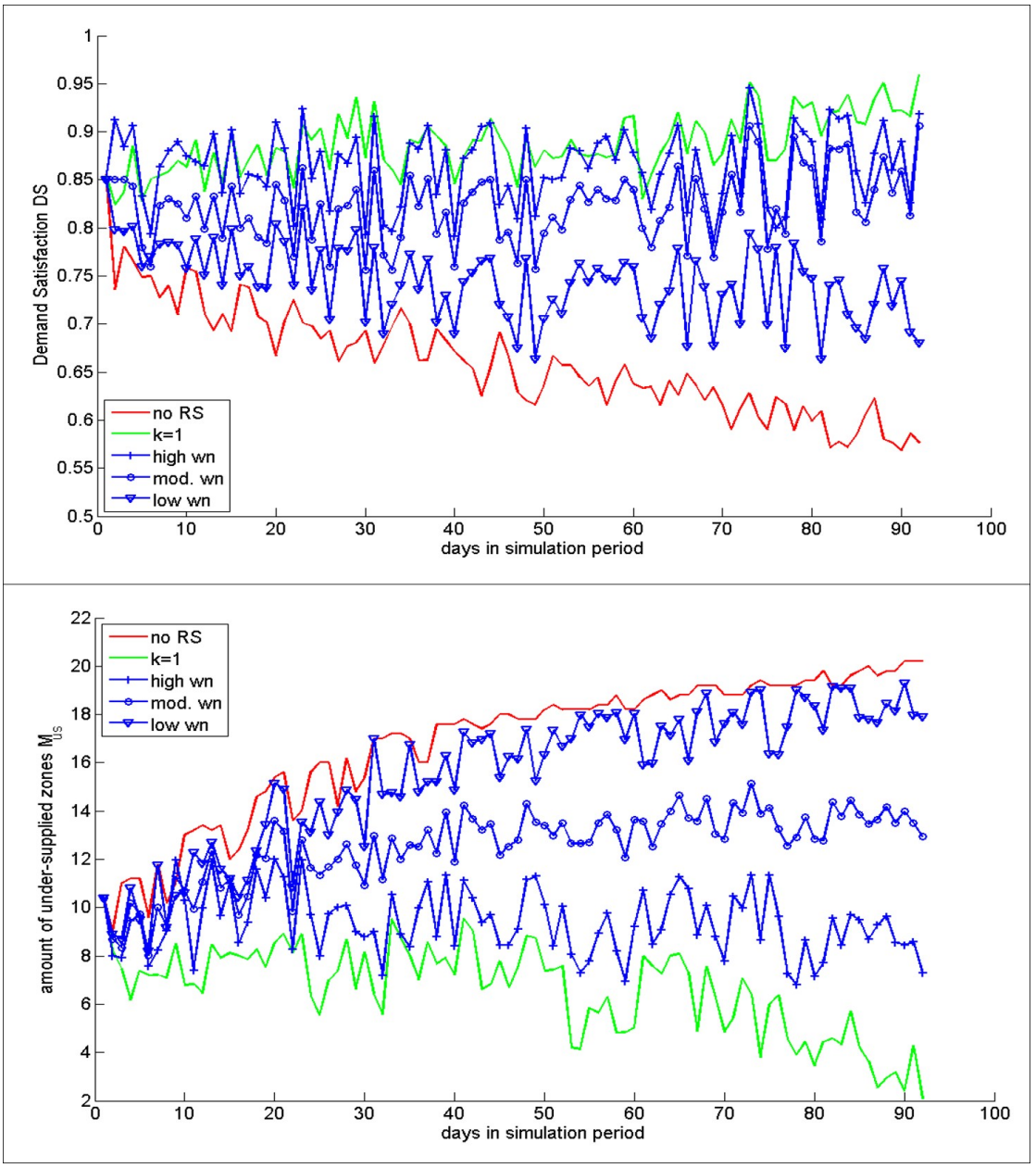


FIGURE 7.9: Results of the user-based RS for different user's willingness scenarios: $DS$ (top) and $M_{us}$ (bottom), real initial FD

Figure 7.9 shows the results for $DS$ (top) and $M_{us}$ (bottom) respectively for all three scenarios within the simulation period, as well as the "no interference" - scenario (in red) and the economic operator-based RS (in green) for reasons of comparability. In case of a high willingness of the users (denoted in blue and "+"), $DS$ is similar to the case of an economic operator-based RS (depicted in green). By assuming a low user's willingness (denoted in blue and "∇") there are only slight enhancements compared to the "no interference" - scenario (in red). The realistic user's willingness (denoted in blue and "∘") features moderate results, i.e. $DS$ ranges between 0.8 and 0.9.

| | no RS | $k = 1$ | high wn. | mod. wn. | low wn. |
|---|---|---|---|---|---|
| $\overline{DS}$ | 0.66 | 0.88 | 0.88 | 0.84 | 0.74 |
| $\overline{DS}_{conv}$ | 0.59 | 0.92 | 0.89 | 0.86 | 0.71 |
| $\overline{M}_{us}$ | 16.98 | 6.60 | 9.95 | 12.64 | 15.31 |
| $\overline{M}_{us,conv}$ | 19.88 | 3.78 | 9.36 | 13.61 | 18.07 |

TABLE 7.9: Comparison of $DS$ and $M_{us}$ for different user-based RS scenarios, real initial FD

Regarding $M_{us}$ in figure 7.9 (bottom), there are still more under-supplied zones by application of the user-based RS for all days of the simulation period compared to an economic operator-based RS. Assuming a low willingness, the user-based RS at least performs slightly better than the "no interference" - scenario. For the presumably most realistic scenario - a moderate user's willingness - the values for $M_{us}$ range between 10 and 14 zones, which is significantly better than around 20 under-supplied zones at the end of the simulation period.

By implication, even if the willingness of the users is high, the economic operator-based RS in time slot $T_1$ outperforms and hence, the user-based RS solely is not an appropriate replacement.

The results of the mean (converged) values are listed in table 7.9.

In order to investigate the impact of the initial FD, the same simulation case was run for an optimal initial FD.

The results concerning $DS$ and $M_{us}$ respectively are illustrated in figure 7.10. A remarkable difference can be read out in the first half of the simulation period: the user-based RS outperforms the economic operator-based RS in case of a high user's willingness. Only in the second half of the simulation period, this RS yields better results than the high willingness scenario.

Assuming a low or moderate user's willingness, the user-based RS is not as effective as the economic operator-based RS (in green). This circumstance shows that the better

| | no RS | $k = 1$ | high wn. | mod. wn. | low wn. |
|---|---|---|---|---|---|
| $\overline{DS}$ | 0.69 | 0.91 | 0.90 | 0.87 | 0.82 |
| $\overline{DS}_{conv}$ | 0.59 | 0.93 | 0.89 | 0.86 | 0.72 |
| $\overline{M}_{us}$ | 13.14 | 3.51 | 3.88 | 7.00 | 11.22 |
| $\overline{M}_{us,conv}$ | 18.73 | 3.73 | 7.03 | 11.81 | 17.34 |

TABLE 7.10: Comparison of $DS$ and $M_{us}$ for different user-based RS scenarios, optimal initial FD

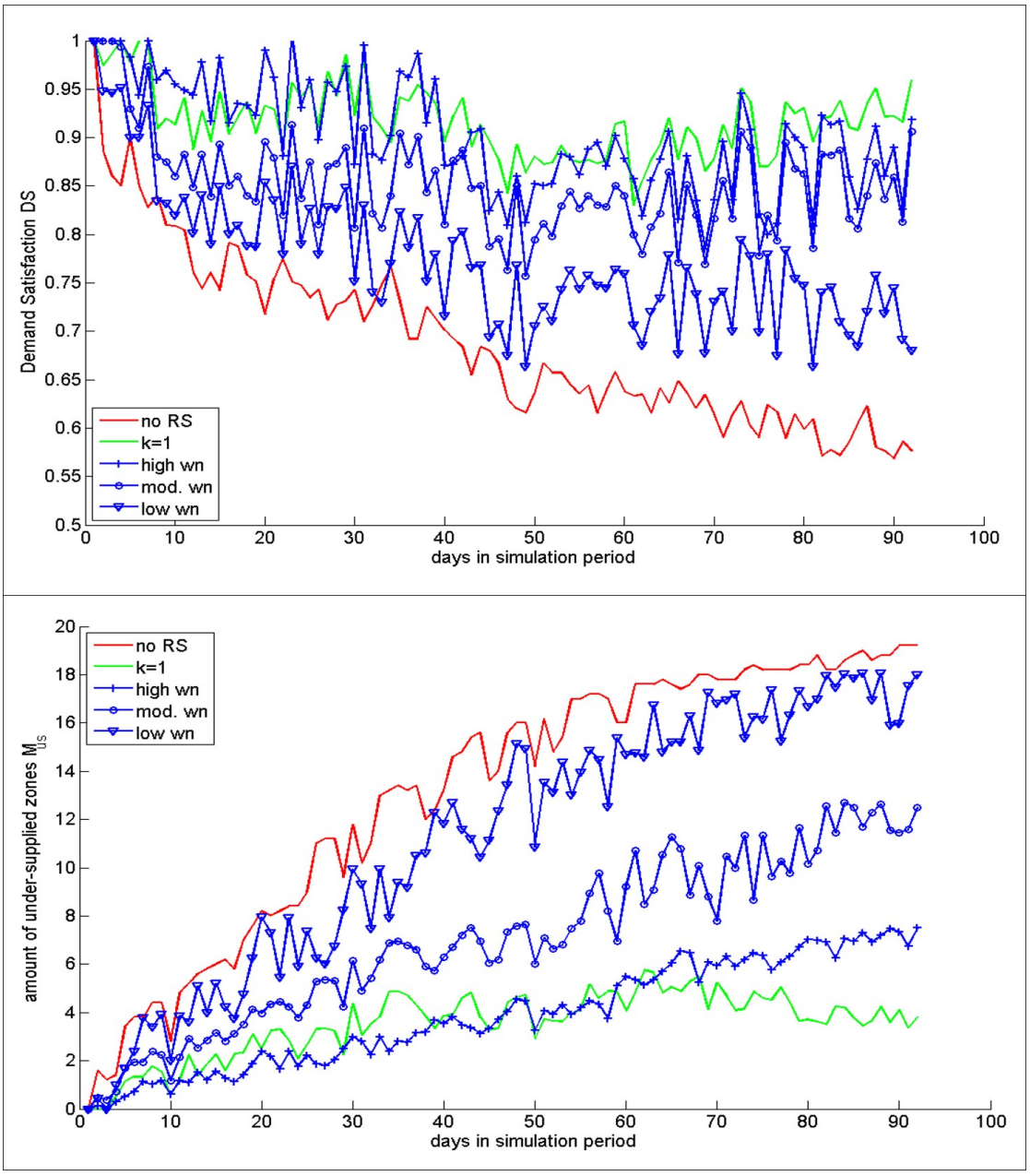


FIGURE 7.10: Results of the user-based RS for different user's willingness scenarios: $DS$ (top) and $M_{us}$ (bottom), optimal initial FD

the initial FD, the better the user-based RS performance.

In the second half of the simulation period, the number of under-supplied zones approximate to the respective level in figure 7.9, i.e. without optimal initial conditions. The mean values and the according converged values are listed in table 7.10. As a consequence, the user-based RS can perform solely in case of a good initial FD. In a long-term sense, this strategy is not sufficient (at least not for the present BS System) and needs support of an operator-based RS.

This is established by applying the hybrid RS. Therefore two different simulations were carried out.

First, a *hybrid eco* RS was simulated. That means, the operator-based RS was applied in one time interval, namely $k = 1$. Additionally, the user-based RS was applied for $k = 3$, when the user-based RS is most efficient (see also section 6.2).

Second, the implementation of a permanent user-based RS was simulated, i.e. the incentives are offered in every time interval $T_k$. This scenario is denoted as *hybrid eco+*

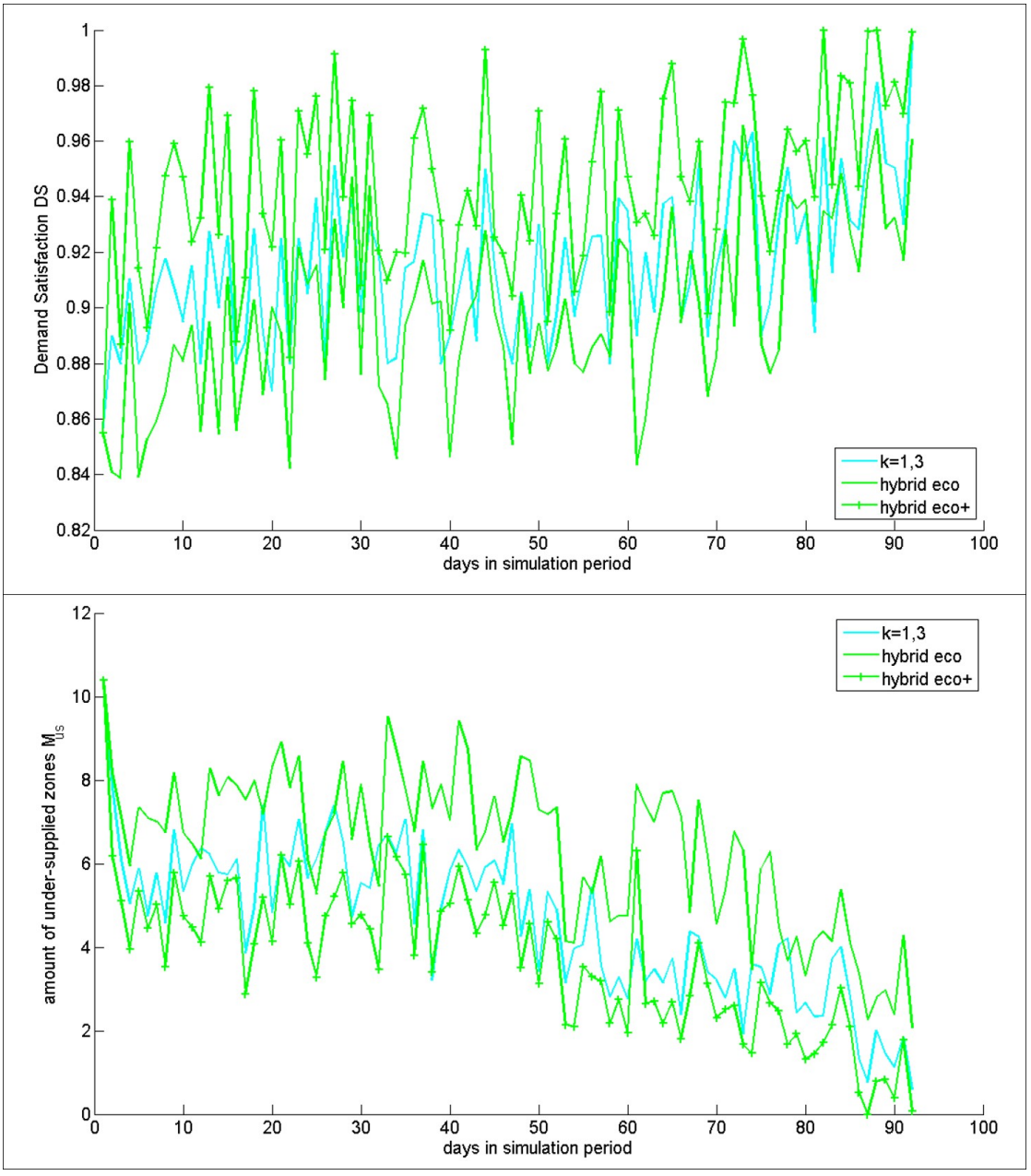


FIGURE 7.11: Results of the hybrid RS, compared to ambitious operator-based scenario: $DS$ (top) and $M_{us}$ (bottom), real initial FD

| | $k = \{1, 3\}$ | hybrid eco | hybrid eco+ |
|---|---|---|---|
| $\overline{DS}$ | 0.91 | 0.89 | 0.93 |
| $\overline{DS}_{conv}$ | 0.94 | 0.93 | 0.95 |
| $\overline{M}_{us}$ | 4.63 | 5.71 | 3.88 |
| $\overline{M}_{us,conv}$ | 2.10 | 2.87 | 1.46 |

TABLE 7.11: Comparison of $DS$ and $M_{us}$ for different hybrid RS scenarios, real initial FD

in the following. The results are illustrated in figure 7.11 for $DS$ and $M_{us}$ respectively. The performance of hybrid eco is depicted in green, hybrid eco+ in green and +. As reference for comparison, the ambitious operator-based RS is plotted in cyan additionally.

Confirmed by both output measures $DS$ and $M_{us}$, the hybrid eco test case performs slightly worse, compared to an operator-based RS applied twice per day. The hybrid eco+ modification, however, outperforms this ambitious RS, although the operator relocates only in one time interval. Regarding the long-term results, the trend for the output measures can be read out in table 7.11 and confirms this observation: by applying the hybrid eco+ RS, less than 1.5 zones on average are under-supplied at the end of the simulation period and $\overline{DS}$ yields a very good result with 0.95.

Based on these results, a clear guidance for fleet relocation is recommended: instead of performing an operator-based RS twice per day, it is more profitable to implement the hybrid eco+ RS, i.e. relocating once by relocation vehicle and applying the user-based RS permanently. Like that, the fleet does not reach a certain skewness and the operator has only moderate relocation effort while keeping the utility level (in terms of $DS$ and $M_{us}$) constantly high.

The final analysis of the simulation case study concerns daily relocation numbers and additionally generated trips due to these relocations. It captures the overall performance of applying different RSs at different time intervals. The summary is depicted in figure 7.12.

For all different RSs, namely user-based concerning a moderate users' willingness (in blue), operator-based (in magenta), hybrid (in green) and hybrid+ for all $k$ (in dashed green), the average number of daily relocations and the respective additional bookings are calculated . This pair of values is obtained for each relocation interval separately.

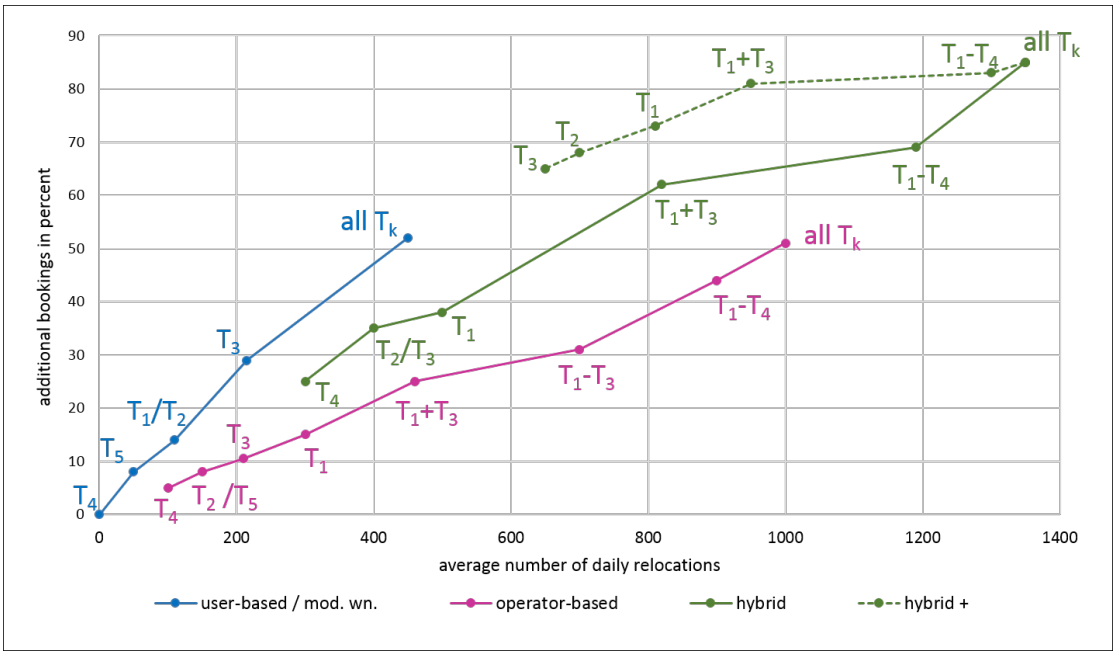


FIGURE 7.12: Average number of daily relocations and according additional bookings per applied relocation interval

Applying the user-based strategy in $T_4$, i.e. for the target interval $T_5$ from midnight to 6 a.m., no effect can be determined, as almost no bookings take place in this time interval. In $T_5$, around 50 relocation trips are performed on average, resulting in around 10% more bookings. $T_1$ and $T_2$ feature the same results regarding the user-based strategy: around 150 relocation trips generate 15% additional bookings. Time slot $T_3$ has the highest impact for user-based relocations, as around 200 relocations lead to 30% more bookings. Putting all time intervals together, the user-based RS results in 450 relocations and more than 50% additional bookings on a daily average. Note that actual user-based relocation trips are already counted as additionally generated trips, as the trip most likely would not have been realized without pricing incentives. Additionally, as these bicycles are parked in *better* zones afterwards, even more bookings are generated.

In case of an application of the operator-based RS, $T_4$ is the weakest time interval, followed by $T_2$ and $T_5$. Applying the RS in these time slots, it results in only around 5% more bookings respectively. Relocating the fleet in $T_3$ and $T_1$ leads to additional bookings of 10% and 15% respectively. By combining different time slots and applying the RS more than once per weekday, up to 1 000 relocations cause up to 50% more bookings.

Taking into account the hybrid RS, it yields the most effective results. In $T_4$ it performs poorly, caused by low effectiveness for both, the user-based and the operator-based RS in this time slot. Combining $T_1$ and $T_3$ within the hybrid RS, 800 daily relocations on average generate up to 60% more bookings. The scenario depicted in green refers to performing the hybrid RSs (user-based and operator-based) in the same respective time interval. If the user-based method is additionally applied for each time slot, the hybrid+ RS yields the results illustrated in the dashed green line: conducting an operator-based RS in $T_1$ and $T_3$ and offering the incentive-regulated user-based RS in all time slots, leads to almost 1 000 daily relocations on average and increases the booking numbers about additional 80%.

In summary it can be stated that both different RSs, the user-based and the operator-based, perform with limitations if applied on their own. The hybrid RS performs better than the operator-based RS in every time interval. Comparing the operator-based RS for both time slots $T_1$ and $T_3$, even more relocations per day are accomplished by the hybrid RS in only one time slot, namely $T_1$. Further, the additional bookings are more than 10% higher as well. If the user-based strategy is applied permanently, i.e. for each time slot per weekday, the overall hybrid + RS leads to 800 daily relocations and more than 70% extra bookings in $T_1$.

The results further show that regularly conducted relocations keep the overall effort to a minimum. If the fleet is fully balanced at one point, the user-based method can rebalance the fleet for a short time period sufficiently, on weekends for instance.
During the week, operator-based relocations are necessary, but by applying the hybrid RS, the economic operator-based RS in time slot $T_1$ is sufficient. Regarding the best-case operator-based RS, i.e. applying the RS in each time interval, it only creates little further value compared to the significant rise in cost.

# Chapter 8

# Conclusions and Future Research

## 8.1 Summary and Conclusions

This section draws conclusions and provides final answers to the research questions (RQ) defined in chapter 1. The summary is outlined in table 8.1, as well as potential future research discussed in the following sections.

The initial RQ 1: *What particular dynamics can be found in free-floating BS Systems?* ought to capture the dynamics and specific characteristics of a free-floating BS System. Within a detailed booking data analysis in chapter 3, the system was examined carefully. Typical usage patterns were identified for different day types and day times: on weekdays, a significant part of the fleet moves from fringe areas into the city center - in the evening, opposed booking patterns were detected as the majority of trips are accomplished from the city center to the outskirts again. This behavior gives the impression of self-regulation at a first glance - the second RQ strove to reassess that.

Groundwork treating RQ 2: *Do fleet imbalances occur in free-floating BS Systems?* was also given in chapter 3. As a result of the empirical booking data analysis, fleet imbalances were presumed and eventually proven by chapter 5. In that chapter, the demand model provided FDs and stock recommendations at a zone level based on the actual demand. For certain zones and time slots, shortages and surpluses of bicycles were identified and the fleet's skewness was quantified.

In RQ 3a: *How can the utility-level of a BS System be increased at best?* the aim to maximize the system's usage was formulated. Therefore diverse strategies were presented in chapter 6 in order to rebalance the fleet. These methods primarily focused on eliminating under-supplied zones, as these zones cannot satisfy users' demand and consequently harm the entire system's utility.

In quest of appropriate relocation strategies (RSs), RQ 3b: *Which strategies are suitable and qualified to reach the desired fleet status?* deals with the application of different RSs. The operator-based RS is capable of rebalancing the fleet, but this strategy can be extremely time-consuming, for instance in case of heavy imbalances at peak hours of traffic. The user-based RS shows its strength exactly in these time slots - when trip numbers and consequently the potential for user-based relocations is highest. This strategy applied on its own does not work effectively though, especially if the fleet currently features high imbalances. Combining both strategies creates the *hybrid Relocation Strategy*, which deploys the respective strengths of both RSs. The best performance results are obtained by running the operator-based RS in the early morning and adding the user-based pricing scheme in the subsequent time period, or even permanently. This combination allows a maximum of bicycle movements at a minimum amount of time and cost and thereby provides a high demand satisfaction and a high utility level of the BS System.

Further, the effects of potential RSs were supposed to be captured, which built up RQ 4a: *Which effects and impacts on the system's performance can be achieved by relocation strategies?* In chapter 7, up to 70% additional bookings were calculated in consequence of a well-distributed fleet compared to a poor FD. Further, a "no-interference"-scenario, i.e. no relocations at all, shows that the system would collapse within a few weeks. A simulation case study proved the long-term effects of applying RSs. Minor imbalances are easier to smooth as a severe skewness of the entire fleet. Therefore it is highly recommended to apply the RS at regular time intervals to maintain a certain fleet balance. By applying the hybrid+ strategy, i.e. one operator-based RS per day and a permanent implemented user-based scheme, the simulation case study revealed that more than 80% extra bookings can be generated.

| Research Question | Answer | Future Research |
|---|---|---|
| **RQ 1**: *What particular dynamics can be found in free-floating BS Systems?* | Referring to chapter 3: on weekdays, a significant part of the fleet moves from fringe areas into the city center / in the evening, opposed booking patterns were detected as major trips are accomplished from the city center to the outskirts. In the long-term: bicycles cluster in fringe areas. | - |
| **RQ 2**: *Do fleet imbalances occur in free-floating BS Systems?* | As a result of the empirical booking data analysis, fleet imbalances were presumed and eventually proven by the demand model in chapter 5, i.e. without any RSs, the FD features a constantly worsening skewness. | application to station-based BS Systems |
| **RQ 3a**: *How can the utility-level of a BS System be increased at best?* | One operator-based and one user-based RS were presented in chapter 6 in order to rebalance the fleet focusing on eliminating under-supplied zones. | a real-word field test is recommended |
| **RQ 3b**: *Which strategies are suitable and qualified to reach the desired fleet status?* | By combination of both strategies the *hybrid Relocation Strategy* was designed, which deploys the respective strengths of both RSs. | refining the inter-zone relocation process |
| **RQ 4a**: *Which effects and impacts on the system's performance can be achieved by relocation strategies?* | In chapter 7 up to 70% additional bookings were calculated in consequence of a well-distributed fleet compared to a poor FD / applying the hybrid RS, around 80% extra bookings can be achieved. | labor cost analyses and staff operation planning |
| **RQ 4b**: *How often does the BS System need support from such strategies in order to maintain the desired fleet status?* | User-based strategies are sufficient on weekends, provided that the initial fleet status does not feature a heavy skewness the best results are achieved by the hybrid+ RS, i.e. one operator-based RS per day and the permanent implementation of the user-based RS. | application to other VS systems / adjustment of algorithms for the station-based case |

TABLE 8.1: Answers to the Research Questions

This leads to the final RQ 4b: *How often does the BS System need support from such strategies in order to maintain the desired fleet status?* The simulation case study shows that moderate relocation interventions are sufficient, as long as the current fleet status is quite balanced. Further, user-based strategies are sufficient on weekends, provided that the initial fleet status does not feature a heavy skewness. In order to compensate poor FDs, one intense relocation performance is necessary, followed by regular, moderate interventions, ideally regulated by the user-based RS. The hybrid RS produces the best performance. Here the operator needs to accomplish a RS once per weekday, which is optimally conducted before 6 a.m. Additionally, the user-based RS offers the incentivizing pricing scheme in each time slot and smooths the occurring fleet imbalances over the course of the day and on weekends.

As a final conclusion, this thesis has proven the essential necessity of fleet redistributions in BS Systems. By applying the given strategies, upcoming demand can be satisfied and every bicycle of the fleet can be optimally exploited. Strategies following a gut feeling, even if supported by experience, are outperformed by the designed RSs.

## 8.2 Transferability to other Cities and Systems

The models and algorithms in this thesis have been designed based on booking data of an existing free-floating BS System in Munich. The resulting RSs were applied to this system - nevertheless it is not only tailored or limited to this specific case. Following steps need consideration in order to apply these strategies to another free-floating BS System:

1. booking data are required for a period of at least four weeks
2. the operating area has to be divided into an appropriate amount of zones, depending on size and booking levels (see section 3.3.1)
3. application of the demand model yields the saturation matrix $S^*$, containing the required amount of bicycles per zone and time slot
4. an efficient RS is recommended, based on the severity of fleet imbalances and the operator's willingness to interfere

The application of the given strategies is not limited to the free-floating case. Taking into account a station-based BS System, however, some modifications are necessary.

Applying the strategies to a station-based system, the procedure mainly remains the same, except that step 2 of the list above is skipped. Instead, the stations of the BS System are considered as zones in the subsequent procedure. In step 4, the main difference will manifest: the full-station-problem, which does not occur in the free-floating case. The designed algorithms indicate over-saturated zones (the equivalent to full stations), but these do not directly cause harm to the system's performance, as users still can return bicycles there. In a station-based BS System, users face issues by returning a bicycle to a full station. Several approaches can solve this problem:

1. allow the users to return the bicycle next to a full docking station - provided that the bicycles are lockable individually
2. use the RS output of over-saturated zones to enlarge the respective stations - like that, the RS can be used as a System Design tool as well (see section 2.2)
3. modify the RS algorithms in such way that over-saturated zones (corr. full stations) harm the BS System as much as under-supplied zones (corr. empty stations)

The last option requires severe changes of the present algorithm and may cause change for the worse in terms of relocation runtime. Referring to the present case of a free-floating BS System, the RS did not always eliminate all over-saturated areas, because of capacity limitations and too high cost - provided that no under-supplied areas occurred at the same time. This circumstance changes for station-based systems, as full stations restrain the current demand and need to be resolved.

## 8.3 Future Research

In this thesis, most research gaps could be closed. Free-floating BS Systems and the respective dynamics were examined in detail as they represent a new component in existing literature. Especially for emerging free-floating BS Systems, for instance *Mobike* in China [81], this research builds a crucial foundation for planning and maintaining such systems in future.

Referring to the previous section, the application to station-based systems depicts an extension to the present research. Depending on the respective system, modifications of the algorithms and tools in this thesis will be necessary.

Further, a field test is recommended to examine the real-world performance of the designed RS. Therefore additional tasks and research questions may arise. For instance, detailed staff planning might be valuable, as well as the coordination of multiple concurrent relocation tours, especially for large-scale BS Systems.

Thorough planning regarding the intra-zone-routing received no consideration within this research. For a more detailed intra-zone analysis, the division of the operating area could be refined and tested, a comparison may give some indication of preferred drop-off areas within a zone. Nevertheless the computing time as well as the relocation performance time might be higher.

BS Systems provide an important module of today's mobility services in urban areas. Such systems need to perform well in order to satisfy upcoming demand and keep the users' confidence. Beyond question, free-floating BS Systems represent the most convenient BS System type for users - provided that bicycles are available for every requesting user. This implies thorough planning of the system's design and system's fleet management.

This thesis makes a contribution to both, better planning and operating of urban BS Systems - and most importantly, to a persisting maintenance of such systems.

# List of Figures

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# Bibliography


[1] P. Angeloudis, J. Hu, and M. G. H. Bell. A Strategic Repositioning Algorithm for Bicycle-Sharing Schemes. In *Proc. Transportation Research Board 91st Annual Meeting*, 2012.

[2] K. W. Axhausen. Social Networks, Mobility Biographies, and Travel: Survey Challenges. *Environment and Planning B: Planning and design*, 35(6):981–996, 2008.

[3] R. Baier, A. Göbbels, and A. Klemps-Kohnen. Sicherheitskenngrößen für den Radverkehr. *Berichte der Bundesanstalt für Straßenwesen - Verkehrstechnik*, 2013.

[4] R. Baier, W. Schuckließ, Y. Jachtmann, V. Diegmann, A. Mahlau, and G. Gässler. Radpotenziale im Stadtverkehr. *Berichte der Bundesanstalt für Straßenwesen - Verkehrstechnik*, 2013.

[5] C. Barnes. Photostream on Flickr. https://www.flickr.com/photos/perspective/11981443374/, retrieved on 14/02/17.

[6] M. Barth, J. Han, and M. Todd. Performance Evaluation of a Multi-Station Shared Vehicle System. In *Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE*, pages 1218–1223. IEEE, 2001.

[7] M. Barth and M. Todd. Simulation Model Performance Analysis of a Multiple Station Shared Vehicle System. *Transportation Research Part C: Emerging Technologies*, 7(4):237–259, 1999.

[8] M. Barth, M. Todd, and L. Xue. User-Based Vehicle Relocation Techniques for Multiple-Station Shared-Use Vehicle Systems, 2004.

[9] T. Bektas. The Multiple Traveling Salesman Problem: an Overview of Formulations and Solution Procedures. *Omega*, 34(3):209–219, 2006.

[10] M. Benchimol, P. Benchimol, B. Chappert, A. De La Taille, F. Laroche, F. Meunier, and L. Robinet. Balancing the Stations of a Self Service "Bike Hire" System. *RAIRO-Operations Research*, 45(1):37–61, 2011.

[11] M. Benichou, J. Gauthier, G. Hentges, and G. Ribiere. The Efficient Solution of Linear Programming Problems — Some Algorithmic Techniques and Computational Results. *Mathematical Programming, 13*, pages 280–322, 1977.

[12] BiCiNg. Official Website of BS System BiCiNg in Barcelona. https://www.bicing.cat/, retrieved on 05/01/17.

[13] Verona Bike. Official Website of BS System Verona Bike in Verona. https://www.bikeverona.it/home, retrieved on 14/02/17.

[14] Copenhagen City Bikes. found in Wikipedia. https://en.wikipedia.org/wiki/Copenhagen_City_Bikes, retrieved on 14/02/17.

[15] C. Black and S. Potter. Portsmouth Bikeabout: An Automated Smart-Card Operated Bike Pool Scheme. In *Velo City'99. The 11th International Bicycle Planning Conference. The bicycle crossing frontiers. Graz, Austria, Maribor, Slovenia, April 13-16, 1999. Proceedings.*, 1999.

[16] Blog of BS System Vélib' in Paris. Triomphe des Bonus V+. http://blog.velib.paris.fr/blog/2008/10/02/triomphe-des-bonus-v-vous-ameliorez-tous-les-jours-le-service-velib/, retrieved on 15/01/17.

[17] P. Borgnat, E. Fleury, C. Robardet, and A. Scherrer. Spatial Analysis of Dynamic Movements of Vélo'v, Lyon's Shared Bicycle Program. In *ECCS'09*. Complex Systems Society, 2009.

[18] T. Bracher, M. Hertel, S. Böhler-Baedeker, T. Koska, C. Beuermann, and O. Reutter. *Innovative öffentliche Fahrradverleihsysteme: Modellprojekte am Start*. Federal Ministry of Transport, Building and Urban Development, 2012.

[19] J. Brinkmann, M. W. Ulmer, and D. C. Mattfeld. Inventory Routing for Bikes Sharing Systems. Technical report, Working Paper (2015-01-12), 2015.

[20] R. Buehler and A. Hamre. Business and Bikeshare User Perceptions of the Economic Benefits of Capital Bikeshare. In *Proc. Transportation Research Board 94nd Annual Meeting*, 2015.

[21] R. Buehler and J. Pucher. Big City Cycling in Europe, North America, and Australia. *Pucher, J. and Buehler, R. eds*, pages 287–318, 2012.

[22] R. Buehler, J. Pucher, and Altshuler A. The Politics of Sustainable Transport in Vienna. In *Proc. Transportation Research Board 96nd Annual Meeting*, 2017.

[23] J. Büttner, H. Mlasowsky, T. Birkholz, D. Gröper, A. Castro Fernández, G. Emberger, T. Petersen, M. Robèrt, S. Serrano Vila, P. Reth, et al. Optimising Bike Sharing in European Cities–Ein Handbuch. *OBIS-Projekt. Online unter: http://www. bikesharing. ch/fileadmin/redaktion/bikesharing/Dokumente/Infotreffen/IT02 _buettner_OBIS_Handbuch_dt_lang. pdf*, 2011.

[24] Call a Bike. Official Website of BS System Call a Bike in Germany. https://www.callabike-interaktiv.de/de, retrieved on 16/01/17.

[25] Capital Bikeshare. The System in (re)Balance. https://www.capitalbikeshare.com/news/2015/04/02/the-system-in-rebalance, retrieved on 11/02/16.

[26] Capital Bikeshare. Capital Bikeshare Survey Report 2014. http://www.capitalbikeshare.com/assets/pdf/cabi-2014surveyreport.pdf, retrieved on 16/01/17.

[27] Capital Bikeshare. Official Website of BS System Capital Bikeshare in Washington D.C. https://www.capitalbikeshare.com/, retrieved on 16/01/17.

[28] Carsharingblog Deutschland. DriveNow bringt Drive'n Save. https://www.carsharing-blog.de/2015/02/drivenow-bringt-driven-save/, retrieved on 03/02/16.

[29] E. M. Cepolina and A. Farina. A New Shared Vehicle System for Urban Areas. *Transportation Research Part C: Emerging Technologies*, 21(1):230–243, 2012.

[30] D. Chemla, F. Meunier, and R. W. Calvo. Bike Sharing Systems: Solving the Static Rebalancing Problem. *Discrete Optimization*, 10(2):120–146, 2013.

[31] C. F. Daganzo. *Logistics Systems Analysis*. Springer Berlin Heidelberg, 2005.

[32] M. Dell'Amico, E. Hadjicostantinou, M. Iori, and S. Novellani. The Bike Sharing Rebalancing Problem: Mathematical Formulations and Benchmark Instances. *Omega*, 45:7–19, 2014.

[33] P. DeMaio. Smart Bikes: Public Transportation for the 21st Century. *Transportation Quarterly*, 57(1):9–11, 2003.

[34] P. DeMaio. Bike-sharing: History, Impacts, Models of Provision, and Future. *Journal of Public Transportation*, 12(4):3, 2009.

[35] P. DeMaio and R. Meddin. The Bike Sharing Blog. http://bike-sharing.blogspot.de, retrieved on 05/01/17.

[36] Deutscher Wetterdienst. Historical Weather Data. http://www.dwd.de/DE/leistungen/klimadatendeutschland/klimadatendeutschland.html?nn=495662, retrieved on 14/10/16.

[37] A. Di Febbraro, N. Sacco, and M. Saeednia. One-Way Car-Sharing: Solving the relocation problem. In *Proc. Transportation Research Board 91st Annual Meeting*, 2012.

[38] T. Döpfner. Rajzefiber - Bahnreiseberichte. http://www.bahnreiseberichte.de/026-Ostsee/26-075Call-a-Bike-Reichstag.JPG, retrieved on 14/02/17.

[39] DriveNow Car Sharing. Offical Website of DriveNow. https://de.drive-now.com/en/, retrieved on 11/01/17.

[40] Environmental Systems Research Institute. ArcGIS 10.2 for Desktop, 2013.

[41] Environmental Systems Research Institute. GIS Dictionary - Thiessen polygons, 2015.

[42] Environmental Systems Research Institute. ArcGIS Resources: An overview of the Network Analyst toolbox. http://resources.arcgis.com/en/help/main/10.2/index.html#/An_overview_of_the_Network_Analyst_toolbox/004800000002000000/, retrieved on 25/03/15.

[43] Federal Environment Agency Germany. Electric Bikes Get Things Rolling - The Environmental Impact of Pedelecs and Their Potential, 2015.

[44] Federal Ministry of Transport, Building and Urban Development. MiD 2008, Mobilität in Deutschland. http://www.mobilitaet-in-deutschland.de, retrieved on 16/09/14.

[45] Federal Ministry of Transport, Building and Urban Development. Trends im Verkehrsmarkt. Detailergebnisse der Studie Mobilität in Deutschland. http://www.mobilitaet-in-deutschland.de/pdf/VortragMiD_VDV_Marketingkongress2010.pdf, retrieved on 19/01/16.

[46] E. Fishman, S. Washington, and N. Haworth. Bike Share's Impact on Car Use: Evidence from the United States, Great Britain and Australia. In *Proc. Transportation Research Board 93nd Annual Meeting*, 2014.

[47] Forschungsgesellschaft für Straßen- und Verkehrwesen. Handbuch für die Bemessung von Straßenverkehrsanlagen (HBS), 2001.

[48] C. Fricker and N. Gast. Incentives and Regulations in Bike-Sharing Systems with Stations of Finite Capacity. *arXiv preprint arXiv:1201.1178*, page 2, 2012.

[49] A. Fyhri and N. Fearnley. Effects of E-bikes on Bicycle Use and Mode Share. *Transportation Research Part D: Transport and Environment*, 36:45–52, 2015.

[50] J. C. García-Palomares, J. Gutiérrez, and M. Latorre. Optimizing the Location of Stations in Bike-Sharing Programs: a GIS Approach. *Applied Geography*, 35(1):235–246, 2012.

[51] K. Gebhart and R. B. Noland. The Impact of Weather Conditions on Capital Bikeshare Trips. In *Proc. Transportation Research Board 92nd Annual Meeting*, 2013.

[52] gobike. Official Website of e-BS System gobike in Copenhagen. http://gobike.com/cities/denmark/copenhagen-1/, retrieved on 16/01/17.

[53] J. Gruber, A. Kihm, and B. Lenz. A New Vehicle for Urban Freight? An Ex-Ante Evaluation of Electric Cargo Bikes in Courier Services. *Research in Transportation Business & Management*, 11:53–62, 2014.

[54] M. Hauer. Fahrradaufkommen gegenüber Fahrradunfällen. Ein Vergleich der Städte München, Hamburg, Zürich und Amsterdam . https://www.muenchen.de/rathaus/dam/jcr:2adace79-fa73-433b-9070-2bf3ed54ab47/mb150204.pdf, retrieved on 19/01/16.

[55] H. Heinrichs. Sharing Economy: a Potential New Pathway to Sustainability. *GAIA-Ecological Perspectives for Science and Society*, 22(4):228–231, 2013.

[56] R. Hemmecke. Nonlinear Integer Programming. In *50 Years of Integer Programming 1958-2008*, pages 561–618. Springer, 2010.

[57] H. Hernández-Pérez and J. Salazar-González. A Branch-and-Cut Algorithm for a Traveling Salesman Problem with Pickup and Delivery. *Discrete Applied Mathematics, 145*, pages 126–139, 1977.

[58] H. Hernández-Pérez and J. Salazar-González. The One-Commodity Pickup-and-Delivery Traveling Salesman Problem: Inequalities and Algorithms. *Published online in Wiley InterScience*, 2007.

[59] G. Hurt. Transport for London. https://www.whatdotheyknow.com/request/barclays_bicycle_redistribution/, retrieved on 15/01/17.

[60] Institute for Mobility Research. 'Mobility Y' – The Emerging Travel Patterns of Generation Y. http://www.ifmo.de/tl_files/publications_content/2013/ifmo_2013_Mobility_Y_en.pdf, 2013.

[61] Institute for Mobility Research. Die Zukunft der Mobilität - Szenarien für Deutschland in 2035. http://www.ifmo.de/tl_files/publications_content/2015/ifmo_2015_Zukunft_der_Mobilitaet_Szenarien_2035_de.pdf, 2015.

[62] Institute for Mobility Research. Mobilität junger Menschen im Wandel - multimodaler und weiblicher. http://www.ifmo.de/tl_files/publications_content/2011/ifmo_2011_Mobilitaet_junger_Menschen_de.pdf, retrieved on 25/03/16.

[63] Institute for Transportation & Development Policy. The Bike Sharing Planning Guide, 2013.

[64] M. Jones and L. Buckland. Estimating Bicycle and Pedestrian Demand in San Diego. *Safe Transportation Research & Education Center*, 2008.

[65] D. Jorge, G. Correia, and C. Barnhart. Comparing Optimal Relocation Operations With Simulated Relocation Policies in One-Way Carsharing Systems. *IEEE Transactions on Intelligent Transportation Systems*, 15(4):1667–1675, 2014.

[66] A. Kaltenbrunner, R. Meza, J. Grivolla, J. Codina, and R. Banchs. Urban Cycles and Mobility Patterns: Exploring and Predicting Trends in a Bicycle-Based Public Transport System. *Pervasive and Mobile Computing*, 6(4):455–466, 2010.

[67] J. P. Kopp. *GPS-gestützte Evaluation des Mobilitätsverhaltens von free-floating CarSharing-Nutzern*. PhD thesis, ETH Zürich, 2015.

[68] G. Krykewycz, C. Puchalsky, J. Rocks, B. Bonnette, and F. Jaskiewicz. Defining a Primary Market and Estimating Demand for Major Bicycle-Sharing Program in Philadelphia, Pennsylvania. *Transportation Research Record: Journal of the Transportation Research Board*, pages 117–124, 2010.

[69] B. Lenz and K. Bogenberger. WiMobil—Wirkung von E-CarSharing-Systemen auf Mobilität und Umwelt in Urbanen Räumen. Halbzeitkonferenz zur Nutzung von E-Carsharing-Systemen am Beispiel von car2go, DriveNow und Flinkster, 2014.

[70] J. Lin and T. Yang. Strategic Design of Public Bicycle Sharing Systems With Service Level Constraints. *Transportation Research Part E: Logistics and Transportation Review*, 47(2):284–294, 2011.

[71] K. Martens. The Bicycle as a Feedering Mode: Experiences from three European Countries. *Transportation Research Part D: Transport and Environment*, 9(4):281–294, 2004.

[72] E. Martin and S. Shaheen. Evaluating Public Transit Modal Shift Dynamics in Response to Bikesharing: a Tale of two US Cities. *Journal of Transport Geography*, 41:315–324, 2014.

[73] L. M. Martinez, L. Caetano, T. Eiró, and F. Cruz. An Optimisation Algorithm to Establish the Location of Stations of a Mixed Fleet Biking System: an Application to the City of Lisbon. *Procedia-Social and Behavioral Sciences*, 54:513–524, 2012.

[74] MATLAB & Simulink. Version R2014a. https://de.mathworks.com/products.html, retrieved on 10/01/17.

[75] MATLAB Documentation. *intlinprog* Algorithm. http://de.mathworks.com/help/optim/ug/mixed-integer-linear-programming-algorithms.html#btwyo05, retrieved on 10/01/17.

[76] J. McKone. The City Fix, Blog. http://thecityfix.com/blog/from-periphery-to-center-does-bike-redistribution-work/, retrieved on 14/02/17.

[77] P. Midgley. The Role of Smart Bike-Sharing Systems in Urban Mobility. *Journeys*, 2:23–31, 2009.

[78] J. Müller. *Statistical Explanatory and Prediction Models for Free-Floating Carsharing Systems*. PhD thesis, Universität der Bundeswehr München, 2016, 2016.

[79] J. Müller and K. Bogenberger. Time Series Analysis of Booking Data of a Free-Floating Carsharing System in Berlin. *Transportation Research Procedia*, 10:345–354, 2015.

[80] J. Müller, S. Schmöller, and F. Giesel. Identifying Users and Use of (Electric-) Free-Floating Carsharing in Berlin and Munich. In *Intelligent Transportation Systems (ITSC), 2015 IEEE 18th International Conference on*, pages 2568–2573. IEEE, 2015.

[81] Mobike. Official Website of BS System Mobike. http://mobike.com/, retrieved on 30/01/17.

[82] H. Monheim, C. Muschwitz, J. Reimann, and M. Streng. Statusanalyse Fahrradverleihsysteme. Potenziale und Zukunft kommunaler und regionaler Fahrradverleihsysteme in Deutschland, 2011.

[83] C. Morency, M. Trepanier, and F. Godefroy. Insight into Montreal's Bikesharing System. In *Transportation Research Board 90th Annual Meeting*, 2011.

[84] MVG Münchner Verkehrsgesellschaft mbH. Flyer of the BS System MVG Rad in Munich. https://www.mvg.de/dam/mvg/services/mobile-services/mvg-rad/folder-mvg-rad.pdf, retrieved on 06/02/17.

[85] L. Nadal. Bike Sharing Sweeps Paris Off its Feet. *Sustainable Transport No. 19*, 2007.

[86] D. Naddef and G. Rinaldi. *The Vehicle Routing Problem*. Society for Industrial and Applied Mathematics, Philadelphia, PA, USA, 2001.

[87] R. Nair and E. Miller-Hooks. Fleet Management for Vehicle Sharing Operations. *Transportation Science*, 45(4):524–540, 2011.

[88] R. Nair, E. Miller-Hooks, R. C. Hampshire, and A. Bušić. Large-Scale Vehicle Sharing Systems: Analysis of Vélib'. *International Journal of Sustainable Transportation*, 7(1):85–106, 2013.

[89] navigo. Vélos en libre service. http://www.navigo.fr/j-organise-mon-deplacement/velos-en-libre-service/, retrieved on 14/02/17.

[90] T. Niels and K. Bogenberger. Booking Behavior of Free-floating Car Sharing Users – Empirical Analysis of Mobile Phone App and Booking Data with Focus on BEVs. In *Proc. Transportation Research Board 96nd Annual Meeting*, 2017.

[91] B. Nielsen and the Ministry of Transport Denmark. *The Bicycle in Denmark: Present Use and Future Potential*. Ministry of Transport, 1993.

[92] O. O'brien, J. Cheshire, and M. Batty. Mining Bicycle Sharing Data for Generating Insights into Sustainable Transport Systems. *Journal of Transport Geography*, 34:262–273, 2014.

[93] Oh-Berlin. Call a Bike Berlin – Das (Miet)-Stadtrad für Berlin. http://www.oh-berlin.com/de/oh-berlin/776/reisefuehrer-berlin/tour/call-a-bike-berlin/, retrieved on 30/01/17.

[94] J. Pfrommer, J. Warrington, G. Schildbach, and M. Morari. Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems. *IEEE Transactions on Intelligent Transportation Systems*, 15(4):1567–1578, 2014.

[95] T. Preisler, T. Dethlefs, and W. Renz. Data-adaptive simulation: Cooperativeness of users in bike-sharing systems. In *Hamburg International Conference of Logistics*, 2015.

[96] T. Preisler, W. Renz, and A. Vilenica. Bike-Sharing System Reliability Problems — A Data-Based Analysis and Simulation Architecture. *Sustainability and Collaboration in Supply Chain Management: A Comprehensive Insight into Current Management Approaches*, page 83, 2013.

[97] E. Press. Online Video about the BS System Vélib' in Paris. http://www.streetfilms.org/velib%e2%80%99/, retrieved on 05/01/17.

[98] PRONTO! Official Website of BS System PRONTO! in Seattle. https://www.prontocycleshare.com/, retrieved on 18/01/17.

[99] J. Pucher and R. Buehler. Why Canadians cycle more than Americans: a comparative analysis of bicycling trends and policies. *Transport Policy*, 13(3):265–279, 2006.

[100] T. Raviv, M. Tzur, and I. A. Forma. Static Repositioning in a Bike-Sharing System: Models and Solution Approaches. *EURO Journal on Transportation and Logistics*, 2(3):187–229, 2013.

[101] S. Reiss and F. Paul. Ergebnisse der Nutzerbefragung des Fahrradverleihsystems *Call a Bike* in Deutschland. 2014.

[102] S. Reiss, F. Paul, and K. Bogenberger. Empirical Analysis of Munich's free-floating Bike Sharing System: GPS-Booking Data and Customer Survey among Bike Sharing Users. In *Proc. Transportation Research Board 94nd Annual Meeting*, 2015.

[103] F. Richter. Bike-Sharing Is Taking Off Around the World . https://www.statista.com/chart/3325/bike-sharing-systems-worldwide/, retrieved on 05/01/17.

[104] J. Rodrigue, C. Comtois, and B. Slack. *The Geography of Transport Systems*. Routledge, 2013.

[105] D. Rojas-Rueda, A. de Nazelle, M. Tainio, and M. J. Nieuwenhuijsen. The Health Risks and Benefits of Cycling in Urban Environments Compared with Car Use: Health Impact Assessment Study, 2011.

[106] J. P. Romero, A. Ibeas, J. L. Moura, J. Benavente, and B. Alonso. A Simulation-Optimization Approach to Design Efficient Systems of Bike-Sharing. *Procedia-Social and Behavioral Sciences*, 54:646–655, 2012.

[107] Santander Cycles. Official Website of BS System Santander Cycles in London. https://tfl.gov.uk/modes/cycling/santander-cycles, retrieved on 19/01/17.

[108] H. Sayarshad, S. Tavassoli, and F. Zhao. A Multi-Periodic Optimization Formulation for Bike Planning and Bike Utilization. *Applied Mathematical Modelling*, 36(10):4944–4951, 2012.

[109] J. Schuijbroek, R. Hampshire, and W. van Hoeve. Inventory Rebalancing and Vehicle Routing in Bike Sharing Systems. https://www.andrew.cmu.edu/user/vanhoeve/papers/bike_sharing.pdf, retrieved on 05/01/16.

[110] R. Seign. *Model-Based Design of Free-Floating Carsharing Systems*. PhD thesis, Universität der Bundeswehr München, Neubiberg, 2015.

[111] S. Seign and K. Bogenberger. Prescriptions for the Successful Diffusion of Carsharing with Electric Vehicles. In *In Proc. Conference on Future Automotive Technology*, 2012.

[112] S. Shaheen, S. Guzman, and H. Zhang. Bike Sharing in Europe, the Americas, and Asia: Past, Present, and Future. In *Proc. Transportation Research Board 89nd Annual Meeting*, 2010.

[113] J. Shu, M. Chou, Q. Liu, C. Teo, and I. Wang. Bicycle-Sharing System: Deployment, Utilization and the Value of Re-Distribution. *National University of Singapore-NUS Business School, Singapore*, 2010.

[114] S. B. Sigurdardóttir. Drivers of Sustainable Future Mobility: Understanding Young People's Travel Trends and the Mediating Factors of Individual Mobility Intentions, 2013.

[115] smart SHANGHAI. Mobike's Shanghai General Manager on the Future of the Company. http://www.smartshanghai.com/articles/tech/mobikes-shanghai-general-manager-on-the-future-of-the-company, retrieved on 14/02/17.

[116] smart SHANGHAI. [Tested]: The Mobike. http://www.smartshanghai.com/articles/tech/tested-the-mobike, retrieved on 14/02/17.

[117] StadtRAD Hamburg. Official Website of BS System StadtRAD in Hamburg. https://stadtrad.hamburg.de/, retrieved on 15/02/17.

[118] H. Stiglbauer. Bicycle Dispatcher, Call a Bike, Munich. Interview about Current Relocations in Munich, 10/07/13.

[119] STREETSBLOG USA. Seattle Just Canned Its Bike-Share System. What Went Wrong? http://usa.streetsblog.org/2017/01/17/

seattle-just-canned-its-bike-share-system-what-went-wrong/, retrieved on 18/01/17.

[120] THE BLOG. by Copenhagenize Design Co. More Bikes Means Fewer Accidents. http://www.copenhagenize.com/2007/11/more-bikes-means-less-accidents.html, retrieved on 24/09/14.

[121] the guardian. How do we fix air pollution? It's simple but it needs political will. https://www.theguardian.com/environment/2017/jan/06/how-do-we-fix-air-pollution-its-simple-but-it-needs-political-will, retrieved on 17/01/17.

[122] TomTom. TomTom Traffic Index 2015. http://tomtom.com/de_de/trafficindex/city/MUN, retrieved on 16/09/16.

[123] Transport for London. Travel in London Report 4 . http://content.tfl.gov.uk/travel-in-london-report-4.pdf, retrieved on 11/06/15.

[124] K. Uesugi, N. Mukai, and T. Watanabe. Optimization of Vehicle Assignment for Car Sharing System. In *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems*, pages 1105–1111. Springer, 2007.

[125] Vélib'. Official Website of BS System Vélib' in Paris. http://www.velib.paris/, retrieved on 05/01/17.

[126] vélo'v. Official Website of BS System vélo'v in Lyon. http://www.velov.grandlyon.com/, retrieved on 05/01/17.

[127] P. Vogel, B. A. Saavedra Neumann, and D. C. Mattfeld. A Hybrid Metaheuristic to Solve the Resource Allocation Problem in Bike Sharing Systems. In *International Workshop on Hybrid Metaheuristics*, pages 16–29. Springer, 2014.

[128] W. von Sassen. Öffentliche Fahrradverleihsysteme im Vergleich - Analyse, Bewertung und Entwicklungsperspektiven, 2009.

[129] Internationaal Instituut voor Sociale Geschiedenis. Witte Fietsenplan. http://www.iisg.nl/collections/provo/b24-706-nl.php, retrieved on 14/02/17.

[130] J. Walker. Basics: Walking Distance to Transit. The Human Transit Blog. http://humantransit.org/2011/04/basics-walking-distance-to-transit.html, retrieved on 07/01/17.

[131] Z. Wang, Z. Kong, and L. Xie, J.and Yin. The 3rd Generation of Bike Sharing Systems in Europe: Programs and Implications. *Urban Transport of China*, 4:7–12, 2009.

[132] A. Waserhole and V. Jost. Vehicle Sharing System Pricing Regulation: A Fluid Approximation, 2012.

[133] A. Waserhole, V. Jost, and N. Brauner. Pricing Techniques for Self Regulation in Vehicle Sharing Systems. *Electronic Notes in Discrete Mathematics*, 41:149–156, 2013.

[134] S. Weikl. *A Mesoscopic Relocation Model for Free-Floating Carsharing Systems*. PhD thesis, Universität der Bundeswehr München, Neubiberg, 2015.

[135] S. Weikl and K. Bogenberger. A Practice-Ready Relocation Model for Free-Floating Carsharing Systems with Electric Vehicles–Mesoscopic Approach and Field Trial Results. *Transportation Research Part C: Emerging Technologies*, 57:206–223, 2015.

[136] S. Weikl, K. Bogenberger, and N. Geroliminis. Simulation Framework for Proactive Relocation Strategies in Free-Floating Carsharing Systems. In *Transportation Research Board 95th Annual Meeting*, 2016.

[137] W. Winston and J. Goldberg. *Operations Research: Applications and Algorithms*, volume 3. Duxbury press Belmont, CA, 2004.

[138] M. Wirtz. *Flexible Tarife in elektronischen Fahrgeldmanagementsystemen und ihre Wirkung auf das Mobilitätsverhalten*. PhD thesis, Karlsruher Institut for Technologie (KIT), 2014.

[139] J. Woodcock, P. Edwards, C. Tonne, B. G. Armstrong, O. Ashiru, D. Banister, S. Beevers, Z. Chalabi, Z. Chowdhury, A. Cohen, et al. Public Health Benefits of Strategies to Reduce Greenhouse-Gas Emissions: Urban Land Transport. *The Lancet*, 374(9705):1930–1943, 2009.

[140] World Health Organization. WHO Global Urban Ambient Air Pollution Database (update 2016). http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/, retrieved on 21/01/17.

[141] G. Wulfhorst. What Cities Want: wie Städte die Mobilität der Zukunft planen: eine Studie von TU München und MAN. *MAN SE*, 2013.

[142] Süddeutsche Zeitung. MVG and Call a bike - Leihen und strampeln. http://www.sueddeutsche.de/muenchen/mvg-und-call-a-bike-leihen-und-strampeln-1.3358104, retrieved on 14/02/17.

[143] ZIV Zweirad-Industrie-Verband. Marktdaten 2015 / Market Data 2015. http://www.ziv-zweirad.de/de/news/detail/article/marktdaten-2015/, retrieved on 13/02/17.

[144] E. Zorn. Radverkehr in München. *Landeshauptstadt München*, 2010.

# Appendix A

# Spatial Analysis for different seasons

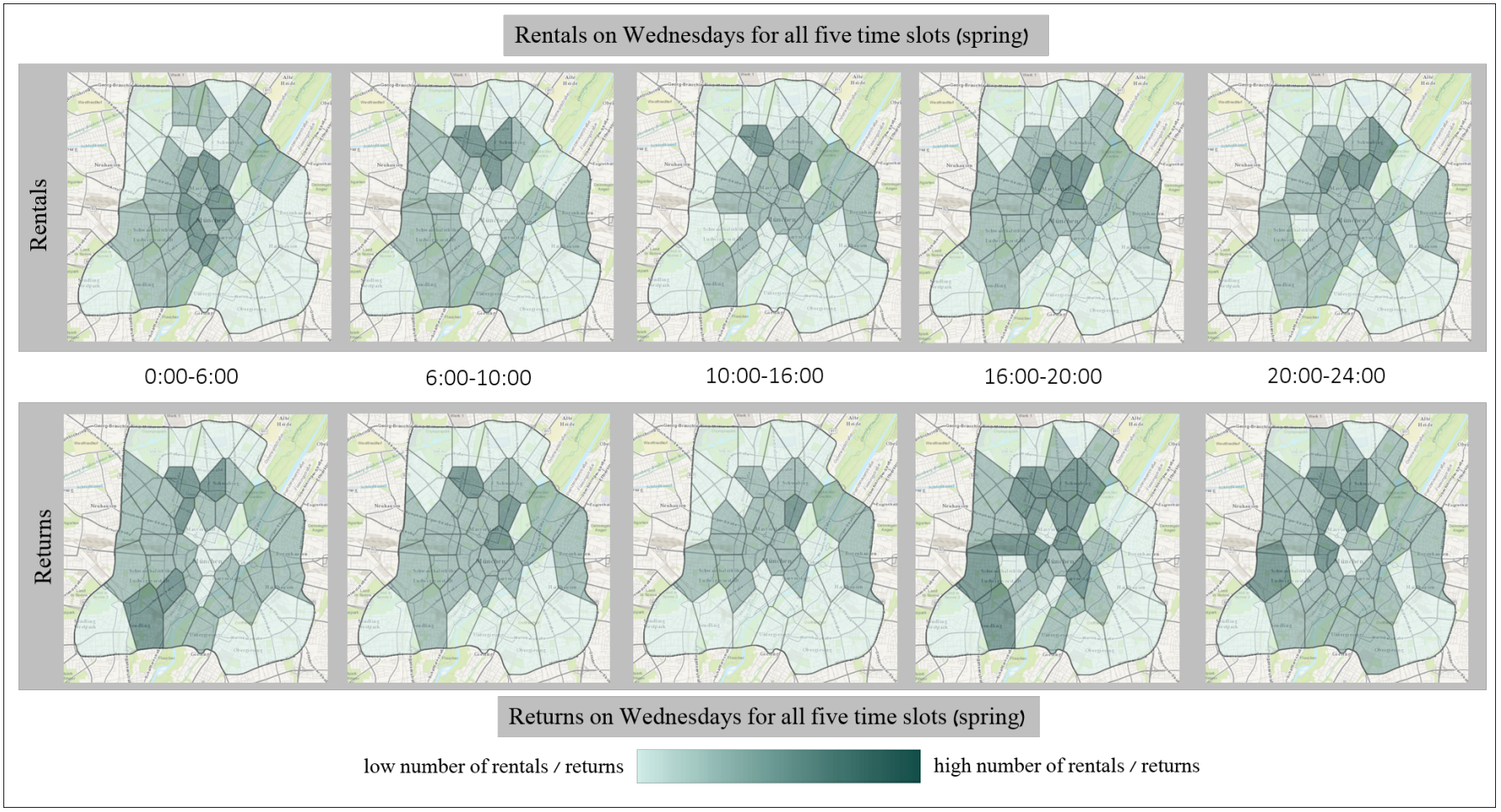


FIGURE A.1: Spatial analysis for all Wednesdays in spring 2014

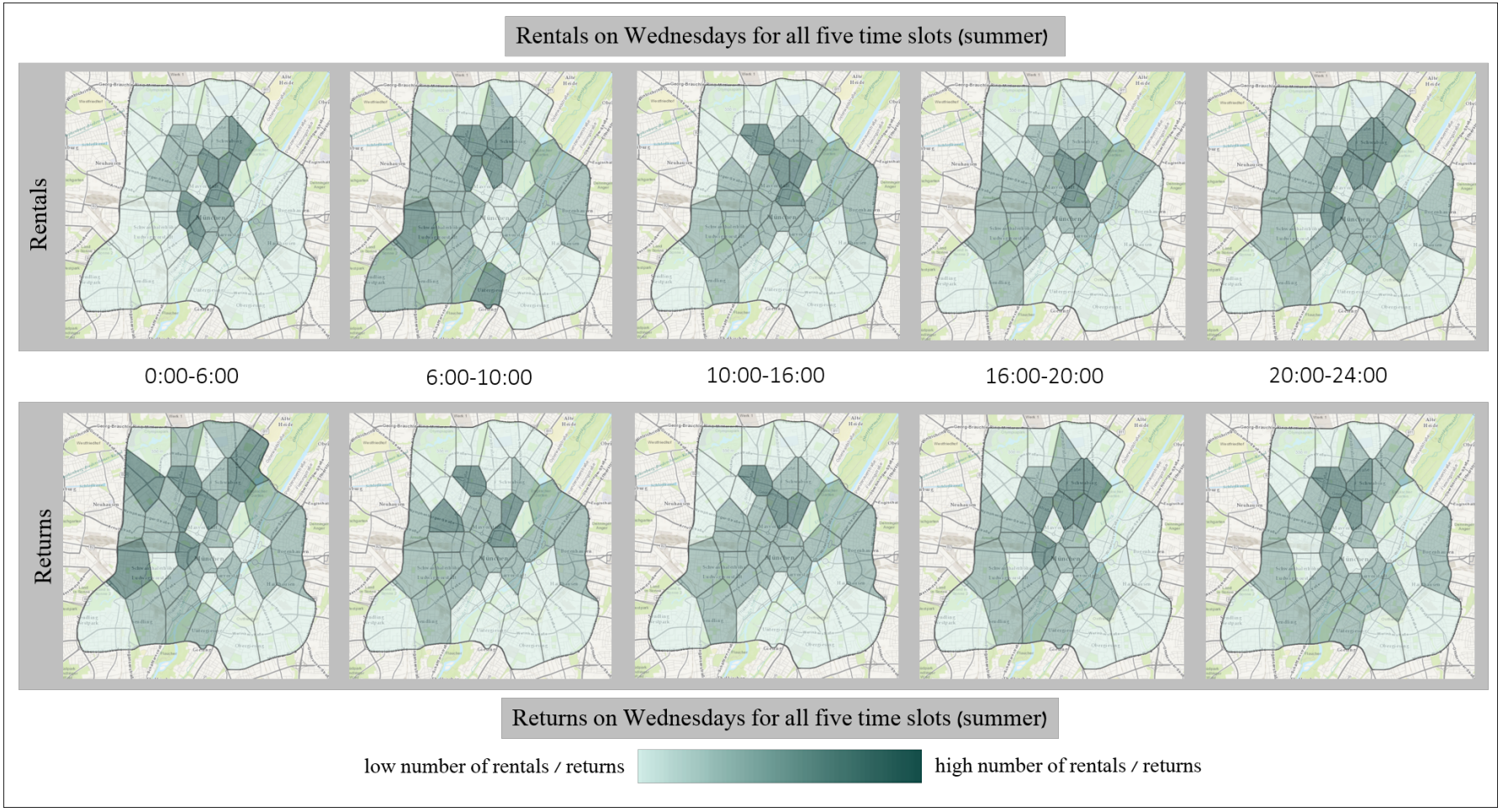


FIGURE A.2: Spatial analysis for all Wednesdays in summer 2014

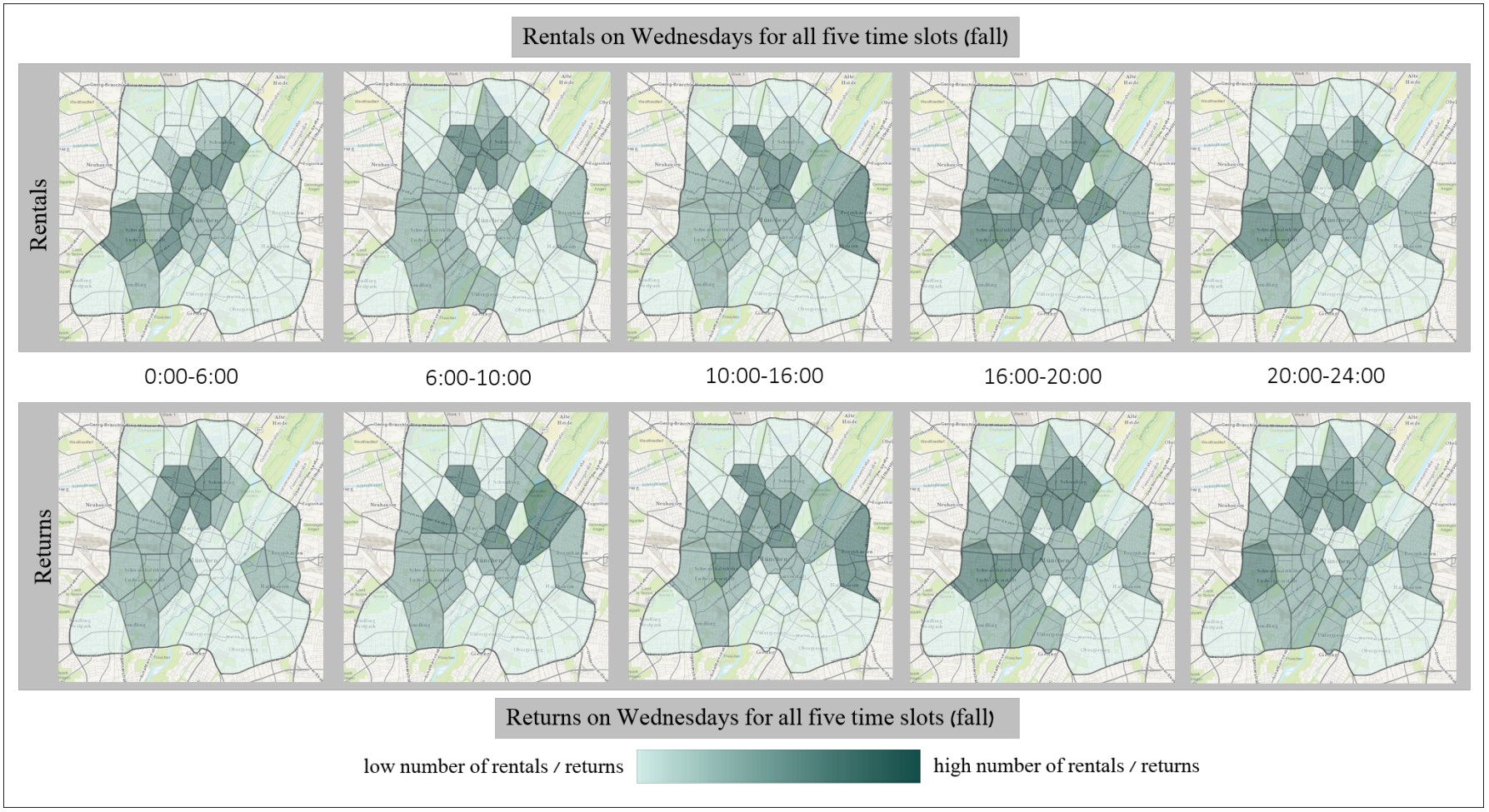


FIGURE A.3: Spatial analysis for all Wednesdays in fall 2014

# Appendix B

# Saturation patterns based on different time periods

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 7 | 15 | 14 | 22 | 12 | 7 | 6 | 9 | 15 | 12 |
| 2 | 7 | 25 | 12 | 24 | 13 | 5 | 8 | 28 | 16 | 9 |
| 3 | 7 | 24 | 15 | 21 | 13 | 12 | 7 | 26 | 13 | 15 |
| 4 | 8 | 13 | 13 | 15 | 10 | 5 | 7 | 15 | 16 | 9 |
| 5 | 6 | 12 | 19 | 21 | 15 | 7 | 7 | 15 | 15 | 11 |
| 6 | 10 | 19 | 18 | 38 | 17 | 13 | 5 | 23 | 25 | 17 |
| 7 | 6 | 17 | 15 | 18 | 15 | 10 | 8 | 12 | 19 | 8 |
| 8 | 9 | 13 | 14 | 18 | 14 | 9 | 8 | 17 | 21 | 18 |
| 9 | 6 | 15 | 18 | 13 | 9 | 5 | 6 | 18 | 15 | 14 |
| 10 | 6 | 18 | 11 | 15 | 12 | 6 | 5 | 18 | 16 | 9 |
| 11 | 8 | 21 | 21 | 29 | 12 | 6 | 6 | 18 | 20 | 17 |
| 12 | 8 | 15 | 13 | 27 | 10 | 11 | 5 | 30 | 16 | 8 |
| 13 | 7 | 17 | 11 | 18 | 13 | 6 | 5 | 12 | 10 | 11 |
| 14 | 8 | 21 | 16 | 32 | 18 | 13 | 9 | 30 | 14 | 15 |
| 15 | 8 | 16 | 23 | 28 | 18 | 13 | 5 | 11 | 11 | 14 |
| 16 | 8 | 22 | 19 | 19 | 18 | 10 | 5 | 21 | 28 | 21 |
| 17 | 5 | 16 | 17 | 19 | 16 | 8 | 7 | 27 | 23 | 14 |
| 18 | 6 | 19 | 18 | 24 | 15 | 6 | 5 | 25 | 25 | 13 |
| 19 | 6 | 15 | 12 | 20 | 11 | 6 | 6 | 17 | 19 | 9 |
| 20 | 10 | 22 | 22 | 27 | 14 | 9 | 5 | 26 | 17 | 19 |
| 21 | 8 | 18 | 17 | 26 | 14 | 9 | 8 | 26 | 14 | 11 |
| 22 | 8 | 14 | 11 | 18 | 14 | 11 | 7 | 24 | 10 | 12 |
| 23 | 6 | 20 | 13 | 25 | 10 | 10 | 7 | 15 | 17 | 15 |
| 24 | 8 | 14 | 16 | 29 | 15 | 14 | 8 | 22 | 25 | 20 |
| 25 | 7 | 13 | 16 | 31 | 15 | 11 | 6 | 30 | 41 | 23 |
| 26 | 7 | 18 | 18 | 24 | 12 | 16 | 10 | 23 | 29 | 9 |
| 27 | 7 | 16 | 13 | 26 | 14 | 8 | 5 | 22 | 12 | 22 |
| 28 | 7 | 21 | 18 | 24 | 17 | 7 | 5 | 30 | 23 | 16 |
| 29 | 5 | 20 | 17 | 22 | 12 | 9 | 7 | 22 | 13 | 6 |
| 30 | 9 | 19 | 17 | 32 | 17 | 11 | 6 | 15 | 23 | 11 |
| 31 | 8 | 29 | 22 | 23 | 20 | 12 | 11 | 26 | 23 | 14 |
| 32 | 8 | 30 | 20 | 34 | 15 | 9 | 6 | 14 | 16 | 16 |
| 33 | 8 | 13 | 24 | 25 | 20 | 12 | 8 | 21 | 23 | 22 |
| 34 | 9 | 13 | 13 | 21 | 16 | 7 | 5 | 27 | 26 | 22 |
| 35 | 8 | 16 | 21 | 24 | 17 | 11 | 6 | 12 | 35 | 20 |
| 36 | 6 | 18 | 13 | 18 | 11 | 5 | 7 | 24 | 19 | 15 |
| 37 | 7 | 21 | 18 | 29 | 16 | 14 | 9 | 16 | 35 | 20 |
| 38 | 7 | 22 | 14 | 27 | 17 | 12 | 6 | 19 | 14 | 18 |
| 39 | 6 | 15 | 17 | 23 | 10 | 12 | 9 | 14 | 22 | 17 |
| 40 | 6 | 20 | 14 | 17 | 9 | 7 | 8 | 10 | 13 | 15 |
| sum | 291 | 725 | 653 | 946 | 566 | 374 | 269 | 810 | 787 | 587 |

TABLE B.1: Saturation pattern based on booking data in April 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 6 | 18 | 17 | 21 | 13 | 8 | 7 | 17 | 16 | 10 |
| 2 | 8 | 24 | 17 | 24 | 14 | 10 | 6 | 28 | 19 | 16 |
| 3 | 9 | 22 | 18 | 30 | 16 | 12 | 8 | 27 | 21 | 20 |
| 4 | 7 | 18 | 16 | 22 | 13 | 8 | 9 | 19 | 22 | 14 |
| 5 | 7 | 18 | 19 | 24 | 14 | 9 | 7 | 21 | 22 | 17 |
| 6 | 10 | 24 | 29 | 36 | 20 | 17 | 9 | 27 | 37 | 19 |
| 7 | 8 | 22 | 20 | 24 | 13 | 11 | 7 | 20 | 19 | 17 |
| 8 | 9 | 19 | 15 | 21 | 16 | 9 | 9 | 16 | 18 | 17 |
| 9 | 8 | 17 | 19 | 18 | 12 | 10 | 8 | 14 | 19 | 10 |
| 10 | 7 | 18 | 15 | 23 | 13 | 8 | 8 | 17 | 19 | 10 |
| 11 | 10 | 22 | 22 | 32 | 18 | 12 | 8 | 19 | 27 | 17 |
| 12 | 9 | 21 | 17 | 26 | 14 | 9 | 8 | 25 | 26 | 14 |
| 13 | 6 | 15 | 13 | 16 | 11 | 8 | 7 | 19 | 13 | 12 |
| 14 | 7 | 18 | 21 | 31 | 17 | 11 | 6 | 22 | 25 | 16 |
| 15 | 9 | 25 | 21 | 31 | 18 | 17 | 8 | 20 | 25 | 16 |
| 16 | 8 | 21 | 19 | 26 | 19 | 12 | 9 | 28 | 25 | 16 |
| 17 | 8 | 19 | 19 | 25 | 15 | 9 | 8 | 25 | 25 | 15 |
| 18 | 9 | 20 | 16 | 25 | 16 | 9 | 7 | 25 | 28 | 18 |
| 19 | 7 | 18 | 16 | 22 | 11 | 9 | 8 | 20 | 15 | 11 |
| 20 | 8 | 24 | 19 | 27 | 16 | 14 | 8 | 25 | 26 | 18 |
| 21 | 8 | 24 | 20 | 29 | 16 | 10 | 8 | 25 | 25 | 17 |
| 22 | 8 | 21 | 16 | 21 | 14 | 11 | 9 | 22 | 16 | 11 |
| 23 | 9 | 21 | 16 | 24 | 14 | 9 | 8 | 21 | 22 | 14 |
| 24 | 8 | 21 | 19 | 23 | 15 | 10 | 9 | 20 | 27 | 13 |
| 25 | 10 | 17 | 23 | 34 | 19 | 12 | 6 | 25 | 30 | 20 |
| 26 | 11 | 22 | 20 | 32 | 17 | 13 | 10 | 26 | 30 | 15 |
| 27 | 7 | 21 | 19 | 31 | 16 | 12 | 7 | 23 | 21 | 18 |
| 28 | 7 | 27 | 18 | 24 | 17 | 9 | 10 | 28 | 24 | 16 |
| 29 | 7 | 21 | 19 | 20 | 13 | 9 | 8 | 22 | 22 | 14 |
| 30 | 8 | 30 | 23 | 27 | 17 | 12 | 7 | 32 | 22 | 16 |
| 31 | 10 | 24 | 24 | 29 | 20 | 14 | 8 | 27 | 22 | 15 |
| 32 | 10 | 32 | 27 | 37 | 20 | 12 | 7 | 28 | 26 | 17 |
| 33 | 9 | 18 | 21 | 35 | 19 | 13 | 7 | 24 | 31 | 22 |
| 34 | 9 | 16 | 19 | 29 | 16 | 10 | 6 | 17 | 26 | 17 |
| 35 | 9 | 22 | 21 | 37 | 21 | 17 | 8 | 26 | 30 | 23 |
| 36 | 7 | 19 | 17 | 21 | 12 | 6 | 9 | 19 | 18 | 13 |
| 37 | 9 | 23 | 23 | 33 | 15 | 12 | 8 | 25 | 25 | 15 |
| 38 | 9 | 21 | 22 | 33 | 20 | 12 | 9 | 23 | 27 | 24 |
| 39 | 8 | 21 | 18 | 23 | 12 | 11 | 7 | 21 | 22 | 16 |
| 40 | 6 | 17 | 16 | 18 | 13 | 10 | 7 | 17 | 18 | 10 |
| sum | 329 | 841 | 769 | 1064 | 625 | 436 | 313 | 905 | 931 | 629 |

TABLE B.2: Saturation pattern based on booking data in May 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 8 | 21 | 18 | 24 | 14 | 10 | 8 | 22 | 21 | 14 |
| 2 | 8 | 25 | 20 | 27 | 16 | 11 | 9 | 27 | 26 | 17 |
| 3 | 9 | 26 | 22 | 31 | 18 | 12 | 8 | 27 | 30 | 22 |
| 4 | 8 | 19 | 17 | 23 | 14 | 10 | 9 | 19 | 20 | 14 |
| 5 | 8 | 18 | 20 | 29 | 15 | 10 | 8 | 23 | 26 | 16 |
| 6 | 12 | 28 | 30 | 45 | 25 | 17 | 10 | 36 | 37 | 24 |
| 7 | 8 | 25 | 20 | 28 | 16 | 11 | 8 | 26 | 24 | 16 |
| 8 | 10 | 19 | 16 | 23 | 17 | 13 | 9 | 22 | 26 | 22 |
| 9 | 8 | 20 | 19 | 22 | 13 | 10 | 9 | 20 | 20 | 13 |
| 10 | 8 | 19 | 17 | 25 | 14 | 10 | 8 | 21 | 22 | 14 |
| 11 | 10 | 26 | 23 | 33 | 20 | 12 | 9 | 26 | 29 | 22 |
| 12 | 9 | 23 | 22 | 29 | 17 | 11 | 8 | 27 | 25 | 18 |
| 13 | 7 | 18 | 16 | 19 | 13 | 9 | 7 | 18 | 18 | 13 |
| 14 | 9 | 21 | 23 | 34 | 20 | 14 | 8 | 26 | 28 | 19 |
| 15 | 10 | 26 | 24 | 33 | 20 | 16 | 9 | 28 | 28 | 22 |
| 16 | 10 | 24 | 22 | 30 | 20 | 14 | 8 | 28 | 28 | 20 |
| 17 | 8 | 23 | 21 | 31 | 19 | 12 | 9 | 28 | 28 | 20 |
| 18 | 9 | 26 | 21 | 27 | 18 | 13 | 8 | 27 | 27 | 18 |
| 19 | 7 | 22 | 19 | 22 | 14 | 9 | 8 | 21 | 19 | 15 |
| 20 | 10 | 29 | 24 | 32 | 20 | 14 | 8 | 29 | 28 | 20 |
| 21 | 9 | 24 | 22 | 30 | 18 | 12 | 8 | 26 | 27 | 17 |
| 22 | 8 | 22 | 19 | 26 | 15 | 11 | 10 | 24 | 24 | 15 |
| 23 | 9 | 23 | 21 | 27 | 16 | 11 | 8 | 24 | 23 | 19 |
| 24 | 9 | 23 | 23 | 29 | 18 | 14 | 9 | 27 | 26 | 18 |
| 25 | 10 | 20 | 27 | 41 | 21 | 13 | 7 | 28 | 35 | 20 |
| 26 | 11 | 23 | 21 | 35 | 21 | 16 | 11 | 27 | 35 | 21 |
| 27 | 8 | 24 | 22 | 34 | 18 | 11 | 8 | 27 | 28 | 20 |
| 28 | 9 | 28 | 23 | 29 | 18 | 11 | 9 | 29 | 27 | 19 |
| 29 | 8 | 25 | 22 | 23 | 14 | 10 | 8 | 24 | 21 | 15 |
| 30 | 9 | 31 | 24 | 33 | 19 | 14 | 9 | 30 | 29 | 20 |
| 31 | 11 | 31 | 27 | 37 | 21 | 15 | 10 | 34 | 31 | 22 |
| 32 | 10 | 33 | 28 | 40 | 21 | 13 | 9 | 35 | 34 | 22 |
| 33 | 11 | 22 | 25 | 40 | 22 | 17 | 8 | 29 | 32 | 22 |
| 34 | 10 | 20 | 22 | 33 | 18 | 13 | 8 | 24 | 27 | 20 |
| 35 | 11 | 26 | 25 | 38 | 23 | 17 | 9 | 26 | 31 | 23 |
| 36 | 8 | 22 | 18 | 23 | 13 | 9 | 8 | 22 | 21 | 13 |
| 37 | 9 | 24 | 24 | 38 | 19 | 13 | 8 | 30 | 32 | 20 |
| 38 | 10 | 24 | 24 | 35 | 22 | 14 | 9 | 27 | 29 | 23 |
| 39 | 9 | 22 | 19 | 25 | 15 | 11 | 8 | 25 | 25 | 16 |
| 40 | 7 | 21 | 18 | 22 | 13 | 9 | 8 | 21 | 20 | 15 |
| sum | 362 | 946 | 868 | 1205 | 708 | 492 | 340 | 1040 | 1067 | 739 |

TABLE B.3: Saturation pattern based on booking data in June 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 9 | 23 | 18 | 27 | 15 | 11 | 7 | 25 | 22 | 17 |
| 2 | 9 | 30 | 21 | 27 | 19 | 13 | 10 | 26 | 31 | 19 |
| 3 | 10 | 25 | 26 | 30 | 19 | 11 | 10 | 29 | 31 | 21 |
| 4 | 8 | 23 | 19 | 25 | 14 | 12 | 9 | 17 | 18 | 13 |
| 5 | 8 | 18 | 23 | 28 | 17 | 11 | 8 | 23 | 27 | 17 |
| 6 | 13 | 29 | 32 | 51 | 27 | 17 | 10 | 43 | 45 | 30 |
| 7 | 9 | 28 | 21 | 30 | 17 | 11 | 8 | 31 | 27 | 19 |
| 8 | 12 | 21 | 19 | 25 | 19 | 13 | 9 | 28 | 28 | 25 |
| 9 | 8 | 21 | 22 | 25 | 15 | 10 | 10 | 21 | 18 | 12 |
| 10 | 9 | 20 | 18 | 29 | 16 | 10 | 8 | 26 | 26 | 13 |
| 11 | 11 | 26 | 27 | 36 | 21 | 12 | 10 | 30 | 30 | 26 |
| 12 | 9 | 23 | 22 | 33 | 17 | 13 | 10 | 24 | 29 | 18 |
| 13 | 8 | 19 | 17 | 21 | 13 | 10 | 7 | 17 | 22 | 14 |
| 14 | 11 | 22 | 25 | 38 | 21 | 18 | 10 | 26 | 33 | 21 |
| 15 | 10 | 26 | 24 | 37 | 20 | 20 | 10 | 27 | 25 | 23 |
| 16 | 10 | 27 | 26 | 31 | 20 | 15 | 9 | 27 | 34 | 19 |
| 17 | 8 | 27 | 21 | 35 | 21 | 12 | 11 | 28 | 32 | 20 |
| 18 | 10 | 26 | 21 | 27 | 18 | 15 | 8 | 26 | 24 | 21 |
| 19 | 7 | 24 | 18 | 26 | 14 | 9 | 9 | 27 | 19 | 19 |
| 20 | 11 | 28 | 25 | 38 | 22 | 15 | 8 | 30 | 27 | 22 |
| 21 | 11 | 27 | 24 | 31 | 18 | 15 | 7 | 26 | 29 | 18 |
| 22 | 9 | 25 | 21 | 30 | 16 | 10 | 11 | 24 | 26 | 17 |
| 23 | 9 | 23 | 22 | 31 | 18 | 11 | 10 | 23 | 21 | 21 |
| 24 | 10 | 22 | 26 | 31 | 20 | 14 | 10 | 31 | 34 | 23 |
| 25 | 10 | 20 | 29 | 44 | 21 | 15 | 9 | 29 | 35 | 19 |
| 26 | 12 | 27 | 24 | 40 | 23 | 19 | 10 | 25 | 35 | 23 |
| 27 | 9 | 24 | 22 | 39 | 20 | 11 | 9 | 31 | 29 | 20 |
| 28 | 11 | 31 | 24 | 32 | 20 | 14 | 9 | 29 | 24 | 21 |
| 29 | 9 | 27 | 22 | 25 | 15 | 11 | 8 | 24 | 23 | 16 |
| 30 | 10 | 35 | 25 | 33 | 20 | 16 | 8 | 28 | 28 | 19 |
| 31 | 12 | 32 | 31 | 40 | 21 | 17 | 12 | 41 | 32 | 20 |
| 32 | 11 | 35 | 29 | 43 | 23 | 13 | 12 | 37 | 42 | 19 |
| 33 | 12 | 23 | 28 | 43 | 22 | 17 | 10 | 26 | 41 | 20 |
| 34 | 11 | 24 | 23 | 38 | 18 | 15 | 10 | 30 | 25 | 20 |
| 35 | 12 | 26 | 28 | 42 | 24 | 22 | 10 | 27 | 35 | 27 |
| 36 | 8 | 23 | 22 | 25 | 15 | 11 | 8 | 24 | 21 | 13 |
| 37 | 10 | 28 | 25 | 39 | 19 | 11 | 8 | 35 | 36 | 23 |
| 38 | 10 | 27 | 27 | 36 | 24 | 13 | 9 | 26 | 31 | 29 |
| 39 | 10 | 23 | 19 | 26 | 16 | 14 | 10 | 31 | 24 | 19 |
| 40 | 8 | 24 | 18 | 22 | 15 | 10 | 8 | 24 | 21 | 16 |
| sum | 394 | 1012 | 934 | 1309 | 753 | 537 | 369 | 1102 | 1140 | 792 |

TABLE B.4: Saturation pattern based on booking data in July 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 8 | 21 | 19 | 24 | 14 | 10 | 8 | 23 | 20 | 14 |
| 2 | 8 | 25 | 21 | 27 | 16 | 11 | 9 | 27 | 26 | 16 |
| 3 | 9 | 26 | 23 | 31 | 18 | 12 | 8 | 28 | 28 | 22 |
| 4 | 8 | 20 | 18 | 22 | 15 | 10 | 9 | 19 | 21 | 14 |
| 5 | 8 | 18 | 20 | 29 | 15 | 11 | 8 | 22 | 26 | 16 |
| 6 | 12 | 28 | 29 | 44 | 24 | 16 | 11 | 37 | 38 | 25 |
| 7 | 8 | 24 | 21 | 28 | 16 | 11 | 8 | 26 | 23 | 17 |
| 8 | 10 | 19 | 16 | 23 | 17 | 13 | 9 | 22 | 26 | 23 |
| 9 | 8 | 19 | 19 | 23 | 14 | 10 | 9 | 20 | 20 | 14 |
| 10 | 8 | 19 | 17 | 24 | 14 | 10 | 8 | 21 | 22 | 14 |
| 11 | 10 | 25 | 24 | 33 | 20 | 12 | 9 | 25 | 29 | 21 |
| 12 | 9 | 23 | 21 | 29 | 17 | 11 | 8 | 26 | 26 | 17 |
| 13 | 7 | 18 | 16 | 19 | 13 | 9 | 7 | 19 | 18 | 14 |
| 14 | 9 | 21 | 23 | 33 | 19 | 15 | 8 | 27 | 28 | 19 |
| 15 | 10 | 25 | 25 | 33 | 20 | 16 | 9 | 28 | 27 | 22 |
| 16 | 10 | 23 | 22 | 29 | 20 | 14 | 8 | 28 | 30 | 20 |
| 17 | 8 | 24 | 21 | 30 | 19 | 12 | 9 | 28 | 28 | 20 |
| 18 | 9 | 25 | 20 | 26 | 17 | 13 | 8 | 26 | 26 | 17 |
| 19 | 7 | 21 | 18 | 23 | 13 | 9 | 8 | 21 | 19 | 15 |
| 20 | 10 | 29 | 24 | 33 | 21 | 13 | 8 | 30 | 29 | 19 |
| 21 | 9 | 25 | 22 | 29 | 18 | 12 | 8 | 26 | 27 | 18 |
| 22 | 8 | 22 | 19 | 27 | 15 | 11 | 10 | 23 | 24 | 15 |
| 23 | 9 | 23 | 21 | 28 | 16 | 11 | 8 | 24 | 24 | 18 |
| 24 | 9 | 22 | 22 | 30 | 18 | 13 | 9 | 26 | 27 | 18 |
| 25 | 10 | 20 | 27 | 40 | 20 | 13 | 7 | 28 | 36 | 20 |
| 26 | 11 | 23 | 21 | 34 | 20 | 15 | 10 | 27 | 35 | 22 |
| 27 | 8 | 24 | 23 | 34 | 18 | 11 | 8 | 28 | 28 | 20 |
| 28 | 9 | 28 | 23 | 29 | 19 | 12 | 9 | 29 | 27 | 18 |
| 29 | 8 | 24 | 21 | 23 | 14 | 10 | 8 | 24 | 21 | 15 |
| 30 | 9 | 32 | 24 | 33 | 19 | 14 | 9 | 31 | 30 | 20 |
| 31 | 11 | 31 | 26 | 37 | 22 | 15 | 10 | 34 | 31 | 22 |
| 32 | 10 | 32 | 29 | 40 | 22 | 13 | 10 | 34 | 33 | 22 |
| 33 | 11 | 21 | 25 | 41 | 22 | 17 | 8 | 28 | 33 | 22 |
| 34 | 10 | 21 | 22 | 32 | 18 | 13 | 8 | 25 | 26 | 19 |
| 35 | 11 | 26 | 25 | 38 | 23 | 17 | 9 | 29 | 31 | 23 |
| 36 | 8 | 21 | 18 | 23 | 13 | 9 | 8 | 22 | 21 | 13 |
| 37 | 9 | 25 | 24 | 38 | 20 | 12 | 8 | 31 | 31 | 21 |
| 38 | 10 | 25 | 24 | 35 | 21 | 14 | 9 | 27 | 29 | 23 |
| 39 | 9 | 23 | 19 | 25 | 16 | 11 | 8 | 24 | 24 | 17 |
| 40 | 7 | 21 | 17 | 22 | 13 | 9 | 8 | 21 | 19 | 14 |
| sum | 362 | 942 | 869 | 1201 | 709 | 490 | 341 | 1044 | 1067 | 739 |

TABLE B.5: Saturation pattern based on booking data in August 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 8 | 22 | 18 | 24 | 14 | 10 | 8 | 22 | 20 | 14 |
| 2 | 8 | 26 | 20 | 26 | 16 | 11 | 9 | 26 | 25 | 17 |
| 3 | 9 | 26 | 22 | 31 | 18 | 12 | 8 | 26 | 29 | 22 |
| 4 | 8 | 19 | 17 | 23 | 14 | 10 | 9 | 18 | 20 | 14 |
| 5 | 8 | 19 | 20 | 28 | 15 | 10 | 8 | 23 | 25 | 17 |
| 6 | 12 | 27 | 30 | 43 | 24 | 17 | 10 | 37 | 37 | 25 |
| 7 | 8 | 24 | 20 | 27 | 16 | 11 | 8 | 25 | 24 | 16 |
| 8 | 10 | 19 | 16 | 24 | 18 | 12 | 9 | 23 | 26 | 23 |
| 9 | 8 | 20 | 19 | 22 | 14 | 10 | 9 | 19 | 20 | 14 |
| 10 | 8 | 19 | 17 | 24 | 14 | 10 | 8 | 21 | 23 | 15 |
| 11 | 10 | 25 | 24 | 34 | 21 | 12 | 9 | 26 | 28 | 22 |
| 12 | 9 | 23 | 21 | 29 | 16 | 11 | 8 | 26 | 25 | 17 |
| 13 | 7 | 18 | 16 | 19 | 13 | 9 | 7 | 18 | 19 | 13 |
| 14 | 9 | 21 | 23 | 34 | 19 | 15 | 8 | 27 | 27 | 19 |
| 15 | 10 | 26 | 24 | 33 | 19 | 16 | 9 | 27 | 26 | 22 |
| 16 | 10 | 24 | 23 | 29 | 19 | 15 | 8 | 28 | 28 | 20 |
| 17 | 8 | 24 | 22 | 31 | 18 | 13 | 9 | 28 | 29 | 20 |
| 18 | 9 | 26 | 20 | 26 | 17 | 12 | 8 | 26 | 26 | 18 |
| 19 | 7 | 22 | 19 | 23 | 13 | 9 | 8 | 22 | 20 | 15 |
| 20 | 10 | 29 | 23 | 33 | 20 | 13 | 8 | 29 | 28 | 19 |
| 21 | 9 | 24 | 21 | 29 | 18 | 12 | 8 | 27 | 26 | 18 |
| 22 | 8 | 22 | 18 | 27 | 15 | 11 | 10 | 23 | 24 | 16 |
| 23 | 9 | 24 | 20 | 28 | 16 | 11 | 8 | 24 | 23 | 18 |
| 24 | 9 | 22 | 22 | 29 | 18 | 14 | 9 | 26 | 27 | 18 |
| 25 | 10 | 19 | 26 | 40 | 21 | 13 | 7 | 28 | 36 | 21 |
| 26 | 11 | 23 | 22 | 34 | 20 | 15 | 10 | 26 | 36 | 22 |
| 27 | 8 | 24 | 22 | 34 | 19 | 12 | 8 | 27 | 29 | 19 |
| 28 | 9 | 29 | 23 | 29 | 18 | 11 | 9 | 28 | 26 | 19 |
| 29 | 8 | 25 | 22 | 23 | 14 | 10 | 8 | 23 | 21 | 14 |
| 30 | 9 | 32 | 24 | 33 | 19 | 13 | 9 | 30 | 28 | 20 |
| 31 | 11 | 31 | 26 | 37 | 22 | 15 | 10 | 33 | 31 | 22 |
| 32 | 10 | 33 | 28 | 40 | 21 | 13 | 9 | 35 | 33 | 21 |
| 33 | 11 | 21 | 26 | 40 | 23 | 17 | 8 | 28 | 33 | 22 |
| 34 | 10 | 21 | 22 | 33 | 17 | 13 | 8 | 24 | 26 | 20 |
| 35 | 11 | 26 | 26 | 37 | 23 | 18 | 9 | 27 | 31 | 22 |
| 36 | 8 | 21 | 18 | 23 | 13 | 9 | 8 | 21 | 20 | 13 |
| 37 | 9 | 24 | 24 | 38 | 19 | 12 | 8 | 31 | 31 | 20 |
| 38 | 10 | 25 | 23 | 36 | 22 | 15 | 9 | 27 | 29 | 22 |
| 39 | 9 | 23 | 20 | 25 | 15 | 11 | 8 | 25 | 24 | 16 |
| 40 | 7 | 20 | 17 | 22 | 13 | 9 | 8 | 22 | 19 | 14 |
| sum | 362 | 948 | 864 | 1200 | 704 | 492 | 339 | 1032 | 1058 | 739 |

TABLE B.6: Saturation pattern based on booking data in September 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 7 | 20 | 16 | 22 | 13 | 10 | 7 | 21 | 18 | 12 |
| 2 | 8 | 24 | 20 | 24 | 16 | 11 | 9 | 27 | 22 | 14 |
| 3 | 9 | 23 | 20 | 29 | 17 | 12 | 8 | 26 | 27 | 22 |
| 4 | 8 | 18 | 16 | 20 | 14 | 9 | 8 | 16 | 18 | 12 |
| 5 | 8 | 17 | 18 | 26 | 14 | 10 | 7 | 21 | 23 | 14 |
| 6 | 11 | 25 | 29 | 40 | 22 | 15 | 10 | 31 | 38 | 25 |
| 7 | 8 | 22 | 20 | 26 | 15 | 10 | 8 | 23 | 21 | 14 |
| 8 | 9 | 18 | 16 | 23 | 17 | 11 | 9 | 21 | 22 | 19 |
| 9 | 7 | 17 | 19 | 21 | 12 | 10 | 8 | 19 | 18 | 12 |
| 10 | 7 | 18 | 17 | 23 | 14 | 9 | 7 | 21 | 20 | 14 |
| 11 | 9 | 23 | 23 | 30 | 19 | 13 | 8 | 25 | 29 | 22 |
| 12 | 8 | 22 | 20 | 29 | 15 | 11 | 7 | 23 | 24 | 15 |
| 13 | 7 | 18 | 16 | 17 | 12 | 8 | 7 | 17 | 16 | 13 |
| 14 | 9 | 19 | 21 | 31 | 19 | 13 | 8 | 27 | 25 | 19 |
| 15 | 9 | 25 | 22 | 32 | 18 | 17 | 8 | 24 | 28 | 22 |
| 16 | 9 | 21 | 21 | 28 | 18 | 14 | 8 | 27 | 29 | 19 |
| 17 | 8 | 21 | 21 | 28 | 17 | 12 | 8 | 24 | 26 | 19 |
| 18 | 8 | 24 | 18 | 25 | 16 | 12 | 8 | 24 | 23 | 18 |
| 19 | 7 | 21 | 17 | 22 | 12 | 9 | 7 | 21 | 18 | 14 |
| 20 | 9 | 27 | 21 | 31 | 20 | 12 | 7 | 25 | 25 | 17 |
| 21 | 9 | 23 | 21 | 26 | 18 | 12 | 7 | 26 | 27 | 16 |
| 22 | 8 | 21 | 17 | 24 | 14 | 10 | 10 | 22 | 21 | 15 |
| 23 | 8 | 21 | 18 | 26 | 15 | 10 | 8 | 24 | 20 | 19 |
| 24 | 9 | 21 | 21 | 27 | 16 | 13 | 9 | 25 | 22 | 19 |
| 25 | 9 | 18 | 24 | 38 | 19 | 12 | 6 | 26 | 32 | 19 |
| 26 | 10 | 23 | 21 | 31 | 20 | 14 | 9 | 25 | 33 | 22 |
| 27 | 7 | 21 | 22 | 31 | 17 | 10 | 8 | 26 | 28 | 18 |
| 28 | 9 | 27 | 20 | 28 | 17 | 11 | 9 | 24 | 26 | 15 |
| 29 | 8 | 22 | 19 | 22 | 13 | 10 | 7 | 22 | 18 | 13 |
| 30 | 8 | 29 | 22 | 31 | 18 | 14 | 8 | 31 | 26 | 16 |
| 31 | 10 | 29 | 25 | 36 | 21 | 16 | 9 | 31 | 28 | 21 |
| 32 | 9 | 32 | 28 | 35 | 20 | 13 | 9 | 33 | 31 | 20 |
| 33 | 10 | 21 | 24 | 37 | 21 | 14 | 8 | 27 | 27 | 19 |
| 34 | 9 | 20 | 20 | 32 | 16 | 12 | 8 | 21 | 25 | 17 |
| 35 | 11 | 24 | 24 | 34 | 21 | 15 | 9 | 27 | 30 | 20 |
| 36 | 8 | 19 | 18 | 21 | 13 | 9 | 7 | 19 | 18 | 12 |
| 37 | 9 | 24 | 22 | 34 | 18 | 11 | 8 | 30 | 28 | 20 |
| 38 | 10 | 22 | 22 | 32 | 20 | 14 | 9 | 24 | 25 | 22 |
| 39 | 9 | 21 | 19 | 23 | 15 | 11 | 7 | 21 | 22 | 15 |
| 40 | 7 | 20 | 16 | 20 | 12 | 8 | 8 | 21 | 19 | 13 |
| sum | 342 | 881 | 814 | 1115 | 664 | 467 | 320 | 968 | 976 | 687 |

TABLE B.7: Saturation pattern based on booking data in October 2014

| Saturation matrix $S^*$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | weekdays | | | | | weekends | | | | |
| Zone | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ |
| 1 | 7 | 14 | 17 | 21 | 13 | 11 | 9 | 15 | 21 | 16 |
| 2 | 7 | 19 | 17 | 24 | 13 | 10 | 7 | 19 | 17 | 13 |
| 3 | 7 | 20 | 17 | 29 | 15 | 13 | 9 | 32 | 30 | 25 |
| 4 | 8 | 19 | 13 | 20 | 10 | 12 | 10 | 10 | 24 | 9 |
| 5 | 6 | 16 | 17 | 27 | 12 | 9 | 9 | 24 | 20 | 9 |
| 6 | 12 | 27 | 26 | 35 | 24 | 14 | 5 | 29 | 25 | 24 |
| 7 | 6 | 15 | 18 | 27 | 13 | 10 | 5 | 16 | 10 | 10 |
| 8 | 9 | 16 | 16 | 23 | 15 | 5 | 6 | 25 | 28 | 11 |
| 9 | 6 | 19 | 12 | 18 | 10 | 12 | 8 | 16 | 19 | 14 |
| 10 | 5 | 13 | 13 | 23 | 13 | 11 | 5 | 16 | 17 | 13 |
| 11 | 10 | 24 | 14 | 32 | 14 | 11 | 6 | 26 | 33 | 24 |
| 12 | 7 | 21 | 19 | 28 | 11 | 7 | 9 | 18 | 24 | 12 |
| 13 | 6 | 12 | 15 | 15 | 8 | 6 | 5 | 21 | 17 | 14 |
| 14 | 8 | 19 | 18 | 30 | 17 | 6 | 5 | 22 | 22 | 20 |
| 15 | 9 | 17 | 15 | 32 | 18 | 13 | 11 | 27 | 30 | 14 |
| 16 | 10 | 15 | 13 | 27 | 17 | 12 | 7 | 26 | 13 | 21 |
| 17 | 7 | 17 | 21 | 29 | 16 | 12 | 5 | 16 | 22 | 13 |
| 18 | 8 | 18 | 14 | 20 | 11 | 5 | 6 | 28 | 17 | 9 |
| 19 | 7 | 16 | 17 | 21 | 11 | 5 | 8 | 23 | 11 | 11 |
| 20 | 9 | 20 | 17 | 32 | 19 | 10 | 7 | 13 | 15 | 11 |
| 21 | 6 | 17 | 16 | 22 | 17 | 8 | 6 | 23 | 29 | 7 |
| 22 | 6 | 20 | 12 | 17 | 11 | 13 | 9 | 14 | 11 | 13 |
| 23 | 6 | 22 | 18 | 25 | 11 | 13 | 5 | 23 | 27 | 17 |
| 24 | 8 | 14 | 17 | 24 | 12 | 15 | 9 | 21 | 25 | 17 |
| 25 | 10 | 14 | 19 | 39 | 18 | 7 | 7 | 29 | 14 | 19 |
| 26 | 10 | 19 | 16 | 27 | 16 | 8 | 8 | 21 | 14 | 23 |
| 27 | 7 | 21 | 17 | 23 | 11 | 9 | 8 | 24 | 30 | 8 |
| 28 | 6 | 26 | 17 | 24 | 14 | 10 | 7 | 16 | 20 | 17 |
| 29 | 6 | 20 | 18 | 22 | 11 | 10 | 8 | 16 | 22 | 12 |
| 30 | 7 | 19 | 21 | 28 | 17 | 8 | 5 | 19 | 16 | 18 |
| 31 | 9 | 26 | 16 | 26 | 20 | 11 | 8 | 36 | 31 | 23 |
| 32 | 9 | 30 | 18 | 31 | 18 | 9 | 8 | 40 | 20 | 13 |
| 33 | 10 | 13 | 20 | 31 | 14 | 8 | 5 | 25 | 38 | 10 |
| 34 | 7 | 15 | 20 | 20 | 14 | 6 | 5 | 27 | 30 | 12 |
| 35 | 9 | 18 | 23 | 31 | 20 | 14 | 6 | 32 | 26 | 23 |
| 36 | 7 | 16 | 15 | 21 | 10 | 6 | 6 | 19 | 23 | 10 |
| 37 | 8 | 17 | 18 | 30 | 13 | 14 | 8 | 31 | 27 | 15 |
| 38 | 7 | 24 | 22 | 25 | 15 | 14 | 5 | 20 | 29 | 12 |
| 39 | 5 | 14 | 13 | 24 | 15 | 9 | 9 | 19 | 20 | 10 |
| 40 | 5 | 14 | 11 | 19 | 10 | 9 | 5 | 9 | 11 | 13 |
| sum | 302 | 736 | 676 | 1022 | 567 | 395 | 279 | 886 | 878 | 585 |

TABLE B.8: Saturation pattern based on booking data in November 2014

# Appendix C

# Zone statuses in respective time slots in percent for 2014

| Zone status in $T_1$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | ov | us | bal | ov |
| 1 | 1.1 | 0.5 | 98.4 | 2.3 | 0.0 | 97.7 |
| 2 | 1.6 | 1.6 | 96.8 | 1.1 | 9.2 | 89.7 |
| 3 | 3.2 | 4.3 | 92.5 | 3.4 | 12.6 | 83.9 |
| 4 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| 5 | 2.7 | 0.5 | 96.8 | 2.3 | 3.4 | 94.3 |
| 6 | 84.9 | 11.3 | 3.8 | 97.7 | 2.3 | 0.0 |
| 7 | 1.1 | 1.1 | 97.8 | 1.1 | 1.1 | 97.7 |
| 8 | 47.5 | 20.9 | 31.6 | 53.0 | 26.5 | 20.5 |
| 9 | 1.1 | 2.2 | 96.8 | 2.3 | 4.6 | 93.1 |
| 10 | 1.1 | 1.1 | 97.8 | 0.0 | 3.4 | 96.6 |
| 11 | 6.5 | 29.0 | 64.5 | 14.9 | 18.4 | 66.7 |
| 12 | 1.6 | 1.1 | 97.3 | 1.1 | 1.1 | 97.7 |
| 13 | 0.5 | 2.7 | 96.8 | 2.3 | 2.3 | 95.4 |
| 14 | 1.6 | 5.4 | 93.0 | 6.9 | 18.4 | 74.7 |
| 15 | 2.7 | 9.7 | 87.6 | 10.3 | 32.2 | 57.5 |
| 16 | 2.2 | 9.1 | 88.7 | 10.3 | 19.5 | 70.1 |
| 17 | 0.5 | 0.5 | 98.9 | 1.1 | 10.3 | 88.5 |
| 18 | 1.6 | 3.2 | 95.2 | 2.3 | 10.3 | 87.4 |
| 19 | 0.5 | 1.1 | 98.4 | 1.1 | 1.1 | 97.7 |
| 20 | 12.0 | 44.3 | 43.7 | 32.9 | 38.8 | 28.2 |
| 21 | 1.1 | 0.5 | 98.4 | 1.1 | 2.3 | 96.6 |
| 22 | 1.1 | 7.5 | 91.4 | 6.9 | 29.9 | 63.2 |
| 23 | 5.4 | 9.7 | 84.9 | 12.6 | 27.6 | 59.8 |
| 24 | 1.1 | 0.0 | 98.9 | 1.1 | 1.1 | 97.7 |
| 25 | 0.5 | 1.1 | 98.4 | 2.3 | 2.3 | 95.4 |
| 26 | 78.4 | 18.9 | 2.7 | 89.7 | 10.3 | 0.0 |
| 27 | 1.6 | 1.1 | 97.3 | 1.1 | 1.1 | 97.7 |
| 28 | 0.5 | 0.0 | 99.5 | 0.0 | 2.3 | 97.7 |
| 29 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| 30 | 4.3 | 5.4 | 90.3 | 12.6 | 36.8 | 50.6 |
| 31 | 1.6 | 0.5 | 97.8 | 0.0 | 3.4 | 96.6 |
| 32 | 2.2 | 10.8 | 87.1 | 3.4 | 11.5 | 85.1 |
| 33 | 2.7 | 16.1 | 81.2 | 13.8 | 27.6 | 58.6 |
| 34 | 0.5 | 5.9 | 93.5 | 0.0 | 5.7 | 94.3 |
| 35 | 1.6 | 10.8 | 87.6 | 6.9 | 26.4 | 66.7 |
| 36 | 0.5 | 2.7 | 96.8 | 0.0 | 2.3 | 97.7 |
| 37 | 1.1 | 2.2 | 96.8 | 4.6 | 18.4 | 77.0 |
| 38 | 4.3 | 14.0 | 81.7 | 10.3 | 21.8 | 67.8 |
| 39 | 1.1 | 1.1 | 97.8 | 0.0 | 8.0 | 92.0 |
| 40 | 3.8 | 1.1 | 95.1 | 3.4 | 4.6 | 92.0 |

TABLE C.1: Zone statuses in time slot $T_1$ in percent for 2014

| Zone status in $T_2$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | ov | us | bal | ov |
| 1 | 3.8 | 1.1 | 95.1 | 0.0 | 2.3 | 97.7 |
| 2 | 20.5 | 46.5 | 33.0 | 1.1 | 2.3 | 96.6 |
| 3 | 43.8 | 51.9 | 4.3 | 2.3 | 0.0 | 97.7 |
| 4 | 1.1 | 1.1 | 97.8 | 0.0 | 0.0 | 100.0 |
| 5 | 4.3 | 10.3 | 85.3 | 2.3 | 1.1 | 96.6 |
| 6 | 100.0 | 0.0 | 0.0 | 83.9 | 13.8 | 2.3 |
| 7 | 13.0 | 33.0 | 54.1 | 2.3 | 0.0 | 97.7 |
| 8 | 78.9 | 16.0 | 5.1 | 45.2 | 17.9 | 36.9 |
| 9 | 9.3 | 9.3 | 81.4 | 2.3 | 2.3 | 95.5 |
| 10 | 4.9 | 3.8 | 91.4 | 1.1 | 0.0 | 98.9 |
| 11 | 66.5 | 23.2 | 10.3 | 5.7 | 18.2 | 76.1 |
| 12 | 4.9 | 13.0 | 82.2 | 0.0 | 2.3 | 97.7 |
| 13 | 7.7 | 9.3 | 83.1 | 0.0 | 2.3 | 97.7 |
| 14 | 34.8 | 37.5 | 27.7 | 0.0 | 1.1 | 98.9 |
| 15 | 67.0 | 31.9 | 1.1 | 2.3 | 4.5 | 93.2 |
| 16 | 55.4 | 38.6 | 6.0 | 3.4 | 4.5 | 92.0 |
| 17 | 25.9 | 39.5 | 34.6 | 0.0 | 0.0 | 100.0 |
| 18 | 40.0 | 47.6 | 12.4 | 1.1 | 0.0 | 98.9 |
| 19 | 4.9 | 16.8 | 78.3 | 0.0 | 1.1 | 98.9 |
| 20 | 96.7 | 3.3 | 0.0 | 5.7 | 21.8 | 72.4 |
| 21 | 11.9 | 36.2 | 51.9 | 0.0 | 1.1 | 98.9 |
| 22 | 64.9 | 32.4 | 2.7 | 0.0 | 23.9 | 76.1 |
| 23 | 71.4 | 22.7 | 5.9 | 4.5 | 12.5 | 83.0 |
| 24 | 7.6 | 11.4 | 81.1 | 0.0 | 1.1 | 98.9 |
| 25 | 3.2 | 15.1 | 81.6 | 0.0 | 1.1 | 98.9 |
| 26 | 100.0 | 0.0 | 0.0 | 64.4 | 32.2 | 3.4 |
| 27 | 20.7 | 53.8 | 25.5 | 0.0 | 1.1 | 98.9 |
| 28 | 15.7 | 43.2 | 41.1 | 0.0 | 0.0 | 100.0 |
| 29 | 2.7 | 0.5 | 96.8 | 0.0 | 0.0 | 100.0 |
| 30 | 86.5 | 13.5 | 0.0 | 4.5 | 6.8 | 88.6 |
| 31 | 21.1 | 55.1 | 23.8 | 0.0 | 1.1 | 98.9 |
| 32 | 51.9 | 45.9 | 2.2 | 1.1 | 2.3 | 96.6 |
| 33 | 42.7 | 40.0 | 17.3 | 0.0 | 9.1 | 90.9 |
| 34 | 22.3 | 50.5 | 27.2 | 0.0 | 4.5 | 95.5 |
| 35 | 65.9 | 33.0 | 1.1 | 0.0 | 3.4 | 96.6 |
| 36 | 14.1 | 25.4 | 60.5 | 0.0 | 3.4 | 96.6 |
| 37 | 41.8 | 50.5 | 7.6 | 0.0 | 2.3 | 97.7 |
| 38 | 58.4 | 35.1 | 6.5 | 2.3 | 5.7 | 92.0 |
| 39 | 11.9 | 38.9 | 49.2 | 0.0 | 2.3 | 97.7 |
| 40 | 13.0 | 32.6 | 54.3 | 3.4 | 2.3 | 94.3 |

TABLE C.2: Zone statuses in time slot $T_2$ in percent for 2014

| Zone status in $T_3$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | ov | us | bal | ov |
| 1 | 3.8 | 0.5 | 95.7 | 2.3 | 1.1 | 96.6 |
| 2 | 19.9 | 35.5 | 44.6 | 34.5 | 42.5 | 23.0 |
| 3 | 43.5 | 43.0 | 13.4 | 54.0 | 41.4 | 4.6 |
| 4 | 1.1 | 0.5 | 98.4 | 0.0 | 2.3 | 97.7 |
| 5 | 6.5 | 6.5 | 87.1 | 8.0 | 14.9 | 77.0 |
| 6 | 98.4 | 1.6 | 0.0 | 100.0 | 0.0 | 0.0 |
| 7 | 11.3 | 26.3 | 62.4 | 17.2 | 35.6 | 47.1 |
| 8 | 69.1 | 24.2 | 6.7 | 85.9 | 11.8 | 2.4 |
| 9 | 10.3 | 11.4 | 78.3 | 16.1 | 10.3 | 73.6 |
| 10 | 3.2 | 4.3 | 92.5 | 5.7 | 6.9 | 87.4 |
| 11 | 53.2 | 31.2 | 15.6 | 54.0 | 34.5 | 11.5 |
| 12 | 4.3 | 14.5 | 81.2 | 6.9 | 31.0 | 62.1 |
| 13 | 6.0 | 8.7 | 85.3 | 10.3 | 8.0 | 81.6 |
| 14 | 25.8 | 39.2 | 34.9 | 42.5 | 47.1 | 10.3 |
| 15 | 67.2 | 29.0 | 3.8 | 72.4 | 27.6 | 0.0 |
| 16 | 51.1 | 41.4 | 7.5 | 78.2 | 20.7 | 1.1 |
| 17 | 10.8 | 41.9 | 47.3 | 43.7 | 40.2 | 16.1 |
| 18 | 32.3 | 51.6 | 16.1 | 52.9 | 40.2 | 6.9 |
| 19 | 4.9 | 11.9 | 83.2 | 5.7 | 14.9 | 79.3 |
| 20 | 89.6 | 10.4 | 0.0 | 96.5 | 3.5 | 0.0 |
| 21 | 5.9 | 26.3 | 67.7 | 12.6 | 49.4 | 37.9 |
| 22 | 58.6 | 37.1 | 4.3 | 80.5 | 17.2 | 2.3 |
| 23 | 48.9 | 41.4 | 9.7 | 70.1 | 25.3 | 4.6 |
| 24 | 7.5 | 9.1 | 83.3 | 4.6 | 21.8 | 73.6 |
| 25 | 2.2 | 8.1 | 89.8 | 10.3 | 42.5 | 47.1 |
| 26 | 100.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| 27 | 9.7 | 44.6 | 45.7 | 32.2 | 58.6 | 9.2 |
| 28 | 12.4 | 46.8 | 40.9 | 19.5 | 46.0 | 34.5 |
| 29 | 1.6 | 1.6 | 96.8 | 0.0 | 2.3 | 97.7 |
| 30 | 82.2 | 17.3 | 0.5 | 83.9 | 16.1 | 0.0 |
| 31 | 22.0 | 53.8 | 24.2 | 36.8 | 52.9 | 10.3 |
| 32 | 44.6 | 48.9 | 6.5 | 64.4 | 35.6 | 0.0 |
| 33 | 16.7 | 53.8 | 29.6 | 74.7 | 21.8 | 3.4 |
| 34 | 17.7 | 41.4 | 40.9 | 37.9 | 43.7 | 18.4 |
| 35 | 53.2 | 41.4 | 5.4 | 50.6 | 42.5 | 6.9 |
| 36 | 16.7 | 20.4 | 62.9 | 13.8 | 26.4 | 59.8 |
| 37 | 23.8 | 44.9 | 31.4 | 71.3 | 28.7 | 0.0 |
| 38 | 39.2 | 48.4 | 12.4 | 42.5 | 46.0 | 11.5 |
| 39 | 12.4 | 30.8 | 56.8 | 16.1 | 40.2 | 43.7 |
| 40 | 10.3 | 26.5 | 63.2 | 19.5 | 31.0 | 49.4 |

TABLE C.3: Zone statuses in time slot $T_3$ in percent for 2014

| Zone status in $T_4$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | ov | us | bal | ov |
| 1 | 4.3 | 1.1 | 94.6 | 2.3 | 0.0 | 97.7 |
| 2 | 41.4 | 46.2 | 12.4 | 33.3 | 43.7 | 23.0 |
| 3 | 73.1 | 26.9 | 0.0 | 56.3 | 41.4 | 2.3 |
| 4 | 1.6 | 1.1 | 97.3 | 0.0 | 2.3 | 97.7 |
| 5 | 11.8 | 16.7 | 71.5 | 8.0 | 20.7 | 71.3 |
| 6 | 100.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| 7 | 26.5 | 35.1 | 38.4 | 23.0 | 31.0 | 46.0 |
| 8 | 90.5 | 7.8 | 1.7 | 85.7 | 11.9 | 2.4 |
| 9 | 14.0 | 22.0 | 64.0 | 17.2 | 16.1 | 66.7 |
| 10 | 8.1 | 11.8 | 80.1 | 6.9 | 6.9 | 86.2 |
| 11 | 80.6 | 10.8 | 8.6 | 69.0 | 17.2 | 13.8 |
| 12 | 14.0 | 36.6 | 49.5 | 10.3 | 28.7 | 60.9 |
| 13 | 10.3 | 10.3 | 79.3 | 11.5 | 6.9 | 81.6 |
| 14 | 54.8 | 39.8 | 5.4 | 28.7 | 49.4 | 21.8 |
| 15 | 91.9 | 8.1 | 0.0 | 71.3 | 27.6 | 1.1 |
| 16 | 87.1 | 12.4 | 0.5 | 73.6 | 25.3 | 1.1 |
| 17 | 40.9 | 49.5 | 9.7 | 50.6 | 32.2 | 17.2 |
| 18 | 71.5 | 22.6 | 5.9 | 56.3 | 37.9 | 5.7 |
| 19 | 9.7 | 27.6 | 62.7 | 4.6 | 13.8 | 81.6 |
| 20 | 100.0 | 0.0 | 0.0 | 97.7 | 2.3 | 0.0 |
| 21 | 24.2 | 47.3 | 28.5 | 11.5 | 50.6 | 37.9 |
| 22 | 93.5 | 5.4 | 1.1 | 82.8 | 14.9 | 2.3 |
| 23 | 84.9 | 11.8 | 3.2 | 72.4 | 21.8 | 5.7 |
| 24 | 10.2 | 29.6 | 60.2 | 3.4 | 23.0 | 73.6 |
| 25 | 8.1 | 59.7 | 32.3 | 24.1 | 49.4 | 26.4 |
| 26 | 100.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| 27 | 51.1 | 46.8 | 2.2 | 40.2 | 50.6 | 9.2 |
| 28 | 38.7 | 48.4 | 12.9 | 19.5 | 52.9 | 27.6 |
| 29 | 1.6 | 1.6 | 96.8 | 0.0 | 2.3 | 97.7 |
| 30 | 98.9 | 1.1 | 0.0 | 88.5 | 11.5 | 0.0 |
| 31 | 54.3 | 41.4 | 4.3 | 21.8 | 59.8 | 18.4 |
| 32 | 89.2 | 10.8 | 0.0 | 72.4 | 27.6 | 0.0 |
| 33 | 71.5 | 25.8 | 2.7 | 66.7 | 24.1 | 9.2 |
| 34 | 43.0 | 50.0 | 7.0 | 27.6 | 51.7 | 20.7 |
| 35 | 86.0 | 14.0 | 0.0 | 54.0 | 39.1 | 6.9 |
| 36 | 27.4 | 33.9 | 38.7 | 16.1 | 27.6 | 56.3 |
| 37 | 79.0 | 21.0 | 0.0 | 82.8 | 17.2 | 0.0 |
| 38 | 82.8 | 15.6 | 1.6 | 44.8 | 46.0 | 9.2 |
| 39 | 26.9 | 53.2 | 19.9 | 23.0 | 40.2 | 36.8 |
| 40 | 19.6 | 41.8 | 38.6 | 19.5 | 25.3 | 55.2 |

TABLE C.4: Zone statuses in time slot $T_4$ in percent for 2014

| Zone status in $T_5$ | | | | | | |
|---|---|---|---|---|---|---|
| | on weekdays | | | on weekends | | |
| Zone | us | bal | ov | us | bal | ov |
| 1 | 2.2 | 1.1 | 96.8 | 2.3 | 0.0 | 97.7 |
| 2 | 8.6 | 21.0 | 70.4 | 9.2 | 18.4 | 72.4 |
| 3 | 19.9 | 35.5 | 44.6 | 31.0 | 37.9 | 31.0 |
| 4 | 0.5 | 0.5 | 98.9 | 0.0 | 0.0 | 100.0 |
| 5 | 4.3 | 7.5 | 88.2 | 4.6 | 8.0 | 87.4 |
| 6 | 98.4 | 1.6 | 0.0 | 100.0 | 0.0 | 0.0 |
| 7 | 6.5 | 8.6 | 84.9 | 3.4 | 21.8 | 74.7 |
| 8 | 71.7 | 18.3 | 10.0 | 79.8 | 11.9 | 8.3 |
| 9 | 4.3 | 5.9 | 89.7 | 5.7 | 10.3 | 83.9 |
| 10 | 3.2 | 4.3 | 92.5 | 2.3 | 4.6 | 93.1 |
| 11 | 47.3 | 33.3 | 19.4 | 44.8 | 33.3 | 21.8 |
| 12 | 3.2 | 4.8 | 91.9 | 2.3 | 6.9 | 90.8 |
| 13 | 5.4 | 5.4 | 89.2 | 4.6 | 5.7 | 89.7 |
| 14 | 14.5 | 29.6 | 55.9 | 17.2 | 26.4 | 56.3 |
| 15 | 31.7 | 41.4 | 26.9 | 32.2 | 52.9 | 14.9 |
| 16 | 32.3 | 48.4 | 19.4 | 28.7 | 48.3 | 23.0 |
| 17 | 8.1 | 28.0 | 64.0 | 14.9 | 42.5 | 42.5 |
| 18 | 15.6 | 46.2 | 38.2 | 9.2 | 46.0 | 44.8 |
| 19 | 3.2 | 2.2 | 94.6 | 2.3 | 6.9 | 90.8 |
| 20 | 76.0 | 23.5 | 0.5 | 75.3 | 18.8 | 5.9 |
| 21 | 3.2 | 10.8 | 86.0 | 3.4 | 8.0 | 88.5 |
| 22 | 27.4 | 57.5 | 15.1 | 23.0 | 58.6 | 18.4 |
| 23 | 31.2 | 45.2 | 23.7 | 49.4 | 36.8 | 13.8 |
| 24 | 3.2 | 7.0 | 89.8 | 2.3 | 3.4 | 94.3 |
| 25 | 1.6 | 9.1 | 89.2 | 4.6 | 18.4 | 77.0 |
| 26 | 100.0 | 0.0 | 0.0 | 98.9 | 1.1 | 0.0 |
| 27 | 6.5 | 30.1 | 63.4 | 9.2 | 35.6 | 55.2 |
| 28 | 2.2 | 8.1 | 89.8 | 2.3 | 17.2 | 80.5 |
| 29 | 0.0 | 1.1 | 98.9 | 0.0 | 0.0 | 100.0 |
| 30 | 47.6 | 36.2 | 16.2 | 50.6 | 35.6 | 13.8 |
| 31 | 4.8 | 25.3 | 69.9 | 0.0 | 31.0 | 69.0 |
| 32 | 19.9 | 41.4 | 38.7 | 18.4 | 47.1 | 34.5 |
| 33 | 26.3 | 39.8 | 33.9 | 29.9 | 40.2 | 29.9 |
| 34 | 4.3 | 24.7 | 71.0 | 5.7 | 28.7 | 65.5 |
| 35 | 22.0 | 46.2 | 31.7 | 14.9 | 44.8 | 40.2 |
| 36 | 6.5 | 12.9 | 80.6 | 3.4 | 16.1 | 80.5 |
| 37 | 11.8 | 41.9 | 46.2 | 26.4 | 49.4 | 24.1 |
| 38 | 25.3 | 45.2 | 29.6 | 25.3 | 41.4 | 33.3 |
| 39 | 4.3 | 12.9 | 82.8 | 5.7 | 14.9 | 79.3 |
| 40 | 7.0 | 10.2 | 82.8 | 9.2 | 12.6 | 78.2 |

TABLE C.5: Zone statuses in time slot $T_5$ in percent for 2014

# Appendix D

# Zone status and related bookings for all time slots and day types

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ |
| 1 | 2 | 3.0 | 0.0 | 1 | 8.0 | 0.0 | 183 | 60.4 | 1.3 |
| 2 | 3 | 4.3 | 0.0 | 3 | 8.0 | 1.7 | 180 | 26.6 | 1.0 |
| 3 | 6 | 5.2 | 0.0 | 8 | 8.9 | 0.8 | 172 | 20.9 | 0.9 |
| 4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 186 | 196.5 | 0.7 |
| 5 | 5 | 3.4 | 0.0 | 1 | 7.0 | 0.0 | 179 | 34.5 | 0.6 |
| 6 | 158 | 5.3 | 1.2 | 21 | 11.7 | 1.0 | 7 | 16.6 | 2.6 |
| 7 | 2 | 5.0 | 0.5 | 2 | 8.5 | 0.0 | 182 | 30.4 | 0.9 |
| 8 | 84 | 4.7 | 0.0 | 37 | 9.6 | 0.1 | 56 | 18.3 | 0.9 |
| 9 | 2 | 2.5 | 0.5 | 4 | 8.3 | 0.5 | 179 | 32.4 | 1.4 |
| 10 | 2 | 4.0 | 0.0 | 2 | 8.5 | 0.0 | 182 | 35.8 | 0.8 |
| 11 | 12 | 5.0 | 0.3 | 54 | 10.0 | 1.0 | 120 | 26.1 | 1.7 |
| 12 | 3 | 5.3 | 0.7 | 2 | 9.0 | 0.0 | 181 | 35.9 | 1.6 |
| 13 | 1 | 4.0 | 0.0 | 5 | 7.2 | 0.0 | 179 | 34.4 | 0.3 |
| 14 | 3 | 4.3 | 0.0 | 10 | 9.4 | 1.2 | 173 | 22.9 | 1.7 |
| 15 | 5 | 5.0 | 0.2 | 18 | 10.9 | 3.2 | 163 | 20.9 | 2.5 |
| 16 | 4 | 3.8 | 0.0 | 17 | 10.7 | 1.5 | 165 | 20.2 | 1.8 |
| 17 | 1 | 6.0 | 0.0 | 1 | 7.0 | 0.0 | 184 | 25.5 | 1.6 |
| 18 | 3 | 5.7 | 0.0 | 6 | 9.0 | 0.8 | 177 | 22.3 | 1.0 |
| 19 | 1 | 1.0 | 0.0 | 2 | 7.5 | 0.0 | 183 | 35.0 | 0.5 |
| 20 | 22 | 4.7 | 0.4 | 81 | 10.0 | 0.6 | 80 | 15.8 | 0.9 |
| 21 | 2 | 5.0 | 0.5 | 1 | 9.0 | 0.0 | 183 | 30.1 | 1.4 |
| 22 | 2 | 3.0 | 0.0 | 14 | 8.2 | 0.6 | 170 | 16.0 | 0.5 |
| 23 | 10 | 5.0 | 0.3 | 18 | 9.2 | 0.3 | 158 | 17.6 | 0.6 |
| 24 | 2 | 6.0 | 0.0 | 0 | 0.0 | 0.0 | 184 | 36.9 | 3.2 |
| 25 | 1 | 6.0 | 0.0 | 2 | 11.5 | 1.0 | 183 | 34.1 | 2.4 |
| 26 | 145 | 5.1 | 0.5 | 35 | 10.5 | 0.9 | 5 | 15.8 | 2.4 |
| 27 | 3 | 3.7 | 0.0 | 2 | 7.0 | 0.0 | 181 | 23.7 | 0.9 |
| 28 | 1 | 3.0 | 0.0 | 0 | 0.0 | 0.0 | 185 | 31.1 | 1.4 |
| 29 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 186 | 131.6 | 1.3 |
| 30 | 8 | 4.4 | 0.6 | 10 | 9.0 | 1.0 | 168 | 18.7 | 1.6 |
| 31 | 3 | 5.0 | 0.0 | 1 | 13.0 | 0.0 | 182 | 33.3 | 4.0 |
| 32 | 4 | 6.0 | 0.8 | 20 | 10.7 | 3.0 | 162 | 25.3 | 2.2 |
| 33 | 5 | 7.0 | 0.0 | 30 | 11.3 | 1.9 | 151 | 23.0 | 3.0 |
| 34 | 1 | 1.0 | 0.0 | 11 | 10.5 | 3.2 | 174 | 23.6 | 2.0 |
| 35 | 3 | 7.3 | 1.7 | 20 | 11.9 | 2.8 | 163 | 22.9 | 4.1 |
| 36 | 1 | 5.0 | 0.0 | 5 | 8.6 | 0.4 | 180 | 26.2 | 0.5 |
| 37 | 2 | 4.5 | 0.0 | 4 | 9.3 | 0.5 | 180 | 21.6 | 1.4 |
| 38 | 8 | 4.3 | 0.4 | 26 | 10.9 | 1.2 | 152 | 21.6 | 1.7 |
| 39 | 2 | 4.5 | 0.5 | 2 | 9.5 | 0.0 | 182 | 27.7 | 0.9 |
| 40 | 7 | 3.4 | 0.1 | 2 | 6.5 | 0.0 | 176 | 25.8 | 0.5 |

TABLE D.1: Zone status and related bookings in time slot $T_1$ on weekdays

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ |
| 1 | 7 | 7.6 | 1.7 | 2 | 21.0 | 4.5 | 176 | 63.4 | 8.4 |
| 2 | 38 | 13.6 | 4.3 | 86 | 25.0 | 6.4 | 61 | 36.3 | 7.7 |
| 3 | 81 | 14.0 | 4.0 | 96 | 24.4 | 3.6 | 8 | 32.4 | 4.5 |
| 4 | 2 | 7.0 | 4.0 | 2 | 18.0 | 7.0 | 181 | 200.6 | 8.0 |
| 5 | 8 | 5.4 | 1.6 | 19 | 17.9 | 4.0 | 157 | 37.4 | 4.6 |
| 6 | 183 | 5.8 | 2.0 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 24 | 13.3 | 3.5 | 61 | 24.2 | 6.9 | 100 | 39.5 | 8.8 |
| 8 | 138 | 7.3 | 0.3 | 28 | 18.6 | 0.7 | 9 | 27.2 | 0.7 |
| 9 | 17 | 10.8 | 2.4 | 17 | 18.5 | 3.8 | 149 | 35.5 | 3.9 |
| 10 | 9 | 9.0 | 1.1 | 7 | 18.3 | 2.3 | 169 | 38.2 | 4.5 |
| 11 | 123 | 12.1 | 4.9 | 43 | 23.5 | 5.2 | 19 | 64.4 | 7.8 |
| 12 | 9 | 9.7 | 3.1 | 24 | 23.7 | 6.6 | 152 | 39.4 | 8.4 |
| 13 | 14 | 9.7 | 1.1 | 17 | 17.8 | 1.4 | 152 | 38.1 | 4.8 |
| 14 | 64 | 12.1 | 2.8 | 69 | 20.3 | 3.8 | 51 | 30.9 | 2.7 |
| 15 | 124 | 14.2 | 4.1 | 59 | 23.8 | 4.6 | 2 | 31.0 | 5.5 |
| 16 | 102 | 13.9 | 2.9 | 71 | 22.0 | 4.5 | 11 | 30.5 | 4.0 |
| 17 | 48 | 15.3 | 4.3 | 73 | 22.9 | 5.6 | 64 | 34.7 | 7.4 |
| 18 | 74 | 15.5 | 4.7 | 88 | 23.6 | 5.8 | 23 | 36.3 | 6.4 |
| 19 | 9 | 9.6 | 1.9 | 31 | 22.5 | 5.0 | 144 | 40.6 | 9.1 |
| 20 | 175 | 12.0 | 4.2 | 6 | 24.5 | 8.2 | 0 | 0.0 | 0.0 |
| 21 | 22 | 14.7 | 4.0 | 67 | 24.3 | 6.6 | 96 | 35.6 | 6.5 |
| 22 | 120 | 12.8 | 2.0 | 60 | 20.3 | 3.9 | 5 | 35.0 | 3.6 |
| 23 | 132 | 12.9 | 3.3 | 42 | 21.6 | 4.5 | 11 | 32.1 | 1.4 |
| 24 | 14 | 11.1 | 3.5 | 21 | 23.7 | 4.6 | 150 | 38.7 | 6.8 |
| 25 | 6 | 8.7 | 2.7 | 28 | 19.3 | 6.9 | 151 | 34.1 | 7.0 |
| 26 | 183 | 5.8 | 0.7 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 38 | 14.8 | 4.7 | 99 | 22.9 | 7.3 | 47 | 31.2 | 7.9 |
| 28 | 29 | 18.7 | 6.4 | 80 | 28.6 | 10.4 | 76 | 39.0 | 12.7 |
| 29 | 5 | 14.6 | 9.2 | 1 | 27.0 | 10.0 | 179 | 136.6 | 15.7 |
| 30 | 160 | 16.7 | 7.3 | 25 | 28.2 | 10.2 | 0 | 0.0 | 0.0 |
| 31 | 39 | 18.8 | 7.7 | 102 | 30.6 | 11.3 | 44 | 42.0 | 13.9 |
| 32 | 96 | 18.9 | 8.8 | 85 | 30.5 | 9.4 | 4 | 42.3 | 13.5 |
| 33 | 79 | 11.9 | 3.3 | 74 | 20.7 | 3.6 | 32 | 30.9 | 4.5 |
| 34 | 41 | 12.2 | 2.9 | 93 | 20.2 | 2.8 | 50 | 30.2 | 2.9 |
| 35 | 122 | 14.7 | 4.3 | 61 | 24.2 | 5.8 | 2 | 37.0 | 5.5 |
| 36 | 26 | 11.9 | 3.5 | 47 | 21.0 | 5.5 | 112 | 32.8 | 4.7 |
| 37 | 77 | 15.3 | 4.6 | 93 | 23.5 | 6.5 | 14 | 33.9 | 6.4 |
| 38 | 108 | 13.5 | 5.2 | 65 | 22.8 | 6.0 | 12 | 35.7 | 8.9 |
| 39 | 22 | 12.6 | 3.8 | 72 | 23.0 | 5.8 | 91 | 34.2 | 6.6 |
| 40 | 24 | 9.5 | 1.7 | 60 | 20.6 | 3.3 | 100 | 32.0 | 3.5 |

TABLE D.2: Zone status and related bookings in time slot $T_2$ on weekdays

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ |
| 1 | 7 | 7.6 | 2.4 | 1 | 17.0 | 6.0 | 178 | 60.7 | 9.4 |
| 2 | 37 | 10.8 | 3.6 | 66 | 20.3 | 4.8 | 83 | 30.6 | 6.0 |
| 3 | 81 | 12.3 | 3.9 | 80 | 22.2 | 4.4 | 25 | 28.4 | 4.0 |
| 4 | 2 | 9.0 | 12.5 | 1 | 15.0 | 5.0 | 183 | 198.7 | 11.0 |
| 5 | 12 | 7.8 | 4.0 | 12 | 19.0 | 8.8 | 162 | 41.7 | 10.7 |
| 6 | 183 | 9.7 | 8.2 | 3 | 26.0 | 11.3 | 0 | 0.0 | 0.0 |
| 7 | 21 | 10.9 | 2.8 | 49 | 20.7 | 5.8 | 116 | 36.2 | 8.4 |
| 8 | 123 | 6.2 | 0.4 | 43 | 16.0 | 1.0 | 12 | 24.4 | 0.8 |
| 9 | 19 | 10.6 | 2.2 | 21 | 19.3 | 2.9 | 144 | 34.8 | 3.8 |
| 10 | 6 | 7.5 | 1.5 | 8 | 16.3 | 4.1 | 172 | 37.6 | 5.8 |
| 11 | 99 | 12.8 | 7.4 | 58 | 21.8 | 7.6 | 29 | 52.8 | 13.9 |
| 12 | 8 | 7.9 | 4.1 | 27 | 22.8 | 9.1 | 151 | 38.0 | 8.7 |
| 13 | 11 | 7.7 | 0.7 | 16 | 16.0 | 0.8 | 157 | 35.8 | 4.1 |
| 14 | 48 | 13.6 | 8.4 | 73 | 21.8 | 11.3 | 65 | 33.0 | 10.6 |
| 15 | 125 | 14.7 | 6.7 | 54 | 23.8 | 8.3 | 7 | 30.3 | 7.9 |
| 16 | 95 | 13.4 | 4.0 | 77 | 20.8 | 5.7 | 14 | 29.5 | 7.4 |
| 17 | 20 | 13.7 | 7.7 | 78 | 20.9 | 8.1 | 88 | 33.2 | 11.4 |
| 18 | 60 | 11.6 | 3.7 | 96 | 19.2 | 4.1 | 30 | 31.0 | 5.1 |
| 19 | 9 | 8.9 | 3.1 | 22 | 19.6 | 4.1 | 154 | 34.8 | 5.6 |
| 20 | 164 | 10.8 | 4.3 | 19 | 20.6 | 6.3 | 0 | 0.0 | 0.0 |
| 21 | 11 | 10.7 | 4.0 | 49 | 21.4 | 8.7 | 126 | 33.7 | 9.1 |
| 22 | 109 | 11.1 | 1.9 | 69 | 17.3 | 2.8 | 8 | 28.8 | 2.8 |
| 23 | 91 | 11.1 | 2.5 | 77 | 18.8 | 3.2 | 18 | 29.9 | 1.6 |
| 24 | 14 | 12.0 | 6.3 | 17 | 23.7 | 7.8 | 155 | 39.0 | 12.1 |
| 25 | 4 | 11.3 | 13.8 | 15 | 27.0 | 20.9 | 167 | 46.5 | 24.9 |
| 26 | 185 | 6.3 | 1.5 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 18 | 12.4 | 5.5 | 83 | 22.2 | 8.1 | 85 | 32.2 | 10.3 |
| 28 | 23 | 13.3 | 7.5 | 87 | 22.4 | 8.2 | 76 | 32.3 | 10.7 |
| 29 | 3 | 12.7 | 11.3 | 3 | 20.0 | 20.3 | 180 | 131.2 | 18.0 |
| 30 | 152 | 12.6 | 5.0 | 32 | 22.2 | 6.9 | 1 | 29.0 | 3.0 |
| 31 | 41 | 16.2 | 12.2 | 100 | 26.0 | 14.7 | 45 | 37.2 | 17.4 |
| 32 | 83 | 16.9 | 11.6 | 91 | 27.4 | 13.0 | 12 | 35.6 | 14.0 |
| 33 | 31 | 14.9 | 9.8 | 100 | 25.0 | 13.2 | 55 | 37.4 | 17.9 |
| 34 | 33 | 14.2 | 8.1 | 77 | 22.3 | 9.3 | 76 | 32.4 | 10.1 |
| 35 | 99 | 15.0 | 9.7 | 77 | 23.4 | 12.4 | 10 | 34.3 | 16.7 |
| 36 | 31 | 10.7 | 2.6 | 38 | 17.8 | 4.3 | 117 | 30.3 | 4.7 |
| 37 | 44 | 16.0 | 7.0 | 83 | 24.4 | 9.2 | 58 | 33.4 | 11.1 |
| 38 | 73 | 14.1 | 7.0 | 90 | 22.8 | 8.7 | 23 | 34.1 | 9.3 |
| 39 | 23 | 11.7 | 4.4 | 57 | 19.7 | 3.6 | 105 | 30.4 | 5.0 |
| 40 | 19 | 7.4 | 1.5 | 49 | 17.6 | 2.5 | 117 | 29.0 | 3.6 |

TABLE D.3: Zone status and related bookings in time slot $T_3$ on weekdays

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ |
| 1 | 8 | 9.1 | 3.3 | 2 | 25.0 | 10.0 | 176 | 60.2 | 11.3 |
| 2 | 77 | 14.2 | 4.6 | 86 | 25.3 | 6.9 | 23 | 35.6 | 6.5 |
| 3 | 136 | 15.7 | 6.0 | 50 | 26.7 | 5.7 | 0 | 0.0 | 0.0 |
| 4 | 3 | 12.0 | 2.3 | 2 | 24.0 | 2.0 | 181 | 201.4 | 8.2 |
| 5 | 22 | 13.5 | 7.2 | 31 | 29.2 | 10.4 | 133 | 44.2 | 12.8 |
| 6 | 186 | 11.0 | 8.2 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 49 | 16.0 | 7.1 | 65 | 27.3 | 8.9 | 71 | 40.3 | 12.0 |
| 8 | 162 | 8.3 | 1.0 | 14 | 21.6 | 1.1 | 3 | 29.7 | 4.3 |
| 9 | 26 | 10.3 | 4.5 | 41 | 22.7 | 5.8 | 119 | 36.5 | 5.0 |
| 10 | 15 | 12.5 | 4.7 | 22 | 25.0 | 6.2 | 149 | 38.6 | 8.2 |
| 11 | 150 | 16.2 | 8.9 | 20 | 29.6 | 8.6 | 16 | 78.4 | 23.1 |
| 12 | 26 | 17.0 | 9.3 | 68 | 29.8 | 10.7 | 92 | 42.4 | 12.7 |
| 13 | 19 | 10.6 | 1.1 | 19 | 19.4 | 2.9 | 146 | 36.0 | 4.9 |
| 14 | 102 | 18.9 | 10.9 | 74 | 31.6 | 11.5 | 10 | 43.6 | 10.5 |
| 15 | 171 | 17.0 | 8.5 | 15 | 28.7 | 10.9 | 0 | 0.0 | 0.0 |
| 16 | 162 | 16.1 | 6.2 | 23 | 27.3 | 7.2 | 1 | 37.0 | 15.0 |
| 17 | 76 | 18.4 | 7.9 | 92 | 29.3 | 10.9 | 18 | 43.1 | 13.3 |
| 18 | 133 | 14.4 | 4.7 | 42 | 24.5 | 5.7 | 11 | 35.8 | 7.1 |
| 19 | 18 | 12.6 | 2.6 | 51 | 21.7 | 3.8 | 116 | 36.7 | 7.3 |
| 20 | 183 | 11.3 | 5.3 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 21 | 45 | 18.5 | 8.8 | 88 | 29.1 | 10.8 | 53 | 40.5 | 10.2 |
| 22 | 174 | 12.9 | 3.2 | 10 | 23.6 | 5.0 | 2 | 32.5 | 5.0 |
| 23 | 158 | 14.0 | 4.8 | 22 | 25.4 | 5.6 | 6 | 34.3 | 1.7 |
| 24 | 19 | 14.8 | 6.9 | 55 | 29.3 | 11.6 | 112 | 42.7 | 15.7 |
| 25 | 15 | 22.5 | 16.3 | 111 | 41.5 | 22.9 | 60 | 57.6 | 26.0 |
| 26 | 184 | 6.6 | 2.2 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 95 | 20.3 | 9.0 | 87 | 32.0 | 14.0 | 4 | 41.3 | 17.3 |
| 28 | 72 | 17.9 | 8.1 | 90 | 27.1 | 9.5 | 24 | 37.2 | 9.9 |
| 29 | 3 | 12.7 | 3.0 | 3 | 22.0 | 2.0 | 180 | 130.9 | 11.6 |
| 30 | 183 | 14.1 | 7.9 | 2 | 28.5 | 13.5 | 0 | 0.0 | 0.0 |
| 31 | 101 | 22.4 | 15.5 | 77 | 34.8 | 19.4 | 8 | 47.4 | 26.0 |
| 32 | 166 | 21.8 | 14.8 | 20 | 35.3 | 16.3 | 0 | 0.0 | 0.0 |
| 33 | 133 | 23.6 | 15.2 | 48 | 36.8 | 20.6 | 5 | 61.8 | 23.2 |
| 34 | 80 | 19.6 | 9.8 | 93 | 30.7 | 11.9 | 13 | 43.4 | 13.1 |
| 35 | 160 | 20.0 | 12.4 | 26 | 34.2 | 17.0 | 0 | 0.0 | 0.0 |
| 36 | 51 | 11.5 | 3.6 | 63 | 22.2 | 5.2 | 72 | 32.2 | 4.6 |
| 37 | 147 | 21.8 | 11.2 | 39 | 34.2 | 16.0 | 0 | 0.0 | 0.0 |
| 38 | 154 | 19.2 | 10.9 | 29 | 31.8 | 11.8 | 3 | 46.3 | 12.0 |
| 39 | 50 | 14.2 | 5.3 | 99 | 24.4 | 6.0 | 37 | 35.1 | 7.2 |
| 40 | 36 | 11.4 | 2.8 | 77 | 20.9 | 4.6 | 71 | 32.2 | 3.9 |

TABLE D.4: Zone status and related bookings in time slot $T_4$ on weekdays

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ |
| 1 | 4 | 6.5 | 1.0 | 2 | 12.5 | 0.5 | 180 | 60.6 | 6.5 |
| 2 | 16 | 7.9 | 1.1 | 39 | 16.0 | 3.2 | 131 | 28.0 | 4.7 |
| 3 | 37 | 11.0 | 3.8 | 66 | 18.4 | 6.3 | 83 | 25.9 | 4.8 |
| 4 | 1 | 10.0 | 1.0 | 1 | 15.0 | 1.0 | 184 | 198.1 | 4.2 |
| 5 | 8 | 4.5 | 1.3 | 14 | 15.4 | 1.8 | 164 | 36.8 | 4.0 |
| 6 | 182 | 7.4 | 3.7 | 3 | 21.7 | 3.7 | 0 | 0.0 | 0.0 |
| 7 | 12 | 9.5 | 1.7 | 16 | 16.6 | 4.1 | 158 | 32.2 | 5.4 |
| 8 | 129 | 6.8 | 1.0 | 33 | 17.3 | 2.6 | 18 | 28.4 | 11.8 |
| 9 | 8 | 6.3 | 0.4 | 11 | 12.9 | 1.8 | 166 | 33.3 | 2.8 |
| 10 | 6 | 7.8 | 1.2 | 8 | 13.9 | 1.8 | 172 | 36.4 | 3.6 |
| 11 | 88 | 10.2 | 2.9 | 62 | 19.2 | 3.7 | 36 | 55.9 | 17.1 |
| 12 | 6 | 7.3 | 1.3 | 9 | 16.4 | 4.0 | 171 | 36.5 | 7.3 |
| 13 | 10 | 7.7 | 0.6 | 10 | 13.9 | 0.9 | 165 | 35.3 | 2.8 |
| 14 | 27 | 12.1 | 3.5 | 55 | 19.3 | 5.8 | 104 | 30.2 | 6.5 |
| 15 | 59 | 11.7 | 5.0 | 77 | 18.9 | 6.2 | 50 | 25.9 | 6.6 |
| 16 | 60 | 11.9 | 3.9 | 90 | 18.9 | 5.6 | 36 | 26.6 | 6.2 |
| 17 | 15 | 12.1 | 2.5 | 52 | 18.4 | 3.9 | 119 | 30.3 | 7.5 |
| 18 | 29 | 10.2 | 3.4 | 86 | 17.3 | 3.6 | 71 | 27.5 | 6.1 |
| 19 | 6 | 7.5 | 0.7 | 4 | 13.8 | 2.0 | 176 | 33.7 | 3.7 |
| 20 | 139 | 10.1 | 2.8 | 43 | 18.6 | 7.3 | 1 | 25.0 | 10.0 |
| 21 | 6 | 10.3 | 2.8 | 20 | 19.3 | 6.3 | 160 | 32.8 | 7.0 |
| 22 | 51 | 9.2 | 1.5 | 107 | 15.0 | 2.0 | 28 | 22.5 | 3.0 |
| 23 | 58 | 9.7 | 1.6 | 84 | 15.7 | 2.1 | 44 | 24.7 | 2.4 |
| 24 | 6 | 9.8 | 2.8 | 13 | 17.7 | 6.6 | 167 | 40.1 | 10.5 |
| 25 | 3 | 9.3 | 2.7 | 17 | 20.7 | 9.3 | 166 | 39.2 | 11.4 |
| 26 | 185 | 6.2 | 1.5 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 12 | 9.5 | 2.0 | 56 | 18.0 | 4.8 | 118 | 27.5 | 5.8 |
| 28 | 4 | 7.8 | 5.8 | 15 | 19.1 | 6.0 | 167 | 31.1 | 8.5 |
| 29 | 0 | 0.0 | 0.0 | 2 | 12.5 | 0.5 | 184 | 130.5 | 7.1 |
| 30 | 88 | 11.6 | 5.0 | 67 | 18.6 | 7.1 | 30 | 25.3 | 5.3 |
| 31 | 9 | 12.4 | 9.9 | 47 | 22.1 | 11.2 | 130 | 35.2 | 15.7 |
| 32 | 37 | 11.9 | 8.0 | 77 | 21.2 | 11.0 | 72 | 30.9 | 10.1 |
| 33 | 49 | 13.0 | 4.7 | 74 | 22.3 | 7.1 | 63 | 32.6 | 9.0 |
| 34 | 8 | 11.1 | 5.0 | 46 | 17.3 | 5.2 | 132 | 29.0 | 6.2 |
| 35 | 41 | 14.3 | 5.2 | 86 | 21.7 | 8.2 | 59 | 31.2 | 9.9 |
| 36 | 12 | 7.7 | 1.1 | 24 | 13.1 | 2.2 | 150 | 27.1 | 2.2 |
| 37 | 22 | 12.1 | 4.0 | 78 | 18.9 | 5.8 | 86 | 27.5 | 7.9 |
| 38 | 47 | 11.9 | 4.4 | 84 | 21.0 | 7.7 | 55 | 31.9 | 9.3 |
| 39 | 8 | 8.6 | 1.4 | 24 | 15.8 | 3.1 | 154 | 28.1 | 3.9 |
| 40 | 13 | 5.1 | 0.8 | 19 | 14.1 | 2.1 | 154 | 26.5 | 2.0 |

TABLE D.5: Zone status and related bookings in time slot $T_5$ on weekdays

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ | # occ. | $\emptyset s^{t_1}$ | $\emptyset r^{T_1}$ |
| 1 | 2 | 7.0 | 1.0 | 0 | 0.0 | 0.0 | 85 | 60.4 | 3.9 |
| 2 | 1 | 7.0 | 4.0 | 8 | 11.9 | 2.5 | 78 | 27.9 | 3.6 |
| 3 | 3 | 7.0 | 0.7 | 11 | 12.5 | 2.0 | 73 | 22.7 | 3.1 |
| 4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 87 | 189.0 | 1.4 |
| 5 | 2 | 3.0 | 0.0 | 3 | 10.3 | 0.3 | 82 | 34.6 | 0.8 |
| 6 | 85 | 6.0 | 3.3 | 2 | 14.0 | 4.0 | 0 | 0.0 | 0.0 |
| 7 | 1 | 6.0 | 1.0 | 1 | 9.0 | 0.0 | 85 | 29.2 | 2.1 |
| 8 | 44 | 5.6 | 0.0 | 22 | 11.9 | 0.4 | 17 | 24.6 | 1.4 |
| 9 | 2 | 5.0 | 0.5 | 4 | 10.8 | 1.3 | 81 | 32.0 | 1.9 |
| 10 | 0 | 0.0 | 0.0 | 3 | 9.0 | 0.3 | 84 | 36.6 | 1.7 |
| 11 | 13 | 6.9 | 2.2 | 16 | 11.8 | 2.3 | 58 | 30.0 | 3.8 |
| 12 | 1 | 8.0 | 1.0 | 1 | 9.0 | 1.0 | 85 | 35.3 | 4.3 |
| 13 | 2 | 5.5 | 0.0 | 2 | 10.0 | 1.0 | 83 | 33.6 | 1.2 |
| 14 | 6 | 9.0 | 4.3 | 16 | 14.4 | 5.4 | 65 | 26.1 | 5.1 |
| 15 | 9 | 8.6 | 8.4 | 28 | 16.7 | 9.6 | 50 | 24.2 | 10.7 |
| 16 | 9 | 8.1 | 4.7 | 17 | 14.8 | 6.2 | 61 | 23.9 | 7.5 |
| 17 | 1 | 9.0 | 3.0 | 9 | 12.2 | 1.7 | 77 | 26.1 | 4.7 |
| 18 | 2 | 5.5 | 1.0 | 9 | 13.3 | 2.9 | 76 | 22.8 | 3.7 |
| 19 | 1 | 7.0 | 1.0 | 1 | 10.0 | 1.0 | 85 | 33.7 | 1.9 |
| 20 | 28 | 8.4 | 1.7 | 33 | 12.8 | 2.0 | 24 | 19.4 | 2.1 |
| 21 | 1 | 7.0 | 0.0 | 2 | 12.0 | 3.0 | 84 | 30.2 | 5.4 |
| 22 | 6 | 7.0 | 0.5 | 26 | 11.2 | 0.9 | 55 | 17.5 | 1.1 |
| 23 | 11 | 6.9 | 1.5 | 24 | 11.3 | 0.8 | 52 | 19.9 | 1.2 |
| 24 | 1 | 9.0 | 1.0 | 1 | 11.0 | 5.0 | 85 | 39.7 | 7.4 |
| 25 | 2 | 10.0 | 8.0 | 2 | 12.0 | 2.5 | 83 | 32.3 | 5.8 |
| 26 | 78 | 6.4 | 2.1 | 9 | 13.6 | 3.9 | 0 | 0.0 | 0.0 |
| 27 | 1 | 8.0 | 0.0 | 1 | 9.0 | 0.0 | 85 | 23.7 | 2.3 |
| 28 | 0 | 0.0 | 0.0 | 2 | 11.0 | 1.5 | 85 | 29.4 | 3.9 |
| 29 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 87 | 126.0 | 3.0 |
| 30 | 11 | 8.2 | 3.2 | 32 | 12.9 | 2.8 | 44 | 21.3 | 3.0 |
| 31 | 0 | 0.0 | 0.0 | 3 | 17.0 | 9.3 | 84 | 32.4 | 12.6 |
| 32 | 3 | 8.0 | 0.3 | 10 | 12.5 | 3.8 | 74 | 25.4 | 5.3 |
| 33 | 12 | 10.3 | 4.2 | 24 | 15.9 | 5.5 | 51 | 27.9 | 8.5 |
| 34 | 0 | 0.0 | 0.0 | 5 | 13.6 | 5.8 | 82 | 25.9 | 5.7 |
| 35 | 6 | 10.8 | 9.0 | 23 | 17.3 | 12.3 | 58 | 28.4 | 14.8 |
| 36 | 0 | 0.0 | 0.0 | 2 | 8.0 | 1.5 | 85 | 26.1 | 1.2 |
| 37 | 4 | 7.5 | 2.0 | 16 | 12.9 | 3.5 | 67 | 21.6 | 3.4 |
| 38 | 9 | 9.0 | 3.2 | 19 | 13.9 | 4.2 | 59 | 24.6 | 5.4 |
| 39 | 0 | 0.0 | 0.0 | 7 | 11.7 | 1.7 | 80 | 27.7 | 2.6 |
| 40 | 3 | 4.3 | 0.0 | 4 | 8.8 | 0.3 | 80 | 25.4 | 1.2 |

TABLE D.6: Zone status and related bookings in time slot $T_1$ on weekends

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ | # occ. | $\emptyset s^{t_2}$ | $\emptyset r^{T_2}$ |
| 1 | 0 | 0.0 | 0.0 | 2 | 7.5 | 0.5 | 86 | 61.4 | 2.4 |
| 2 | 1 | 7.0 | 0.0 | 2 | 9.0 | 0.5 | 85 | 26.7 | 2.2 |
| 3 | 2 | 5.5 | 0.0 | 0 | 0.0 | 0.0 | 86 | 20.6 | 0.9 |
| 4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 88 | 188.5 | 1.5 |
| 5 | 2 | 2.5 | 0.0 | 1 | 9.0 | 1.0 | 85 | 35.4 | 1.1 |
| 6 | 73 | 4.0 | 0.3 | 12 | 9.2 | 0.4 | 2 | 14.0 | 0.5 |
| 7 | 2 | 5.5 | 1.5 | 0 | 0.0 | 0.0 | 86 | 31.5 | 2.1 |
| 8 | 38 | 4.9 | 0.0 | 15 | 8.7 | 0.2 | 31 | 16.5 | 0.3 |
| 9 | 2 | 3.0 | 0.0 | 2 | 10.0 | 0.0 | 84 | 31.8 | 1.2 |
| 10 | 1 | 5.0 | 1.0 | 0 | 0.0 | 0.0 | 87 | 36.8 | 1.2 |
| 11 | 5 | 5.2 | 0.6 | 16 | 8.9 | 0.6 | 67 | 25.1 | 1.2 |
| 12 | 0 | 0.0 | 0.0 | 2 | 7.5 | 0.0 | 86 | 35.7 | 2.2 |
| 13 | 0 | 0.0 | 0.0 | 2 | 7.0 | 0.5 | 86 | 34.5 | 1.3 |
| 14 | 0 | 0.0 | 0.0 | 1 | 9.0 | 0.0 | 87 | 21.8 | 0.8 |
| 15 | 2 | 5.5 | 2.0 | 4 | 8.5 | 1.0 | 82 | 19.6 | 1.4 |
| 16 | 3 | 4.7 | 0.0 | 4 | 7.3 | 0.3 | 81 | 18.7 | 0.9 |
| 17 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 88 | 24.7 | 1.7 |
| 18 | 1 | 5.0 | 0.0 | 0 | 0.0 | 0.0 | 87 | 21.3 | 1.3 |
| 19 | 0 | 0.0 | 0.0 | 1 | 9.0 | 1.0 | 87 | 35.5 | 1.8 |
| 20 | 5 | 4.2 | 0.6 | 19 | 8.2 | 0.8 | 63 | 14.4 | 1.0 |
| 21 | 0 | 0.0 | 0.0 | 1 | 9.0 | 0.0 | 87 | 29.6 | 1.4 |
| 22 | 0 | 0.0 | 0.0 | 21 | 10.0 | 0.5 | 67 | 17.1 | 0.7 |
| 23 | 4 | 4.5 | 0.0 | 11 | 8.6 | 0.8 | 73 | 17.5 | 1.0 |
| 24 | 0 | 0.0 | 0.0 | 1 | 10.0 | 0.0 | 87 | 38.7 | 1.5 |
| 25 | 0 | 0.0 | 0.0 | 1 | 8.0 | 1.0 | 87 | 31.9 | 2.0 |
| 26 | 56 | 5.1 | 0.2 | 28 | 9.4 | 0.2 | 3 | 14.0 | 0.0 |
| 27 | 0 | 0.0 | 0.0 | 1 | 9.0 | 0.0 | 87 | 24.5 | 1.3 |
| 28 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 88 | 30.9 | 2.3 |
| 29 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 88 | 127.5 | 3.3 |
| 30 | 4 | 5.3 | 1.0 | 6 | 9.3 | 1.2 | 78 | 18.8 | 2.3 |
| 31 | 0 | 0.0 | 0.0 | 1 | 10.0 | 2.0 | 87 | 30.4 | 3.4 |
| 32 | 1 | 6.0 | 4.0 | 2 | 9.5 | 2.0 | 85 | 25.7 | 3.2 |
| 33 | 0 | 0.0 | 0.0 | 8 | 8.1 | 0.4 | 80 | 20.0 | 1.1 |
| 34 | 0 | 0.0 | 0.0 | 4 | 8.5 | 0.5 | 84 | 22.9 | 0.8 |
| 35 | 0 | 0.0 | 0.0 | 3 | 8.7 | 2.0 | 85 | 21.8 | 1.7 |
| 36 | 0 | 0.0 | 0.0 | 3 | 7.7 | 0.7 | 85 | 27.4 | 1.3 |
| 37 | 0 | 0.0 | 0.0 | 2 | 9.0 | 0.5 | 86 | 20.8 | 1.5 |
| 38 | 2 | 7.0 | 0.0 | 5 | 9.6 | 0.6 | 81 | 21.7 | 1.2 |
| 39 | 0 | 0.0 | 0.0 | 2 | 7.5 | 0.0 | 86 | 28.1 | 1.7 |
| 40 | 3 | 3.7 | 0.0 | 2 | 8.0 | 0.0 | 83 | 26.2 | 0.8 |

TABLE D.7: Zone status and related bookings in time slot $T_2$ on weekends

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ | # occ. | $\emptyset s^{t_3}$ | $\emptyset r^{T_3}$ |
| 1 | 2 | 7.5 | 2.5 | 1 | 22.0 | 10.0 | 84 | 62.1 | 13.3 |
| 2 | 30 | 15.9 | 9.1 | 37 | 25.6 | 10.1 | 20 | 39.0 | 12.4 |
| 3 | 47 | 16.2 | 9.2 | 36 | 24.3 | 6.7 | 4 | 34.3 | 7.3 |
| 4 | 0 | 0.0 | 0.0 | 2 | 20.0 | 4.0 | 85 | 193.3 | 8.9 |
| 5 | 7 | 10.9 | 5.4 | 13 | 22.8 | 6.3 | 67 | 39.2 | 8.2 |
| 6 | 87 | 5.6 | 5.4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 15 | 14.3 | 4.5 | 31 | 25.1 | 10.9 | 41 | 39.2 | 12.4 |
| 8 | 73 | 7.8 | 1.7 | 10 | 20.4 | 4.9 | 2 | 28.0 | 3.5 |
| 9 | 14 | 11.3 | 3.0 | 9 | 17.9 | 5.2 | 64 | 36.4 | 6.4 |
| 10 | 5 | 10.4 | 6.2 | 6 | 22.7 | 7.7 | 76 | 39.4 | 9.0 |
| 11 | 47 | 12.3 | 6.2 | 30 | 23.0 | 7.3 | 10 | 69.1 | 20.8 |
| 12 | 6 | 13.7 | 9.0 | 27 | 26.0 | 11.2 | 54 | 41.4 | 13.0 |
| 13 | 9 | 11.2 | 3.3 | 7 | 19.1 | 4.0 | 71 | 37.9 | 6.4 |
| 14 | 37 | 14.9 | 10.1 | 41 | 24.7 | 9.6 | 9 | 37.7 | 11.4 |
| 15 | 63 | 15.9 | 8.0 | 24 | 24.9 | 9.8 | 0 | 0.0 | 0.0 |
| 16 | 68 | 14.9 | 8.1 | 18 | 25.4 | 9.9 | 1 | 36.0 | 19.0 |
| 17 | 38 | 17.8 | 7.9 | 35 | 26.7 | 9.5 | 14 | 39.2 | 14.8 |
| 18 | 46 | 15.7 | 8.0 | 35 | 24.1 | 9.3 | 6 | 39.2 | 11.5 |
| 19 | 5 | 13.2 | 5.4 | 13 | 22.2 | 7.2 | 69 | 38.7 | 8.8 |
| 20 | 83 | 12.1 | 6.2 | 3 | 24.0 | 6.0 | 0 | 0.0 | 0.0 |
| 21 | 11 | 17.5 | 8.6 | 43 | 25.9 | 9.8 | 33 | 37.4 | 12.7 |
| 22 | 70 | 13.7 | 4.1 | 15 | 21.3 | 4.9 | 2 | 31.0 | 8.5 |
| 23 | 61 | 13.0 | 4.1 | 22 | 21.7 | 4.5 | 4 | 35.3 | 1.3 |
| 24 | 4 | 16.3 | 9.5 | 19 | 26.6 | 12.8 | 64 | 43.4 | 15.9 |
| 25 | 9 | 16.3 | 9.6 | 37 | 28.1 | 14.7 | 41 | 40.5 | 16.6 |
| 26 | 87 | 6.8 | 2.4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 28 | 17.2 | 8.7 | 51 | 25.9 | 8.5 | 8 | 35.9 | 14.9 |
| 28 | 17 | 19.5 | 9.8 | 40 | 28.0 | 14.8 | 30 | 38.9 | 18.7 |
| 29 | 0 | 0.0 | 0.0 | 2 | 19.0 | 5.5 | 85 | 130.3 | 15.3 |
| 30 | 73 | 15.1 | 8.0 | 14 | 26.6 | 12.6 | 0 | 0.0 | 0.0 |
| 31 | 32 | 21.7 | 15.1 | 46 | 31.7 | 23.5 | 9 | 43.8 | 25.8 |
| 32 | 56 | 20.6 | 15.3 | 31 | 31.4 | 18.5 | 0 | 0.0 | 0.0 |
| 33 | 65 | 15.2 | 9.9 | 19 | 27.3 | 10.6 | 3 | 40.7 | 12.0 |
| 34 | 33 | 15.3 | 7.9 | 38 | 23.5 | 8.0 | 16 | 33.6 | 7.3 |
| 35 | 44 | 16.9 | 8.5 | 37 | 24.8 | 11.0 | 6 | 37.5 | 11.8 |
| 36 | 12 | 12.3 | 4.1 | 23 | 20.1 | 5.7 | 52 | 33.2 | 6.4 |
| 37 | 62 | 17.2 | 7.5 | 25 | 27.6 | 10.6 | 0 | 0.0 | 0.0 |
| 38 | 37 | 16.2 | 7.8 | 40 | 25.7 | 7.1 | 10 | 35.9 | 10.2 |
| 39 | 14 | 14.9 | 6.4 | 35 | 23.8 | 8.0 | 38 | 35.2 | 10.6 |
| 40 | 17 | 11.5 | 3.6 | 27 | 21.5 | 5.2 | 43 | 31.8 | 6.0 |

TABLE D.8: Zone status and related bookings in time slot $T_3$ on weekends

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ | # occ. | $\emptyset s^{t_4}$ | $\emptyset r^{T_4}$ |
| 1 | 2 | 7.5 | 1.5 | 0 | 0.0 | 0.0 | 85 | 59.2 | 9.0 |
| 2 | 29 | 14.6 | 6.3 | 38 | 24.5 | 6.7 | 20 | 37.9 | 8.4 |
| 3 | 49 | 15.8 | 5.9 | 36 | 26.0 | 6.4 | 2 | 35.0 | 8.0 |
| 4 | 0 | 0.0 | 0.0 | 2 | 20.0 | 0.5 | 85 | 191.7 | 5.1 |
| 5 | 7 | 12.0 | 4.1 | 18 | 25.1 | 9.4 | 62 | 41.1 | 8.2 |
| 6 | 87 | 8.1 | 4.9 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 20 | 14.5 | 3.3 | 27 | 23.3 | 6.7 | 40 | 35.9 | 7.1 |
| 8 | 72 | 8.8 | 1.6 | 10 | 23.3 | 9.5 | 2 | 32.0 | 9.5 |
| 9 | 15 | 11.4 | 2.9 | 14 | 19.6 | 4.4 | 58 | 37.1 | 5.1 |
| 10 | 6 | 13.5 | 5.3 | 6 | 22.3 | 6.5 | 75 | 38.7 | 6.0 |
| 11 | 60 | 13.7 | 4.1 | 15 | 25.1 | 4.0 | 12 | 82.3 | 26.8 |
| 12 | 9 | 14.3 | 6.3 | 25 | 25.5 | 5.8 | 53 | 41.7 | 9.9 |
| 13 | 10 | 11.5 | 1.4 | 6 | 18.2 | 1.3 | 71 | 36.7 | 4.0 |
| 14 | 25 | 15.1 | 4.7 | 43 | 27.3 | 9.2 | 19 | 38.5 | 14.0 |
| 15 | 62 | 15.8 | 5.9 | 24 | 25.3 | 7.3 | 1 | 35.0 | 20.0 |
| 16 | 64 | 15.3 | 5.6 | 22 | 25.3 | 7.1 | 1 | 34.0 | 5.0 |
| 17 | 44 | 17.3 | 4.9 | 28 | 26.6 | 7.5 | 15 | 43.3 | 12.8 |
| 18 | 49 | 15.8 | 5.1 | 33 | 25.0 | 9.2 | 5 | 40.0 | 11.0 |
| 19 | 4 | 11.0 | 1.3 | 12 | 20.8 | 3.2 | 71 | 36.7 | 6.0 |
| 20 | 84 | 11.9 | 3.9 | 2 | 24.0 | 5.0 | 0 | 0.0 | 0.0 |
| 21 | 10 | 16.2 | 5.3 | 44 | 26.5 | 8.8 | 33 | 37.6 | 8.1 |
| 22 | 72 | 13.1 | 2.6 | 13 | 21.0 | 4.1 | 2 | 30.5 | 6.5 |
| 23 | 63 | 12.6 | 2.3 | 19 | 21.6 | 3.1 | 5 | 33.2 | 0.4 |
| 24 | 3 | 14.7 | 5.3 | 20 | 26.4 | 10.2 | 64 | 44.2 | 13.1 |
| 25 | 21 | 22.3 | 10.3 | 43 | 35.4 | 13.3 | 23 | 48.9 | 18.2 |
| 26 | 87 | 8.1 | 3.1 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 27 | 35 | 18.7 | 7.5 | 44 | 26.6 | 6.5 | 8 | 38.0 | 14.4 |
| 28 | 17 | 17.5 | 7.0 | 46 | 25.5 | 8.2 | 24 | 35.6 | 12.6 |
| 29 | 0 | 0.0 | 0.0 | 2 | 18.0 | 1.5 | 85 | 126.9 | 9.8 |
| 30 | 77 | 13.4 | 6.1 | 10 | 25.7 | 7.3 | 0 | 0.0 | 0.0 |
| 31 | 19 | 20.4 | 9.6 | 52 | 29.6 | 15.2 | 16 | 40.8 | 20.6 |
| 32 | 63 | 19.3 | 10.9 | 24 | 30.6 | 11.1 | 0 | 0.0 | 0.0 |
| 33 | 58 | 18.6 | 7.5 | 21 | 31.1 | 12.9 | 8 | 46.8 | 19.6 |
| 34 | 24 | 16.6 | 3.9 | 45 | 26.3 | 7.1 | 18 | 36.8 | 9.7 |
| 35 | 47 | 19.2 | 7.4 | 34 | 29.4 | 10.6 | 6 | 43.2 | 12.7 |
| 36 | 14 | 12.2 | 3.3 | 24 | 19.9 | 3.5 | 49 | 31.6 | 3.8 |
| 37 | 72 | 16.2 | 5.5 | 15 | 26.9 | 6.6 | 0 | 0.0 | 0.0 |
| 38 | 39 | 17.1 | 6.3 | 40 | 27.6 | 7.2 | 8 | 37.3 | 9.9 |
| 39 | 20 | 15.5 | 4.5 | 35 | 24.5 | 6.0 | 32 | 35.2 | 8.7 |
| 40 | 17 | 10.5 | 1.7 | 22 | 19.2 | 3.3 | 48 | 29.9 | 3.6 |

TABLE D.9: Zone status and related bookings in time slot $T_4$ on weekends

| | under-supply | | | balanced | | | over-saturation | | |
|---|---|---|---|---|---|---|---|---|---|
| zone | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ | # occ. | $\emptyset s^{t_5}$ | $\emptyset r^{T_5}$ |
| 1 | 2 | 7.5 | 0.0 | 0 | 0.0 | 0.0 | 85 | 59.7 | 5.6 |
| 2 | 8 | 10.0 | 1.9 | 16 | 16.6 | 3.1 | 63 | 29.4 | 4.4 |
| 3 | 27 | 13.3 | 3.6 | 33 | 21.6 | 4.5 | 27 | 28.9 | 5.5 |
| 4 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 87 | 188.6 | 2.5 |
| 5 | 4 | 6.0 | 0.5 | 7 | 16.3 | 0.4 | 76 | 36.8 | 2.5 |
| 6 | 87 | 6.9 | 2.1 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 |
| 7 | 3 | 8.3 | 0.7 | 19 | 16.3 | 2.3 | 65 | 32.0 | 3.5 |
| 8 | 67 | 8.1 | 0.9 | 10 | 19.3 | 2.2 | 7 | 39.3 | 15.6 |
| 9 | 5 | 7.4 | 0.6 | 9 | 13.2 | 0.8 | 73 | 33.6 | 2.2 |
| 10 | 2 | 8.0 | 1.5 | 4 | 14.5 | 1.3 | 81 | 36.9 | 2.8 |
| 11 | 39 | 10.9 | 2.1 | 29 | 20.9 | 2.9 | 19 | 63.8 | 20.4 |
| 12 | 2 | 7.5 | 0.5 | 6 | 18.8 | 4.7 | 79 | 37.4 | 6.6 |
| 13 | 4 | 7.8 | 0.0 | 5 | 12.6 | 0.6 | 78 | 34.7 | 1.9 |
| 14 | 15 | 12.3 | 2.5 | 23 | 19.3 | 3.4 | 49 | 29.5 | 3.7 |
| 15 | 28 | 12.3 | 3.3 | 46 | 20.3 | 5.1 | 13 | 27.8 | 5.8 |
| 16 | 25 | 11.6 | 3.3 | 42 | 18.8 | 4.1 | 20 | 28.0 | 5.9 |
| 17 | 13 | 13.2 | 1.9 | 37 | 19.7 | 4.0 | 37 | 34.4 | 8.1 |
| 18 | 8 | 9.9 | 3.0 | 40 | 16.9 | 2.8 | 39 | 26.7 | 4.0 |
| 19 | 2 | 8.0 | 0.0 | 6 | 16.0 | 1.3 | 79 | 34.5 | 2.8 |
| 20 | 64 | 10.9 | 2.2 | 16 | 18.8 | 4.6 | 5 | 23.4 | 3.8 |
| 21 | 3 | 10.0 | 1.3 | 7 | 18.0 | 4.6 | 77 | 31.7 | 4.8 |
| 22 | 20 | 8.7 | 1.0 | 51 | 14.9 | 1.6 | 16 | 21.5 | 2.4 |
| 23 | 43 | 10.7 | 1.1 | 32 | 17.7 | 1.5 | 12 | 28.7 | 1.1 |
| 24 | 2 | 11.0 | 1.0 | 3 | 20.7 | 5.0 | 82 | 41.1 | 6.9 |
| 25 | 4 | 12.8 | 2.3 | 16 | 21.1 | 4.4 | 67 | 36.3 | 6.5 |
| 26 | 86 | 7.2 | 0.9 | 1 | 19.0 | 8.0 | 0 | 0.0 | 0.0 |
| 27 | 8 | 13.1 | 1.8 | 31 | 19.9 | 3.5 | 48 | 27.5 | 3.8 |
| 28 | 2 | 11.0 | 3.0 | 15 | 18.5 | 2.0 | 70 | 31.1 | 6.6 |
| 29 | 0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 87 | 124.8 | 5.1 |
| 30 | 44 | 11.2 | 3.5 | 31 | 18.3 | 4.0 | 12 | 26.4 | 4.9 |
| 31 | 0 | 0.0 | 0.0 | 27 | 22.0 | 6.9 | 60 | 34.1 | 11.8 |
| 32 | 16 | 12.8 | 6.8 | 41 | 21.3 | 7.2 | 30 | 29.6 | 7.1 |
| 33 | 26 | 13.0 | 2.0 | 35 | 21.7 | 4.5 | 26 | 33.9 | 7.0 |
| 34 | 5 | 12.2 | 3.8 | 25 | 20.1 | 3.0 | 57 | 29.8 | 4.0 |
| 35 | 13 | 14.0 | 3.5 | 39 | 22.5 | 6.2 | 35 | 32.6 | 6.9 |
| 36 | 3 | 9.3 | 2.0 | 14 | 13.3 | 1.4 | 70 | 28.2 | 2.1 |
| 37 | 23 | 12.5 | 2.6 | 43 | 18.9 | 3.8 | 21 | 27.8 | 4.7 |
| 38 | 22 | 13.6 | 4.0 | 36 | 21.4 | 4.7 | 29 | 31.3 | 7.6 |
| 39 | 5 | 10.4 | 1.4 | 13 | 17.6 | 2.1 | 69 | 28.8 | 3.4 |
| 40 | 8 | 7.1 | 0.5 | 11 | 14.6 | 1.4 | 68 | 27.0 | 1.7 |

TABLE D.10: Zone status and related bookings in time slot $T_5$ on weekends

# Publications

Some ideas and figures have appeared previously in the following publications:

1. S. Reiss, F. Paul and K. Bogenberger. Empirical Analysis of Munich's free-floating Bike Sharing System: GPS-Booking Data and Customer Survey among Bike Sharing Users. *Proceedings of the Transportation Research Board 94rd Annual Meeting,* (Washington D.C., 2015)

2. S. Reiss and K. Bogenberger. GPS-Data Analysis of Munich's Free-Floating Bike Sharing System and Application of an operator-based Relocation Strategy. *Proceedings of the 18th International Conference on Intelligent Transportation Systems,* (Las Palmas de Gran Canaria, 2015)

3. S. Reiss and K. Bogenberger. Validation of a Relocation Strategy for Munich's Bike Sharing System. *Proceedings of the International Scientific Conference on Mobility and Transport mobil.TUM,* (Munich, 2016)

4. S. Reiss and K. Bogenberger. A Relocation Strategy for Munich's Bike Sharing System: Combining an operator-based and a user-based Scheme. *Proceedings of the 19th EURO Working Group on Transportation Meeting,* (Istanbul, 2016)

5. S. Reiss and K. Bogenberger. Optimal Bike Fleet Management by Smart Relocation Methods: Combining an Operator-based with a User-based Relocation Strategy. *Proceedings of the 19th International Conference on Intelligent Transportation Systems,* (Rio de Janeiro, 2016)