Short-Term Forecast of Demand for Train Station-based Round-Trip Bikesharing

A Case Study of OV-fiets in The Netherlands

Florian Lukas Wilkesmann

Short-Term Forecast of demand for Train Station-Based Round-Trip Bikesharing

A Case Study of OV-fiets in The Netherlands

By

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An electronic version of this thesis will be made available at http://repository.tudelft.nl/.

Preface

This report is the result of 2 ½ years of living and studying in the Netherlands. It is the last step of my academic career (so far). In hindsight, I must thank the postal service in Berlin for loosing my application for a master's degree at TU Berlin, because this led to me reconsidering what I expect from returning to university (application of knowledge, learning for the future and not only from the past, ...). So, I changed my destination and set my course towards the beautiful town of Delft. This was the best decision I could have done: A challenging and eye-opening master's programme Transportation, Infrastructure and Logistics, engaging teachers and supervisors supporting me on my way through the world of (public) transportation, and a lot of new friendships with people from all around the world broadening my transport and personal horizon. In the following, I want to thank those who travelled with me on this journey, and even further:

First, I would like to thank my parents for giving me the opportunity to follow my fascination for everything that moves people since I am a child. The more time I spend in this world I realise what a privilege it is to do something I love, and to have a family which supports me in any way possible to achieve whatever I want to achieve. The same holds for my brother Finn, and for always being my critical sparring partner when it comes to smaller and bigger life decisions. Rike, I would like to thank you for always having my back, no matter how close or far apart we live, and letting each other follow our dreams even if that means being separated by several hours of train rides for now almost eight years.

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Thanks to the Onderzoek Team from NS Stations for letting me instantly becoming part of the family even with my limited Dutch skills, for having online Christmas events and board games, and for discovering the NS network together. Special thanks to Luca for helping me with figuring out how to implement forecasting methods into code, and to Jeroen for making this NS-TU Delft thesis possible in the first place, your valuable feedback and motivational way of leading the team.

Lastly, thanks to all the classmates and people who made my life in Delft so fantastic, before, within, and after the COVID-19 restrictions, with cooking, board games, and during peak-COVID just walks around the city. A special mention here to Philipp and Ali for always being there, and to the glorious design team for your various perspectives on transportation and life brought together.

Florian Lukas Wilkesmann

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Table of Contents

List of Tables

List of Figures

Terminology

Booking	Entire process of an individual using an SBRT, including → rental and → return
LSTM	Long Short-Term Memory, → TSFM using multiple → RNNs to develop the forecast model
MLR	Multiple Linear Regression
NN	Neural Network
SBRT	Station-based round-trip bikesharing
TSFM	Time-Series Forecast Model
PT	Public Transport
Rental	Moment at which a → booking started
Return	Moment at which a → booking ended
RNN	Recurring → NN
RQ	Research Question

1. Introduction

Urban areas all around the world face the challenge of a growing population, leading to increased traffic demand resulting in negative external effects such as road congestion and greenhouse-gas emissions (Buchanan, 2015). One way to reduce the external effects caused by road traffic is by increasing the attractiveness of car-independent multimodal trip chains. These allow individuals to shift away from car usage towards alternative, resource-efficient modes of transportation. Multimodal trips often consist of one main mode (e.g., a rail service) and different modes used for the so-called first and last mile (sometimes referred to as access and egress leg, respectively) to connect the main mode with the travellers' origin and destination (see Figure 1).

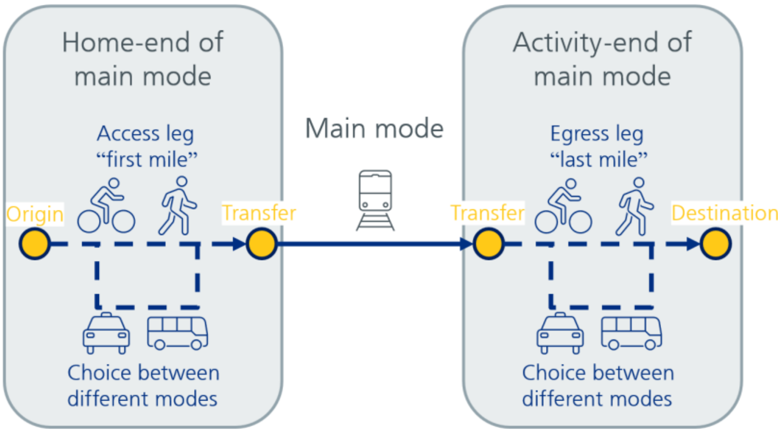

Figure 1: Multimodal trip chain from home (= origin) to activity (= destination) (own visualisation)

When discussing travel behaviour, it is important to understand that the individual perceived disutility of a trip is the result of the disutility caused by its distinct characteristics. In the case of multimodal trip chains, the access and egress modes are found to have a higher impact on the overall trip disutility than the main mode (Hoogendoorn-Lanser, van Nes, Hoogendoorn, et al., 2006). Thus, to increase the attractiveness of multimodal trip chains, it is necessary to create a seamless travel experience by making the usage of the access and egress modes easily accessible. This is supported by the finding that the transfers between different modes are generally considered to decrease the attractiveness of a trip (Hoogendoorn-Lanser, van Nes, & Hoogendoorn, 2006).

To achieve seamless multimodal trip chains, current developments go in various directions: From demand-responsive busses connecting rural areas over smartphone-based multimodal booking platforms to urban bikesharing schemes (Jittrapirom et al., 2017). In the Netherlands, amongst others the Dutch public rail operator NS is encouraging the bike-train multimodal combination. This is done by providing bike parking facilities to ease the access to train services by bike, and OV-fiets (Dutch for Public Transport bike), a bikesharing scheme with stations next to public transport (PT) stations allowing arriving PT travellers to rent a bike for their egress leg. OV-fiets is a so-called station-based round-trip bikesharing (SBRT) scheme, in which a bike is booked and returned at the same fixed station.

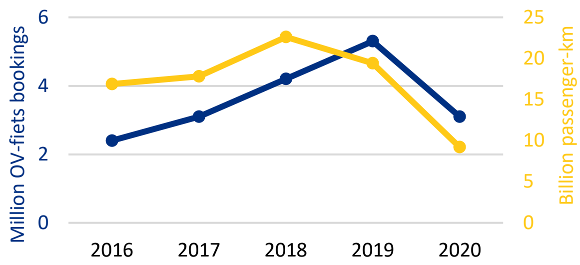

Figure 2: Development of annual OV-fiets bookings and train-passenger-kilometres in NL throughout last years; Sources: NS, 2021 (OV-fiets); OECD, 2021 (pkm)

Throughout the last decade, OV-fiets experienced a sharp increase in trips done by users per year, with a drop in 2020 related to the COVID-19 pandemic. This is in line with the development of the passenger-kilometres travelled in the corresponding train system (see Figure 2; NS, 2021; OECD, 2021; Villwock-Witte & van Grol, 2015). SBRT-systems with comparable numbers of trips per bike are almost non-existent in other countries, with BlueBike in Belgium being the only noteworthy system in terms of trips per bike (de Visser, 2017)[1]. Furthermore, to date most literature researching bikesharing focusses on the understanding, prediction and optimisation of one-way bikesharing while little attention is paid to round-trip schemes (see for example Gu et al., 2019a; Médard de Chardon, 2019; Shui & Szeto, 2020; Todd et al., 2021). This might be caused by the high number of one-way bikesharing services evolving around the world, leading to a higher relevance of related research. In addition, most one-way services provide real-time online booking data and/or open access to their data, which eases data gathering for researchers (Todd et al., 2021). With regard to SBRTs, first research has been done on OV-fiets' potential impact on modal shift (X. Ma et al., 2020). Also, the business perspective of OV-fiets' success story was investigated within multiple theses (Brandjes, 2016; de Visser, 2017; Hoekstra, 2015; van Zessen, 2017). While the existing studies examined OV-fiets' role in combination with rail services, to date no data-driven research was performed on the systems' usage patterns and underlying determinants.

This leads to the *objective of this research* to fill the knowledge gap about SBRT-systems by identifying potential temporal and weather-related determinants for rentals of SBRT-bikes using past booking data. This knowledge is used to predict the short-term availability of bikes for the following days on an hourly basis for different SBRT-stations using the earlier identified impact determinants.

To do so, booking data obtained from the world's largest SBRT-system integrated in existing PT infrastructure, OV-fiets, is analysed. The data is provided by the state-owned train station operator NS Stations, which operates OV-fiets. The data used for this project will be complemented using further internal and external data sources such as historical passenger flows leaving the train stations next to the considered OV-fiets stations and historical weather data to identify potential determinants for the number of bikes rented per hour. The generated insights are then used as contextual input to implement and assess three different forecasting methods.

The identification of determinants for SBRT-rentals is performed on an hourly level of aggregation using multiple linear regression (MLR) and descriptive analysis. For forecasting, three methods are used and assessed: MLR, Prophet, and LSTM.

[1] To avoid confusion, this report uses the abbreviation SBRT to refer to public transport-related systems such as OV-fiets in The Netherlands, BlueBike in Belgium, or Call-a-Bike in Germany with most stations located at local public transport hubs. Other non-PT-bound SBRT-systems exist (see section 2.1) but are considered out of scope for this project.

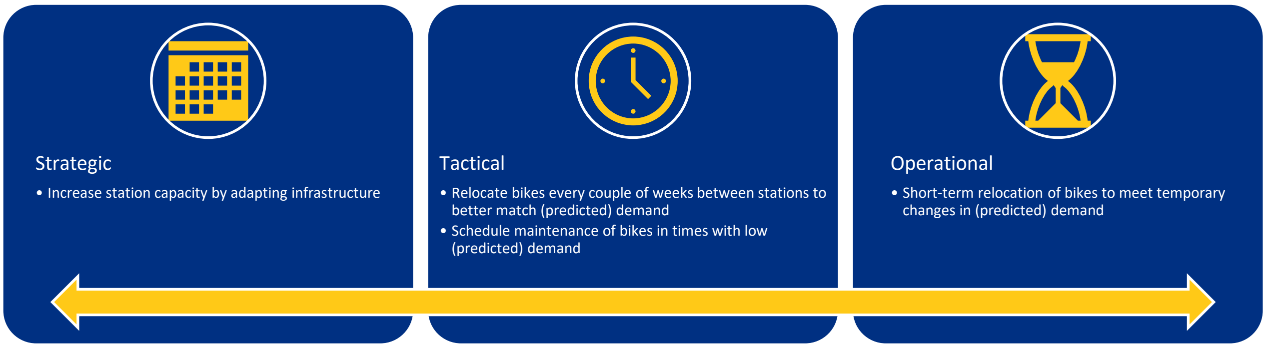

Figure 3: Three levels of transport planning and potential application of this research

This research aims to provide data-driven insights in the ways the SBRT-system OV-fiets is used. This information can help operators on all three levels of transport planning (see also Figure 3): On a strategical level, insights into the determinants of SBRT-demand can help to estimate if a change in available bikes is required on a longer term. On a tactical level, both the determinants and the forecasting results can help to identify a bike relocation potential between different stations to better match demand and supply as well as to assign more staff to stations with higher predicted demand. Also, in times of low predicted demand bikes it can be decided to maintain unused bikes. On an operational level, the forecast results can help to relocate bikes between close stations to better match short-term changes in demand.

Hence, the prediction contributes to a maximisation of the system occupancy while providing a higher availability for individuals planning to use the system. While this can help existing operators such as NS Stations and BlueBike to improve their existing services, the insights might also provide a scientific foundation for new institutions to invest in SBRT-systems as part of their multimodal portfolio. It should be acknowledged that the results will be obtained for the Netherlands, a country with a unique level of cycling infrastructure and modal split (Rietveld, 2000), thus having limited representativeness for other countries. Nevertheless, the insights can be used as inspiration for other regions throughout the world, as cycling is to date experiencing a renaissance in urban planning (for example the Plan Vélo in Paris (Mairie de Paris, 2021) or the Berlin Mobility Pact (Henneberger, 2021)). For applicability of the results, cultural and societal differences and their impact on the adaptation of cycling should be kept in mind (Ricci, 2015).

The following sections 1.1 – 1.4 provide additional information about the context of the thesis regarding societal and scientific relevance, the research questions which ought to be answered, and both scope and structure of the conducted research. Section 2 follows a general literature review of current research regarding bikesharing to identify potential determinants for bikesharing demand as well as most suitable forecasting methods. In section 3 the methods used for the identification of determinants as well as the selected forecast methods are described before assessing their results in section 4. Lastly, section 5 discusses the obtained results and sets them in a broader context.

1.1 Relevance of research

This research provides a concept to get further insights into the determinants influencing the demand for SBRT-bikes. This knowledge will then be used to forecast its short-term demand. The outcome is expected to provide an added value for multiple stakeholders (S 1-4) as well as additional insights for research on bikesharing usage (R 1,2):

S 1	For **current operators of SBRT-systems**, the research provides **information about the different determinants for the usage of their system** as well as its projected demand. This information can **increase the occupancy of the available fleet** when being used for relocation between stations at which for a projected time more or less users are expected. Also, it allows for service operation managers to plan the shifts of their employees more efficient and conduct **maintenance of bikes** in times of low demand. Further, the predicted availability of bikes at a station might be included in the trip information app by the operator to better inform travellers of the probability to have a SBRT-bike available. This can help match their expectations, supporting the overall user satisfaction.
S 2	For **potential operators of SBRT-systems** such as public transport operators and authorities, insights into the usage of SBRT-systems can help to understand the system as promising addition to enhance multimodal transportation.
S 3	For (potential) **SBRT-users**, the **improved matching of demand and supply** by the SBRT-operator **allows more individuals to use the system** at stations with predicted temporal high demand, increasing the ease of multimodal trip chains.
S 4	For **local stakeholders**, the increased attractiveness of multimodal trip chains including SBRT-systems can result in **more users of the bike-train combination,** which is in line with current targets to increase the share of sustainable transport modes. While this might result in fewer individuals choosing to walk, according to Ma et al. (2020) the modal shift towards SBRT-systems is expected to come from cars and public transportation as well. Thus, SBRT-systems might **reduce car usage** and **shift train egress trips from crowded local metro, tram, or bus services towards the bike**.
R 1	For researchers of bikesharing usage patterns, the results provide **insights on to what extent** the learnings from **station-based round-trip bikesharing schemes differ from those operating one-way**.
R 2	For researchers investigating forecasting methods for shared mobility in general and bikesharing more specifically, the results provide a **comparison of different forecasting methods**, including their advantages and shortcomings when it comes to predicting short-term SBRT-demand.

1.2 Research question

The previous section shows that in current scientific literature few is known about the use of SBRT-systems in general. This research aims to fill parts of this knowledge gap by answering the following research question:

What determinants influence the variety in hourly rentals of a train station-based round-trip bikesharing scheme, and how can these determinants contribute to a short-term ridership prediction model?

To answer this research question, it is divided into further research sub-questions (RQs):

RQ 1	What are significant determinants for rentals of bikes at SBRT-stations?
RQ 2	To what extent can historical SBRT booking data be used to identify temporal usage similarities and differences among different SBRT-stations?
RQ 3	To what extent can the rented bikes per hour at a SBRT-station be predicted using time-related determinants only?
RQ 4	To what extent can additional determinants increase the accuracy of the implemented forecast models?

In what environment and how these research questions are adressed is briefly described in the following sections. In addition to providing answers to the defined questions, this thesis will provide ideas on how its results can provide an added value for both SBRT-operators and the public.

1.3 Scope of research

Two-way SBRT schemes currently lack in-depth research, which is reasoned in their limited spread around the world and usage data being available to operators only (see also section 2). Therefore, it is important to disclaim which research directions this thesis will leave aside, may it be either to the lack of related data or the researchers' capacity. The results of this thesis are subjected to the characteristics of the OV-fiets scheme in The Netherlands. The competition with other modes is considered out of scope for complexity reasons, whereas the availability of alternatives such as PT or other shared mobility providers might have an impact on the schemes' usage.

Also, the dataset only captures revealed information about performed bookings, and lacks information on potential demand in times when no bikes are available at a station. This makes the results of this research vulnerable to an underestimation of demand at station at which all bikes are often rented out. Figure 4 shows that the number of moments in which no bikes are available at a station highly differs across stations in the network: In the provided year 2019, for example in Beilen never all 16 bikes are rented out. Across the multiple OV-fiets stations at Amsterdam Zuid

(Mahlerplein and Zuidplein) it occurs more often that a high number of bikes is booked at the same time, while almost never reaching the absolute maximum of more than 400 bikes. In Apeldoorn, in more than 25% of the timesteps more than three hundred bikes are rented out at the same time, indicating that for this station there might exist situations in which the demand for additional bookings might not be satisfied due to a lack of available bikes.

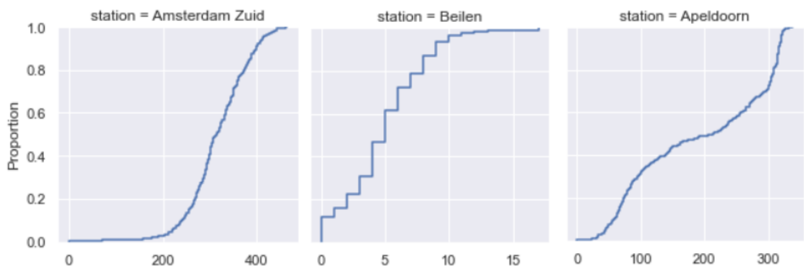

Figure 4: Aggregated distribution of the number of OV-fiets booked at the same time throughout the year 2019 (1 = all timesteps); visualisation by NS Stations

Moreover, to maintain consistency mainly data from 2018 and 2019 is used for analysis to avoid the impact of COVID-19-related restrictions. It must be acknowledged that these restrictions are known to have led to significant changes in the mobility demand and supply in The Netherlands and throughout the world (Gkiotsalitis & Cats, 2021; Ton et al., 2022). When it comes to forecasting, in addition to the application on 2018/19, another exemplary forecast is performed for 2020/21, years in which COVID played a significant role. This is done using few exemplary cases to illustrate the suitability of the different forecasting methods during COVID-related uncertainty.

1.4 Research structure

The thesis is divided in three parts to answer the different research questions: The first part aims to identify determinants for the hourly number of rentals (RQ1) and to find differences in usage patterns among different SBRT-stations (RQ2) (see upper blue box in Figure 5). This is done by conducting a literature review to detect determinants identified for services similar to SBRT such as one-way free-floating bikesharing. Then, the outcome of the literature review is used to identify the most significant determinants using the provided booking dataset by the SBRT-operator NS and additional data sources from NS and the Royal Meteorological Institute of the Netherlands KNMI. The identification of significant determinants is performed using a MLR across a filtered set of stations in combination with a backward search algorithm with hourly SBRT-rentals in the year 2018 serving as dependent variable. To gain further insights and to assess to what extent the significance level of the identified determinants might differ between stations, an additional descriptive in-depth analysis of eight exemplary stations is conducted. The exemplary stations are selected based on their R^2-performance when conducting a station specific MLR using the previously identified determinants.

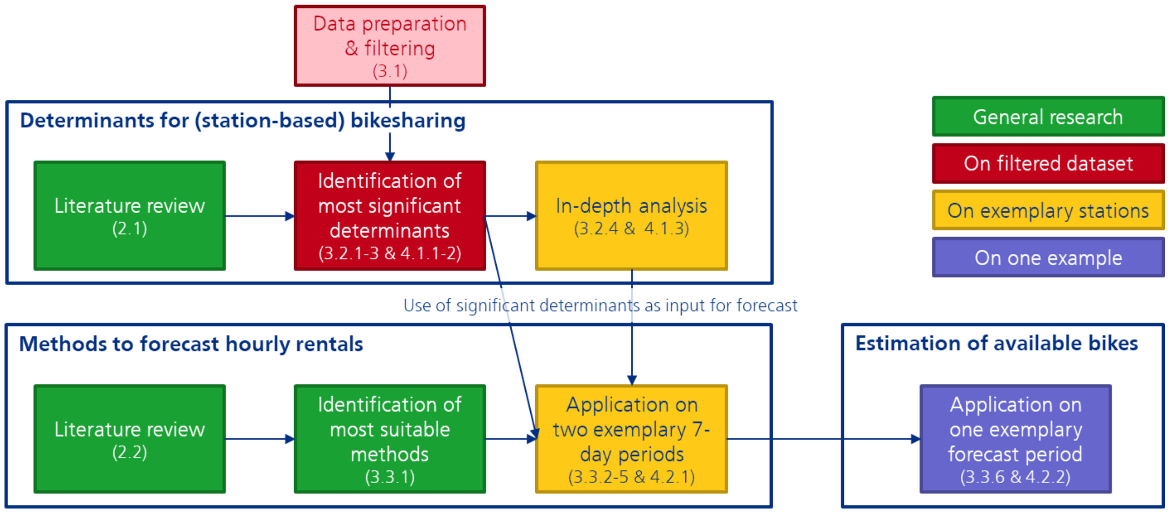

Figure 5: Conceptual structure of the relationships between the different sections of the thesis (corresponding sections in the report)

The second part aims to answer to what extent the evidence obtained from the first part can be used to predict future hourly rentals at a SBRT-station using time-related information only (RQ3), and whether forecasting models including additional determinants can improve the predictability (RQ4) (see lower left blue box in Figure 5). This part also begins with a literature review to identify existing forecasting methods for (bike-) sharing schemes. The resulting insights are then used to identify forecasting methods most suitable to predict hourly SBRT-rentals. Three methods are selected, one using time-related information only (a univariate model), and one being able to use multiple determinants as input (a multivariate model). An additional distinction is made regarding their statistical explanatory power. The forecasting methods are then applied on two different periods of the year 2019. They are separately performed for the eight exemplary stations and each use training data of the preceding 365 days to predict the following seven days on an hourly basis. The results of the different methods are then compared to identify a most suitable forecast method for the given SBRT-system.

Relying on the results from the second part, in the third part the results of one forecasting method for one SBRT-station are used to illustrate how an hourly rental forecast allows an estimation of the number of bikes available per hour within the forecasted period (lower right blue box in Figure 5). To achieve this, a combination of the forecasted rentals per hour with historical information about rental durations at that station is used.

2. Literature review

To capture the two different pillars this thesis is based on, bikesharing and time series forecasting, first a literature review is conducted to assess the status quo of research in both domains. First, section 2.1 discusses the different concepts of bikesharing, the determinants for bikesharing usage, and the combination of bikesharing as part of the multimodal combination with PT. Then, section 2.2 explains and assesses existing methods used for time series forecasting in the context of bikesharing and round-trip sharing.

2.1 Bikesharing

The following section provides an overview of scientific research regarding bikesharing. While multiple existing studies analysed bikesharing schemes in a specific city or region, only a limited number gathered the impact across multiple cities. Also, there is a high number of studies related to one-way bikesharing, but few existing studies investigate SBRT-systems. Thus, the insights gathered of this literature review are intended to provide a general overview of the topic. This acts as starting point to identify potential determinants for SBRT-demand by discussing the applicability of the results obtained from other bikesharing-systems on SBRT.

2.1.1 Introduction

As mentioned in section 1, bikesharing is a part of modern shared mobility, but has a history dating back more than 50 years. The first bikesharing scheme was implemented as experiment in 1965 in Amsterdam using private bikes made freely available on the streets. Individuals could just grab a bike when- and wherever available and leave it at their destination for other users (i.e., a free-floating one-way scheme). This scheme, nowadays referred to as the 1st generation of bikesharing, only survived a couple of days because of vandalism. Later, in the nineties, a first station-based system emerged across cities in Denmark, in which the bikes could be used after placing a coin as deposit, and therefore could only be used to cycle from station to station (i.e., a station-based one-way scheme). This is later referred to as the so-called 2nd generation of bikesharing. By the end of the nineties, emerging technological and digital improvements such as electrical locks or on-board computers allowed an easier implementation and upscaling of bikesharing schemes, leading to the 3rd generation of bikesharing. Schemes relying on the new technologies were implemented in around 120 different cities throughout the world, with most of them remaining station-based one-way schemes. (DeMaio, 2009; Ploeger & Oldenziel, 2020; Shaheen et al., 2010)

With the further rise of the internet came the integration of real-time tracking and availability information. Since 2010, these innovations, in combination with mobile payments and the cheap production of robust bikes, led to the emergence of so-called dockless bikesharing systems (i.e., free-floating one-way schemes) first in China, then followed by a tremendous increase of fleets throughout the world (Z. Chen et al., 2020). These smartphone- and algorithm-driven bikesharing schemes are referred to as the 4th generation of bikesharing by Boor (2019) and Chen et al. (2020). Shaheen et al. (2010) provide a different definition of the 4th generation, namely bikesharing systems which are 'integrated in public transportation using smartcards.' This led to Si et al. (2019) defining dockless, smartphone-based bikesharing schemes as 5th generation. To better distinguish the different, currently existing types of bikesharing, they are described in the following and visualised in Figure 6 based on a classification by van Waes et al. (2018). The authors classify systems based on their use case (one-way vs. round-trip) and availability (station-based vs. free-floating).

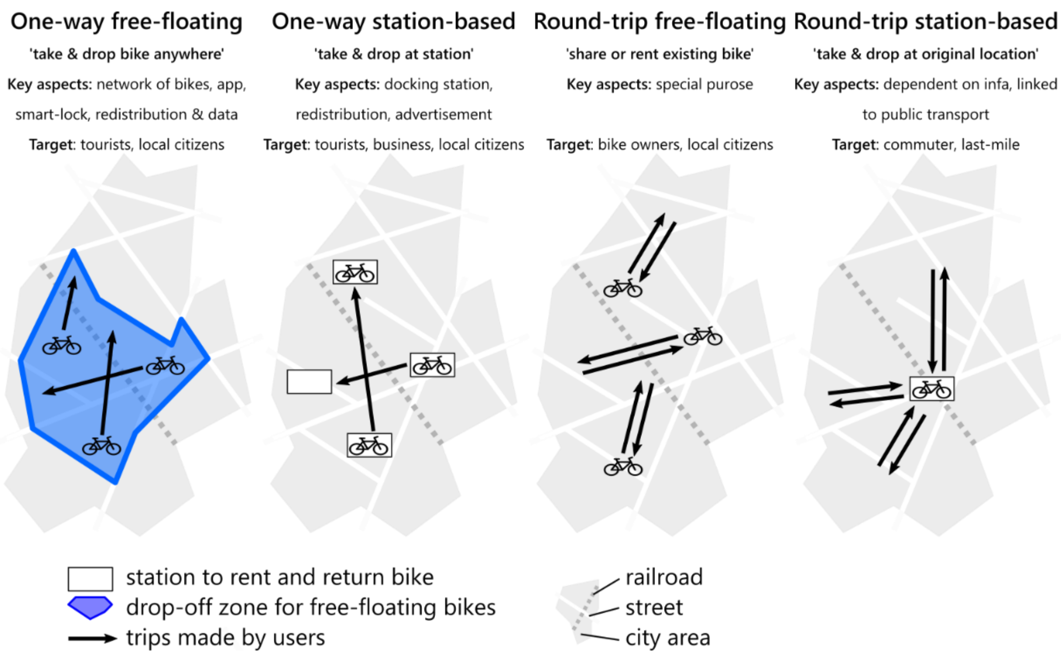

Figure 6: Bikesharing typology based on van Waes et al. (2018) (own visualisation)

One-way: The service design currently most present around the world is the one-way system, which allows users to travel from one point to another without the necessity of returning a the bike to its origin. *One-way station-based* systems are often established on behalf of or in cooperation with public institutions with the aim to enhance cycling among citizens and tourists. Users can take and leave the bikes at predefined fixed and/or virtual stations. *One-way free-floating services* are more flexible as bikes can be parked at any place within a predefined zone, which is often restricted using geo-fencing. These systems are often implemented by global companies such as Mobike or Lime, without public funding, but a variety of local operators implemented similar systems throughout the world as well. (DeMaio, 2021; Todd et al., 2021; van Waes et al., 2018)

Round-trip (or two-way): Round-trip bikesharing schemes can be described as 'rent-a-bike', as users are able to rent a bike at a defined spot to which they must return it after usage. These systems are implemented on a large scale in only two countries, OV-fiets in The Netherlands and Bluebike in Belgium. This is remarkable as, in comparison, there are currently almost 1.900 operating one-way schemes throughout the world (DeMaio, 2021). But *station-based round-trip* (SBRT) systems experience an increased popularity as addition to rail-services to be used for the 'last-mile' between a train station and the activity-end of a multimodal trip especially in the two previously mentioned systems in The Netherlands and Belgium (de Visser, 2017; Jonkeren et al., 2021). Other use cases are hotels allowing tourists to visit a city by bike (Genikomsakis et al., 2021) or companies encouraging employees to use bikes for work-related trips as part of a company-wide mobility management

(Vanoutrive et al., 2010). While these concepts are all relying on fixed stations at which often multiple bikes are made available, for these services a free-floating counterpart exists as well: The sharing of (privately owned) bikes, often referred to as peer-to-peer (P2P) bikesharing. According to van Waes et al. (2018) these services are considered as *free-floating round-trip* even though technically each location a bike is made available by an individual person serves as a 'station'. By combining the P2P-approach with train travel, van Goeverden & Homem de Almeida Correia (2018) conclude that individuals having reciprocal commuting relations could share each other's bikes to reduce the total number of required bikes.

Bikesharing generates a lot of data (real-time location, time of pick-up and drop-off, bike-identification numbers), which is either made available to scientists by operators or gathered through data mining (O'Brien et al., 2014). With the sharp rise of one-way bikesharing all over the world throughout the last decade, the availability of data accessible for scientific research led to multiple studies investigating different service components. The results will be presented and discussed in the following sections.

2.1.2 Impact factors on bikesharing usage

To be able to grasp the high number of studies on bikesharing published within the last years, multiple authors summarised the relevant results. These can be divided into two categories: The ones being written before the rise of the 3rd generation of bikesharing, thus focussing on station-based bikesharing (Fishman et al., 2013; Ricci, 2015; Shaheen et al., 2010), and those including the 4th generation covering the recent popularity of the topic (Eren & Uz, 2020; Gu et al., 2019a; Médard de Chardon et al., 2017; Shaheen & Cohen, 2021; Si et al., 2019; Todd et al., 2021). Many studies rely on data obtained from systems in China and the USA, with results having limited applicability to Europe and The Netherlands. In the following, a selection of the factors considered to be most relevant will be discussed and set in relation to SBRT-schemes based on categorisations by Todd et al. (2021) and Eren & Uz (2020):

System accessibility and availability:
A higher density of stations and/or a higher spatial availability of free-floating bikes throughout an area has a positive impact on the number of bookings as people prefer having available bikes as close to them as possible (Médard de Chardon et al., 2017), while 500 m is considered to be the distance most users are willing to walk to a station of a station-based scheme (Gu et al., 2019b). The same holds for the capacity of stations and the number of available bikes within a station-based system in case that the general trip generation around a station provides sufficient demand (Eren & Uz, 2020).
No research has been done yet on the catchment areas of SBRT-services, as these are mostly included in public transport transfer hubs. In case of SBRT-stations in or close to train stations, it might be interesting to investigate whether the distance between the train station platforms and the SBRT-station, i.e., the transfer distance between both modes, might influence the number of SBRT-bookings. The same holds for the number of bikes available at a station, as it is yet unknown

to what extent the general probability of being able to get a bike at a certain time affects the demand.

Bike availability:

For one-way systems the availability of bikes is a significant impact factor (Ricci, 2015). In the US, for optimal usage 10-30 bikes per 1000 residents are likely to be the best match of supply and demand, as a low number of bikes available leads to a low availability and thus low usage, while a high number of bikes reduces operational and resource-efficiency (S. K. J. Chang & Ferreira, 2021). In the case of SBRT-schemes, no recent scientific evidence exists on the causality between the availability of bikes and the number of bookings. According to Villwock-Witte & van Grol (2015), the OV-fiets-scheme shows an increase from 800 bikes and 8.500 bookings in 2003 to 8.500 bikes and 1.5 million bookings in 2013. Until 2019, the fleet expanded even further to 20.000 bikes while having 5.3 million bookings and the operator NS is having plans to further expand the service as there are still stations in which sometimes demand exceeds supply (Ploeger & Oldenziel, 2020).

Weather conditions:

Eren & Uz (2020) created an extensive literature overview regarding the impact of weather conditions on the number of one-way bikesharing rentals (see Table 1). There is to date no literature on the impact of weather conditions on SBRT-demand, but as their impact might be similar to one-way systems, the corresponding results are shown in Table 1.

The results show that sunny, not windy summer days with temperatures between 10°C and 30°C are likely to attract most trip demand for bikesharing, while colder temperatures, precipitation, wind, and high humidity lead to people avoid using bikesharing and cycling in general. But these results are general tendencies: According to a study using bike counting stations and weather data in 30 German cities, cyclists in cities with a higher share of young people and a denser cycling network are more robust to unfavourable weather conditions (Goldmann & Wessel, 2021).

Table 1: Weather condition impact factors on bikesharing trip demand based on a literature review by Eren & Uz (2020) (+++ = strong positive correlation to --- = strong negative correlation, o = no correlation, ? = correlation unknown)

Season	Impact	Weather type	Impact	Precipitation	Impact	Temperature	Impact
Winter	---	Sunny	+++	Snow	---	< 0°C	---
Summer	+++	Partially sunny	++	Light rain	-	0-10°C	+
Spring	++	Rainy	---	Intermittent rain	-	10-20°C	++
Autumn	++	Windy	---	Heavy rain	---	20-30°C	+++
		Cloudy	+	High Chance of rain	o/-	> 30°C	?
		Foggy	o/-	Low chance of rain	o/+	Scorching heat	---

Wind	Impact	Humidity	Impact
Light wind	++	Rel. humidity	---
Strong wind	---		

Cycling infrastructure:

According to the Dutch 'Design Manual for Bicycle Traffic', there are five quality design principles to engage citizens to cycle: *Safety* (minimise risk of accidents), *Directness* (minimise detours), *Cohesion* (maximise connectivity within a network), *Attractiveness*, and *Comfort* (minimise physical and mental effort) (CROW, 2017). Implementing these design principles to improve cycling infrastructure is expected to lead to a higher usage of bikesharing-schemes. Improving the cycling

infrastructure, no matter whether it is a cycling lane on the road or a separate pathway, is found to have a positive impact on one-way bikesharing usage (Eren & Uz, 2020).
The positive impact of cycling infrastructure is likely to be the case for SBRT demand as well, even though no study investigated this causality yet. As this research focusses on the revealed booking data without having knowledge about the exact routes, the impact of cycling infrastructure will be left out, but should be kept in mind, as the Netherlands is known for having a more advanced cycling infrastructure compared to most other countries (Fishman, 2016).

Topography:
According to the studies gathered by Todd et al. (2021) a hillier topography has a negative impact on the bikesharing usage. For one-way systems, a main problem in hillier areas is that people are more likely to use the system downhill than uphill, making rebalancing necessary to even out the imbalance of available bikes, especially when slopes exceed more than 2%. First schemes include e-bikes in their fleets to overcome this problem (Eren & Uz, 2020).
To the knowledge of the author there is no literature in the context on SBRT and topography. In general, topography might have an impact on the overall acceptance because of the higher effort of using the system. In the following research, the topography as determinant is left out as the Netherlands is a mostly flat country.

Land use:
In their literature overview, Eren & Uz (2020) pay special attention on the impact of land use on bikesharing-usage: A higher density of residential housing around bikesharing-stations shows a high positive correlation regarding trip generation. On the other end of trips, a higher density of office and commercial buildings as well as a short distance to schools and universities leads to a higher attraction during the week, while recreational areas such as parks, lakes, and the seaside result in higher attraction during weekends. (Eren & Uz, 2020)
Even though no distinct literature exists for round-trip schemes, it can be expected that especially multimodal trip chains, in which SBRT-systems are expected to play a significant role, are likely to show similar patterns (Nello-Deakin & Brömmelstroet, 2021). The bike-train combination will be further discussed in section 2.1.3.

Temporality:
As previously described, the usage of bikesharing-schemes changes over different seasons, with a higher usage in summer than winter. Most studies investigating the usage throughout the week for specific systems see a clear difference in usage patterns between weekdays and the weekend (Gu et al., 2019a; O'Brien et al., 2014) The findings are confirmed by a cluster-analysis performed by Todd et al. (2021) including 322 station-based free-floating systems. According to the authors, the distribution throughout the day slightly differs between systems (e.g., different starting time of morning peak), but the general patterns are quite similar: There exist both a morning and an evening peak throughout weekdays and a moderate usage during afternoons on weekends. Regarding the usage during peak hours, Jensen et al. (2010) discovered that during these times bikesharing competes with cars in terms of travel time due to congestion, making the modal shift towards cycling more attractive. Todd et al. (2021) also revealed that while some systems with a comparatively high

overall usage have a high number of trips per bike and day (TBD) on weekdays (4.6-4.9) and a lower one on weekends (3.8-4.2), 72% of all systems included in their comparison have TBD-values around 0.9-1.0 on both weekdays and weekends. The authors conclude that these schemes are operated 'inefficiently'.
It is to be investigated whether the booking patterns of SBRT show similar patterns, as the temporal use is likely to differ from one-way schemes. This is reasoned by the fact that users do not stop a booking after reaching their destination, instead their booking continues until returning their bike at the same station.

Socio-demographic characteristics:
The population in the area served by a bikesharing scheme plays a significant role in its success: A higher population density in an area is found to have higher bikesharing usage (Todd et al., 2021). But when investigating the impact of income distribution, no overarching trend can be found as user profiles differ between different bikesharing-systems. Additionally, more bikes tend to be provided in wealthier areas, leading to self-selection and the image of 'wealthy early-adopters' (Todd et al., 2021). But as Goodman & Cheshire (2014) found out, also people living in more deprived areas are willing to use bikesharing when receiving a sufficient supply and an affordable pricing policy. More distinguishable throughout systems around the world are other user characteristics: bikesharing-systems tend to be used by a higher proportion by male, white and/or higher education individuals compared to the average population (Eren & Uz, 2020; Todd et al., 2021).
There is to date no literature focussing solely on socio-demographics of SBRT-schemes due to the limited availability of studies and considered out of scope for this study due to a lack of available data.

Existing transportation network:
First studies existing regarding the potential competition between bikesharing and existing PT. It was found that PT trips requiring transfers are more likely to be replaced with bikesharing, leading to the suggestion that areas with comparatively low public transport service quality might be *'a promising target for [bikesharing]'* (Leth et al., 2017, p. 149). Eren & Uz (2020) concluded in their literature review that bikesharing competes with PT services on trips with a shorter distance, while on longer trips it substitutes these by serving as access and egress mode to and from PT stations. Also, in times when PT service quality is reduced, e.g. at night, the usage of bikesharing is found to increase due to a lack of alternatives (Fishman et al., 2013). Furthermore, the overall number of PT stations in an area, may it be bus, metro, or train, are found to have a positive correlation with the expected number of rides starting and ending in that area. Especially having a short distance to PT hubs is found to increase the number of bikesharing-rentals. (Eren & Uz, 2020)

To conclude: If a bikesharing-scheme is successfully integrated into the existing public transportation network, it can *'synergise rather than compete'* (Böcker et al., 2020, p. 399) with existing PT, allowing for a modal shift away from the car towards multimodal trip chains (Böcker et al., 2020). In The Netherlands, research has been done on the combination of bike and train within a multimodal trip chain. As most SBRT-stations are located at or close to public transport stops and the focus of this thesis will be on these public-transport related SBRT-stations, the characteristics of the bike-train combination will be discussed in further detail in the following section.

2.1.3 Bikesharing usage in combination with train travel

Throughout the last decade more research evolved investigating multimodality in trip chains. According to the literature review by Eren & Uz (2020), combining public transportation and bikesharing can provide various advantages to traffic (see also Figure 7). According to the authors it is important to acknowledge that different bikesharing systems have different targets: While some systems seek to provide an alternative for the (overcrowded) PT network, others aim to increase accessibility in areas underserved by PT. In general, the authors note that bikesharing stations being closer to PT hubs have an increased usage. The same goes for bikesharing systems which can be booked using PT smart cards, as this is reducing the hurdles to use the system. (Eren & Uz, 2020)

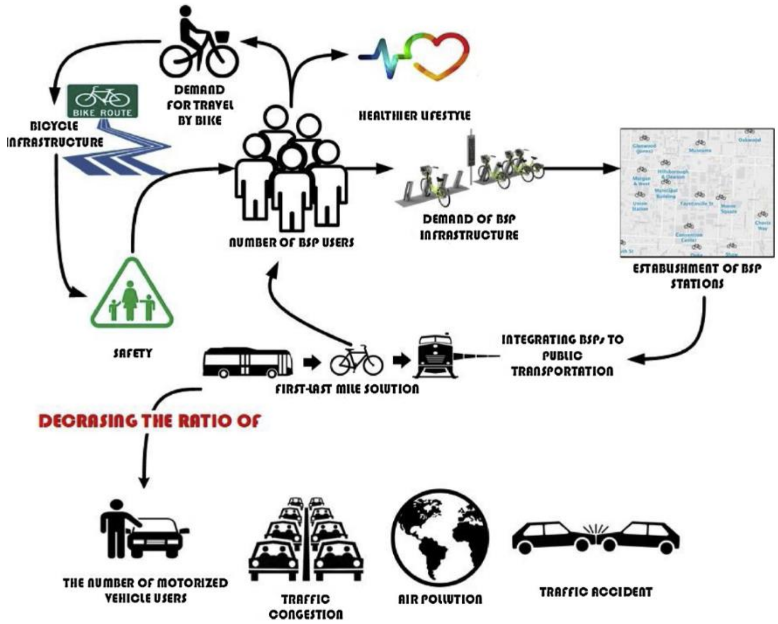

Figure 7: Integration of bikesharing into public transportation (Eren & Uz, 2020)

To unravel the implementation barriers and solutions of the bike-train combination, the EU developed, based on Dutch experiences and in cooperation with stakeholders from different regions in Europe, a report to be used by railway authorities willing to enhance the bike-train combination. The report emphasizes the usefulness of SBRT on the activity-end of train trips using OV-fiets and BlueBike as examples (van Zeebroeck, 2017). The following will dig a bit deeper into these and additional scientific findings:

Regarding the relevance of modes in multimodal trips it was found that individuals travelling by train assign a relatively high importance to quality of access and egress legs of their trip, even when these have a comparatively low share of the overall travel time (Brons et al., 2009; Hoogendoorn-Lanser, van Nes, & Hoogendoorn, 2006; van Nes et al., 2014). Hence, when trying to enhance multimodal trips, SBRT can help in making the egress leg of train trips more accessible if being well integrated into the train system. This is in line with Kager & Harms (2017, p. 8) stating that *'…'feeder' transit systems typically are (and need to be) better developed at the travellers' destination side of a transit journey compared to the travellers' home-side.'* According to the authors, here lies a potential for SBRT-systems, as walking is only covering a limited distance, while PT is often not suitable to the diffusion of destinations.

In total, van Mil et al. (2020) identified forty-two factors impacting the choice of people to use this combination, stating how complex the decisions are to decide for or against completing a trip using both bike and train. The authors reflect that while some factors such as weather, employment, demography are context dependent, other factors such as cycling infrastructure and seamless transfers between the different modes can be influenced by local authorities. Regarding the integration of train and SBRT on the egress leg of trips, this can be supported by the direct integration of OV-fiets bookings into the nationwide smartcard-system used for PT and the steady increase of ridership in The Netherlands (NS, 2021; Villwock-Witte & van Grol, 2015).

First research also observed the user characteristics of bike-train travellers: According to a survey amongst individuals within the panel of the Dutch rail operator NS conducted by Jonkeren et al. (2021), around 44% of train travellers who travel to one of the five bigger cities in The Netherlands can be considered as 'bike-train travellers'. More than 16% of their trips are done using this combination of modes. These travellers are on average younger and more likely to hold a university degree compared to travellers using the bike-train combination less frequent. The research also indicates that bike-train travellers are more inclined to use major train stations having frequent short- and long-distance train services as their location of transfer and are likely to skip stations closer to them in case these only provide local train services. This leads to the conclusion that major stations have a wider catchment area. This finding is supported by other Netherlands-related research indicating that bike-train travellers are willing to cycle five minutes longer to avoid an additional transfer (van Mil et al., 2021) and that individuals living in the Amsterdam area are willing to cycle longer to shorten the train leg of their multimodal trip (Nieves, 2018).

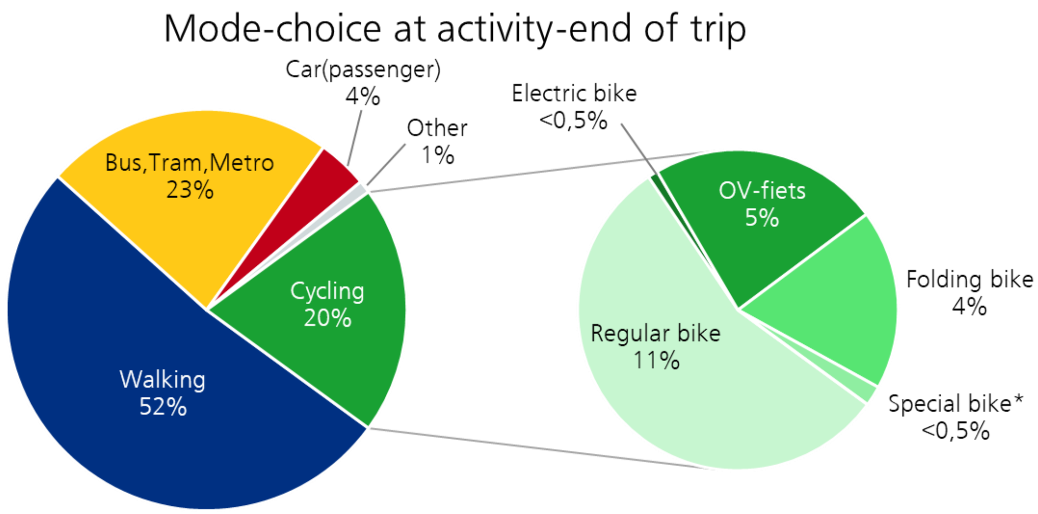

Figure 8: Mode-choice at the activity-end of train trips among the respondents within the survey conducted by Jonkeren et al. (2021), *Special bikes include racing bikes, mountain bikes, etc. (own visualisation)

When focussing on the egress-leg, the respondents of the survey conducted by Jonkeren et al. (2021) use the bike less often: As shown in Figure 8,only 20% of the trips done by the respondents include absolving the last mile by bike (For comparison: over 50% of the respondents cycled the first mile to a train station). Of those using the bike for their egress leg, around 23% indicate using an SBRT-system, in this case OV-fiets, to reach their destination, while most cyclists still use regular bikes. Also, in this case there are big differences between different cities: While 44% travellers having a destination in Utrecht indicated using OV-fiets after their train trip, in Amsterdam or Rotterdam only 12-13% indicated to do so. In other Dutch towns the average lies around 23%. When looking at the results of Jonkeren et al. (2021) it needs to be emphasized that the survey was conducted among members of the survey panel by the Dutch National Rail operator NS, and therefore is unlikely to be representative for general train travellers in the Netherlands.

2.1.4 Summary & Discussion

In general, various literature exists on the determinants to assess one-way bikesharing, while little is known about those influencing SBRT-systems (see also Table 2). And even though the findings for one-way schemes might be to a certain extent applicable for SBRT, there is to date no scientific evidence supporting this. It is likely that the use cases for SBRT differ from one-way schemes, as a rented SBRT-bike is required to be brought back to its origin. According to literature, SBRT is especially suitable for the activity-end of multimodal trips, which is supported by the continuously increasing number of trips in the existing systems. Therefore, this research will contribute a better understanding of SBRT-systems by investigating determinants for the hourly demand, which in return can help to forecast future demand.

Table 2: Summary of literature findings provided in sections 2.1.2 and 2.1.3 regarding one-way and round-trip bikesharing schemes (Orange circle = factors this research aims to fill the research gap)

Determinant	One-way schemes	Round-trip schemes
System accessibility and availability	500m walking distance to stations acceptable More bikes in neighbourhood support usage	?
Bike availability	Large-scale supply needed to generate demand	Demand is growing as supply grows
Weather conditions	Comfortable cycling weather (sunny, 20-30°C) correlates with higher demand	?
Cycling infrastructure	More advanced cycling network leads to higher demand	?
Topography	Hilly areas result in lower demand and imbalance of trips	?
Land Use	Higher density of origins and destinations (e.g., residency, offices) lead to higher demand	?
Temporality	In most systems highest demand during morning and evening peaks	?
Socio-demographic characteristics	Tendency to attract 'wealthy early adopters' as result of providing service mostly in these areas	(?) Younger and higher educated than average (only for all bike-train travellers)

Using the available historical OV-fiets booking data, a special focus of this research will be weather-related and temporal determinants, as these can be identified using the available dataset only (temporal distribution) and by combining the dataset with historical weather data (weather conditions). Further factors such as land use and system accessibility are left out due to their location-specific characteristics, which are considered out of scope for this research. Cycling infrastructure and topography are left out as the available data allows for an analysis of the Dutch context only, and both topography and cycling infrastructure are assumed to be similar amongst different Dutch cities. Socio-demographic characteristics cannot be investigated as the used dataset does not allow for any connection between bookings and the related users for privacy reasons. While the determinants identified in this section will be used as input to identify significant determinants for the provided dataset, the following section will provide insights into existing research regarding forecasting of SBRT- and general bikesharing rentals on a short-term.

2.2 Time series forecast

The following section provides an overview of scientific research regarding time series forecasting in the domain of new mobility services. First, an introduction is given in the general concept of time series forecasting in the general domain of forecasting in section 2.2.1. Then, in section 2.2.2 based on recent literature, an overview of different forecast methods already applied for use cases on shared mobility being like SBRT, is provided. In addition, studies comparing the performance of the identified methods are described in section 2.2.3.

2.2.1 Introduction

With the increase in bikesharing services all around the world, the need to predict the demand for bikes at a certain location and time to allow for an optimisation of the service design evolved (S. K. J. Chang & Ferreira, 2021). As identified in section 2.1, temporality is expected to have a high impact on the demand for bikesharing. The so-called time series forecast models (TSFM) are suitable for data with information across multiple timesteps such as SBRT-booking data, as they are specifically developed to identify patterns in historical data to predict the future. Multiple highly advanced TSFM already exist in various domains such as the prediction of weather, electricity consumption or the global population. What these models share is that they use general learnings and identified patterns found in historical data to predict an unknown future development.

While some models solely rely on historical data of the dependent variable to predict the future (i.e., univariate models), others add further determinants as independent variables to explain variation in the given dataset and thus increase accuracy of the prediction (i.e., multivariate models) (see Figure 9 for visualisation). Univariate models have the advantage of comparatively low requirements in terms of data acquisition as they solely rely on historical data of the predictable variable. Multivariate models require, in case of temporal varying determinants, data representing the determinants having the same time-step length as the given data to allow for a matching of the datasets. Furthermore, additional data representing the determinants is required for the predictable time horizon, as these are then used as an input to increase the accuracy of the predictable variable.

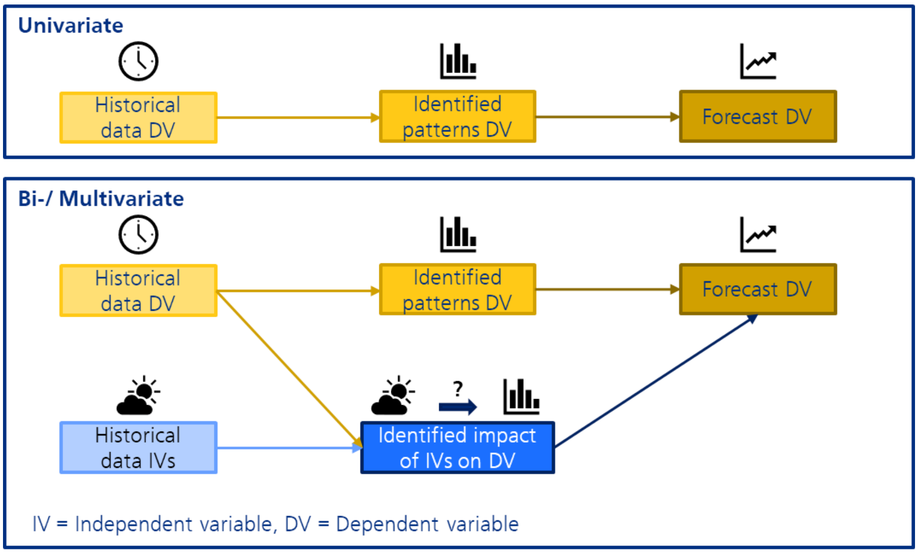

Figure 9: Visualisation of differences in univariate and multivariate prediction and required data (yellow = dependent variable, blue = independent variables, using weather as example)

2.2.2 Method description

Each forecast model comes with advantages and limitations for specific cases of forecasting, and there is no *'one fits all'* solution to forecast time series data in general and travel demand in particular (Tsai et al., 2009). To overcome the limitations of applying a single model, hybrid models become more and more popular, using different models to capture distinct characteristics of time series patterns (Kaltenbrunner et al., 2010; Z. Ma et al., 2014; Pohlmann & Friedrich, 2013). According to Tan et al. (2009), the process of hybrid prediction commonly consists of three steps: Pattern identification, pattern modelling, and pattern combination. The second step, pattern modelling, is highly determined by the previously identified patterns. In the case of bikesharing, these patterns can be separated into patterns differing per time of day, day of week, and month of year, amongst others (Todd et al., 2021). While in a single forecasting model all these different patterns are estimated using the same method, a hybrid model uses different models to assess the different patterns as reliable as possible, and then combines the outcomes of their forecasts by weighting them against each other (Z. Ma et al., 2014). This weighting combination is often done using models based on neural networks due to their good performance (Karlaftis & Vlahogianni, 2011).

According to Sohrabi & Ermagun (2021), multiple methods exist to predict the future demand of one-way bikesharing services. The authors identify an increase of research published starting 2017, with most studies moving away from statistical-based methods towards the application of neural networks (NN) Karlaftis & Vlahogianni (2011) describe the differences between the two 'schools of thought' in transportation research, statistics, and neural networks, as following:

'… [Statistics] is the mathematics of collecting, organizing and interpreting numerical data […]. Statistics have solid and widely accepted mathematical foundations and can provide insights on the mechanisms creating the data. However, they frequently fail when dealing with complex and highly nonlinear data […]. The second, [Neural networks], combines elements of learning, adaptation,

evolution and fuzzy logic to create models that are 'intelligent' in the sense that structure emerges from an unstructured beginning (the data).' (Karlaftis & Vlahogianni, 2011, p. 387)

To assess the differences between statistical- and NN-based methods used for forecasting shared mobility, a brief description of the different methods is shown in the following table:

Table 3: Common forecast methods used for station-based and free-floating mobility service time series forecasting, based on Alencar et al. (2021) and Saadi et al. (2017) (methods considered for further analysis)

Name	Abbreviation	Characteristics	Description
Auto Regressive Integrated Moving Average	ARIMA	Statistical based Univariate	Regression model in which the dependent variable depends on its past values (auto-regression) in combination with an indication of the regression errors as a linear combination of the past errors (moving-average)
Seasonal ARIMA	SARIMA	Statistical based Univariate	Same as ARIMA, but also includes parameter(s) representing seasonality.
Prophet	Prophet	Statistical based Univariate	Trend model consisting of separate Fourier-models capturing overall trends, seasonality, and holidays, making it able to capture extreme events in seasonal patterns
Multiple linear regression	MLR	Statistical based Multivariate	Regression model in which the dependent variable is a result of the values of multiple input variables, which each are assigned a different weight
(Bagged) Decision Tree	BDT	NN-based Multivariate	Decision tree (DT) follows branches for which the case expression at a node = TRUE (e.g., weather_rain = TRUE, month_september = FALSE). The decision nodes are defined based on machine learning. Bagged DT (BDT) includes multiple trees to better capture decision-making, then averaging outcomes of all decision trees
Gradient boosted tree	GBT	NN-based Multivariate	Ensemble method combining 'weak learner' predictions created by a decision tree into a 'strong learner' by optimizing each learning iteration using a predefined loss function
Random Forest	RF	NN-based Multivariate	Like BDT, but in addition random selection of subset of predictors to perform decision splits
Long Short-Term Memory	LSTM	NN-based Multivariate	Based on Recurrent Neural Network (RNN), LSTMs learn iteratively over time while having a short-term memory to influence forecast of next time interval in case of differences compared to the general trend

Of the described statistical methods, solely the MLR allows an easy implementation of multivariate input. NN-methods are more flexible in terms of using multivariate input, as the NNs autonomously decide which independent variables to use to predict the dependent variable. Further, while statistical methods are found to have more explanatory power by providing insights into the data's structure, NN-based methods try to accurately represent the underlying, unknown properties of a dataset to provide good predictions. At the same time, the learning process of NN-based methods is likely to differ per applied iteration, resulting in not only one, but multiple models with different outcomes, making interpretation and further use of the results less reliable. Also, the weighting of variables within the NN-method and/or the reasoning behind decisions made by it when applying for example Decision Trees, remain unknown, resulting in NN-methods being sometimes titled as *'black boxes'*, making it difficult for practitioners to interpret the results. (Karlaftis & Vlahogianni, 2011)

2.2.3 Method performance

This research uses both a statistical and a NN-based forecast method to predict SBRT-rentals, as using two separate methods allows for a comparison regarding their prediction accuracy and explanatory power. The selection of the methods is based on multiple papers investigating the performance of different forecast methods for shared mobility services. The most common used indicators, which are also used to evaluate the forecasting performance in this thesis, are the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), which are both calculated using the difference between the observed number of rentals per hour y_i and the corresponding predicted value $\hat{y}_i$ per predicted timestep i across the sample size n, as shown below. While the MAE scales the error linearly, the RMSE squares the errors which assigns a higher weight to larger errors between the observed and predicted values. The RMSE is thus more useful when the aim is to avoid large errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

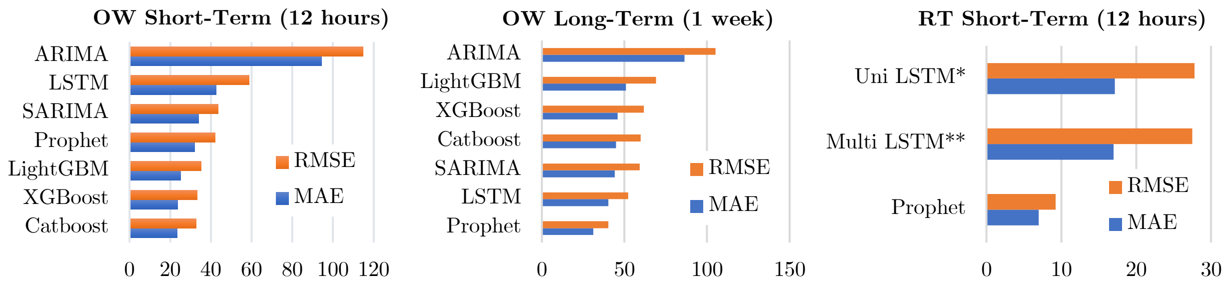

Figure 10: Performance indicators for carsharing rental prediction by Alencar et al. (2021)
(OW: One-way, RT: Round-trip, *Univariate LSTM, **Multivariate LSTM)

Multiple studies investigated the performance of different forecasting methods on both short- and long-term for one-way bikesharing and one-way and round-trip carsharing schemes using RMSE and/or MAE as performance indicators. The study focussing on carsharing is selected as this is to date the only study assessing forecast methods for two-way sharing schemes. Alencar et al. (2021) assessed the performance of different forecasting methods to predict the hourly rentals of both one-way and round-trip carsharing. While boosting methods perform best when it comes to predicting the following twelve hours, the statistical method Prophet and the NN-based method LSTM performing best when predicting one week in advance (see Figure 10, left & middle). When applying these two methods to predict the short-term rentals of a round-trip carsharing scheme, which concept-wise is has similarities to SBRT-systems, Prophet is found to outperform both uni- and multivariate LSTMs (see Figure 10, right). Here, it needs to be emphasized that the forecast was performed on one period only, and it thus cannot be guaranteed that the models would perform similar when being applied for various times of the week/year.

Table 4: Identified forecast methods for bikesharing schemes based on Sohrabi & Ermagun (2021) and Albuquerque et al. (2021), with additional literature

Authors	Model	Spatial Scale	Time Horizon	Location
Froehlich et al. (2009	Bayesian network	Station-level	10 minutes	Barcelona
Kaltenbrunner et al. (2010)	ARIMA	Station-level	1 hours	Barcelona
Yoon et al. (2012)	ARIMA	Station-level	5 minutes	Dublin
Gallop et al. (2011)	SARIMA	System-level	12 hours	Vancouver
H. Xu et al. (2013)	Support vector machine	System-level	1 day	Hangzhou
Y. Li et al. (2015)	GBT	Cluster of stations	1 hour	Washington, DC & New York City
Yang et al. (2016)	RF	Station-level	1 hour	Hangzhou
Ashqar et al. (2017)	RF	Station-level	15 minutes	San Francisco
P.-C. Chang et al. (2017)	NN	System-level	1 day	Washington, DC
P.-C. Chen et al. (2017)	RNN	System-level	1 day	New York City
Feng & Wang (2017)	RF	Station-level	1 hour	Washington, DC
Hulot et al. (2018)	GBT	Station-level	1 hour	Montreal
Lin et al. (2018)	Graph convolutional NN	Station-level	1 hour	New York City
C. Xu et al. (2018)	LSTM	Area-level	10/15/20/30 minutes	Nanjing
Zhang et al. (2018)	HA, MLR, LSTM	Station-level	15 minutes	Ningbo
H. Xu et al. (2019)	MLR, RF	Cluster of stations	1 hour	Chicago
Xiao et al. (2020)	Spatiotemporal graph convolutional NN	Station-level	10 minutes	Wenling
Boufidis et al. (2020)	GBT	Station-level	1 hour	Thessaloniki
Du et al. (2020)	RNN, LSTM	Area-level	1 hour	New York City
D. Li et al. (2020)	High-Order Singular Value Decomposition LSTM	Cluster of stations	1 hour	New York City
Luo et al. (2021)	Local spectral graph convolution LSTM	Station-level	5 minutes	Zhejiang
Gao & Chen (2022)	MLR, RF, Support vector machine	Station-level	1 hour	Seoul

When it comes to predicting rentals one-way bikesharing schemes, a systematic literature review on machine learning applications conducted by Albuquerque et al. (2021) recommends the usage of LSTMs to predict future demand, as this method is able to recognise patterns over multiple time sequences. Other promising approaches identified by the authors are the usage of random forest (RF) and gradient boost trees (GBT). Additionally, because of the increase in available data throughout the last years, the usage of LSTM-based methods to predict one-way bikesharing demand increased both for free-floating and station-based systems (see Table 4).

In recent literature investigating the performance of NN-based methods, MLR is used as reference method, as it provides weights for the different determinants in terms of their correlation with the dependent variable (Feng & Wang, 2017; Gao & Chen, 2022; Zhang et al., 2018). The added value of the MLR is its capability of capturing multiple determinants while providing a good interpretability of the results and a low computational complexity. Further, the assigned weights per variable allow for an interpretation of the magnitude of their correlation with the dependent variable, and whether the correlation has a positive or negative sign. The limitation of MLR is that it is only able to capture linear correlations between the determinants and the dependent variable and becomes less reliable when the dependencies are not of a linear nature. Thus, the model serves as multivariate, statistical method which allows for first insights into dependencies in a data set. In terms of forecasting of hourly bikesharing rentals, in recent studies on one-way bikesharing MLR applications were outperformed by more advanced, NN-based methods (Feng & Wang, 2017; Gao & Chen, 2022; Zhang et al., 2018). To date there is no assessment on whether this is the case for SBRT-systems as well.

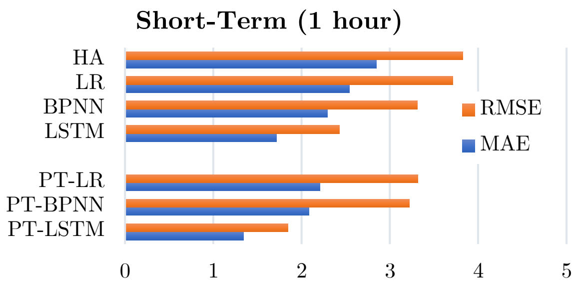

Figure 11: Performance indicators for bikesharing rental prediction by Zhang et al. (2018)

When focussing on the performance of uni- and multivariate forecasting methods for a station-based bikesharing scheme, Zhang et al. (2018) applied different methods on a short-term horizon of one hour being split up into 15-minute intervals. The authors perform a comparison between the statistical approaches historical averaging (HA) and (multiple) linear regression (LR), a back-propagation NN (BPNN), and a LSTM. Additionally, the latter three methods are transformed into multivariate models, using the number of PT travellers at the closest PT station as additional input variable. The performance of the different models is shown in Figure 11, showing LSTM outperforming the other models in both uni- and multivariate applications.

To conclude, Prophet seems most suitable to forecast the demand for a round-trip sharing system, while LSTM is more suitable for bikesharing due to the satisfactory performance across multiple studies. Additionally, LSTM allows to include independent variables, making it suitable as multivariate model. Further, MLR allows multivariate input for a statistical model, thus serving as a bridge between the univariate, statistical model Prophet and the NN-based, uni- and multivariate LSTM.

To conclude, the conducted literature review provides potential determinants for SBRT-demand and identifies forecast methods which might be promising when it comes to forecasting short-term demand for SBRT-systems. These findings provide the baseline for the following research methodology and application.

3. Methodology

The following section describes the methods used and assumptions taken to identify significant determinants of SBRT-demand, and to later predict short-term demand for SBRT-systems. To do so, the following is structured based on the research structure described in section 1.4:

First, in section 3.1 the data preparation, selection, and combination are described, which is necessary to understand and prepare the environment the following analysis is based in. Then, in section 3.2 the approach is described to identify significant determinants for hourly SBRT-rentals. The method used for the identification is a MLR, as this method allows for an identification of the different variables in terms of their explanatory power for the variance in the hourly rental data. Two different steps are conducted: First, an MLR is performed on a dataset including all stations to identify overarching determinants. Then, multiple MLRs are performed, one per individual station to evaluate whether the significant determinants differ across stations. For all MLRs, both temporal and weather-related determinants are used as independent variables. Lastly, an in-depth comparative analysis of eight exemplary stations is performed to unravel usage patterns within the dataset. Based on the findings of the analysis, the selection of most suitable forecasting methods is briefly described in section 3.3. The underlying concepts of the chosen forecasting methods Prophet, LSTM, and MLR are then further described in sections 3.3.2 to 3.3.4. Last, in sections 3.3.5 and 3.3.6 the performance comparison and the application of the forecast results to estimate the number of bikes available per hour are described. While the identification of determinants is based on data obtained for the year 2018, for forecasting data from both 2018 and 2019 is used. The choice of these two years was made as from 2020 onwards, the COVID-19 pandemic and related restrictions on public life had a substantial impact on mobility behaviour, making it difficult to capture recurring and year-long effects.

3.1 Data preparation

The following section provides information about the data analysis and processing to answer the first two research questions. First, the different data sources used for this research are described. Then, the filtering of resulting dataset is described, which is done to include only SBRT-stations in this analysis which are deemed suitable for potential relocation of bikes and short-term changes in the number of bikes available. Lastly, the combination of the different datasets used for this research into one dataset suitable for further analysis is briefly described.

3.1.1 Data gathering

The following research uses data provided by the Dutch national rail operator NS, which also operates the SBRT-system this research focusses on. Additionally, weather data obtained from weather measurement stations throughout The Netherlands is included, extracted from the website of the Dutch Royal Meteorological Institute KNMI. As additional time-related determinant, the

Dutch national and school holiday calendars are included. The different datasets used are described in the following and visualised in Figure 12. A full list the data used is provided in Appendix A 1.

The *SBRT-dataset* contains all individual bookings separately. It is important to mention that while bookings often consist of one bike only, there might also be multiple bikes being rented out per booking (or no bikes at all in case of maintenance or error bookings). Per booking, two timestamps are collected, one for the moment the booking started (rental) and one for the booking ended (return). These timestamps are provided one a minute-level. The dataset only contains trips having the same origin and destination.[2]

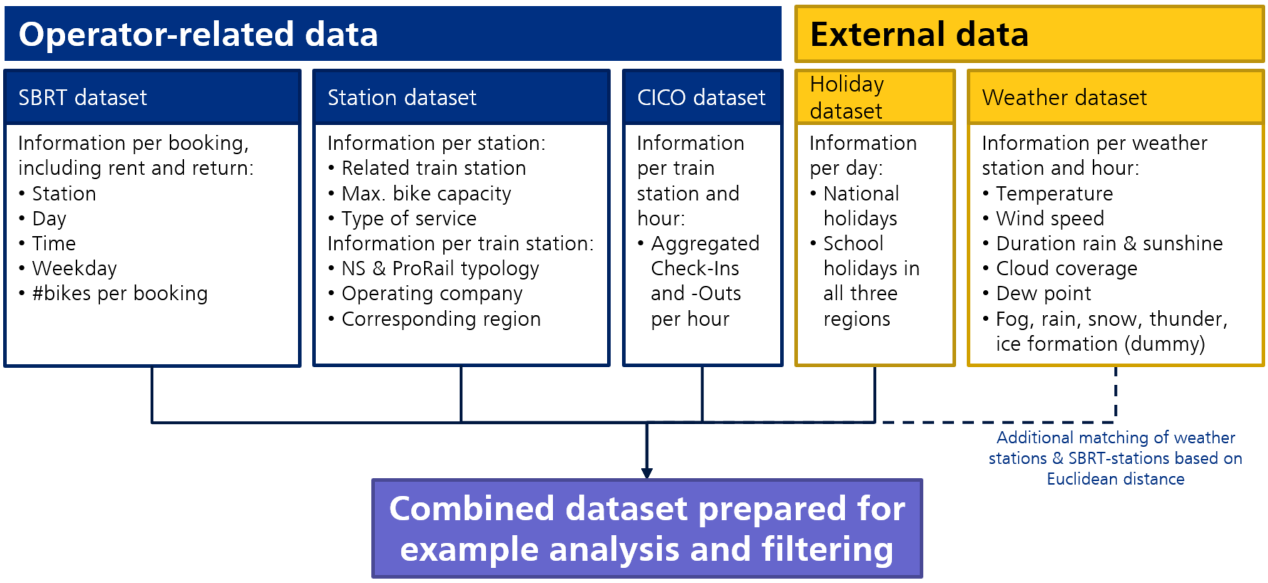

Figure 12: Used datasets

The *station dataset* includes general information about the different SBRT-stations, such as the related train station and its role in the train network. Furthermore, information is provided on what service type is used in each station[3], in which region they are located, and which the main train operators are at the corresponding train station. This dataset is available for 2019 only, leading to the assumption that the maximum number of bikes available as well as the service type are the same throughout the different years used for analysis, even though these characteristics might have changed over time.

The third operator-related dataset, the *check-in/check-out (CICO) dataset*, provides the estimated number of train passengers entering (check-in) and leaving (check-out) the train system at a certain train station, aggregated on an hourly level. The number of travellers is estimated and provided by passenger train operator NS.

Holiday-related data is external data gathered from the public-school holiday calendars as well as the national holiday calendar. The school holidays in The Netherlands are split up in three regions

[2] Technically trips between different SBRT-stations are possible, but strongly discouraged by the operator by adding a fine on each bike returned at a different station. (NS, n.d.)

[3] Within the SBRT-system provided by NS, multiple different service types can be distinguished: Staffed stations, in which service personnel takes care of the bikes, hands them out, and takes them back after a return; Different types of self-service stations with one main registration device, which after verification with a chipcard either provides access to a key box or automatically provides a bike; Self-service stations with separate boxes per bike, which each can be opened with a chipcard.(NS, n.d.)

(north, middle, south). As SBRT-system users are expected to use the service for their last mile, not only the school holidays of the region in which a station is located are relevant, but also those of the other regions, as for example users that have school holidays might travel to stations having no holidays.

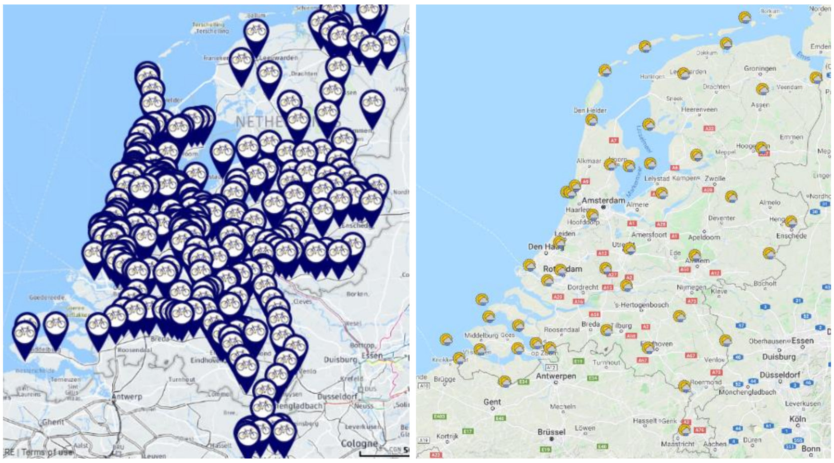

Figure 13: OV-fiets locations (left) and KNMI weather-stations (right) in NL

The other dataset acquired from an external source is the *weather-related data* provided by the KNMI. The dataset offers information on the weather at the different weather stations throughout The Netherlands on an hourly basis. Amongst others, this dataset includes information about the average temperature within an hour, the rain duration, and the occurrence of fog (for a full overview see section 3.2.1 and Appendix A 1). As the weather stations are mostly not located next to SBRT-stations, a matching algorithm is used to match the SBRT-stations to the closest weather station based on the Euclidean distance between the weather stations and the SBRT stations. As shown in Figure 14, not all train stations have the same distance to a weather station: While some stations show a comparatively short distance, for others the closest weather station is more than 20 km away. The longer the distance, the higher is the potential of providing weather data not representing the actual weather at a SBRT-station. This must be kept in mind when doing further analysis. It needs to be emphasized that this analysis only includes the weather within the hour a bike was rented. This assumes that the choice for a bike is based on the weather in that hour, leaving out the potential impact of weather forecasts for later hours.

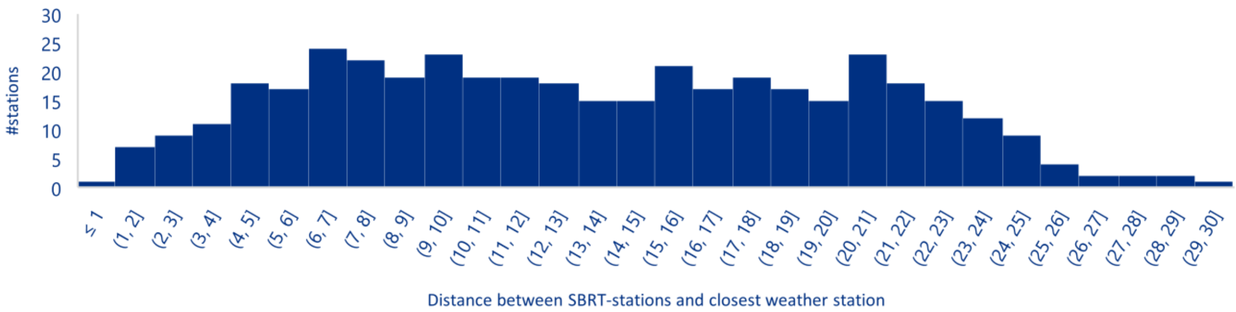

Figure 14: Distribution of distances to next weather station across all train stations

3.1.2 Data filtering

Filtering becomes necessary as not all bookings available within the SBRT dataset are relevant for this analysis. The filtering process and its impact on the size of the dataset is shown in Figure 15 and discussed in the following.

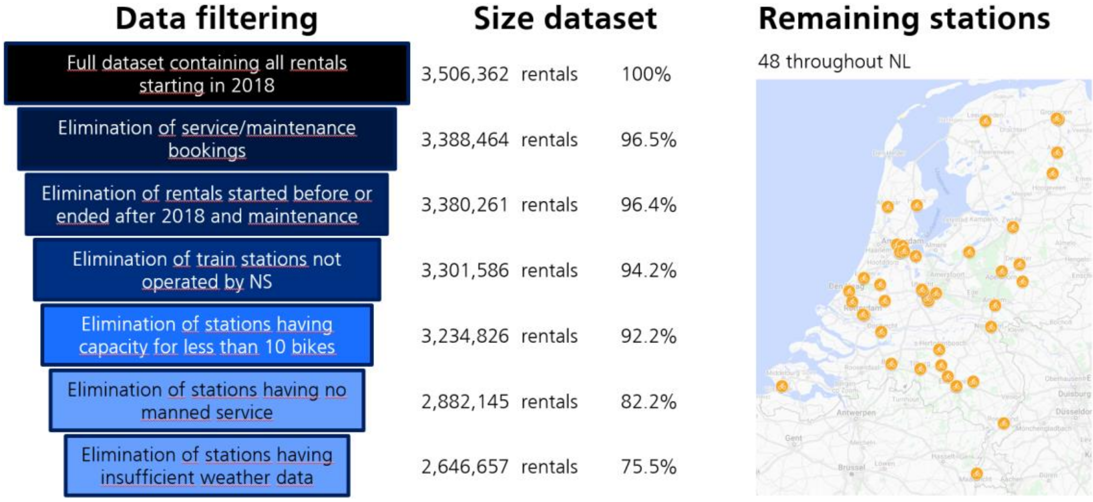

Figure 15: Filtering process, resulting reduction of the dataset, and map showing locations of stations considered for further analysis

First, bookings having a return timestamp in the considered year, but a rental timestamp in the previous year, are excluded to have a consistent year-long time window. Then, bookings are eliminated which indicate no number of rented bikes, as these are assumed to be bikes taken out of service for maintenance or other reasons. Furthermore, all SBRT-stations related to train stations not having any train services operated by the national rail operator NS, which also operates the SBRT-system, are excluded, as there is no CICO-data available for these stations.[4] Also, stations having a capacity of less than ten bikes are excluded. This is done to focus on SBRT-stations with a higher number of bikes which might be available for relocation. The relocation constraint also results in exclusion of SBRT-stations without staffed service, as the infrastructure of the other service types does not allow for a short-term change in the number of bikes available.[5] Lastly, a filtering is done excluding SBRT-stations for which no sufficient corresponding weather data is available. The final dataset still contains 75.5% of all SBRT-bookings available, while considering only forty-eight of the overall 313 SBRT-stations available in the dataset. The resulting dataset is then combined with the other datasets, as described in the following section.

3.1.3 Data fusion

The combination of all information per hourly timestep and station is necessary to allow for the further steps of this research, as this format allows for further processing of the data. To do so, the multiple datasets are matched into one (see Figure 16 as visualisation). To do so, first the SBRT-data is aggregated on an hourly level to provide a dataset compatible with the other datasets only providing hourly information. Then, the resulting dataset is matched with the station dataset based on the SBRT-station name to add station-related information such as the maximum number of bikes available and the corresponding train station. Together with the information on the corresponding train station, the hourly data is then matched with the CICO dataset. After that, the matching algorithm is used to identify the closest weather stations, which is then used to add

[4] While filtered out in this process, the data available for these stations might still be suitable for analysis and prediction when leaving out CICO-data. But in this thesis, the decision was made to exclude them.

[5] When looking on the mid- and long term, amendments in the infrastructure might be possible, or the introduction of smart locks might overcome the problem with the limited number of slots in a key box. But as this thesis focusses on short-term prediction, these changes in the service are considered out of scope.

weather-related information to the dataset. Lastly, the Holiday dataset is matched based on the dates, and all holidays are added for all stations.

Initial OV-fiets dataset

SBRT: Datetime Rental	SBRT: Weekday Rental	SBRT: Datetime Return	SBRT: Weekday Return	SBRT: #bikes rented	...
2018-01-01 06:31:00	Monday	2018-01-01 17:15:00	Monday	2	
2018-01-01 06:48:00	Monday	2018-01-02 20:30:00	Tuesday	1	

Hourly aggregation rentals

SBRT: Datetime	SBRT: Weekday	SBRT: Rentals	S: Station	S: Bike capacity	ST: Region	ST: Operator	ST: KIS
2018-01-01 06:00:00	Monday	7	Rotterdam Centraal	655	Randstad-Zuid	NS	1

Adding columns for potential determinants from other datasets

OV: Datetime	S: Station	W: Wind-speed	W: Tempe-rature	W: Sun-shine dur.	W: Rain duration	H: National holiday	...	CICO: Check-Outs
2018-01-01 10:00:00	Rotterdam Centraal	70 [in 0.1m/s]	68 [in 0.1°C]	5 [in 0.1h]	0 [in 0.1h]	1 [dummy]	...	511

Figure 16: Visualisation of dataset combination
(SBRT: SBRT dataset; S: Station dataset; W: Weather dataset, CICO: CICO dataset, H: Holiday dataset)

3.2 Identification of significant determinants

The following section explains the process to identify determinants which can describe the variance in the number of hourly SBRT-rentals. To do so, a MLR is used to assess whether these determinants show a correlation with the number of rentals. First, a MLR performed across the dataset including all stations to identify general tendencies. Then, the identified significant determinants will be included in a second round of MLR-applications, which are performed on each stations' data separately to assess how well they can describe the variance within each stations' hourly rentals.

3.2.1 Definition of variables

As described in the literature review in section 2.1, there are multiple determinants identified regarding the number of hourly rentals of a bikesharing-system. For complexity reasons, this thesis is unable to fill the knowledge gaps of all different determinants regarding SBRT-systems. Instead, the focus will be on weather- and time-related determinants (see also Table 2). These groups of determinants are selected as the required information can either be obtained directly from the operator (most time-related information) or is publicly available (holiday calendars and weather-related information). Further, based on research conducted for bikesharing forecasting, the meteorological and temporal factors are found to be most promising when it comes to forecast short-term demand (Du et al., 2020). The other factors identified in the literature review correspond to the circumstances in which a SBRT-station is located, such as its accessibility, the surrounding cycling infrastructure, topography, and land use, and are thus considered out of scope of this thesis.

Additionally, the hourly checkouts in the SBRT-corresponding train stations are added, as the analysed SBRT-system OV-fiets is integrated into the national train system. This determinant allows for an assessment on whether the SBRT-rentals depend on the number of train travellers leaving the corresponding train station. The specific variables used to represent the determinants are visualised in Figure 17 and further explained in the following:

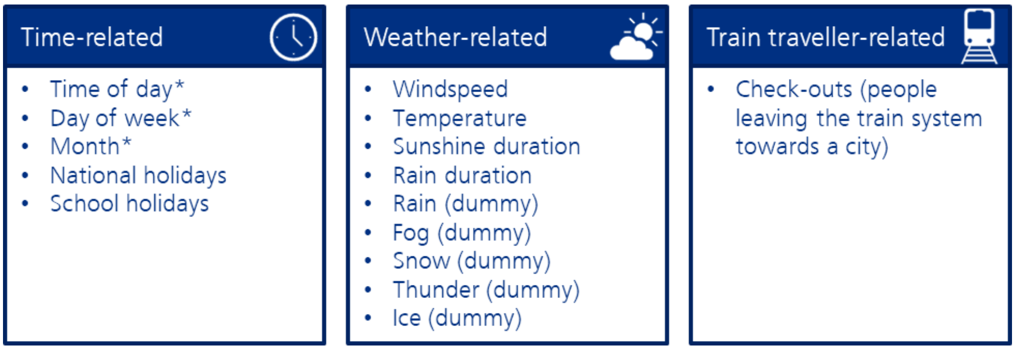

Figure 17: Grouping of determinants considered for the multiple linear regression
*see Appendix A 1 for a detailed description of these variables

Time-related determinants:
According to literature (Gu et al., 2019a; Todd et al., 2021) temporal components play a significant role when it comes to assessing variance in the hourly rentals in a bikesharing-system (see also section 2.1.2). To see whether this is the case for SBRT-systems, the temporal component requires preparation to be suitable for further analysis. While for temporal determinants such as time of day, weekday, and month nominal scales exist (e.g., hour 1 to 24 for the time of day, or weekday 1 to 12 for months), these cannot be translated into numerical variables for further analysis as no order exists among the characteristics of the different determinants. Thus, each of the characteristics must be analysed independently to assess their impact on the hourly rentals. This is done by breaking into multiple dummy-variables, on which each becomes 1 if the characteristic is present in the related hour, and 0 otherwise. For example, the variable $hour_{14}$ becomes 1 if the related hour is in the 14th hour of the day and remains 0 in the case of any other hour of the day. The same holds for the day of the week and the month of the year, resulting in a high number of dummy variables, as each the characteristics of each determinant have a nominal scale. Thus, they need to be represented by $n-1$ dummy variables, with n being the number of characteristics per determinant (23 to represent the hours, 6 to represent the weekdays, 11 to represent the months). The reference variables were selected arbitrary based on the applied algorithm in the programming language R, selecting the first variable in an alphabetical order to be the reference variable. To reduce the number of variables, an aggregated representation of the temporal determinants is added: Hours are aggregated into five different times of day (namely Night, Morning peak, Daytime, Evening peak, Evening, based on the definition of peak hours by the corresponding train operator[6]), the weekdays are reduced into one dummy-variable indicating whether it is weekend or a weekday, and the months are aggregated on the four seasons (Spring, Summer, Autumn, Winter). Holidays, national and school in the three holiday regions, are represented by one dummy-variable each,

[6] According to NS, the morning peak occurs between 6:30am and 9:00 am, while the evening peak occurs between 4:00am and 6:30pm. As this analysis is performed on hourly basis, it was decided to include the hours 6am to 9am in the morning peak and 4pm to 7pm in the evening peak, respectively.

becoming 1 if the related day is a holiday and 0 otherwise. For a further description of the aggregation, see Appendix A 1.

Weather-related determinants:
As discussed in section 2.1.2, weather-related determinants are assumed to have a significant impact on the number of rentals of one-way bikesharing schemes. To see to what extent these determinants can explain variance in hourly SBRT-rentals, they are included in the dataset based on the closest KNMI weather station providing suitable data for further analysis. Following up on the weather determinants identified by Eren & Uz (2020) shown in Table 1 and considering the data available by the KNMI, multiple determinants are selected for further analysis: Windspeed, Temperature, Sunshine Duration, and Rain Duration, which are included using the provided interval scales: Windspeed and Temperature are assessed using averages for the last hour in in 0.1 m/s and 0.1°C, respectively. Rain and Sunshine Duration are indicated based on their occurrence, measured in tenths of an hour (see also Appendix A 1). Additionally, dummy variables are included indicating whether Rain, Fog, Snow, Thunder, or Ice occurred within an hour. These dummy variables become 1 in case the event occurred and 0 otherwise.

Train traveller-related determinants:
According to literature it is likely that a link exists between the usage of both systems, especially as this thesis analyses a train station-based SBRT-system. As discussed in section 2.1.3, bikesharing is likely to serve as first- and last-mile solution to access/egress the corresponding rail services, with SBRT being especially suitable as egress mode. Therefore, the number of train travellers leaving a train station is used to assess its explanatory power on the hourly rentals of a SBRT-system. As the focus of this research lies on the distribution of rentals only, the estimated number of individuals checking out of a station is used as numeric variable to represent the train travellers. While it might also be interesting to further assess the other side of train station-based SBRT-trips, namely the correlation between bikes being returned at a train station and the number of train travellers entering the train system, this is considered out of scope of this research, as the return time of each rented bikes is estimated using historical rental duration data.

Table 5: Number of unique variables per group

Group	Number of variables n	
Time-related		
- Non-aggregated	40	
- Aggregated		8
Weather-related	9	9
Train traveller-related	1	1
Total		
- Extensive	50	
- Aggregated		18

To conclude, as shown in Table 5 in total there are fifty different independent variables to assess their explanatory power regarding hourly SBRT-rentals. Additionally, the number of variables can be reduced to eighteen if deciding to use aggregated time-related variables instead of determining each temporal component independently. Both approaches are used to assess to what extent the aggregated level able to capture the variance in comparison to the disaggregated one.

3.2.2 Identification of significant determinants

To assess the explanatory power of the different variables defined above, a MLR is used, an established statistical method which is conducted in R roughly following the work done by Feng & Wang (2017). The basic mathematical formulation is shown below:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

In this formula, Y represents the dependent variable (in this case the number of SBRT-rentals per hour), while X_1 to X_n represent the independent variables, and β_0 to β_n the corresponding weights of the independent variables. n represents the total number of considered independent variables, as described in the previous section. Lastly, ε is the error term of the equation.

The considered selection of variables results in up to fifty unique variables (see Table 5). When adding potential interaction effects between the variables (for example between the number of check-outs and the dummy-variable morning peak or temperature and season), this is expected to result in an excessive number of variables to be considered in the MLR and the following research process. Thus, to limit the number of variables while keeping as much explanatory power as possible, the backward search method is applied based on Miller (2002) and the corresponding R package developed by Lumley (2020). In this case, four different combinations of variables are used as input to identify the variables with the highest explanatory power. The split into four combinations is done to reduce computational complexity while including the time-related variables on an aggregate and disaggregate level and to consider interaction effects between the different variables. A visualisation of the four combinations is shown in Table 6.

Table 6: Number of variables considered per backward search (excluding intercept)

	No interaction effects	*Including interaction effects*
Aggregated variables	24	56
Disaggregated variables	55	104

Per combination of variables, a stepwise backward search is performed, based on which a selection of variables with the highest explanatory power is done. The method is based on A. J. Miller (1984) and is selected due to the lower computational effort compared to exhaustive and sequential selection methods. When comparing other stepwise search methods, the backward search is considered in favour of the forward search as within the given dataset it can be expected that among variables collinearity might exist (e.g. sunshine and rain duration; see also Figure 19).

Backward search:
This method begins with a regression model including all considered variables, and then removes the least significant variables one after another based on a defined criteria (highest p-value, lowest drop in R^2, ...) until a predefined threshold is met (e.g. p-value < 0.05). Even though this method therefore does not consider all combinations and therefore cannot guarantee to find the best possible combination, it requires lower computational effort compared to more extensive searching methods. The common limitation that stepwise variable selection methods result in a comparatively unstable variable selections can be overlooked as the given dataset is sufficiently big to eliminate the risk on an unstable selection (Steyerberg et al., 2001). Also, as all variables are in the model from the beginning, different from forward search the backward search might be forced to keep correlated variables within the model.

Forward search:
Like backward search, but the method begins with an empty model and then stepwise adds the most significant variable based on a predefined rule (smallest p-value, highest increase in R^2, ...) until a predefined threshold is met (e.g. p-value > 0.05). While this method is advantageous when having a high number of variables in a comparatively small dataset, in models with collinear variables the forward search might result in considering either of the correlated variables.

The backward search is performed on the dataset containing all remaining stations after the previously conducted filtering. It is chosen to conduct the search across all stations to identify variables which can explain variation existing within most stations. To make the stations comparable, the dependent variable is defined as shown below:

$$RR_{sh} = \frac{R_{sh}}{C_s}$$

In this equation, the relative number of rentals RR_{sh} stands for the number of rentals R_{sh} at SBRT-station s in hour h divided by the identified, fixed bike capacity C_s at the corresponding SBRT-station s. By performing the MLR across all stations combined, the results can provide a general tendency of the most significant determinants. The selection of variables considered for further analysis is based on the relative decrease of the R^2 per removed variable. The magnitude of this decrease R^2 represents the reduction of the ability of the remaining model to explain the variance in the data. Thus, the higher the decrease after removing a variable, the higher its explanatory power in the model.

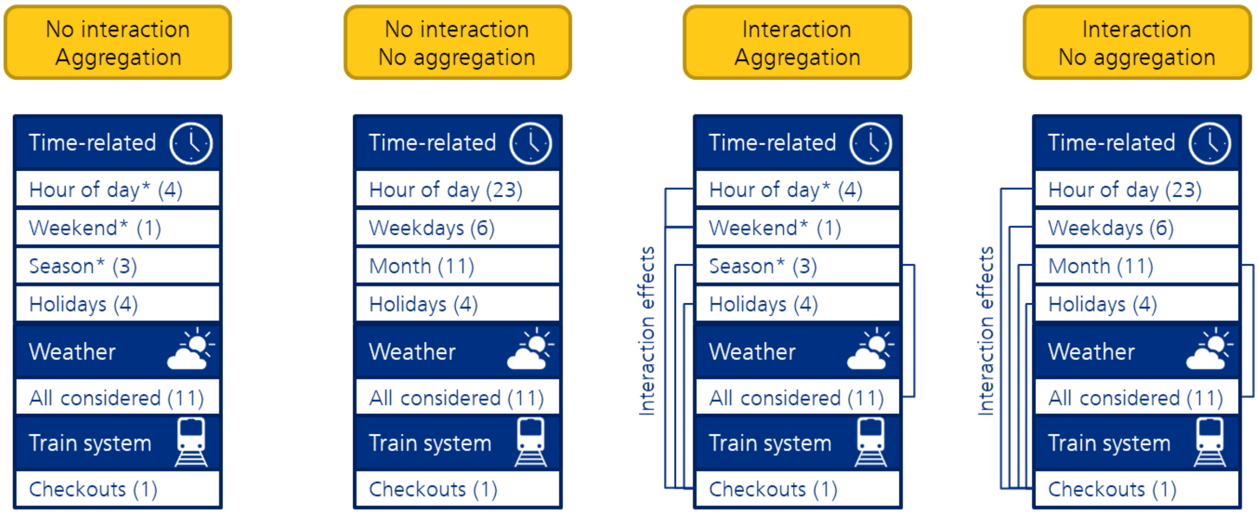

Figure 18: Four different scenarios considered for backward search application
(*Aggregated variables, Holidays: One variable for each of the school holiday regions plus one representing the national holidays)

As shown in Figure 18, the first backward search includes the least number of variables, by capturing using the aggregated time-related variables without interaction effects. The other backward search applications consider the aggregated variables with interaction effects as well, and all non-aggregated variables with and without interaction effects, respectively. Interaction effects in this case only refer to interactions including two variables at the same time, such as checkouts interacting with time of day-variables, or season-variables interacting with sunshine duration.

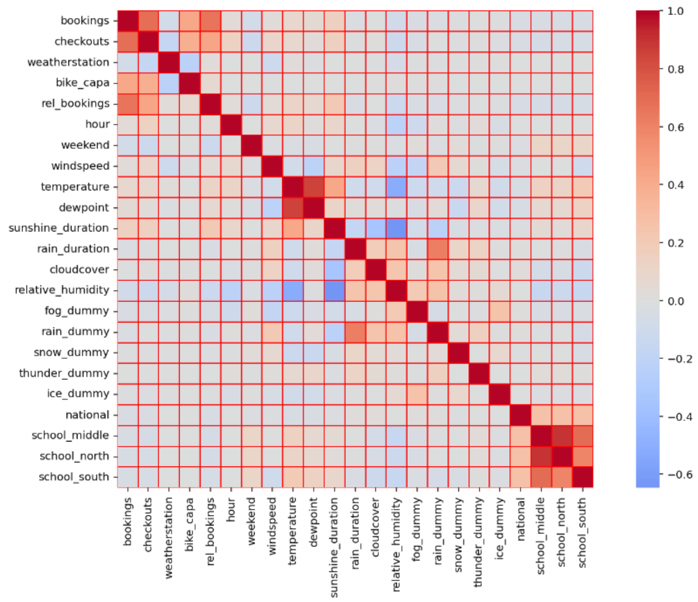

Figure 19: Indication of correlations between the different variables (red indicates positive correlation, blue negative correlation)

The selection which interaction effects to include is based on the results of a preliminary conducted test for correlations among the different variables (see Figure 19). It becomes visible that the weather-related variables Dewpoint and Temperature are highly correlated. Also, correlations are found between Sunshine Duration, Relative Humidity, Cloud Coverage, and Rain duration. As these weather-related variables are likely to have a different impact on the hourly rentals depending on the time of the year (e.g., rain in winter might be perceived worse for cyclists compared to summer), in the aggregated backward search all these weather-related variables are assessed for potential interaction effects with the seasons of the year. In the disaggregated backward search, only the interaction between the seasons and Sunshine Duration is included due to limited computational power. On a temporal level, interactions between the number of checkouts and hour/time of day, weekday/weekend, and the four different holiday types are included as it is expected that the number of travellers in the corresponding PT system differs across these different temporal variables, which again has an impact on the number of rentals in the SBRT-system according to literature (Zhang et al., 2018). Further two- and multi-variable variables effects might be interesting to investigate but are considered out of scope for this thesis to reduce computational complexity. Then, the variables contributing to a change of R^2 higher than 0.001 within the backward search are selected for a further analysis on a station level.

3.2.3 Performance of identified determinants per station

When performing the regression on a station-level, the local circumstances can result in different usage patterns when it comes to using the bike-train combination (Schakenbos & Ton, 2021) and also one-way bikesharing (Todd et al., 2021). Thus, to examine whether there are differences in terms of the determinants being significant amongst stations, additional MLRs are performed per station using the variables selected based on the method from the previous section. Then, the results of these MLRs using the number of significant variables per station to assess how good previously conducted variable selection allows for the explanation of the variance at a specific station. Additionally, the number of significance levels per variable are compared across all stations and variables. In the station specific MLR performances, instead of RR_{sh} the absolute number of bikes rented per hour is used as dependent variable. This is done to allow for an easier interpretation of the outcome of the model and makes it more suitable for the following application for forecasting. While this change is expected to change the magnitude of the weights, it does neither have an impact on the significance of variables nor on their sign.

Additionally, the resulting R^2-value from each MLR-application is used to assess to what extent the noise in the data can be explained by using the selected variables. This indicator is used as a high R^2-value suggests that the selected variables can capture most noise within the hourly bookings throughout the assessed dataset (Miles, 2005).

3.2.4 In-depth analysis

Based on the performance of the different stations in the previous section, eight stations are selected and investigated in more detail to generate a further understanding of the determinants. The station selection is based on the distribution of the R^2-values of the station-specific performed MLRs. The selection of exemplary stations involves two stations with a low and a high remaining noise, selected using the highest and lowest R^2-value across all stations, respectively. Additionally, the stations being closest to the mean, the median, as well as the 25% and 75% quantile are selected to provide a wide range of exemplary stations. This is only a small selection of both the forty-eight stations filtered for analysis and the in total 313 SBRT-stations in the system but is deemed sufficient to provide first insights into the data and reduces complexity of the research. The selected stations are then compared using a visual representation of the average hourly rentals across days and weeks in combination with the identified determinants. The aim of this descriptive analysis is to assess whether the determinants have a similar impact across different stations, or whether the patterns are so different that no overarching findings can be concluded.

Based on the identified determinants and the descriptive analysis, in the following section the approach to forecast the hourly SBRT-rentals on a period of one week is described. The results of the station specific MLRs also serve as multivariate, statistical forecasting method and will be compared to the other identified forecasting methods in the following section.

3.3 Forecasting

To forecast the number of available bikes at a SBRT-station, both the moment of renting a bike and the moment of a bike being returned must be estimated. To achieve this, in the following the forecasting methods to estimate the number of bikes rented per hour are described, of which the results are then combined with the historical booking durations per hour to estimate when how many bikes will be available at a station. To avoid the bias of local differences between stations, the forecasting is performed on the previously selected exemplary SBRT-stations using a predefined training dataset as well as a forecast horizon of one week. The predicted hourly rentals are then compared with the observed number of rentals to assess the performance of the different models. The performance assessment is done to identify whether one forecasting method is sufficient to predict the demand across all stations in the system, or whether for different stations different models perform best. This is considered necessary as, based on the descriptive analysis, remarkable differences between stations might lead to a similar disparity when it comes to suitable forecasting models. In The Netherlands NS Reizigers, the train-operating sister company of the SBRT-operator NS Stations, applies different forecasting methods for different stations when it comes to predicting the future number of train travellers due to the difference in the underlying patterns and available information. Thus, also in this case multiple forecasting methods are compared to identify the most suitable method to answer the forecast-related research questions.

To achieve that, the insights identified on determinants and different patterns of SBRT-rentals in the previous sections are used as a foundation to build different short-term forecast methods of the hourly SBRT-rentals. First, in section 3.3.1, based on the preliminary literature research three different forecasting methods are selected regarding their performance to predict short-term (bike-)sharing rentals. Then, the selected methods and their underlying concepts are explained more detailed in sections 3.3.2 to 3.3.4. Then, the different methods are applied on two different forecasting periods and their results are compared to assess whether there are better- and worse-performing forecasting methods. Then, the forecast for one exemplary station is combined with the historical booking durations assessed in section 3.3.6 to estimate the number of SBRT-bikes available at a station at a certain hour.

3.3.1 Method selection

Based on the literature review on the performance of different forecast methods in section 2.2.3, it is decided to use Prophet as statistical univariate, MLR as statistical multivariate, and LSTM as NN-based multivariate forecast method (see Figure 20 for an overview). The decision for Prophet is based on the satisfactory performance for two-way carsharing and its ability to capture and visualise recurring daily, weekly, and monthly time-related patterns within a dataset (more information on the method in the following section). Additionally, MLR is chosen due to its capability of including multivariate information while also providing insights into the impact of the explanatory variables on the dependent variable, which is included in two ways: One MLR includes time-related determinants only, thus performing as univariate model, while the other assumes to have perfect information about the external variables for the forecasted week as well (i.e. how many checkouts will occur in a to be forecasted hour). Even though in reality no perfect information exists, this multivariate MLR is included to assess whether a model that has perfect information can outperform a model that has only time-related, univariate input. Regarding the choice of an NN-based method, LSTM is chosen as it performs comparatively well when performing uni- and bivariate forecasting of one-way bikesharing demand. Furthermore, throughout the last years LSTM evolved to be a commonly applied method when it comes to NN-based bikesharing forecasting, as researchers adapted the basic LSTM to better match the actual demand. But as no research so far investigated SBRT-systems, in this thesis a basic LSTM will be applied. In the following sections, the chosen methods in general and their application within this research are described.

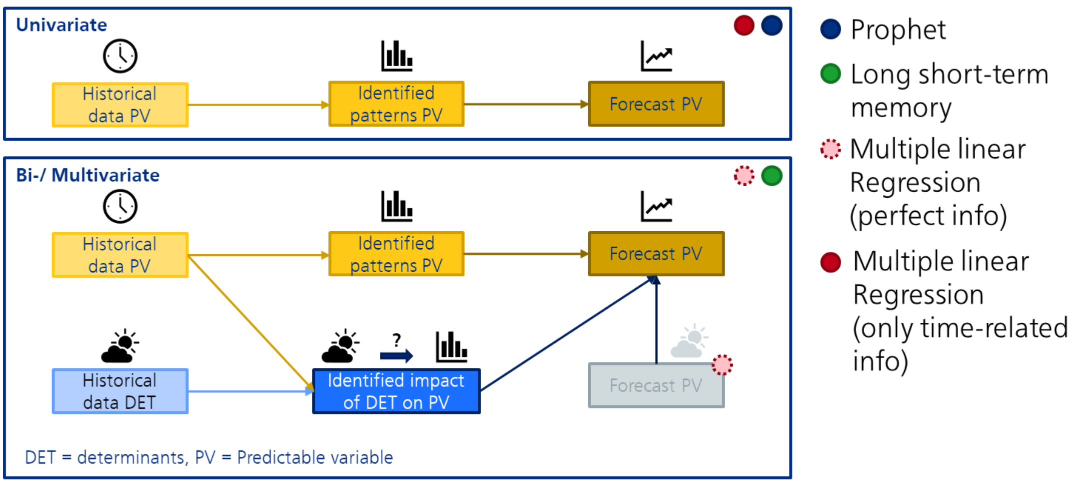

Figure 20: Visualisation of the applied forecast methods and their uni-/multivariate characteristics

3.3.2 Prophet

Prophet is a statistical model developed by Facebook/Meta to capture seasonality in time series data, which is available open source. According to the project's website, it is *'a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects'* (Facebook, n.d.). The model is a decomposable time series model consisting of three main components as shown in the equation below, with $y(t)$ representing the dependent variable per timestep t, $g(t)$ representing the trend function modelling non-periodic changes throughout time, $s(t)$ representing periodic changes such as weekly and yearly seasonality, and $h(t)$ representing the impact of holidays. In addition, the error term ε_t represents changes the model is unable to capture:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

According to the Taylor & Letham (2018), the publishers of Prophet, the model performs best on time series data having '*piecewise trends, multiple seasonality, and floating holidays.*' The authors state that Prophet aims to be an approach between pure statistical and judgemental (i.e., domain knowledge-based) forecasts by allowing a knowledge-based adaptation of the parameters of the statistical Prophet-model. In the following, the different components of the model are briefly described as well as the implementation of the method for hourly SBRT-station rental data. For a full description of the functionality of the model, the reader is referred to Taylor & Letham (2018).

Trend model $\boldsymbol{g(t)}$*:*
The trend model captures general trends in the data, which are modelled using either a saturating growth function or linear trends. While the former is suitable for developments with a saturation level, the latter performs better for problems not showing a saturating growth. In both models, additional changepoints are used to adjust the trend. These changepoints can either be identified by the model itself or be predefined as additional model input. The selection of the trend model is done by the researcher based on context. When it comes to forecasting, the trend model is extrapolated and extended by a random component assuming that the future will experience the same rate of changes as seen in the training data used to fit the model.

Seasonality model $\boldsymbol{s(t)}$*:*
To capture the seasonality of data, Fourier-series are used to represent seasonal effects. Fourier-series are periodic functions consisting of multiple sinusoids, which are combined using a weighted summation to approximate a given function, in this case the historical demand (an example is shown in Figure 21). In this case, this is done using the equation shown below, in which P represents the duration of a recurring period (e.g. 365.25 days per year or 7 days per week), while N represents the number of partial functions and a_n, b_n are the parameters to be estimated per partial function. There is no error term as this the error component is already included in the trend model. To simplify the starting point of the model, an additional smoothing priori is added with $\beta \sim Normal(0, \sigma^2)$.

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P} \right) + b_n \sin\left(\frac{2\pi nt}{P} \right) \right) * \beta$$

While Prophet provides P for yearly, monthly, and weekly seasonality, this can be manually adapted by the researcher if necessary. The same holds for N, for which either the best-performing values according to the authors can be used ($N = 10$ for yearly and $N = 3$ for weekly seasonality), it can also be manually defined by the researcher. Changing N should be done with caution, as a higher value might be able to better fit quickly changing patterns but comes with the risk of overfitting.

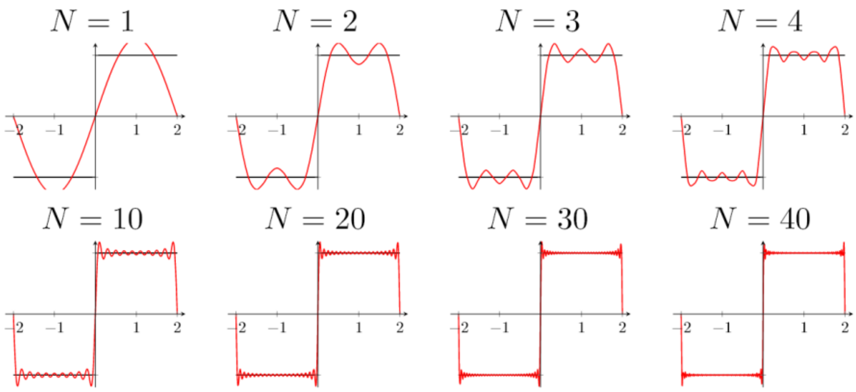

Figure 21: Fourier-series with different values of N plotted on $f(x) = \begin{cases} -1 & -2 < x < 0 \\ 1 & 0 < x < 2 \end{cases}$ by Lasser (1996)

Holiday and events $\boldsymbol{h(t)}$*:*

Holidays and/or events and their impact on the dependent variable are assumed to be independent from one another and are added to the overall model using an indicator function including a specific parameter per timestep being defined as holiday/event as shown in the equation below. Per holiday/event i, D_i is the set of past and future days of that holiday L. Per holiday, a parameter κ is assigned providing the corresponding change in the forecast. As a prior, it is assumed that $\kappa \sim Normal(0, \nu^2)$.

$$h(t) = [1(t \in D_1), \ldots, 1(t \in D_L)] * \kappa$$

To define which days are holiday/events, Prophet provides a library of national holidays. Additionally, the researcher can provide a custom list of past and future events or holidays, with the option to add a name per event to identify recurring events. Prophet also allows to include additional parameters for days surrounding the defined holidays/events, as these are likely be influenced by the holiday as well.

Implementation for use case:

As an input, basic Prophet solely requires a dataset with two columns, one being the properly formatted timestamp of an observation, the other one being the corresponding observed value of the relevant variable. Furthermore, as mentioned previously, information such as holidays or predefined trend turning points can be provided as additional input as well as the number of Fourier-series dimensions per considered seasonality. If deciding to use a saturating growth trend model, both the minimum and/or the maximum saturation boundaries can be defined. In the case of SBRT, the minimum is set to 0 as the number of rented bikes per hour cannot be negative, while the maximum is the maximum capacity of bikes per station. In addition to the yearly, monthly, and weekly seasonality, additional regressors can be added if deemed necessary.

The implementation of the Prophet-model is done using Python 3.7.4, with additional data processing tools numpy (v. 1.21.2) and pandas (v. 1.3.5) as well as the fbprophet package (v. 0.7.1) for the actual application of Prophet. In addition, the holidays package (v. 0.12) is used to include national holidays for The Netherlands. While the growth model is assumed to be *linear*, the seasonality is set to *multiplicative*. The latter means that the values of the seasonality are multiplied with the growth values of each timestep. Another change is made to the model as the daily seasonality assumes a recurring pattern throughout every day of a week. This does not allow to capture the expectation that hourly SBRT-rental patterns show large differences between weekends and weekdays (Todd et al., 2021). To solve this, the daily seasonality is abolished while providing the weekly seasonality a higher value for N, as a higher number of partial functions allows the weekly seasonality to capture patterns throughout each individual day. In this case, it was decided to set N to $7 * 12 = 84$, providing the model on average twelve partial functions to approximate each of the seven weekdays. Twelve partial functions for each of the seven weekdays are chosen after assessing the goodness of fit on more complex recurring patterns in the data. Nevertheless, for stations with less complex rental patterns, a lower N might be sufficient. Testing for the optimal N per station is considered out of scope for this research.

3.3.3 LSTM

Long short-term memory (LSTM) is a recurrent NN (RNN) model specifically suitable for time series data. It was first published in 1997 to overcome the problem of other RNNs which were gradually forgetting previous inputs over time (Hochreiter & Schmidhuber, 1997). LSTM solves this by providing a combination of a forget, an input, and an output gate (see further explanation below). Since its implementation, LSTMs were performed on various use cases, and show satisfactory performance results when it comes to predicting bikesharing demand (see section 2.2.3). The underlying mechanics of an LSTM-cell will be briefly explained in the following, based on (Dolphin, 2020):

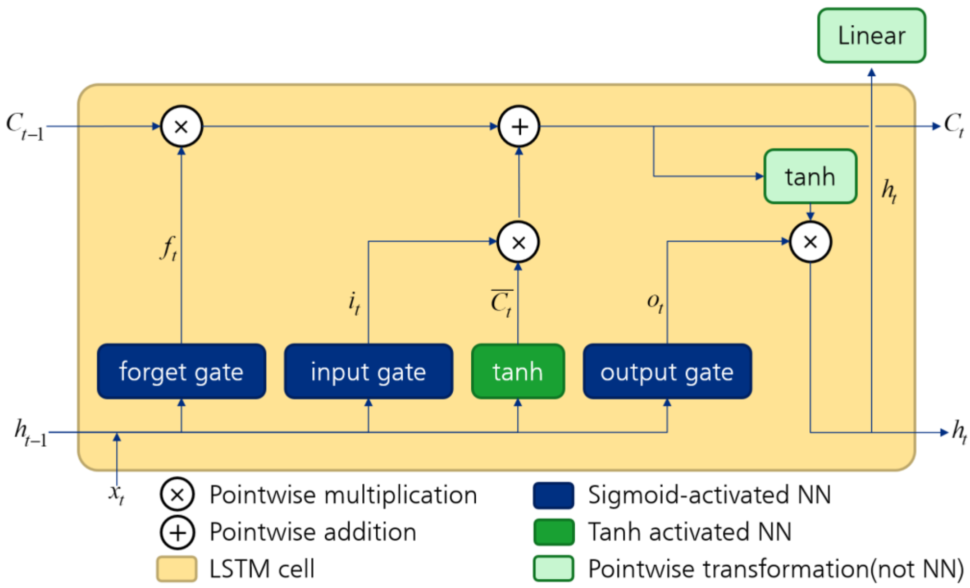

Figure 22: Data transmission within a single LSTM cell, based on Zhang et al. (2018)

General explanation:

An LSTM consists of multiple LSTM-cells as shown in Figure 22. In the visualisation, the procedure of an LSTM-cell processing data can be read from left to right, with the variables outside of the LSTM-cell being the inputs and outputs. For an LSTM-cell to work, different inputs are required:

While x_i represents the input of a time series at timestep t, C_t represents the long-term memory of the network, the so-called cell state, and h_t represents the output per timestep, the so-called hidden state. The first step within a LSTM-cell is the *forget gate*, which assesses how to deal with the cell state of the previous iteration C_{t-1}. The forget gate assesses which parts of C_{t-1} should have less weight in future iterations based on the previous hidden state h_{t-1} and the new input data x_t. This is done by a NN using a sigmoid activation fed with information from the previous hidden state and the new input data (see explanation of activation functions in the separate box). The result is a vector in which each element is close to zero when a component of the input x_t is deemed irrelevant, and closer to one if deemed relevant. This vector is then pointwise multiplied with the elements of the previous cell state C_{t-1}, thus changing the influence of the cell state's components on the following steps.

Activation functions:
An activation function is required to decide to what extent the information captured by a neuron within a NN should be forwarded to the following neurons. Depending on the purpose of the NN, different activation functions can be used. In case of an LSTM, the sigmoid and tanh activation functions are used. While the sigmoid function provides an output within the interval [0,1], the tanh function provides an output between [-1,1]. See Sharma et al. (2017) for further explanation on the use of activation functions.

The next step uses the previous hidden state h_{t-1} and the new input data x_t, thus the same inputs also used for the forget gate, to determine which added information should be included in the cell state C_t. This is done by creating a cell state update vector $\overline{C_t}$ using a tanh activated NN to generate an update vector, which tells us how much to update each component of the cell-state given the new data. Tanh is used as its values lie within the interval [-1,1]. It is required to provide negative values as well to allow for a reduction of the cell state's components. This resulting vector $\overline{C_t}$ is then pointwise multiplied with the results of another sigmoid-activated NN i_t, the so-called *input gate*, which adds information on which components of $\overline{C_t}$ shall be kept for further processing. Then, $\overline{C_t}$ and i_t are pointwise multiplied and the results are added to the cell state, resulting in the new cell state C_t.

After having updated the cell state using the forget and input gates, the new hidden state h_t is created using h_{t-1}, x_t and C_t, with the latter being processed by a tanh-function to transform to values within the interval [-1,1]. Then the result is pointwise multiplied with the outcome of the *output gate*, another sigmoid-activated NN, which is operating as a filter make sure that only the relevant information from the cell state is assigned to the new hidden state h_t. To make the results interpretable, as a last step the final h_t is processed using a linear layer. As shown in Figure 23, the information within an LSTM model is forwarded from one LSTM-cell to the next one per iteration.

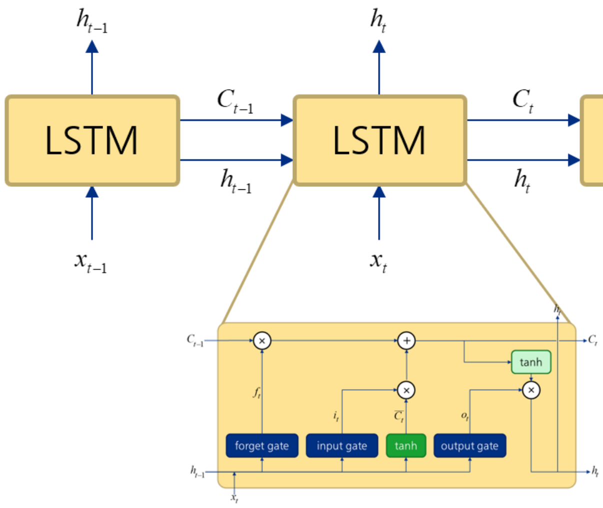

Figure 23: Data transmission among LSTM cells, based on Zhang et al. (2018)

Implementation for use case:

For an LSTM to process multiple timesteps and/or variables as input per timestep of the dependent variable, multidimensional vectors are required to represent C_t, h_t, and x_t. In the given case, the dataset provided in section 3.1 is processed to result in a three-dimensional matrix which is then used as input for the LSTM-cells. An example is shown in Figure 24, with each two-dimensional matrix x_t representing one input per LSTM-iteration t to estimate $\widehat{b_{t+1}}$, which is the value of the dependent variable b in the following timestep. The first column is treated as the dependent variable (in this case b), the following columns are treated as input variables. Thus, the researcher decides how many previous timesteps and which variables are considered, and how many timesteps the LSTM will learn from. In this case, each two-dimensional matrix includes the values of the current timestep t and the preceding 24 hours, while v represents the variables considered as input. Additionally, the time window which shall be forecasted after creating the LSTM-model is required. Furthermore, it is up to the researcher to decide how many times to run through each training set (the so-called epochs), the number of samples passed to the network at the same time (the so-called batch size), and the dimensions of the hidden layer, i.e. the dimensions of the used NNs (the so-called dimensionality of the output space).

The implementation of the LSTM is done using Python 3.7.4, with additional data processing tools numpy (v. 1.21.2) and pandas (v. 1.3.5) as well as the machine learning tools scikit-learn (v. 1.0.2). Further, the API Keras (v. 2.6.0) is used to ease working with the machine learning library TensorFlow (v. 2.6.0). Additional common packages are used for visualising the results. The applied code is based on the chapter *'Encoder-Decoder LSTM Model With Multivariate Input'* developed by Brownlee (2018), using a loss function aiming

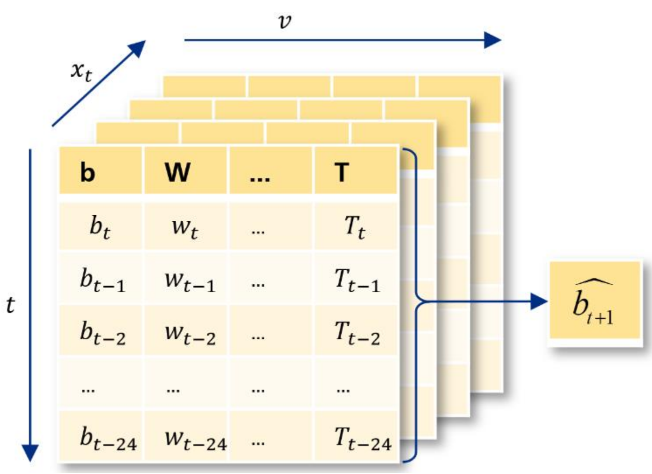

Figure 24: Schematic visualisation of input for LSTM (b, w, T: exemplary variables)

to minimise the MSE by applying an Adaptive Moment Estimation (so-called *adam*) optimisation algorithm. The dataset used to train the LSTM includes the following information per hour for the last 24 hours to predict the following hour: The normalised rentals and checkouts per hour, normalised information about the corresponding hour of the day, and dummy variables indicating whether the corresponding hour is on a national holiday and/or whether it is a school holiday in one of the three holiday regions. The normalisation is performed using the Min-Max-normalisation method (Patro & Sahu, 2015).

Due to complexity and the scope of this thesis, no tuning and optimisation of the hyperparameters of the LSTM-model is performed. The hyperparameters used are based on the LSTM-prediction model for free-floating one-way bikesharing developed by Bhatti (2020), who used the following parameters: 128 units, 5 epochs, 64 batches. The dimensions of the hidden layer are equal to the input layer. To account for the higher amount of datapoints in the given case compared to the data used by Bhatti (2020), in this case the number of epochs is increased to 30, while the other hyperparameters remain unchanged. Due to the stochastic nature of NNs, usually a high number of separate LSTMs is performed and then the results are combined. In the given case, due time constraints only two iterations are performed, using two different random seeds in python (20 and 21). While this comes with the risk of gaining results which are not the optimum which could be achieved when iterating e.g. a thousand times, using the results of two different seeds highlights the stochastic uncertainty of LSTM-applications.

3.3.4 Multiple linear regression

In addition to the univariate, statistical method Prophet and the multivariate, NN-based method LSTM two types of multiple linear regression are used for forecasting. The aim of including the multiple linear regression in the forecast comparison is to twofold: First, it allows for an assessment whether a comparatively basic, linear forecasting method is able to provide sufficient accuracy when it comes to forecasting hourly SBRT-demand, i.e. as reference to compare the two other models against (Feng & Wang, 2017; Gao & Chen, 2022). Second, MLR can apply both a univariate and multivariate statistical forecast, whereas the second can assume perfect information for the determinants. This allows for an assessment of using forecasts for additional determinants such as checkouts or weather-related information could provide an increase in accuracy when being added to the time-related univariate model. The univariate time-related information does not require any forecasting, as this information is given. In the end, two separate MLRs are applied per forecast comparison, one including only univariate, time-related information (MLR_time), while the other one assumes perfect information for the additional included determinants as well (MLR_All). The latter model includes the additional determinants identified in section 3.2.3. The same forecast periods and training sets are used as for Prophet and LSTM.

3.3.5 Forecast performance

The results of the different forecasting methods are compared using the prediction accuracy indicator RMSE, as described in section 2.2.3. Furthermore, the predicted and observed counts of weekly and daily rentals are compared, and the number of cases in which the prediction over- or underestimates the observed values. The latter is done to assess the performance of the forecasting accuracy in specific hours, as satisfactory level of accuracy is essential and high over-, or underestimations might lead to operational conflicts This might especially be relevant for stations which often experience a lack of available bikes, as the provided method is unable to capture the unsatisfied demand (see also section 1.3. In line with statements of individuals responsible for operating the SBRT-system OV-fiets, it is decided to use the number of hours in which a high underestimation of the demand occurred as main objective to minimise. The additional performance criteria are considered to provide additional insights, as it needs to be acknowledged that a high number of overestimated hours does not provide an added value for both operator and customers either. For scoping reasons, in the following only the number of underestimated hours will be considered to select the most suitable method, while it is recommended to include the other presented criteria as well to select the best-performing method per situation in future research.

3.3.6 Forecast application

As all rented bikes are assumed to return to the same station where they were rented out, it can be assessed whether the number of bikes available at a station is expected to be sufficient for the projected booking demand. As shown in Figure 25 this is done by multiplying the predicted hourly rentals $\hat{b}_{r,t}$ with the historical relative distribution of rental durations for a specific hour, day, and month to estimate when the bikes rented within this timestep will return. Before doing so, it is assessed if the number of bikes predicted to be rented out $\hat{b}_{r,t}$ is smaller or equal to the number of bikes available at the station for that timestep $b_{a,t}$, as this the maximum number of bikes which can be rented out. In case $\hat{b}_{r,t} > b_{a,t}$, then $\hat{b}_{r,t}$ is set equal to $b_{a,t}$, meaning that no more bikes can be rented out than there are available. After the multiplication with the historical distribution, the results are rounded up/down to an absolute number of bikes per timestep to be returned. The results of this step are then stored, and in the following timesteps the number of bikes expected to be returned are added to the number of bikes available at the station.

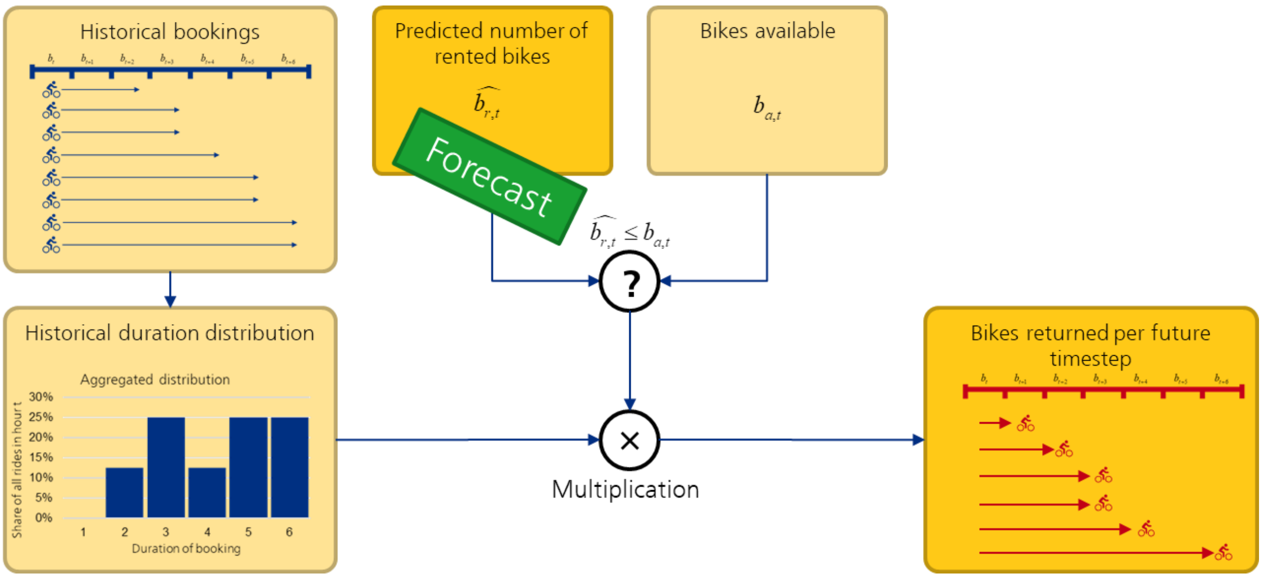

Figure 25: Visualisation of approach to estimate moments of return of bookings

After explaining how the presented forecast methods can be used to estimate the number of bikes available at a station, the different methods are applied on more recent data from 2020 and 2021. This is done to assess to what extent the methods allow for a forecast in times of uncertainty, in which the COVID-19 pandemic and the corresponding restrictions imposed by governments had a significant impact on travel behaviour around the world. To assess the different forecast methods, they are applied in the same way as described previously, but for the 'March'-period in 2021 using data of the preliminary 365 days.

4. Results

The following section provides insights into the results obtained by applying the methods described in section 3. First, determinants identified to explain most variance in hourly SBRT-rentals are identified across all stations as well as their performance per station in section 4.1. This also includes the in-depth analysis of the selected determinants for exemplary stations. The insights gained are then used to define the input variables for the following forecasting process. After applying the forecasting methods as described in the previous sections, their results are compared in section 4.2, and for one station an exemplary application of the forecasting results is performed to determine the number of available bikes per hour. In the end, in section 4.3 the results of the two preliminary sections set in context to existing literature.

4.1 Identification of significant determinants

The backward search method is applied on the dataset to identify the most significant variables, using four different combinations of variables as explained in section 3.2.2. A visualisation of the results for the different backward searches is shown in Figure 26: Each bar indicates the magnitude of drop in R^2 caused by removing the corresponding variable.

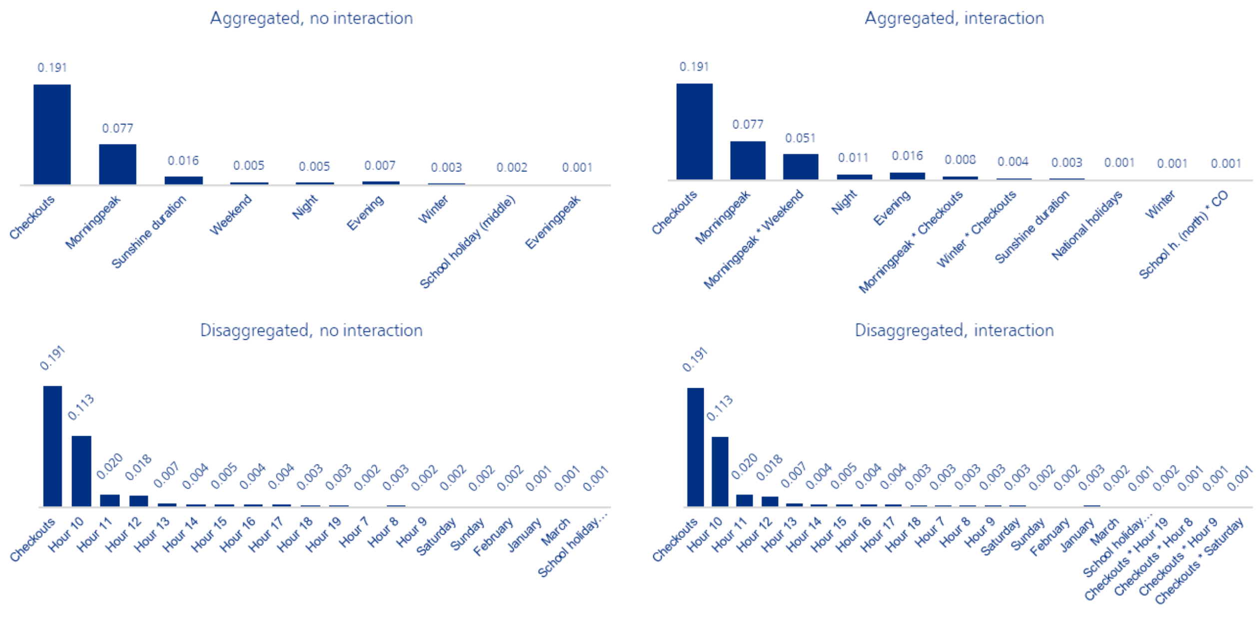

Figure 26: Backward search –Change in R^2 per removed variable for the four different search methods

When comparing the results, it can be concluded that Checkouts is the variable having the highest explanatory power across all backward searches when determining the relative number of rentals per station, as almost 20% of the variance in the hourly rentals across all stations can be explained using this variable. Further, all time-related variables together are found to allow for an explanation of another 22% of the variance in the data. Especially the disaggregated hours 8-18 and the aggregated variables Morningpeak, Evening, Eveningpeak, and Night. Other considered variables are the time-related variables Saturday and Sunday (and weekends on an aggregated level, respectively) and holidays (both national and school holidays). The weather-related variables allow for an explanation of the variance in the data of around 5%, while the only weather-related variable resulting in a change of R^2 of more than 0.001 is the Sunshine Duration. All variables causing a drop of R^2 of more than 0.001 across all four different backward search applications are shown jointly in Figure 27.

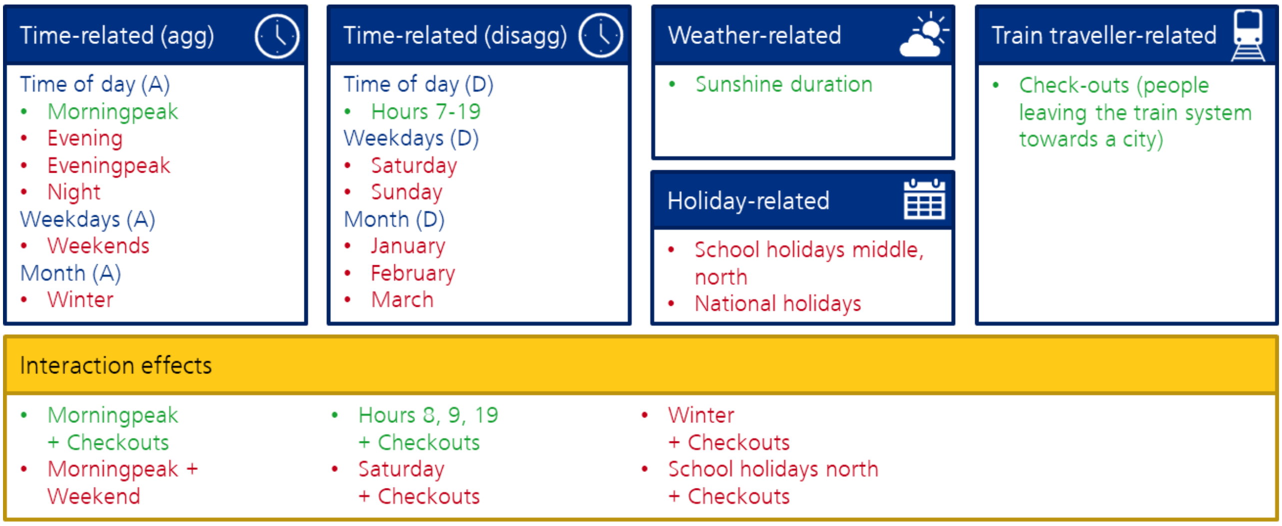

Figure 27: Summary of variables resulting in a change of R^2 of at least 0.001 across all four backward search iterations (green: positive correlation, red: negative correlation)

The colour of the variables indicates the positive or negative correlation with the hourly bookings in relation to the reference variable. For example, when looking at the time-related variables on an disaggregate level, the hourly rentals in hours 7-19 show a positive significant difference from the reference hour 0. As on the aggregate level of the time of the day the reference variable is Daytime based on the automatic reference variable selection within R, in this case the morning peak has a significantly higher number of rentals compared to the reference, while the other three times of day show significantly fewer hourly rentals. Lastly, the interaction effects can be interpreted as combinations of two variables: For example, the positive significance of the interaction effect Morning Peak + Weekend indicates that in hours being in the morning peak on a weekend, fewer bikes are rented per hour in comparison to morning peak hours during the week.

4.1.1 Performance of variables across all station-specific MLRs

While all these findings are identified on a dataset across all stations providing general tendencies of the determinants, this does provide limited information on which determinants are able to explain the variance of the hourly rentals on the individual station level. To assess to what extent the identified variables are suitable to explain the variance in hourly rentals per station, additional MLRs are performed (see also Figure 28). It is decided to include only the previously identified variables which are significant across all stations to reduce complexity and limit computational effort. The following decisions are made regarding the level of aggregation

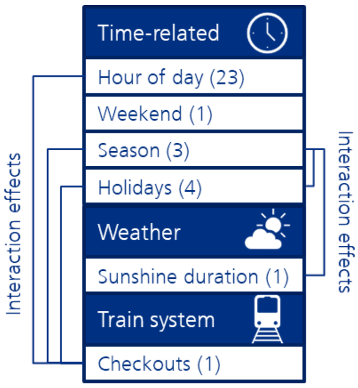

Figure 28: Variables considered for station specific MLRs

for the time-related variables to allow for an appropriate representation: It is decided to keep the time of day on a disaggregate level and include all hours as dummy variables, while both the weekdays and months are used on an aggregate level. The decision is based on the fact that for the latter two variables the aggregate versions include the corresponding non-aggregated variables: *Winter* includes the months *January*, *February*, and *March*, while *Weekend* includes both *Saturday* and *Sunday*.

Different from the MLR performed across all stations, for these MLRs the absolute number of hourly bike rentals is used as dependent variable to make the resulting station specific MLRs suitable for forecasting. Then, forty-eight separate MLRs are performed, one per station. For each station, the baseline for the dummy variables consists of the time-of-day *Hour 0* (midnight), the season *Autumn*, and a day being not on a *Weekend*, and not in Holidays. The selection of the reference variables is done automatically by the applied algorithm in the programming language R, selecting the first level in an alphabetical order to be the reference level.

Figure 29 provides aggregated results of the forty-eight separate MLRs across the different variables. This is done by counting the significance levels per variable across all station specific MLRs. The significance levels are counted separately based on their value using the following upper boundaries of the corresponding p-value: 0.0001, 0.001, 0.01, 0.05, 0.1. An additional overflow-category is included for p-values higher than 0.1, to show how often a variable is included across the 48 MLRs while remaining insignificant. For five variables (Interaction between checkouts and hour), less than 48 occurrences were counted. This is a result of multiple stations having neither checkouts nor SBRT-rentals in the corresponding hours, making it impossible to assess a corresponding impact. It needs to be emphasized that the following analysis of the results shown in Figure 29 relies solely on the significance levels of the station-specific MLRs, leaving out information about the positive or negative correlation of the variables with the hourly rentals as well as their magnitude. In the following, the different variables will be analysed in more detail. The results aim to provide additional insights in the variables, which form the foundation of the following forecasting process.

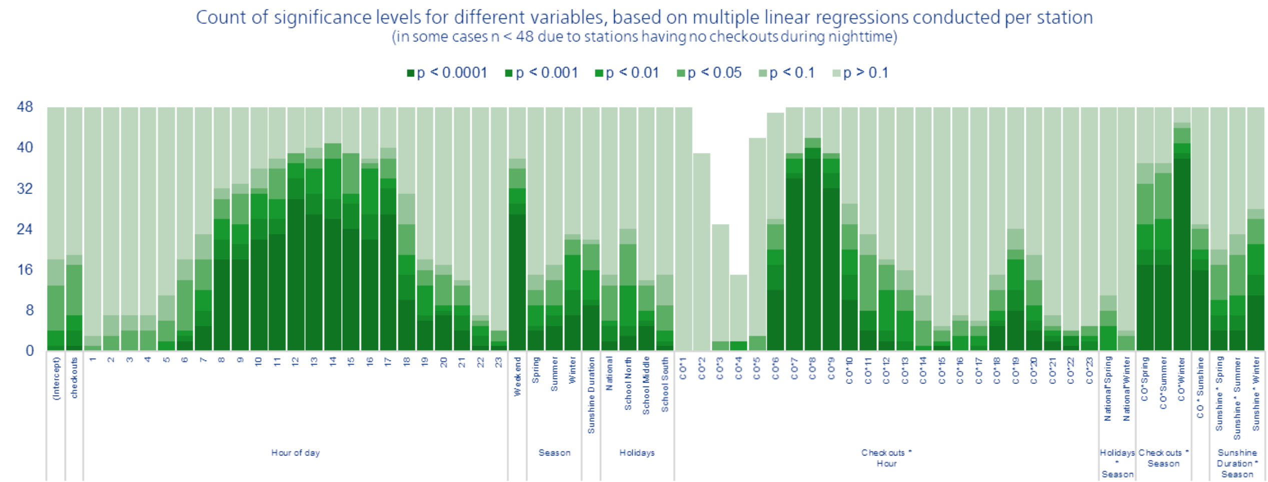

Figure 29: Number of significant variables across significance levels and stations per variable (reference levels: autumn, midnight, no weekend)

Train traveller-related variables:
When it comes to the train traveller-related checkouts, it is shown that the variable itself shows a high significance level on few stations only, while many stations show interaction variables including checkouts having a high significance (see below).

Weather-related variables:
The only weather-related variable considered in this analysis, Sunshine Duration, is significant on a 95%-level (i.e., a p-value below 0.05) for 44% of all stations. A similar result shows the interaction variable between sunshine duration and checkouts (50% of stations on 95%-level). The interaction variables covering sunshine duration and the different seasons are included to account for the fact that in different seasons the maximum possible duration of sunshine differs. They are found to have a high significance across fewer stations, with 36% and 39% of stations showing this variable having a 95%-significance level for the seasons spring and summer, respectively. This translates to these seasons being less different in terms of hourly rentals when interacting with sunshine duration compared to the baseline autumn. When it comes to the interaction between sunshine duration and winter, this interaction variable has a 95%-significance level impact on even more stations, namely 54%, suggesting that hourly rentals in winter often differ compared to the baseline autumn.

Time-related:
When investigating the independent hour-of-day variables and the interaction variables combining time-of-day and checkouts, it becomes visible that the timeslots of hours 22, 23, and 1-5 are insignificant even on a 90%-significance level. It is important to mention that this does not necessarily translate to unreliable data for these timeslots, but instead means that the data does not provide sufficient information to distinguish the rentals in these timeslots from the rentals in the reference-timeslot hour 0. In addition, for some stations no interaction variables could be assessed for the timeslots between hour 1 and hour 6, as either no check-out and/or no SBRT-booking data is available for these timeslots. This can be a result of the corresponding facilities being closed during that time. The timeslots in the morning peak (hours 7-9) show a high significance among most stations when interacting with the number of checkouts in that timeslot compared to their independent counterparts. The opposite effect can be seen for the following hours throughout the day, which are mostly significant on an independent level and thus seem to be less explainable by an interaction with checkouts. An exception can be seen for the evening timeslots (hour 18-20), where up to 42% of the stations indicate a high significance of interaction variables with the checkouts. A further analysis on this is done in the following section.
The fact of a timeslot being on a weekend has significant correlation with the hourly rentals across most stations, with 75% of the stations having a significance level >95%, and 56% even higher than 99.99%.
The variables representing the seasons are found to be significant across few stations when considered separately but show a higher interaction when being combined with sunshine duration and checkouts (for the interaction with the sunshine duration, see above). The interaction with the checkouts is prominent in winter, as for 92% of the stations this variable is significant on a >95%-level.
Lastly, the variables representing the national and school holidays are found to be significant on a

95%-level for at least nine stations, but none of the variables is significant across more than 50% of the stations. Also, the interaction variables combining both national holidays and seasons are found to be insignificant on a 95%-level for at least 83% of the stations, suggesting that the presence of holidays is only relevant for a small number of stations[7]. An investigation on whether the correlation of the explanatory variables with the hourly rentals differs between negative and positive across the different stations or is the same across all stations is considered out of scope due to the expected extensiveness. Nevertheless, such an analysis could provide additional understanding in the similarities and differences among the different stations.

4.1.2 Performance of variables per station-specific MLR

While the aggregated analysis of the MLR-results provides first insights into the significance of different variables regarding the hourly number of rentals, it lacks information on the magnitude of the correlation between the independent and dependent variables. To further investigate this, a descriptive analysis of selected SBRT-stations is provided in the following section.

Among the forty-eight stations analysed in the previous sections, a selection of exemplary stations is done to represent the dataset in an in-depth analysis. The selection is done using the R^2-values resulting from the MLRs performed per station in the previous section. The selected stations and their performance in comparison to the other SBRT-stations are shown in Figure 30. The two best and worst performing stations are selected to assess why the station-specific MLRs perform so good/bad in explaining the variance in the corresponding hourly rentals. In addition, four stations are selected to assess whether stations performing comparatively good/bad (25%- and 75%-quantile, respectively) and those providing the middle of the dataset (median and mean) show significant differences compared to the best/worst performing stations and between one another.

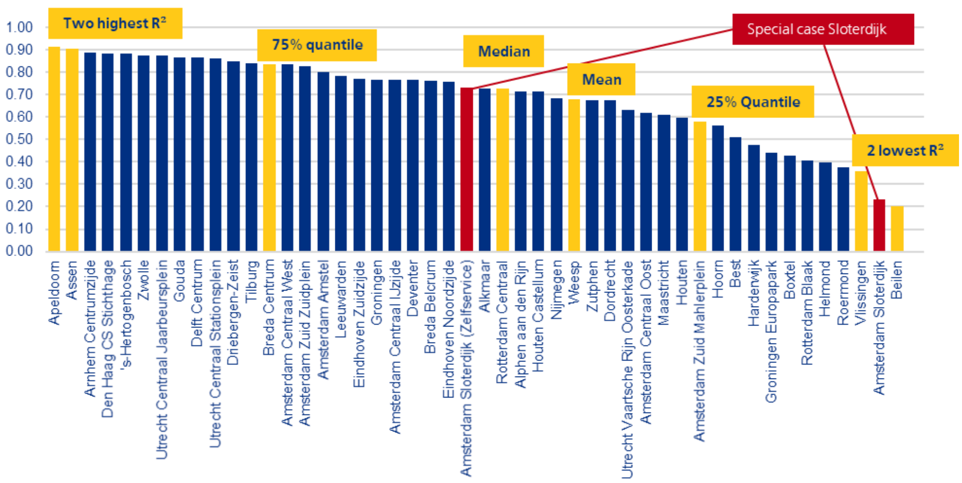

Figure 30: R^2 of multiple linear regression per station using the variables selected in section 4.1

Amsterdam Sloterdijk is a special case as there is an overlap of the datasets for these SBRT-stations at the corresponding train station (see Appendix B 1), making it impossible to analyse the two

[7] There is no interaction variable between summer and national holidays as no national holidays take place in the summer period.

stations independently. According to employees of the SBRT-operator, this anomaly in the data is caused by a temporary self-service facility which was implemented at Sloterdijk throughout 2018, but then closed again. Thus, it is decided not to include both stations in the in-depth analysis conducted in the next section.

Figure 30 shows that the chosen linear variables can explain more than 92% of the variance in the hourly bookings for stations like Apeldoorn and Assen, and in 75% of the stations the MLR is able to explain more than 58% of the variance. When assessing the R^2-performance of the different stations in combination with the number of significant variables per station (see Figure 31), it is remarkable to see that some stations achieve a high R^2-value with a comparatively low number of significant variables (Apeldoorn, Assen). For other stations a higher number of variables is significant (e.g., Den Haag CS Stichthage, Amsterdam Centraal West, Nijmegen) to explain the variance in the hourly rentals, while their overall R^2-value is comparatively low. When investigating stations with a lower R^2-value, the visualisation should be read with caution as it only considers the preselected variables. While the high significance level of some variable suggests that the variance in the hourly rentals might be explainable by the selected variables, the low R^2-value suggests much uncaptured noise in the data.

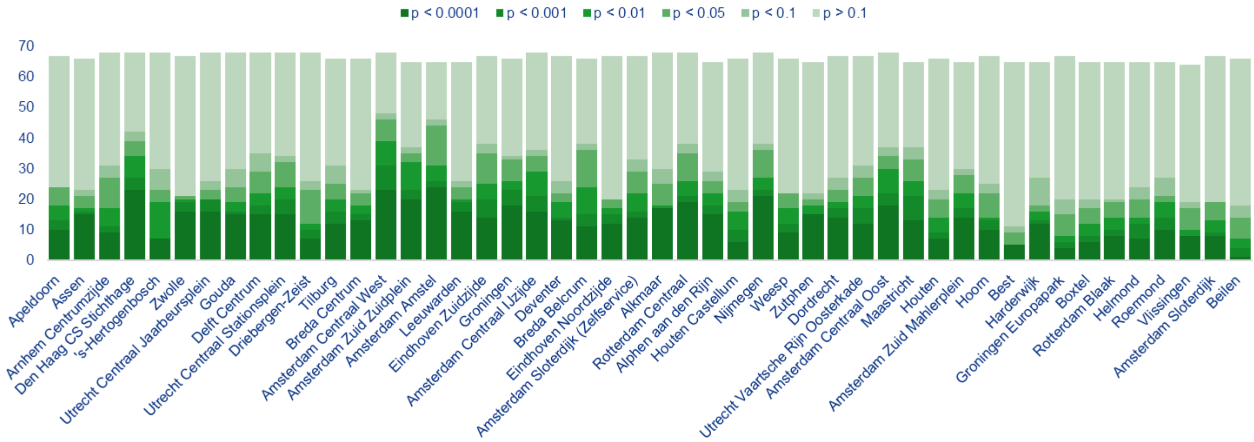

Figure 31: Number of significant variables across significance levels and stations per station (stations sorted by R^2-performance, descending)

Therefore, it can be concluded that while there are variables which are significant across most stations, there are differences in terms of the number of significant variables per station. These discrepancies in the performance of the MLR per station suggests separate models for the different stations. It might require further research to investigate whether for some stations, a lower number of variables and/or additional variables can provide an added value to the models, which is considered out of scope for this research for complexity reasons. Instead, this researches further investigates to what extent the different variables influence the hourly/ weekly/ monthly rentals in the following section, using eight selected stations as examples.

4.1.3 In-depth analysis of determinants

The following section provides a descriptive in-depth analysis of different determinants using selected exemplary stations. This includes a discussion on potential causes when identifying recurring patterns among multiple stations. The exemplary stations are selected based on the performance of the MLR conducted per station in the previous section as described in section 3.2.4. Then, the determinants are descriptively analysed to unravel their potential dependency with the rental patterns, which are aggregated or averaged on a monthly, daily, and hourly level. Per determinant and level of aggregation, only a selection of the eight selected stations is shown to reduce the report's complexity. A visualisation for all selected stations can be found in Appendices B 2 – B 8 The following abbreviations will be used to refer to the different stations: Beilen (*Be*), Vlissingen (*Vl*), Weesp (*We*), Rotterdam Centraal (*Ro*), Amsterdam Zuid Mahlerplein (*AZM*), Breda Centrum (*Br*), Assen (*As*), and Apeldoorn (*Ap*). The selection of determinants considered for comparison differs per level of aggregation: On a monthly and daily level, the aggregated rentals and checkouts are compared, while on an hourly level further time- and weather-related variables are analysed. This is reasoned in the time- and weather-related variables which cannot be compared on a daily/monthly level due to the potential loss of hour-specific information.

In the following, first the monthly, then the daily and hourly levels will be compared to identify recurring patterns across multiple stations. The aim of this descriptive analysis is to investigate whether usage patterns are similar enough to allow for a generalisation. If it is found that the patterns are unique per station across multiple variables, this leads to the conclusion that distinct models per station are required. The interpretation of the differences amongst stations were discussed with and confirmed by individuals working for the operational department of the SBRT-scheme. While the performed MLRs provide first insights into these causalities, the following results should be read with caution, as a descriptive analysis lacks the scientific foundation to prove causalities while allowing for a visual high-level analysis.

Monthly patterns

When comparing the distribution of rentals per month (see blue lines in Figure 32), six of the eight stations show a similar pattern (*AZM*, *We*, *Ro*, *Br*, *As*, *Ap*) with an increase in rentals throughout the first half of the year, followed by a decline in July and August. The decrease might be caused by the school summer holidays and the resulting decrease in the total number of travellers using the corresponding train stations in these months. This is confirmed by parallel decrease in the number of checkouts per month, visualised by the red lines in Figure 32. In Autumn, the number of rentals rises again, which is in line with the increasing number of checkouts (with *We* as an exception). The patterns of the other two stations, *Be* and *Vl*, show limited similarity with the other stations, which might be caused by the noise in the data (*Be*) and/or the stations being located close to outdoor recreation areas, suggesting a higher usage throughout summer compared to winter (*Vl*). To conclude, the patterns of the stations themselves and in combination with the monthly checkouts provide little potential for generalisation.

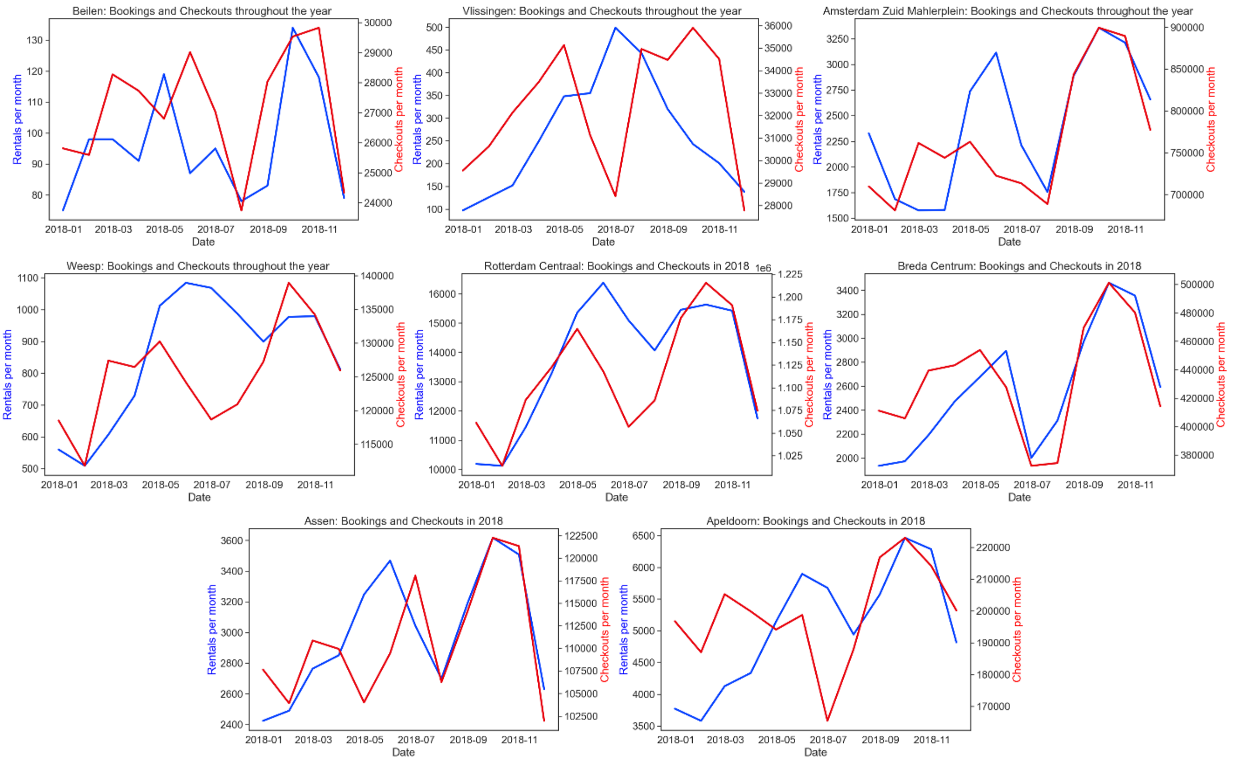

Figure 32: Aggregated monthly rentals and checkouts in 2018 for the exemplary stations

Daily patterns

To compare the average number of rentals per weekday throughout the week, two different patterns occur at more than one of the selected stations, while for one station, *Vl*, the high variance in the data provides limited interpretability. In Figure 33, the patterns of *Rt*, *Ap*, and *Vl* are shown to highlight the differences among the selected stations, while the results for all stations are provided in Appendix B 2.

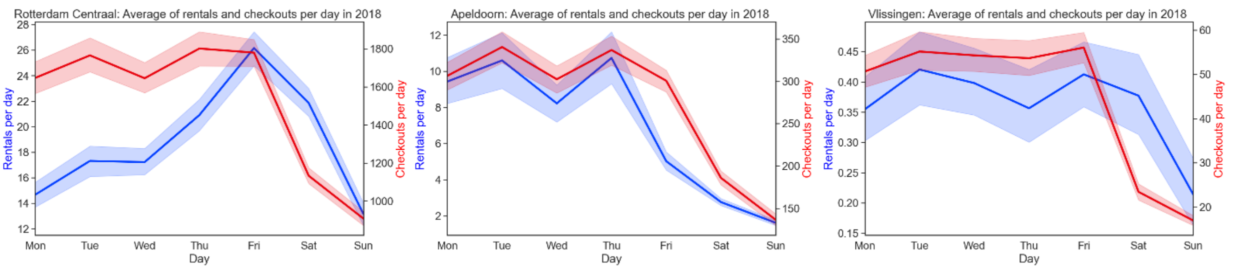

Figure 33: Average hourly rentals and checkouts per day throughout the year 2018 for *Ro*, *Ap*, and *Vl* (light filled areas indicate 95%-variance interval)

The first pattern appears across the stations *Be*, *We*, *Br*, *As*, and *Ap* (*Ap* displayed as example) and shows a stable level of rentals throughout the working days Monday to Thursday, with a small drop on Wednesdays and a sharp decrease from Friday to Sunday. The checkouts of these stations follow a similar pattern, which suggests that the dips in rentals on Wednesdays and Fridays might be caused by less commuters on these days. The second pattern occurs at both *Ro* and *AMZ*, showing an increase in rentals from Monday to Friday which is followed by a sharp decrease towards the end of the week. When comparing these daily rentals with the daily checkouts, the latter shows a shape like the other stations, with a stable level throughout the week and a drop towards the weekend (*Rt* displayed as example). This might be reasoned by both stations being in bigger cities and thus having a high attraction when it comes to recreational trips in the evening or for multiple days on a weekend. To further investigate whether this is the case, a look on the hourly rentals per the day in general as well as the comparison between weekends and weekdays might provide additional insights. This investigation will be done in the following, among the analysis of other hour-specific determinants.

Hourly patterns

When further analysing the average hourly rentals throughout an average day, again two patterns become visible across multiple stations, with *Vl* being an exception having the highest number of rentals around noon (see Figure 34 for *Rt*, *Vl*, and *Ap* as examples, all stations are shown in Appendix B 3). While *We*, *Br*, *As*, and *Ap* show a high peak in rentals in the morning peak between 7-9am, the hourly rentals remain comparatively low throughout the rest of the day. This pattern is different from the hourly checkouts throughout the day, which have an increase in the evening peak (4-7pm). These evening peak checkouts might be train commuters on their way back home, which are not using an SBRT-system for their egress as they might have a bike available at the station which they used for their access leg in the morning. The high number of SBRT-rentals in the morning peak could be reasoned in commuters travelling by train to the corresponding city for work, using the SBRT-system for their last mile to reach their workplace.

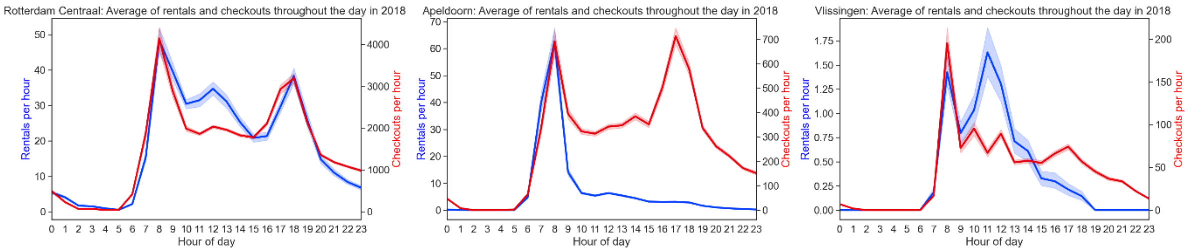

Figure 34: Aggregated hourly rentals throughout the year 2018 for *Ro*, *Ap*, and *Vl* (light filled areas indicate 95%-variance interval)

In comparison, *Rt* and *AMZ* show a less steep decrease after the morning peak. Instead, the number of hourly rentals remains on a comparatively elevated level before showing a second rise in the evening peak. Remarkable is that for these two stations the hourly SBRT-rentals are following a pattern like the hourly checkouts at the corresponding train station. This suggests that at these two stations SBRT-bikes are rented for multiple purposes throughout the day. For example, the evening peak could be reasoned by a higher attraction of the corresponding cities to serve recreational purposes, a finding in line with the previous weekly pattern analysis.

To further unravel the outlines obtained from the daily and weekly patterns, the daily patterns are divided based on the time-related determinants ‘weekend’, ‘national holiday’, and ‘school holiday’. The results are visualised Figure 35 for *Ro* and *Ap*, while all selected stations are shown in Appendices B 4 – B 6. It is found that a day being either on a weekend or a national holiday has a similar effect on the daily pattern across all stations, with the morning and evening peaks disappearing and being replaced by an increase in rentals around noon and the early afternoon. While this new peak is more elevated in stations located in big cities (*Ro* and *AMZ*), in smaller cities such as *Br*, *Ap*, and *As*, the peak is less distinct. On days being school holidays in at least one of the three holiday regions, the change of patterns is less severe: In this case, a slight decrease in the morning peak can be seen across all stations, but the general pattern remains the same. This might be reasoned in the fact that, different to weekends and national holidays, the overall mobility behaviour remains unchanged, with only those having holidays (pupils) or taking holidays (employed people) changing their mobility behaviour.

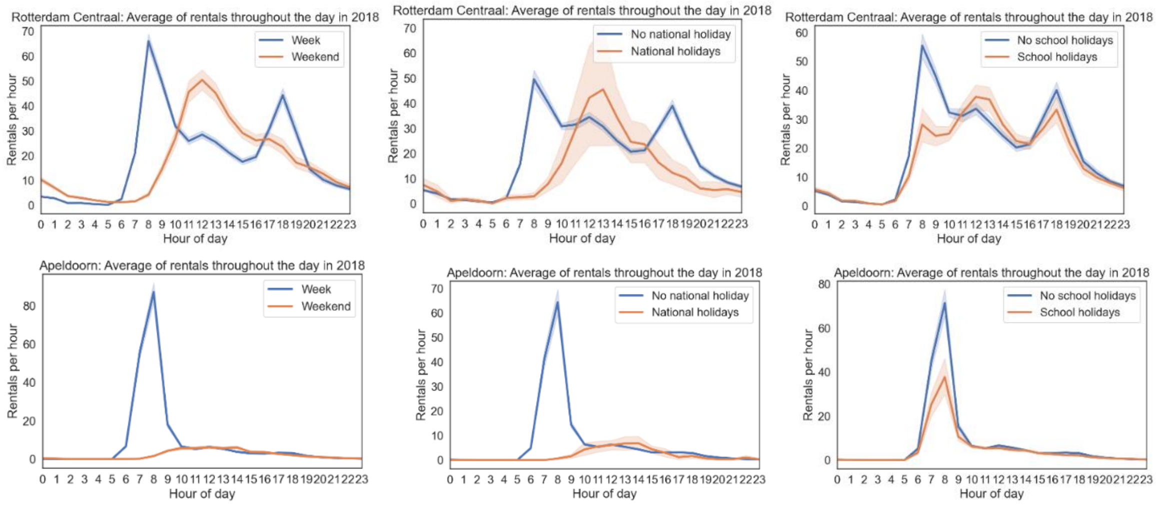

Figure 35: Aggregated hourly rentals throughout the year 2018 for *Ro* and *Ap*, compared regarding the related days being on a weekend or a national holiday, or in school holidays (light filled areas indicate 95%-variance interval)

Further, the impact of the different seasons and the fact of rain occurring within an hour are investigated. The results are shown in Appendices B 7 and B 8. When having a closer look on the impact of seasons on the hourly bookings, for *Be* no conclusion can be made due to the high variance in rentals per hour and season. *AMZ*, *We*, *Ro*, *Br*, *As*, and *Ap* show similar effects of the different seasons, with an overall higher level of rentals per hour in Summer and Autumn and a lower level in Winter. An exception, again, is *Vl*: Here, in Winter the average hourly rentals remain below one bike an hour. In Spring and Summer, an increase of rentals can be seen around noon, supporting the interpretation in these seasons, people are using the SBRT-system for recreational purposes during the day. The impact of rain occurring within an hour is having almost no effect on the number of rentals within the morning peak among the selected stations, while slightly decreasing the hourly rentals in the other hours of the day at *AMZ*, *Ro*, and *Vl*. The other exemplary stations show no significant impact of occurring rain on their overall patterns. This might be reasoned in the fact that travellers decide forehand to use the SBRT-system in the morning peak, which is a decision which might be independent by the occurrence of rain. A potential reason could be the lack of other options to reach a destination. The rain-related results should be read with caution, as the used indicator only checks for rain occurring within an hour without considering how long the rain lasted and/or how heavy the rain was.

It can be summarised that while there are similar patterns among some exemplary stations, the patterns across the different determinants differ too much to use generalised models trying to capture the variance across all stations. Instead, to capture the local differences between the stations, it is decided to apply models separately per station, which is also done in the following forecasting process.

4.2 Forecasting

The following sections describe the application of four different forecasting methods to predict the hourly number of rentals for a period of seven days across the eight exemplary stations. In section 4.2.1 , the performance of the different models is compared across the eight selected stations. Then, in section 4.2.2, the results of one forecasting method are used to visualise how they can be used to assess whether a shortage or oversupply of SBRT-bikes can be expected in the forecasted week. Lastly, it is assessed how the different forecasting methods can forecast hourly rentals in the uncertain times of COVID-19.

To assess the performance of the different forecasting models, the prediction is performed for the rentals per hour over a period of seven days. An overview of the four applied models and the considered variables are shown in Table 7, with the LSTM being performed two times to visualise the randomness in its predictability. The numbers 20 and 21 stand for the random seeds used as input for the two otherwise identical LSTMs to distinguish their results.

Table 7: Overview of models used for forecasting (* using additional holiday information to identify tipping points, ** time-related information split-up into multiple dummy-variables, ^{n} normalised using the Min-Max scaling method)

	LSTM 20/21	Prophet	MLR-All	MLR-Time
Approach	Multivariate	Univariate*	Multivariate	Univariate**
Method	Recurring neural networks	Statistical model using Fourier series	Statistical model assuming perfect information	Statistical model using only time-related information
Considered variables	Time-related information Holidays Checkouts^n Sunshine duration	Time-related information Holidays (National only)	Time-related information Holidays Checkouts Sunshine duration	Time-related information Holidays

All forecasting methods are trained the same dataset covering the 365 days ahead of the forecasting period. They are performed on two exemplary periods, the seven days from 15.3.2019 – 22.3.2019 ('March') and 15.8.2019 – 22.8.2019 ('August'), respectively. These forecasting timeframes are used as exemplary cases, as they provide results for two different periods throughout a year. While this does not necessarily allow for an assessment of the performance of the different models throughout the year, it provides a first indication on how the models perform for different periods of time. The following section will assess the results using different performance indicators.

4.2.1 Result comparison forecasting

The results of the different forecasting methods are assessed to identify the forecasting method most suitable to predict hourly SBRT-demand for a period of seven days. This is done from an aggregated to a more disaggregated performance comparison, starting with a comparison of the RMSE-indicators. Then the accuracy of the number of predicted rentals on a daily aggregation is compared. To conclude, on a higher level of detail the number of hours in which the different models show a significant over- or underestimation compared to the observed values are used for comparison to assess how reliable the different forecasting models are.

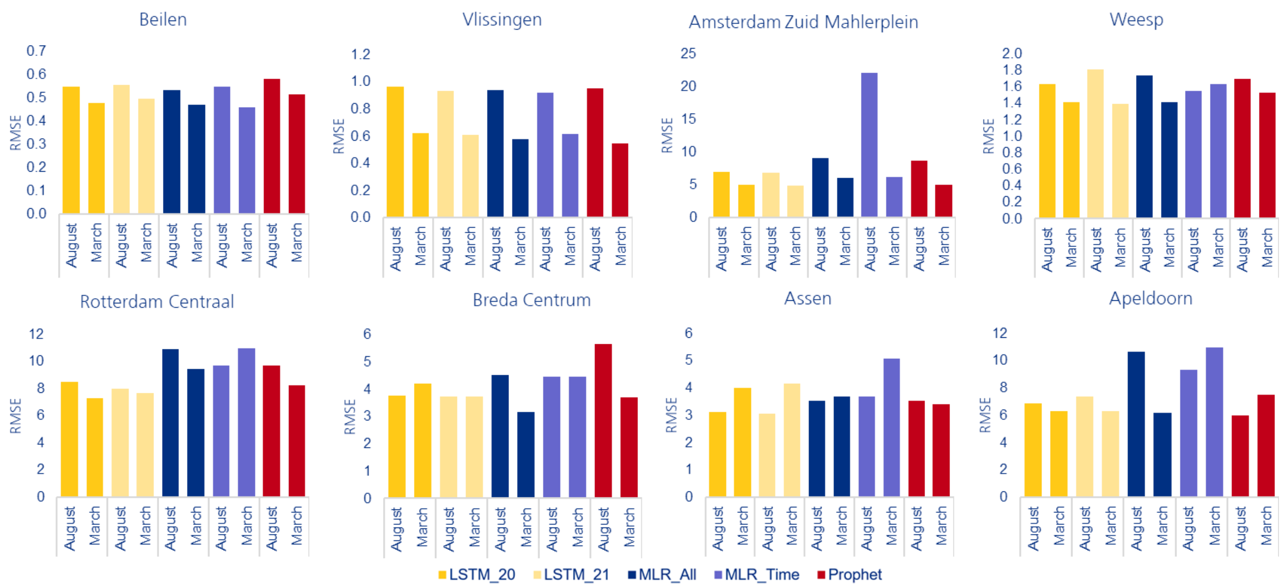

Figure 36: RMSE-indicator per model performed across all selected station for the 'March' and 'August' period

First, the results of the different models are compared using the indicator RMSE, which represents the error between the predicted and the actual hourly rentals within the forecasted period. Thus, the lower the RMSE, the more accurate is the prediction of a model compared to the real observations. As shown in Figure 36, the performance of the models differs per station. While LSTM slightly outperforms Prophet and the time-MLR among three stations (*AMZ*, *Ro*, *Ap*), for all other stations no clear best-performing method can be identified. Also, the models using multivariate input (LSTM, MLR_All) are not found to outperform the univariate, only time-related models Prophet and MLR_Time. Another finding is that for multiple stations, namely *Be*, *Vl*, *AZM*, the models have a lower RSME for the 'March'-period compared to 'August', with *AZM* having an extreme outlier of the MLR_time. This might be reasoned in the 'August'-period being in summer school holidays, which might be less consistent in terms of commuting and more vulnerable to the impact of weather.

A shortcoming of using the RMSE as performance indicator is that it treats all datapoints evenly, also the hours with zero rentals at night, in which stations were closed. To overcome this, the performance of the different models is compared using the errors on an aggregated level per week and day. The relative deviation of the forecasted weekly rentals from the observed values is shown in Figure 37. When comparing the results for the different stations, no model can be identified which clearly outperforms the others across multiple stations. The results for *Be* and *Vl* are not further analysed due to the randomness in their data: Caused by the sparse number of hourly rentals, an accurate prediction cannot be conducted as it cannot be identified whether the right predictions are just 'lucky shots' caused by randomness or not. For visualisation of the problem, see the forecast patterns for the 'March'-period for *Be* and *Vl* compared to *Ap* in Appendices B 9 - B 11. Further, the two different LSTM-models show differences in their performance, which is caused by the random nature of the NNs used by the LSTMs.

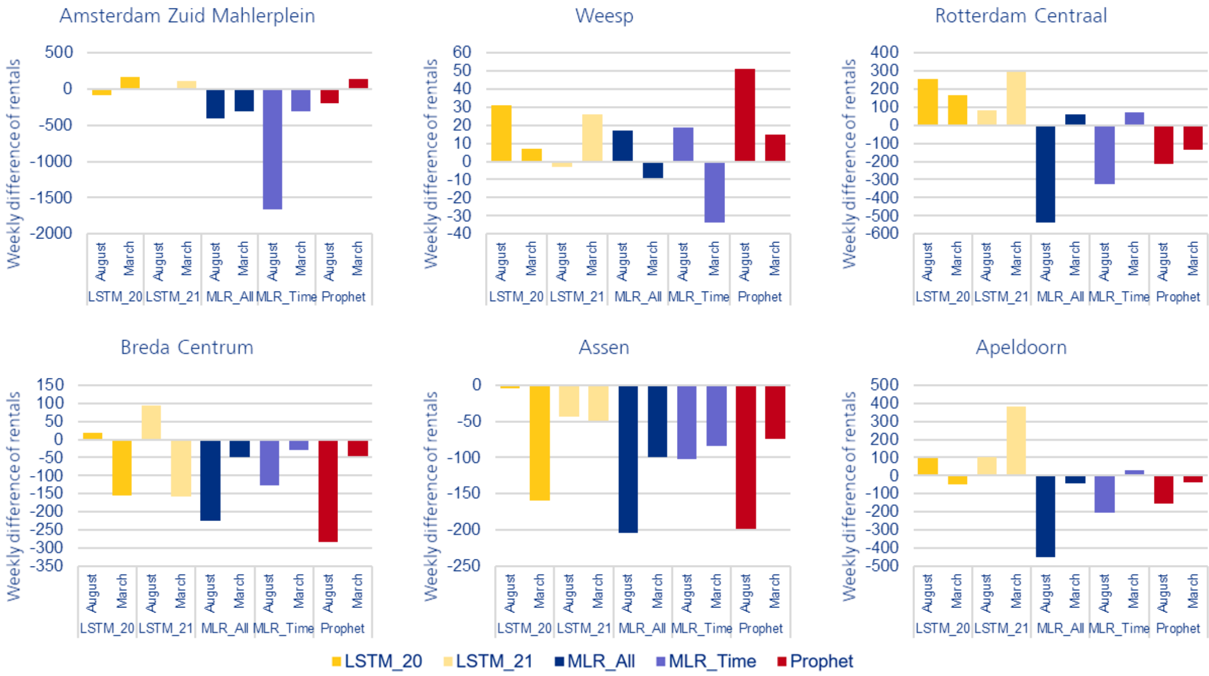

Figure 37: Deviation of the predicted number of weekly rentals divided by the observed number of rentals
(- less rentals predicted than observed, + more rentals predicted than observed)

When further comparing the deviation of daily rentals throughout the predicted week as shown in Appendix B 12, it becomes clear that for some stations, all forecasting models over- or underestimate the number of rentals for the weekdays (*We*, *Br*, *As*). Therefore, the error might be caused by determinants not captured by either of the models, or uncapturable randomness. Further, it is remarkable that in most cases, the performance of the models varies across the different days, i.e. a model which overestimated the number of rentals on one day might underestimate the number of bikes rented on another day.

To summarise the findings so far, the performance of the different models highly differs across both stations and weekdays, leaving no straightforward conclusion on which model performs best. Thus, as third level of comparison is introduced: A count of the hours in which in which the prediction error exceeds a predefined percentage of the number of a stations bike capacity. In Figure 38, *AZM*, *Ro*, and *Ap* are used as examples. This approach allows to select a model which provides the lowest number of 'high' outliers per station.

In accordance with representatives from the SBRT-operator, it is decided to use 1%, 2%, and 5% of the fixed bike capacity of an SBRT-station as thresholds to determine a models' accuracy. Furthermore, it is decided to prioritise the number of underestimations per station. This is done as an underestimation of demand might lead to demand which cannot be fulfilled, while an overestimation would solely result in unused bikes at the SBRT-station.

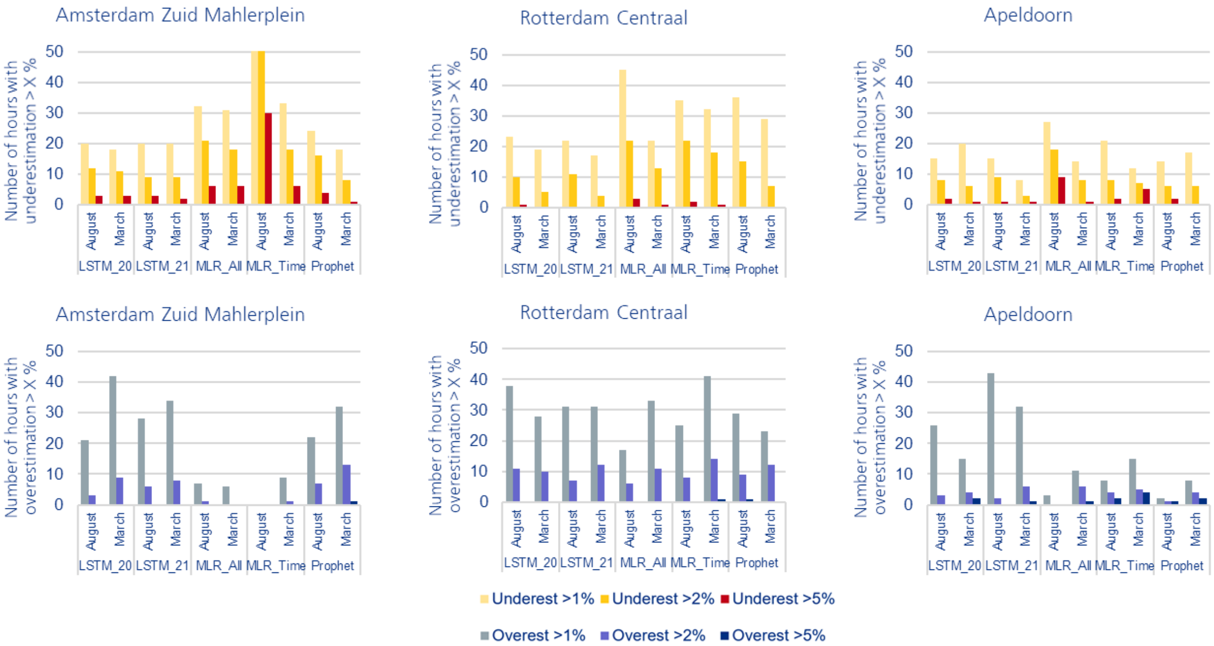

Figure 38: Count of hours in which the prediction over- or underestimates the observed number of rentals, relative to the absolute number of bikes available per station for three of the exemplary stations (Bike-capacities: *AZM*: 350, *Ro*: 655, *Ap*: 460)

To give an example, for both periods at *AMZ* the two LSTM-models have up to 40 hours in which the overestimation is higher than 1% of the total fleet available at this station (i.e. at least seven bikes), while having less than 10 hours with an overestimation of more than 2% of the fleet (i.e. at least 14 bikes) and no overestimations with more than 5% of the fleet (i.e. at least 32 bikes), respectively. On the other hand, the same models underestimate the number of rented bikes per hour by more than 5% of the fleet in three out of the 168 hours, with around 10 hours being overestimated by more than 2% and around 20 hours by more than 1% of the fleet, respectively. In comparison to the other models applied for AZM, the LSTMs show a lower number of underestimations compared to the two performed MLRs, they perform like Prophet, with the latter even outperforming the LSTMs for the ‘March’-period. As the performance for the underestimations of LSTMs and Prophet is similar, the overestimations are compared: While the LSTMs have a higher number of overestimations by more than 1%, Prophet has more hours with overestimations of more than 2% and 5% of the fleet, respectively. Thus, it can be concluded that regarding the hourly under- and overestimations, for the case of *AZM* the LSTMs outperform the other methods. When applying the same line of reasoning on the two other visualised stations, *Ro* and *Ap*, for both stations the MLR-methods are performing worst as they have the highest number of underestimations by more than 5% of the stations’ SBRT-fleets. While for *Ro*, the LSTMs perform better in terms of underestimations of 1% and 2% of the fleets, respectively, for *Ap* Prophet provides a similar performance in terms of underestimations, while outperforming the LSTMs in terms of overestimations. Thus, it can be concluded that across these three stations, the LSTM seems more suitable for the analysed ‘big cities’, while Prophet provides promising results for the demand of stations with in the exemplary ’middle-sized’ cities like Apeldoorn and Assen.

To summarise, there is no ‘one-fits-all’ forecasting method suitable for the selected stations, making it unlikely that this will be different across the other stations within the SBRT-system. But, depending on the identified performance criteria, the selection of a most suitable method per station can be done by comparing the forecast results for multiple time periods. However, to achieve the number of bikes available at a station at a certain hour, the results of the forecast method require a further combination with the historical distribution of the booking durations to assess when the rented bikes will be returned to the station. This process will be described in the following section, using the station *AMZ* and the forecast results of LSTM_20 for the 'March'-period as an example.

4.2.2 Application of forecast results

As explained in section 3.3.6, the historical distribution of booking durations is required to estimate the number of bikes returned in a defined timestep per month, weekday, and hour of day. The provided comparison is just an example to visualise the approach used to estimate the number of bikes returned per hour. A further analysis of the booking durations as well as comparison among hours, days, months, and amongst stations is considered out of scope for this research. The example of *AZM* shown in Figure 39 provides exemplary distributions for the different hours of a Friday morning (left) and of 9pm across multiple days of the week. It can be concluded that in this exemplary case, the duration of bookings differs per time of day as well as throughout the week. Remarkable is the difference of rentals occurring on a Sunday at 9am compared to the rest of the week: While for the other days of the week 90% of the rented bikes are returned after at least 36 hours, on Sundays this threshold is reached after 46 hours. Also, the less steep incline of the curve indicating the distribution for Sunday, 9am, suggests that of bikes rented in this hour, bikes on average are rented longer compared to the other days.

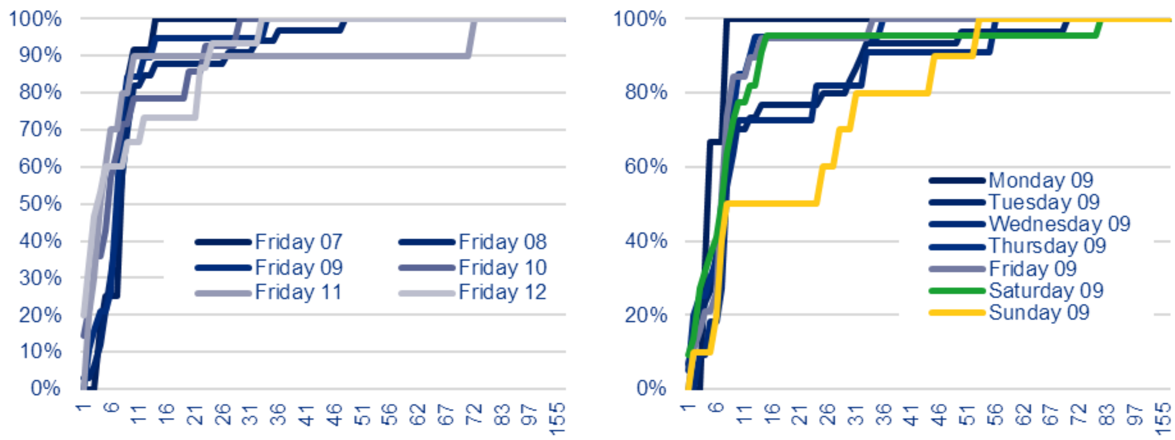

Figure 39: Aggregated historical distribution of booking durations for *AZM* for exemplary hours on Friday morning in March (left) and for hour 9 across the different weekdays in March (right)

The hourly results are then multiplied with the forecasted number of rentals for every timestep (if available) to estimate what number of bikes which will return to the station in the following timesteps[8]. The results are shown in Figure 40. It is important to mention that this forecast is performed for an isolated period of seven days, in which no returns of bookings having started before the considered period are included. To improve the accuracy of the forecast as well as to improve its applicability for SBRT-operators, when applying the forecasting method over multiple

[8] According to https://ovfietsbeschikbaar.nl, on 15th of March 2019 at midnight 220 bikes were available at *AMZ*.

periods it is required to combine the number of bikes being returned between the different periods to allow for a more consistent, accurate representation of the reality.

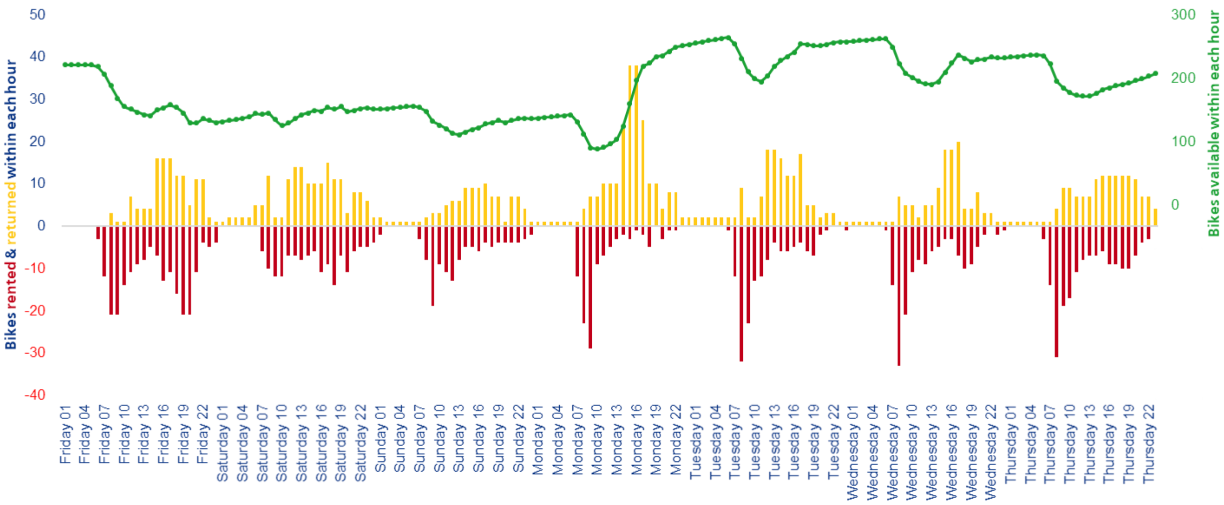

Figure 40: Forecast of hourly rented and returned bikes (red and yellow), resulting in the number of bikes available per timestep (green) for the forecasted 'March'-period and the station *AMZ*

Thus, the provided approach allows for a prediction of both the both the bikes rented per hour and the number of bikes available at a station. In the exemplary case, the forecast suggests that the number of bikes available at *AMZ* within the predicted period will never fall below one hundred bikes, thus for in this period there might be no shortage of bikes. When combining these results with forecasts performed for different stations, the operator might consider moving the surplus of bikes to another station in case this station expects a shortage in bikes based on the corresponding forecast, and a relocation is applicable. Otherwise, one might consider reducing the fleet or perform maintenance on the unrented bikes. It should be acknowledged that this exemplary case uses the results of one forecasting method only, LSTM_20, while different forecasting methods are expected to lead to different results.

4.2.3 Applicability during uncertainty

In the previous sections data from 2018 and 2019 was used as these years we not affected by the uncertainty in changes in traveller behaviour introduced by the COVID-19 pandemic, which led to various governmental restrictions. The introduction of the restrictions often implemented on short notice resulted in significant changes in the travel behaviour (Ton et al., 2022). Also during these uncertain times, SBRT-systems are operating, while experiencing high differences in terms of usage patterns. To assess to what extend the different forecasting models can predict hourly rentals, an exemplary forecast is conducted for the two stations *AZM* and *Ro*. The 'March'-period from 15$^{\text{th}}$ to 21$^{\text{st}}$ of March is forecasted, this time in the year 2021, again using training data from the preliminary 365 days. The results of the forecasts are visualised in Figure 41. It becomes visible that most forecasting methods manage to capture the patterns for *Ro*, with MLR_time being an exception as this model overestimates the afternoon peaks while highly underestimating the weekend usage on the 20$^{\text{th}}$ of March. For *AMZ*, it is more difficult for the models to accurately forecast the rentals due to the inconsistency in the observed hourly rentals, with for example Prophet predicting only one rental throughout the entire 21st of March. This might be caused by the overall decrease in hourly rentals at the station, making the prediction more likely to differ significantly from the observed number of rentals (see also the previously described examples of *Be* and *Vl*).

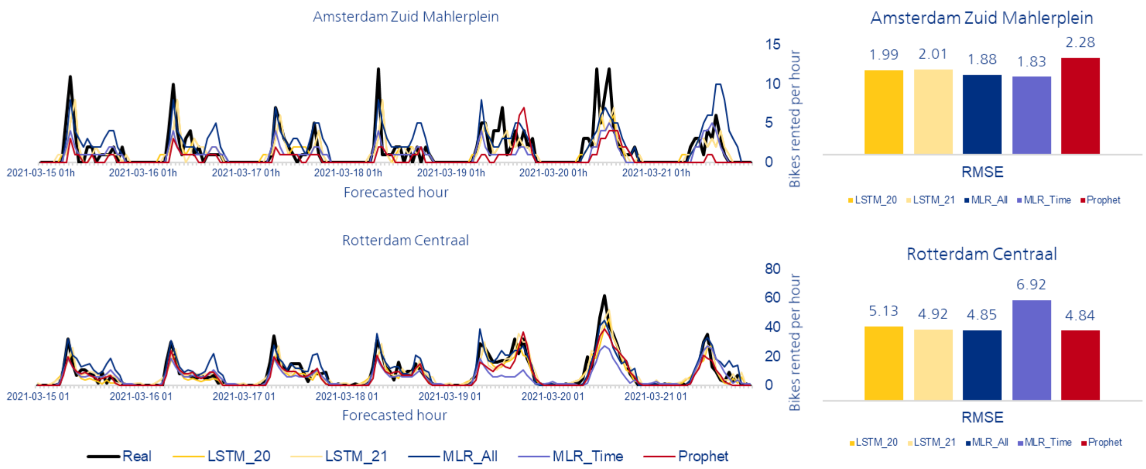

Figure 41: Results of the forecast during uncertainty for the 'March'-period for *AZM* and *Ro*; the corresponding RMSE-results

In terms of the RMSE, there is a reduction across all forecasting methods for both methods when being compared with the corresponding results in the 2018/19 period. This is reasonable as the COVID-19 pandemic led to a general reduction of hourly rentals, resulting in lower values for both forecast and observation. As the RMSE is an indicator for the absolute error between forecast and observation, the results between the two applications pre- and in-COVID cannot be compared. The same holds for the defined indicator for the number of over- and underestimations, as can be seen in Figure 42. Due to the reduced number of rentals during the pandemic, the forecast methods are less likely to highly under- or overestimate the hourly rentals, as the indicator is based on the total number of bikes available at a station. Thus, it is difficult to decide upon a best-performing method: While for *AZM* the LSTMs and the MLR_time perform well in terms of few high underestimations, for *Ro* MLR_time and Prophet indicate only very few underestimations compared to the other methods, while having a comparatively high number of overestimations.

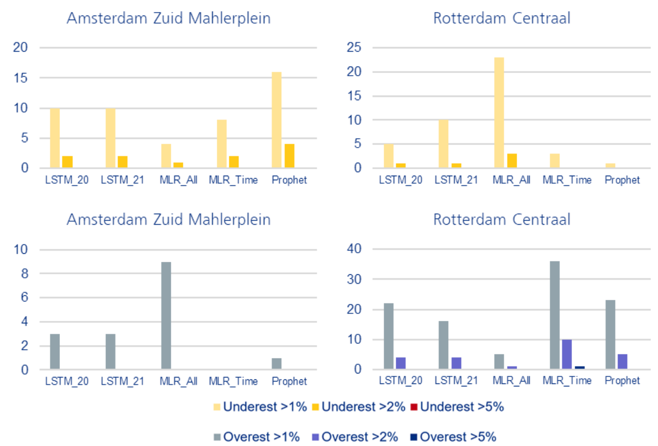

Figure 42: Count of hours in which the prediction over- or underestimates the observed number of rentals, relative to the absolute number of bikes available per station for three of the exemplary stations (Bike-capacities: *AZM*: 350, *Ro*: 655)

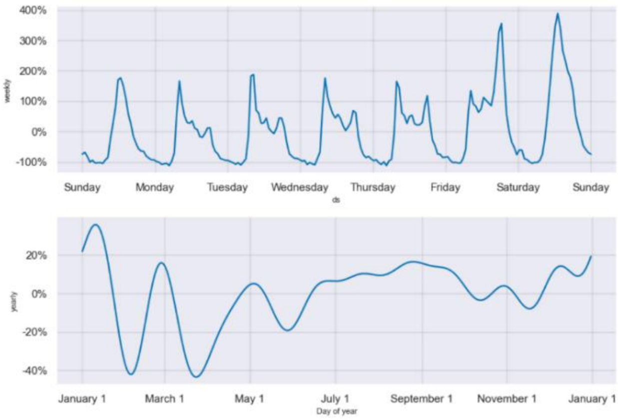

Figure 43: Prophet-model for weekly and yearly patterns for *Ro*

The good performance of MLR_time and Prophet in terms of overestimation for *AZM* and underestimation for *Ro* might be caused by the fact that the models reproduces patterns which occurred during the 'March'-period of the previous year (see also Figure 43 for a visualisation of the patterns used by Prophet). Thus, the finding that these patterns fit the patterns of the following year might be coincidence. This is supported by the fact that both models simultaneously over- and underestimate for the two stations, making it likely that the difference is caused by changes in the data not captured by the models. The MLR_all uses a similar approach as MLR_time, but as it assumes perfect information for the following week in terms of Checkouts and Sunshine Duration, it can adapt to different weather and/or the fact that less train travellers leave the corresponding train station compared to the previous year. The LSTMs are the only models able to incorporate short-term changes in the data as well, such as the impact of new COVID-related regulations. And while both LSTM-applications manage to capture the general rental patterns, they have difficulties in capturing the right moment of peaks, leading to a comparatively high number of under- and overestimations compared to the other models.

Seeing that in the given case the statistical models perform like the LSTMs, it might thus be recommended to use LSTMs for forecasting, as the unique capability of adapting to short-term changes is likely to provide an added value when it comes to uncertain changes in demand patterns. But it also needs to be emphasized that only one period was used for forecasting, and that the results might be different when considering a different week.

4.3 Discussion of results

After analysing the results of the methods used in this thesis, they are set in context to existing literature to identify similarities and difference with preliminary findings. To do so, the discussion of the results is divided in two parts following the two overarching topics of this thesis, determinant identification and forecasting.

4.3.1 Discussion of determinant identification

In the following, the identified determinants and their impact are compared to the findings identified in the literature review in section 2.1. The discussion is structured based on the overarching groups of determinants defined in the previous sections, weather conditions and temporality.

Weather conditions:

The finding of this research that a higher sunshine duration has a positive correlation with the number of rentals is supported by the findings for one-way bikesharing systems (Eren & Uz, 2020).

Another result is different from the literature: The identified small impact of the occurrence of rain on hourly rentals in the morning peak, which differs from the negative impact rain has on the number of rentals in one-way bikesharing systems according to literature. This might be caused by commuters relying on the SBRT-system for the egress leg of their trip as there might be no or few (less attractive) alternatives to reach their destination. Thus, they might be less sensitive to occurring rain. Additionally, when renting an SBRT-bike the users are assured to also have it available for their return trip to the station. This results in a certainty of availability which differs from one-way bikesharing systems in which users cannot be certain that a bike will be available at a certain time and location when they need it. Trips including SBRT-bikes might be planned in advance as part of a multimodal trip, while one-way bikesharing with its ad-hoc booking flexibility is also used for more isolated trips (Médard de Chardon, 2019).

Regarding the positive correlation between hourly rentals and sunshine duration, this is in line with the findings for one-way bikesharing (Eren & Uz, 2020). This finding is also supported by the fact that the train and SBRT-operator NS is using a separate model to forecast train traveller demand for stations with a high recreational attraction in times of sunshine and elevated temperature. This model accounts for the fact that stations close to the beach experience a significant increase in demand on sunny days, when having warm weather as well. This finding can be translated to the analysed SBRT-system OV-fiets, as the results of an additional MLR performed for the station Vlissingen indicated that both sunshine duration and temperature have a positive correlation with hourly rentals. The same holds for the combination of a day being on a weekend and the two weather determinants, suggesting that most SBRT-rentals at this station are done on sunny, warm days on weekends (see Appendix B 14 for results).

Temporality:

The findings for patterns within the rentals throughout the year, aggregated on a monthly basis, are to a certain extent in line with literature findings summarised by Eren & Uz (2020). Different from their conclusions, the results of this thesis identify the highest number of monthly rentals during autumn, while the authors identify a peak of rentals during summer for one-way bikesharing. In the given case, the SBRT-system has a smaller number of rentals during summer months compared to autumn and spring, which is reasoned in the holiday season and lower numbers of commuters and train travellers according to the operator and supported by the provided results. A special case, again, are SBRT-stations located at destinations with a high attraction for recreational trips: For example, Vlissingen has the highest number of rentals in summer, which is more in line with findings for one-way bikesharing. This might be reasoned in a similar trip purpose, namely recreation. Regarding winter, this season shows the lowest number of monthly rentals for the analysed SBRT-system and, according to literature, for one-way bikesharing.

Regarding rental patterns aggregated per day throughout the week, some of the SBRT-patterns selected for the in-depth analysis are in line with the findings by Todd et al. (2021): Both SBRT- and one-way bikesharing show a higher number of rentals on weekdays compared to weekends. Among the different one-way bikesharing schemes identified by the authors, they defined a cluster of systems they named *inefficient systems with low occupancy numbers*, which show a similar number of rentals per hour as two of the selected stations, namely *Be* and *Vl*. This connection between the systems needs to be read with caution, as it is unsure whether the lower usage at the mentioned

stations is caused by a dissatisfying system design or a lack of a sufficient user potential. Another pattern identified among the selected stations has no similar counterpart in one-way bikesharing literature: The peak of rentals at bigger stations such as *Ro* and *AZM* between Thursday and Saturday. This might be caused by the 24-hour pricing scheme of the OV-fiets making long-term bookings cheap in comparison to one-way bikesharing systems. Another reason might be the round-trip nature of the system, making it more attractive to book a bike overnight and/or for an entire weekend in comparison to one-way bikesharing.
When comparing the literature findings for the distribution of rentals throughout the day, the distinct morning peak is in line with literature for one-way schemes. But, different from one-way schemes, the evening peak is less distinct. A potential reason is that the individuals renting the bikes in the morning still have their rented bikes available to return to the station in the evening. In the one-way-schemes discussed in literature, these return-trips are separately booked, thus leading to distinct evening peaks (Todd et al., 2021). Still, evening peaks exist in the SBRT-systems across some stations, but they occur later compared to one-way schemes and only at stations located in bigger cities such as *Ro* and *AZM*. On weekends, the hourly patterns throughout the day show peaks in the early afternoon, which is in line with findings for one-way schemes.

Thus, while there exist determinants with similar effects on both SBRT- and one-way bikesharing schemes like sunshine duration, temperature and time of the year, other determinants show noteworthy differences between the two schemes such as the higher number of rentals on Fridays or the differences and/or the lack of evening peaks at SBRT-stations. It therefore can be concluded that SBRT-usage requires research independent from one-way bikesharing schemes in terms due to its distinct characteristics. Whether the same when it comes to forecasting the hourly rentals will be discussed in the following.

4.3.2 Discussion of forecasting

The known literature does not allow the identification of a most suitable method to predict short-term SBRT-demand, as to date no similar systems were researched. As shown in section 4.2.1, none of the identified methods outperforms the others across multiple stations, making it impossible to identify a best-performing forecasting method for hourly SBRT-rentals, especially as the identified literature compares the performance of the forecasting methods for one period of time only. To contribute to this knowledge gap, the results of this research indicate a slightly better performance of LSTMs when forecasting demand for stations in the selected big cities, while Prophet slightly outperforms the other methods for the selected stations having a distinct morning peak and lower hourly rentals. As LSTM is a multi- and Prophet a univariate model, no clear answer can be given to the question whether providing additional determinants per se improves the performance of a model. Instead, it is likely that per station, a different model might perform best. Here, it is important to mention that, different from literature, the performance assessment in this research uses the number of high errors between forecasted and observed rentals. This is done as the performance indicator used in literature, RMSE, does not allow for a method outperforming the others and is incapable of assessing the magnitude of distinct over- or underestimations.

The only stations in which one model outperforms for both forecasting periods are *Ro* and *AZM*, for which LSTM shows the best performance on the general indicator RMSE and the indicators providing information about the over- and underestimation of rentals. For all other stations, no clear best-performing forecasting method can be identified, and it is unclear whether the additional information provided for the multivariate models leads to them outperforming univariate models due to the differences in their performance between the two periods. Thus, in comparison to results obtained from literature, no favourable method can be suggested which is applicable across all stations. But it is important to mention that the papers discussed in the literature review perform a forecast for one period only, and do not capture different results of the NN-based LSTM-method. Therefore, it cannot be insured that the results obtained by Alencar et al. (2021) and Zhang et al. (2018) are reproducible and their best-performing methods would also perform best for other periods of their selected sharing schemes.

To conclude, there is no clear best-performing method found in this research: While the advantage of both Prophet and MLR is the interpretability as well as the comparatively easy applicability of the methods, LSTM shows a more consistent performance for stations in bigger cities and might allow for a better performance when adding additional variables or tuning the hyperparameters. An additional advantage of applying LSTM in comparison to the statistical models is that it has the capability of adapting to short-term changes, which is valuable in times of uncertainty. While Prophet and MLR reproduce learnings from the entire training data, LSTMs can forget historical knowledge when significant changes in data occur on shortly before the forecasted period, then weighting the recent changes higher than long-passed ones. Still, it needs to be emphasized that only limited periods of time are used for forecasting, and that the results might be different when considering different periods. These and other assumptions and limitations of this thesis' results will be discussed in the following section.

5. Conclusion & discussion

The present research aims to provide new insights on station-based round-trip bikesharing, as scientific evidence analysing this type of bikesharing is scarce, especially compared to the more common one-way bikesharing evolving throughout the world. By analysing the existing usage patterns and assessing potential forecast methods, this research allows for a unique view into the concept of SBRT. The findings generated in this research can help operators and policymakers to make SBRT, alone or as part of multimodal trips, an attractive and sustainable way of travelling.

The following sections set the results of the conducted research in a broader context. After summarising the performed research in section 5.1 and discussing its limitations in section 5.2, section 5.3 provides recommendations for both SBRT-stakeholders and future research in the domain.

5.1 Conclusion

To identify significant determinants for bike rentals at SBRT-stations (RQ1), the rentals done in 2018 throughout the Dutch SBRT-system OV-fiets are aggregated on an hourly level. The results are then filtered, normalised using the total capacity per station, and combined with information on national and school holidays as well as hour-specific information about the weather conditions. The latter is gathered from the national weather stations closest to each SBRT-station. The resulting dataset is used to perform MLRs across the entire dataset as well as per individual SBRT-station to identify significant weather- and time-related determinants. It is found that while for some stations few variables are sufficient to explain most variance in the data, there is no connection between the number of significant variables and per station and their ability to explain the variance in the data.

To further investigate whether the available data can be used to identify temporal usage similarities and differences among SBRT-stations (RQ2), a descriptive analysis is done using eight selected stations. The hourly rentals per station are then aggregated on a monthly, daily, and hourly level and compared with the previously identified determinants. When comparing the patterns of the different stations, it is found that while the patterns mostly differ across the stations, a number of general trends can be identified: For example, on average all stations have their highest number of hourly rentals in the morning peak between 7-9 am, and the two selected SBRT-stations located in bigger cities also experience a second peak in the afternoon between 5-7 pm. The latter suggests a different use case of the SBRT-system in the evening peak compared to the morning peak. Another identified difference becomes visible between the patterns of hourly rentals on weekends and weekdays, as on weekends neither morning nor evening peaks appear. Instead, the rentals either stay on a low level throughout the day or experience a peak during the early afternoon between 12-2 pm. Another finding is that the occurrence of rain has is unlikely to impact the number of rentals in the morning peak, while the number of rentals throughout the rest of the day slightly drops when rain occurs.

To assess to what extent the rented bikes per hour at a SBRT-station can be predicted using time-related determinants only (RQ3) and what added value additional determinants might provide to a forecast (RQ4), different forecasting methods are applied using the given dataset. Based on literature research, the univariate, statistical forecasting method Prophet and the multivariate, NN-based method LSTM are selected and applied to predict the hourly rentals for seven days in advance. Further, the station specific MLRs identified in the previous part of the thesis are used as additional forecasting method for reference. Two different MLRs are applied per station, one assuming multivariate, perfect information, the other including only univariate, time-related information. The forecasting methods are applied on the previously identified eight exemplary stations and for two different timeslots. The comparison of the forecasting results shows that all methods only have limited applicability for stations with a sparse number of rentals. For stations having a higher number of rentals, the performance of the models differs across the exemplary stations, making it difficult to distinguish which method is most suitable, and whether the additional information in the multivariate models provides an added value. Further, whether the performance of the models is considered sufficient to be implemented in practice highly depends on the service level the operator wants to achieve, and how much slack in the forecast the operator accepts. Here, it is relevant to distinguish

Once the forecast is applied, it can provide a high added value for the different stakeholders: It allows *current operators of SBRT-systems* information about the projected demand for their system, which allows to both increase the occupancy of the fleet by providing additional supply in locations with higher projected demand and to ease the organisation of maintenance schedules to happen in times of low demand. The forecast can also be used to provide projected availability information for *(potential) SBRT-users*, which might provide additional certainty in terms of planning the own multimodal trip due to the added information of knowing whether a bike is likely to be available when arriving at a station. This additional certainty in terms of trip planning is likely to increase the attractiveness of including the SBRT-system in a trip. Both, the improved match of supply and demand and the increased attractiveness of multimodal trips might motivate more individuals to perform PT-based multimodal trips instead of using a car, which is in line with the goals of *local stakeholders* such as municipalities and governments to reduce pressure from car networks and contribute to a more sustainable way of getting around.

5.2 Discussion

The following section discussed the limitations of this thesis due to taken assumptions and scoping. First, general limitations will be discussed, followed by limitation of the determinant identification and the forecasting, respectively.

General:

A limitation of this research is that, as all studies analysing patterns in bikesharing data, only revealed data of performed bookings is available for analysis. This leaves out the fact that there might be unfulfilled demand due to a lack of available bikes in some cases. Thus, the current approach might underestimate the demand at stations which often have too few bikes available.

The aggregation of SBRT-rentals on an hourly level leads to a loss of information regarding the specific moments in which rentals took place. Instead, the aggregation leads to the assumption that the rentals were evenly distributed throughout an hour, whereas most rentals within an hour might have happened within a comparatively brief time window, for example after a train arrives at a station. To overcome this, one might consider using a less aggregate approach, such as 15-minute intervals, as performed by Zhang et al. (2018). At the same time, for some stations with few hourly rentals (such as Be or Vl), the aggregation on an hourly level might be too detailed to successfully investigate rental patterns. In these cases, for many timesteps the number of hourly rentals is just equal to zero, making it difficult to assess the dataset appropriately using MLR. In the present study, the hourly aggregation was chosen as historical weather data is available on this level only. Further, the filtering of stations is likely to result in a bias, as selecting staffed stations can result in a selection of stations having a higher service level, and potential users might be more inclined to using stations with human service instead of self-service stations. So the findings of this research cannot directly be applied on the stations which are filtered out but might provide a first indication as it is found that station-specific models are most suitable for appropriate forecasting. Another limitation is that this research was applied using data for the years 2018 and 2019: It is likely that the drastic changes in mobility usage patterns caused by the COVID-19 pandemic and the accompanying restrictions, as identified by Ton et al. (2022), affect the rentals of SBRT-schemes as well. As to date there is no consistent 'post-COVID' mobility in place, and travel restrictions are about to be eased, it is yet unknown to what extent the results can be applied into future. This thesis thus aims to identify general learnings about the system using COVID-19 independent data from 2018/19. The forecast for more recent, COVID-19 affected data can is an exemplary case to provide a first insight to what extent the applied methods might be suitable for uncertain times as well. In this case, models with the capability to adapt to short-term changes like LSTM might provide more reliable results in comparison to those modelling historical patterns such as MLR.

Lastly, in the provided thesis it was decided to *perform analysis and forecasting models on a station level* instead of including the differences between stations as additional variables within one overarching model. This was done as the station-related usage is expected to differ in terms of demand structure, location in the corresponding city, etc. The assessment of multiple location-specific determinants to distinguish different stations was considered out of scope for this research to limit complexity. Still, results from such research might have an added value when developing one model capturing all stations, using the location-specific determinants as input for the model to provide the required accuracy on a station-level.

Identification of determinants:

While for the identification of determinants the hourly rentals of all stations generalised using the bikes available at each station, no information is included in the MLR on *location-specific determinants* such as local service quality, the general availability of bikes, or spatial information such as centrality and accessibility of a station regarding both the corresponding train station and potential destinations of users. These location-specific determinants are excluded as the following in-depth analysis and the forecasting are performed on a station level, making both analysis and forecast station-specific and thus independent from differences between stations. Another limitation is that while trying to capture weather- and time-related determinants, *other external determinants were* *left out*. An additional determinant, as mentioned by the operator, are events, which are accessed by travellers from outside using the SBRT-bikes. A problem here is that while bigger events such as concerts, festivals, and big football matches have the access and egress of visitors organised and/or distinct public stations and publicly available calendars, smaller events as for example local sports competitions or student festivities are difficult to grasp. And while the number of train travellers caused by the events might be available within the checkout-dataset, the problem is that it is not known whether the attendants of an event will rely on the SBRT-system for their egress leg, or whether they will use other modes. Due to this complexity and the lack of data available for local events, it was decided to exclude events from this analysis.

Additionally, using checkout data as determinant comes with the limitation that *the provided checkout data is estimated by a model* by the operator, which in addition to the occurring checkouts with smartcards adds an estimation for trips not being performed using such a smartcard, leading to a potential error of the resulting data by 1-2%. Also, checkout data is available for the train system operated by the SBRT-operator NS only, leaving out travellers using other train operators. While most of the forty-eight analysed stations solely have NS as train operator, others such as Groningen, Maastricht, or Almelo have multiple train operators. Thus, the checkout data used only captures a part of the travellers at these stations. To a certain extent this can be solved by applying stations-specific models, but then relies on only a part of the required data.

Regarding the *weather data*, as mentioned earlier, the main limitation is the distance between weather stations and SBRT-stations, leading to some weather-related determinants such as rain providing less reliable data. In general, the MLR as well as the in-depth analysis only captured the *interaction between two determinants at the same time*, while some rentals might require a higher dimensionality of interaction effects to appropriately explain the hourly rentals (e.g. an interaction between time of day, weekday, holiday, and occurrence of rain).

Lastly, the *in-depth analysis covered only eight exemplary stations*, leaving out the other forty. While the exemplary stations allow for a first insight and provide some insights which might be translated onto other stations as well (distinct morning peak for mid-sized stations, additional evening peak and higher demand on weekends at stations in bigger cities), the differences among the exemplary stations are too remarkable to be able to generalise findings across all forty-eight stations. An analysis covering the results for all forty-eight stations might provide additional insights on this.

Forecasting:

A limitation of the forecasting process is that the *focus is on forecasting rentals only*. While the chosen approach to estimate the number of returned bikes per hour using a historical distribution of bookings keeps the number of bikes at a station consistent, the historical distribution of bookings might not be suitable for future rentals, as it is especially sensitive in cases in which in the past only few rentals occurred and in the future many rentals are predicted. An alternative option would be to use a second forecast model predicting the number of bikes returned within a timestep using the same approach as described in this thesis for rentals. Such a method is likely to increase the accuracy of bikes returned per hour as it includes more information. But it also bears the risk that if applying two forecast models separately, there are also two uncertainties regarding the predictive accuracy, which might result in more bikes returning to a station than there are available in total.

Alternatively, the usage of the historical booking duration could be improved by identifying more specific distributions by including additional variables such as holidays. In general, it is assumed in both the dataset used for analysis and in the applied forecasts that *all bikes rented at a station also return to that same station*, whereas in practice it is possible to return a bike at another station (even though this comes with a high fine for the user).

Regarding the application of the forecasting methods, a limited number of variables was included in each model to reduce computation complexity, whereas an *addition of the variables considered less significant* (e.g. temperature, dew point, cloud coverage, ...) in the selection process might still provide an added value for the forecast application. Overall, separate models were developed per station, whereas the station and its location-specific information could also be used as input variables for a more complex, but *generalised model*. This generalisation was considered out of scope due to the identified differences in rental patterns between the stations. A generalised model might provide a better applicability for operators. But as NS is already using different forecast models for different stations when it comes to forecasting the number of travellers, it is considered sufficient to develop station-specific models, which might be generalised in the future by researchers or operators. This, and other recommendations on how to use the provided insights for further implementation and research will be described in the following section.

5.3 Recommendations

The findings regarding the identified determinants and the applicability of the different forecasting methods for SBRT-systems provide first insights into this less-researched type of bikesharing. For current and future operators of similar schemes, the findings can provide information on the potential future occupation of their system, allowing for an increase in efficiency in terms of scheduling of staff, maintenance of bikes, and a potentially higher user satisfaction due to an improved match of supply and demand. Still, some additional steps might be considered to assure an added value for the operators:

The operator should develop a sharp vision on how the aimed performance and the related performance indicators should look like, e.g. how many times it is acceptable to run out of bikes at a facility or how many bikes which remain unused at a station are acceptable in a predefined period. The definition of this indicator is important as it defines the level of accuracy a forecasting method should achieve in terms of over- or underestimating the demand, and thus needs to be discussed before implementing forecasting on a larger scale.

Further, for some smaller station the prediction on an hourly level might be impossible due to the higher randomness in rentals and/or the small number of rentals (see *Be* and *Vl* as examples). In these cases, it should be investigated to what extent a higher level of aggregation, e.g. on a daily basis, might be sufficient to assess the (future) performance of the station.

Regarding the forecast model selection per station, the present research only includes staffed stations. Thus, it might be interesting for an operator to investigate to what extent the forecasting methods might be feasible for the remaining, smaller stations in the system.

When it comes to the actual application of forecast methods, one might try different periods for the training data instead of the 365 preliminary days used in this research. It could also be assessed

whether for example using two years of data might provide more accurate results due to more learning data, or whether using only the last two to three preliminary months of data might result in a model relying less on long-gone data, which might make it more flexible to adapt to recent changes in rental patterns. The latter would especially be of interest for the current situation, with COVID-19 and the related travel restrictions constantly changing the way both the SBRT- and the related train-system are used by individuals. A forecasting method able to incorporate these changes on a short-term basis might provide a high added value for both operators and individuals wanting to use the SBRT-system. Also, for complexity reasons, the operator might consider to, based on the desired level of accuracy, select a single model to be performed across all stations. This might lead to a reduction in accuracy for some stations. Nevertheless, this decision comes with the advantage of having a single overarching model, making it easier to be performed on a regular basis within a company environment due to the reduced complexity.
Lastly, neither in the determinant analysis nor in the forecast application, events apart from national holidays were considered, even though it is mentioned by the operator that smaller, local events with individuals participating from other parts of the country are reasons for especially smaller SBRT-stations to unexpectedly run out of bikes. Due to the difficulty of gathering data on the occurrence of these types of events, and the complexity of determining which events are more and which less likely to attract a high number of SBRT-users, this was considered out of scope for this thesis. But as it can be expected to provide a high additional value in terms of improving the forecast accuracy, it might be a suggestion for future research to identify these causalities.

Many of the mentioned recommendations for operators can also be of interest for future research from a scientific perspective. Additionally, for the scientific analysis of SBRT-schemes it might be interesting to perform this research or parts of it on another SBRT-system, e.g. Bluebike in Belgium, to evaluate whether the findings of this research are applicable for other countries and locations. Regarding the determinant identification and the descriptive research, it might be of interest to investigate the smaller stations left out in this research to see whether insights might also be generated for these types of stations.
Also, this research is performed on a station-level and lacks location-dependent determinants such as the number of bikes available as well as the quality and accessibility of a station, or the spatial components of the surrounding area. Research capturing these determinants might help to develop an understanding on the reasons behind the differences amongst stations identified in the in-depth analysis in this research.
Furthermore, the conducted forecast for a period affected by the COVID-19 pandemic only provides a first insight. To further assess the potential of the different forecast methods to predict during uncertain times, it might be interesting to evaluate to what extent the introduced restrictions led to short- and/or long-term changes in the way SBRT-systems are used. These insights might also help in adapting the applied forecasting models accordingly, and/or updating the determinants used as input for forecasting.
In general, the application of the forecasting methods and the resulting performance might be further researched, as this research does not perform a tuning of the hyperparameters for the LSTM-methods or Prophet. Additionally, an alternative selection or definition of input variables might provide additional value to make the forecasting results more accurate. Also, all models apart from

MLR_all currently use historical data only to predict the future seven days. To improve the forecast accuracy, one might consider adding (uncertain) information for e.g. the number of predicted hourly checkouts or weather forecasts as 'determinants for the future' to increase the accuracy of the model, as these forecasting models already exist. Also, individuals might make the choice on whether to use an SBRT-bike or not based on weather-forecasts, making it even more interesting to add this as additional determinant.
Another added value of this research is the use of two LSTM-models to visualise the variance in NN-based methods and the forecast for two different periods to assess whether the performance of models per period are consistent. Still, only two LSTM-models and/or two periods of time might not be sufficient to account for the potential variance in the model performance. Thus, further research might focus on performing multiple LSTMs and then forecasting based on the outcome of multiple runs to overcome the limitation of the randomness. To compare the performance of different models, a valuable application would be to assess the performance of models over multiple forecasted periods of time. This might result in one model outperforming all others or could also lead to different forecasting methods performing better for different periods of time. Also, one might consider changing the loss function of the forecast methods to assign a higher weight for hours in which a high number of rentals occurs. This would result the models being trained more for being accurate in times of higher demand compared to times of low demand, which then might result in a reduction of heavy outliers.

To conclude, this research provides new insights into a new, barely researched type of bikesharing. The learnings provide a first indication on where SBRTs have similarities and differences with the widely known one-way bikesharing and provides existing and potential operators new insights on how these learnings can be used to forecast the occupancy of their services to improve the service availability and efficiency. Further research can deepen the understanding of the system and help SBRT-systems to gain a wider acceptance by raising awareness on the added value of the system.

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Appendix A: Data

A 1:Detailed explanation of considered variables within the thesis

Variable	Dataset	Data format in R	Purpose	Representation as determinant
OV-fiets station of rental & return	SBRT	Name of station [character]	Input	
Time and day of rental	SBRT	YYYY-MM-DD hh:mm:ss [Datetime]	Input, Determinant	• Each hour of day as dummy-variable • Aggregation on time-of-day level, then as dummy variables[9]
Time and day of return	SBRT	YYYY-MM-DD hh:mm:ss [Datetime]	Input	
Weekday of rental	SBRT	ma-di-wo-do-vr-za-zo [character]	Input, Determinant	• Each weekday as dummy-variable • Weekend vs. no weekend dummy variable
Month of rental	SBRT	0-12 [integer]	Input, Determinant	• Each month as dummy-variable • Aggregated on season-level, then as dummy variables[10]
Number of rented bikes per booking	SBRT	Between 0 and 8 [integer]	Input	
Name of train station	SBRT, Station, CICO, Combination	Name of related train station [character]	Matching	
Type of OV-fiets station	Station	Staffed station, self-service, 0, NA [character]	Filter	
NS train station typology	Station	Between 1 and 6, 0, NA [integer]	Filter, Input	
Prorail train station typology	Station	Kathedraal, mega, plus, basis, halte, 0, NA [character]	Filter	
Maximum bike capacity	Station	Between 0 and 1000, NA [integer]	Filter, Input	
Corresponding region	Station	Noord-Oost, Randstad-Noord/-Zuid, Zuid, Zuid Nederland, 0, NA [character]	Filter, Input	
Company operating station	Station	Arriva, Connexxion, Keolis, R-Net, NS, 0, NA [character]	Filter	
Check-in per hour and station	CICO	0 or positive number [double]	Determinant	Numeric values (rounded to full numbers)

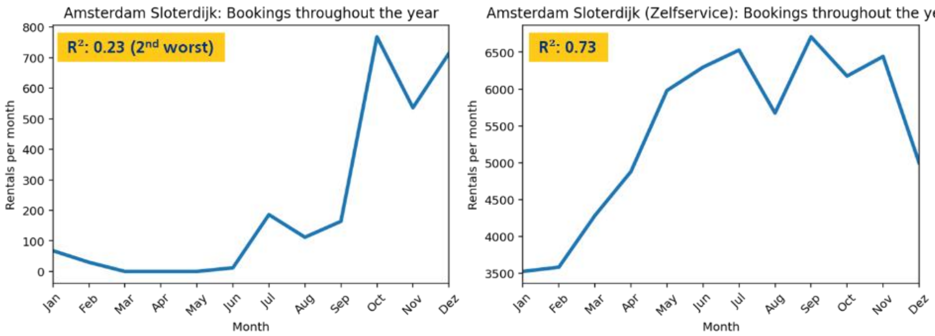
[9] The hours of day were assigned to the time of day using the following scheme: 1-5am = Night, 6-9am = Morning Peak, 10am-3pm = Daytime, 4-7pm = Evening Peak, 8pm-12am = Evening. This scheme follows the peak-period definition

[10] The months were assigned to the seasons using the following scheme: January-March = Winter, April-June = Spring, July-September = Summer, October-December = Autumn. This scheme following the meteorological seasons.

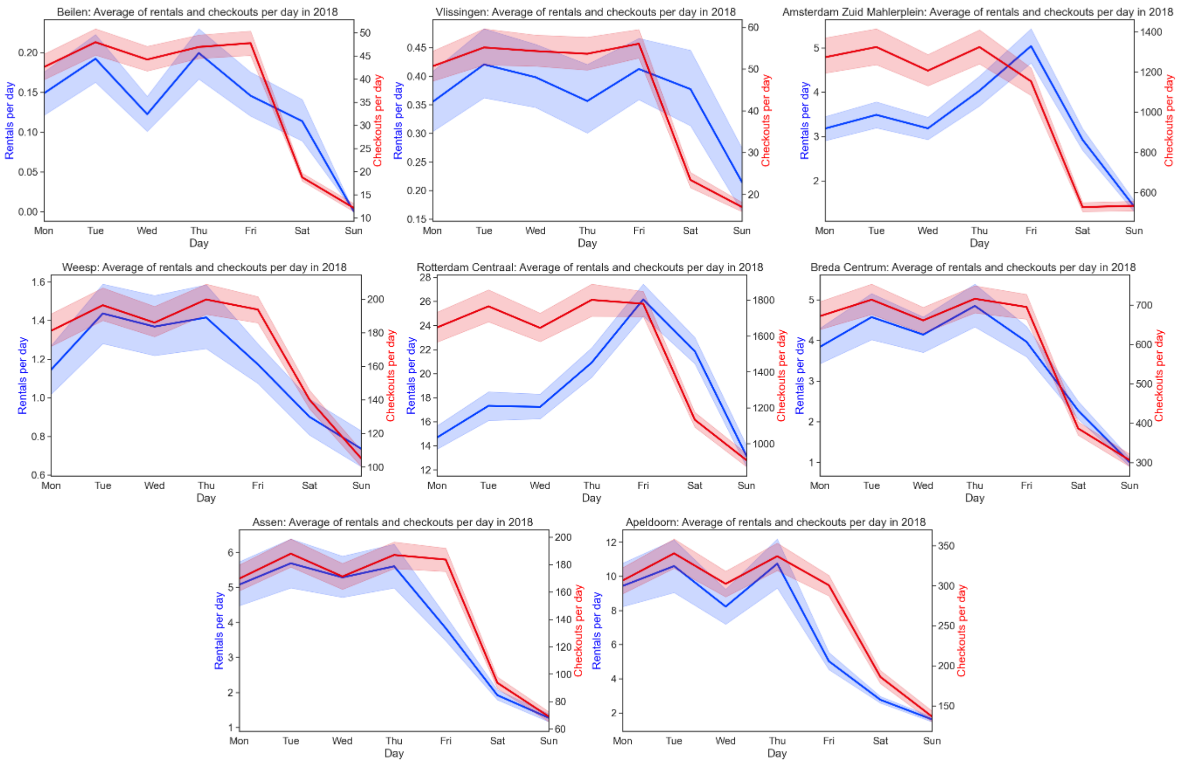
Variable	Dataset	Data format in R	Purpose	Representation as determinant
Weather station location	Combination	Longitude and Latitude of each weather station [double]	Matching	
Train station location	Combination	Longitude and Latitude of each train station [double]	Matching	
Weather station	Weather, Combination	KNMI-defined number [integer]	Matching	
Wind speed	Weather	Average wind speed within the last hour in 0.1m/s [double]	Determinant	Numeric values
Temperature	Weather	Temperature on 1.50m at the time of observation in 0.1°C [integer]	Determinant	Numeric values
Sunshine duration	Weather	Sunshine duration in 0.1 hours during hourly division, estimated based on global radiation [integer]	Determinant	Numeric values
Rain duration	Weather	Rain duration in 0.1 hours during the hourly division [integer]	Determinant	Numeric values
Cloud coverage	Weather	Cloud cover in octants at time of observation, scale 0-9, 9 = sky invisible [integer]	Determinant	Numeric values
Relative humidity	Weather	Relative atmospheric humidity in % at 1.50m at time of observation [integer]	Determinant	Numeric values
Fog	Weather	Occurrence of fog during preceding hour or at time of observation, 0 = no occurrence, 1 = occurred [integer]	Determinant	Dummy variable
Rain	Weather	Occurrence of rain during preceding hour or at time of observation, 0 = no occurrence, 1 = occurred [integer]	Determinant	Dummy variable
Snow	Weather	Occurrence of snow during preceding hour or at time of observation, 0 = no occurrence, 1 = occurred [integer]	Determinant	Dummy variable
Thunder	Weather	Occurrence of thunder during preceding hour or at time of observation, 0 = no occurrence, 1 = occurred [integer]	Determinant	Dummy variable
Ice	Weather	Occurrence of ice formation during preceding hour or at time of observation, 0 = no occurrence, 1 = occurred [integer]	Determinant	Dummy variable

Appendix B: Descriptive analysis

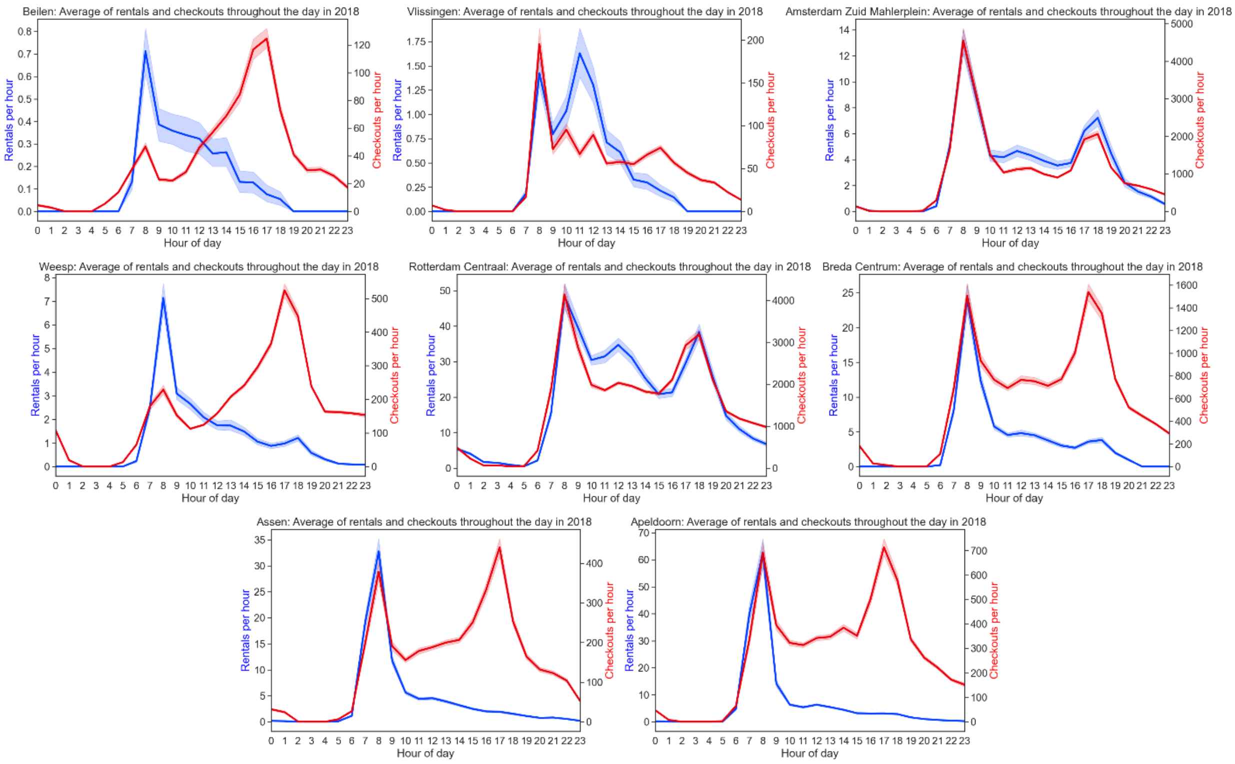
B 1: Comparison of monthly bookings for the stations Amsterdam Sloterdijk and Amsterdam Sloterdijk (Zelfservice) as well as information about their R² performance



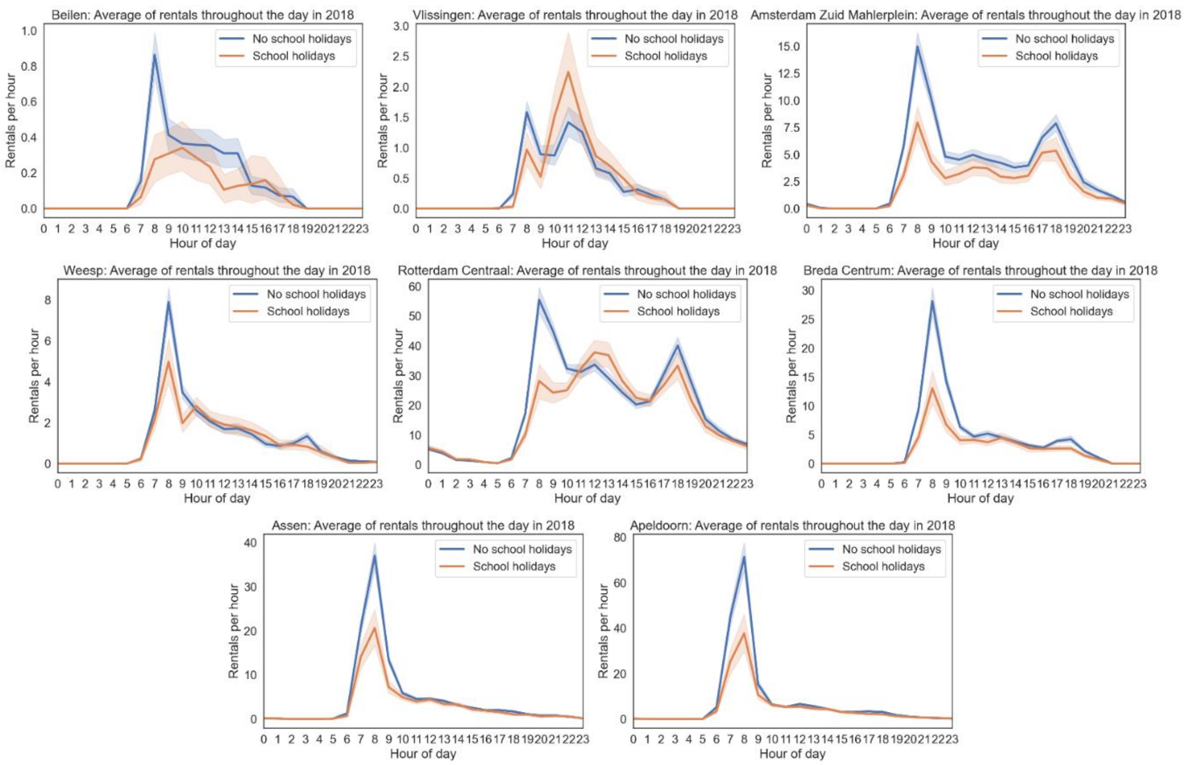
B 2: Average daily rentals and checkouts per week in 2018 for the exemplary stations (light filled areas indicate 95%-variance interval)



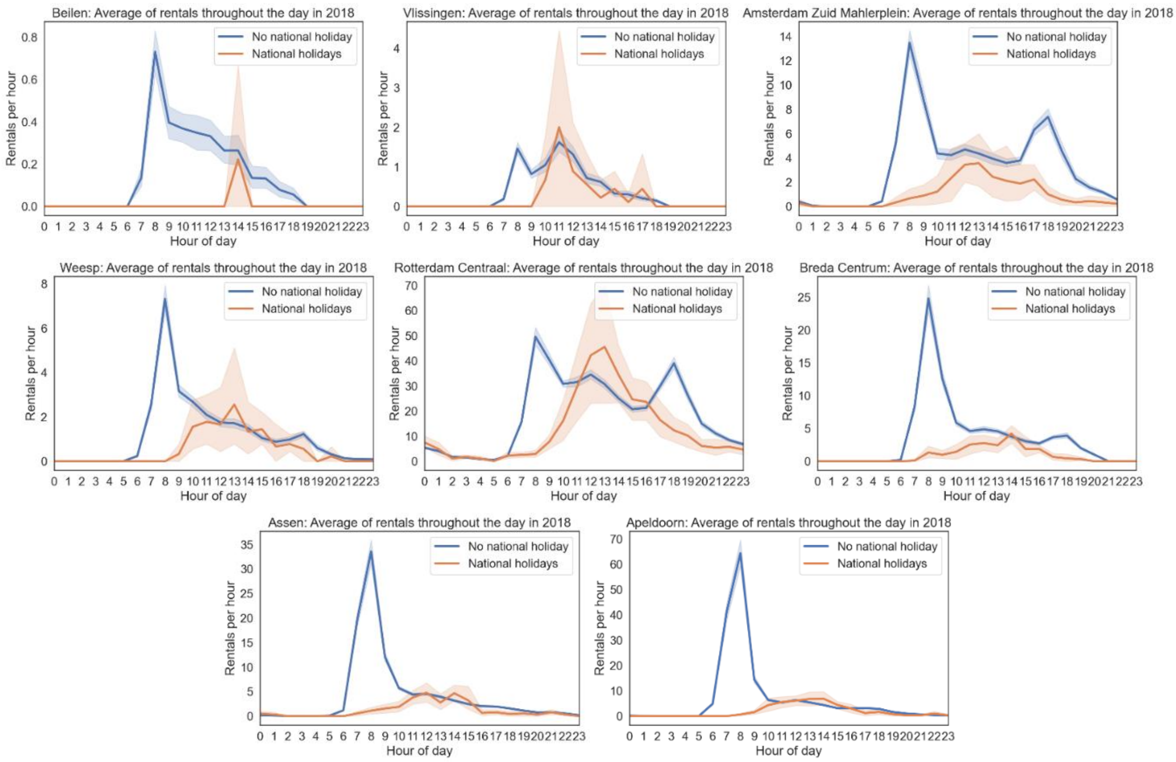
B 3: Average hourly rentals and checkouts per day in 2018 for the exemplary stations



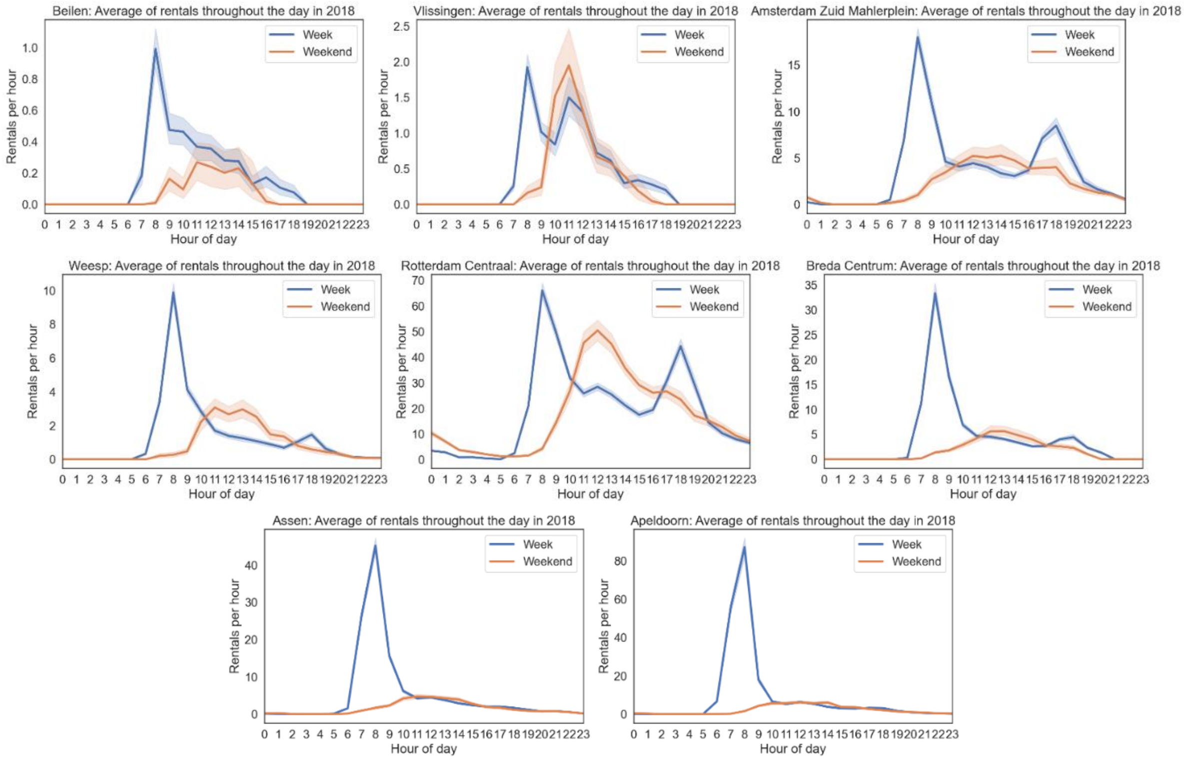
B 4: Average hourly rentals per day in 2018 on school holidays and non-school holidays for the exemplary stations



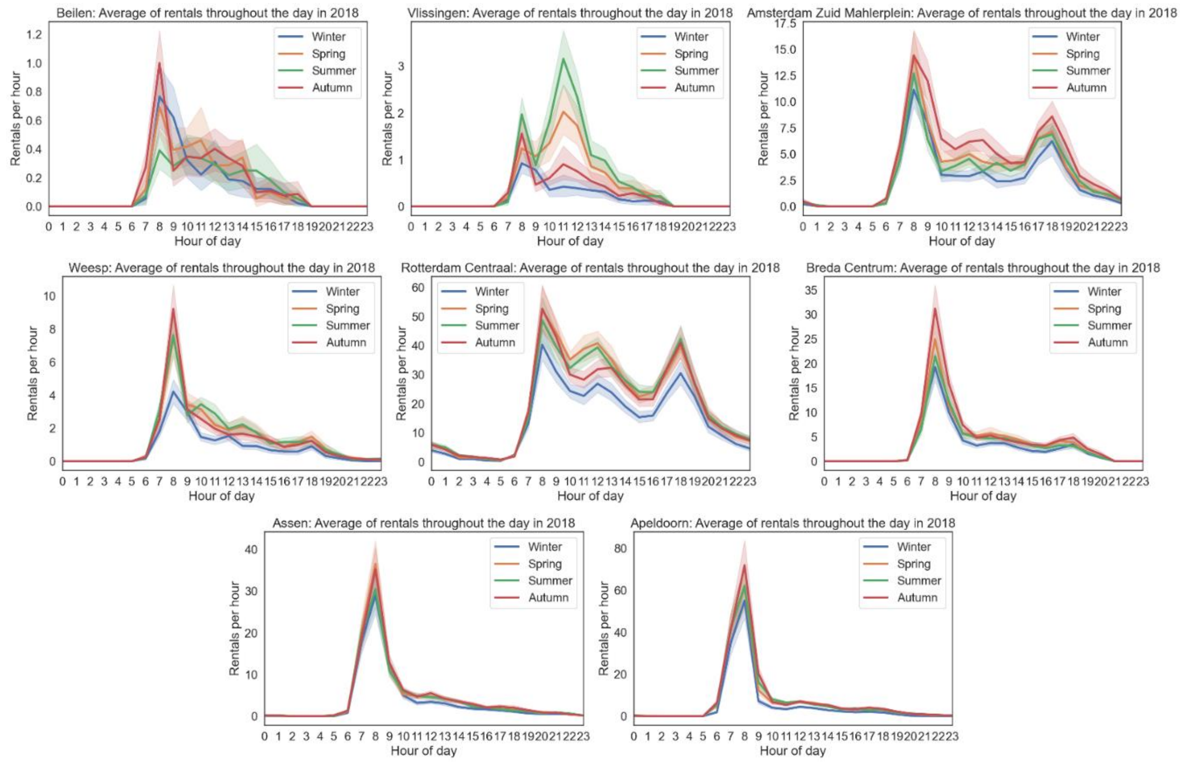
B 5: Average hourly rentals per day in 2018 on national holidays and non-national holidays for the exemplary stations



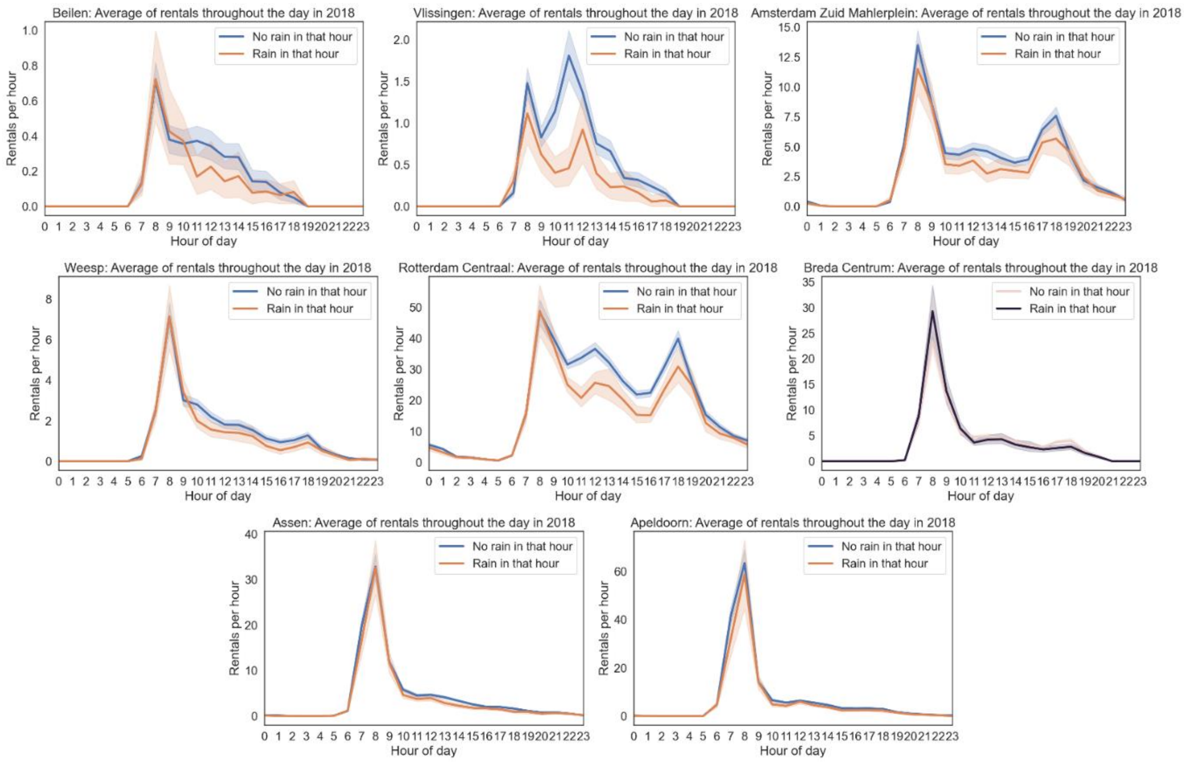
B 6: Average hourly rentals per day in 2018 on weekends and weekdays for the exemplary stations



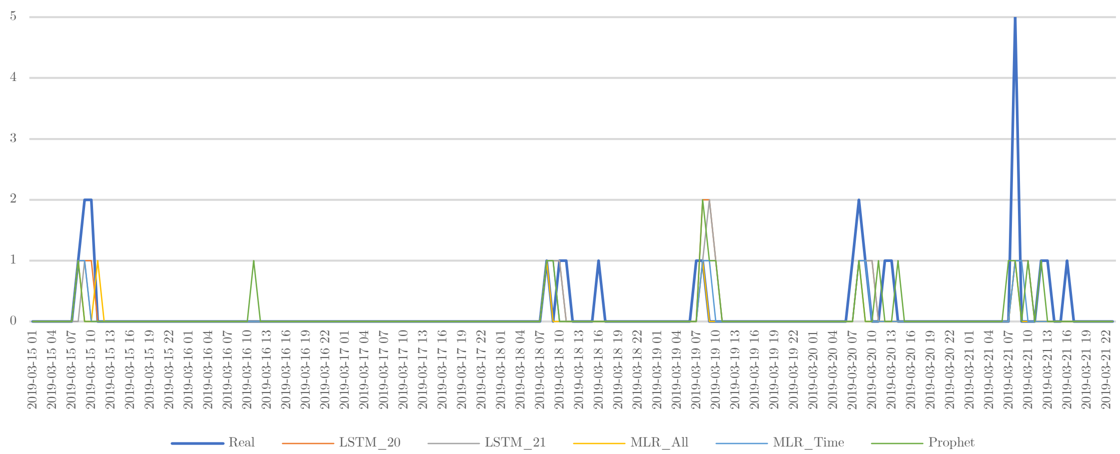
B 7: Average hourly rentals per day in 2018 across the seasons Winter, Spring, Summer, Autumn for the exemplary stations



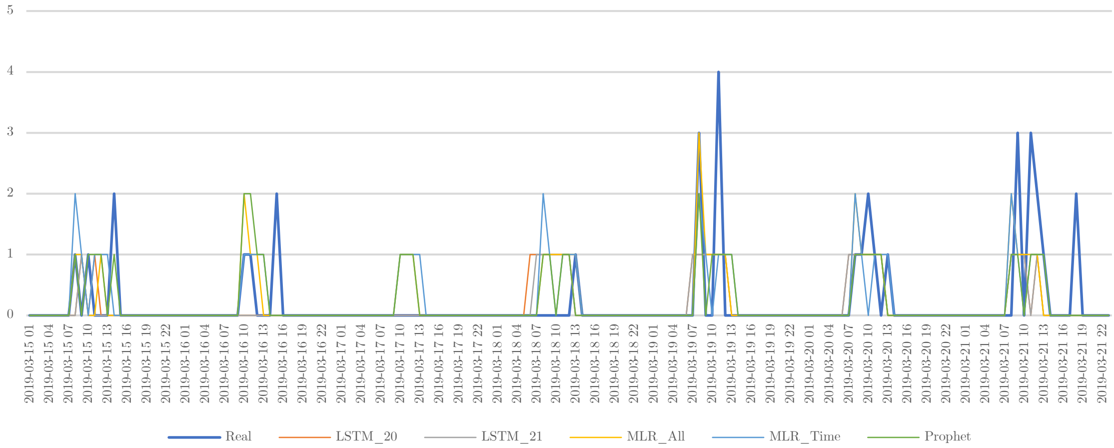
B 8: Average hourly rentals per day in 2018 for hours in which rain did and did not occur for the exemplary stations



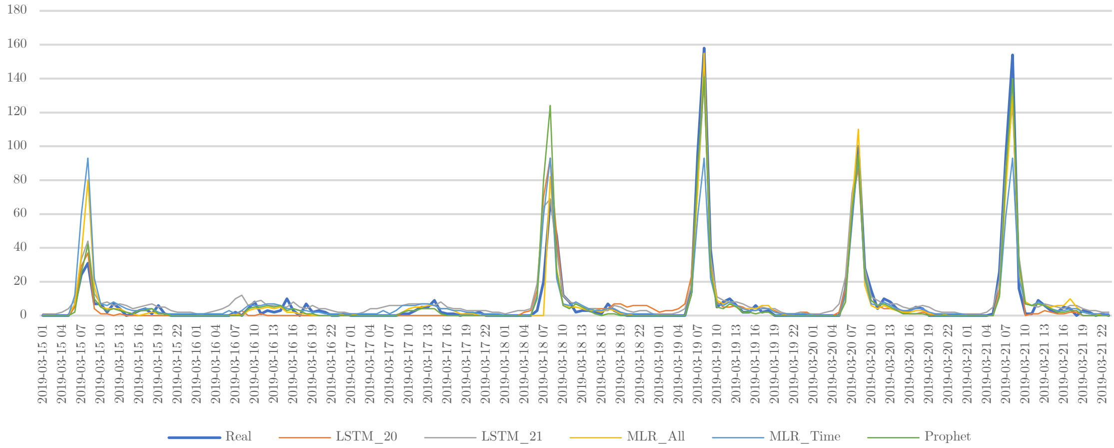
B 9: Forecast of hourly rentals across different models for Beilen for the 'March'-forecast



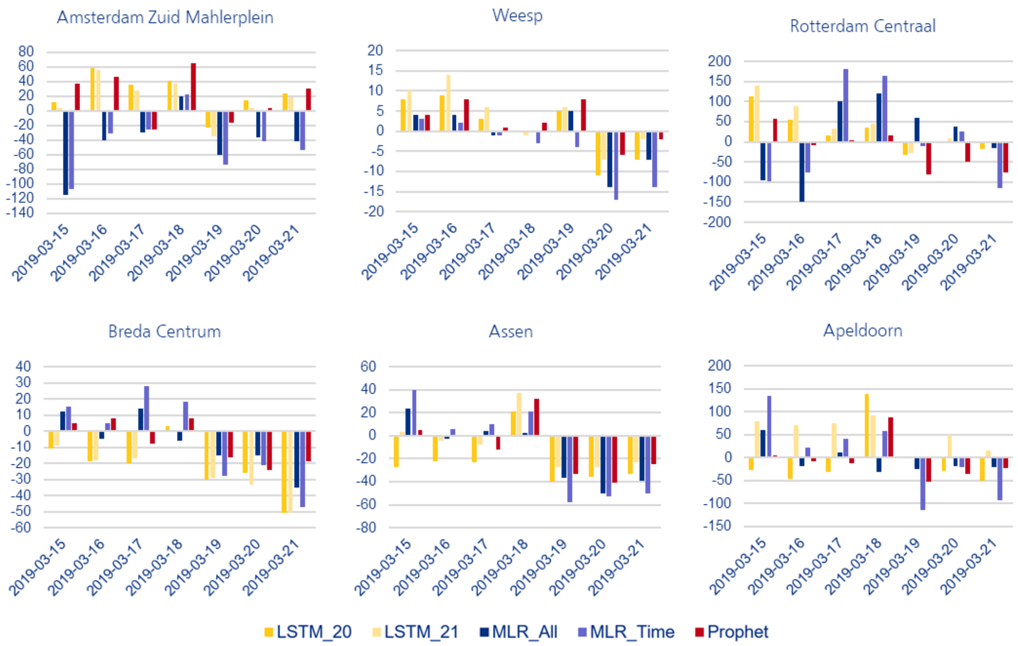
B 10: Forecast of hourly rentals across different models for Vlissingen for the 'March'-forecast



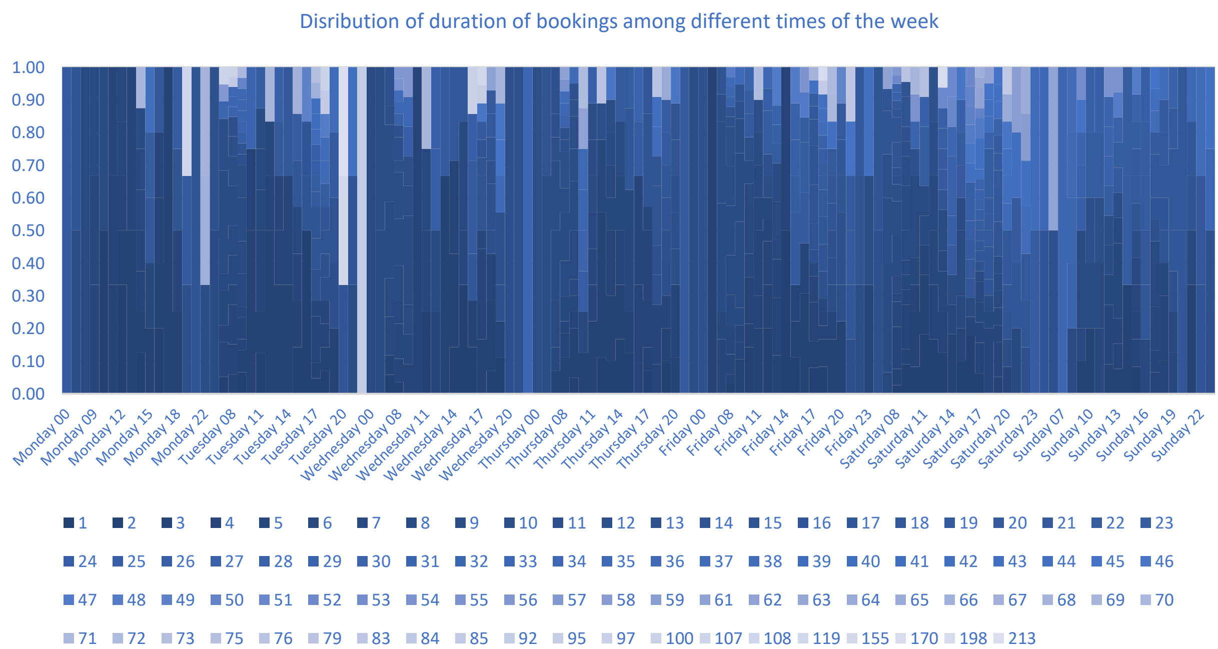
B 11: Forecast of hourly rentals across different models for Apeldoorn for the 'March'-forecast



B 12: Deviation between predicted and observed daily rentals per predicted day and model for six of the eight exemplary stations



B 13: Distribution of duration of bookings among various times of the week for the exemplary case of *AZM*, for an exemplary week in March



B 14: MLR results for *Vl* considering checkouts, time of day, sunshine duration, and temperature (Time of day Daytime is reference)

	Model 1
(Intercept)	-0.5227^{***}
	(0.0502)
checkouts	0.0061^{***}
	(0.0004)
timeofdayEvening	0.5269^{***}
	(0.0682)
timeofdayEveningpeak	0.3812^{***}
	(0.0802)
timeofdayMorningpeak	0.4471^{***}
	(0.0673)
timeofdayNight	0.5282^{***}
	(0.0636)
sunshine_duration	0.0212^{***}
	(0.0048)
temperature	0.0065^{***}
	(0.0003)
weekend	-0.0274
	(0.0426)
checkouts:timeofdayEvening	-0.0059^{***}
	(0.0013)
checkouts:timeofdayEveningpeak	-0.0022^{*}
	(0.0009)
checkouts:timeofdayMorningpeak	-0.0004
	(0.0004)
checkouts:timeofdayNight	-0.0062
	(0.0154)
timeofdayEvening:temperature	-0.0067^{***}
	(0.0004)
timeofdayEveningpeak:temperature	-0.0064^{***}
	(0.0005)
timeofdayMorningpeak:temperature	-0.0049^{***}
	(0.0005)
timeofdayNight:temperature	-0.0067^{***}
	(0.0004)
timeofdayEvening:sunshine_duration	-0.0273
	(0.0368)
timeofdayEveningpeak:sunshine_duration	-0.0160^{*}
	(0.0078)
timeofdayMorningpeak:sunshine_duration	0.0006
	(0.0077)
timeofdayNight:sunshine_duration	-0.0248
	(0.0232)
temperature:weekend	0.0007^{*}
	(0.0003)
sunshine_duration:weekend	0.0146^{*}
	(0.0057)
R^2	0.3079
Adj. R^2	0.3061
Num. obs.	8759

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Appendix C: Code

C 1: Data filtering and combination syntax for the year 2018 using R

```
# define environment and import libaries for data manipulation
Sys.setenv(tz="Europe/Amsterdam")
Sys.setlocale("LC_TIME","English")
library(dplyr)
library(tidyverse)
library(lubridate)
library(reshape2)

# define start- and enddate of considered timeslot
startdate <- as.POSIXct("2020-01-01 00:00:00", tz = "")
enddate <- as.POSIXct("2021-04-21 00:00:00", tz = "")

# read station dataset
stations <- read.csv("D_Station_Dataset.csv", sep=";")

# read SBRT booking data and transform into data suitable for further analysis
data_raw <- read.csv("D_2018 all.csv", sep = ";")
names(data_raw) <- tolower(names(data_raw))
dataset <- data_raw %>%
  mutate(booking_date = gsub(" .*","",startdatum),
         return_date = gsub(" .*","",einddatum),
         booking_datetime = ymd_h(paste0(booking_date,startuurnr..kort.), tz = ""),
         return_datetime = ymd_h(paste0(return_date,einduurnr..kort.), tz = ""),
         booking_datetimemin = ymd_hm(paste0(booking_date,starttijd, tz = "")),
         return_datetimemin = ymd_hm(paste0(return_date,eindtijd), tz = ""),
         booking_weekday = wday(booking_datetime, label = T),
         return_weekday = wday(return_datetime, label = T)) %>%
  select(locatienaam, booking_datetime, return_datetime, booking_datetimemin, return_datetimemin,booking_weekday, return_weekday,
aantal.verhuringen) %>%
  mutate(booking_hour = hour(booking_datetime),
         return_hour = hour(return_datetime),
         booking_date = date(booking_datetime),
         return_date = date(return_datetime),
         duration = difftime(return_datetimemin,booking_datetimemin, unit = "min")) %>%
  mutate(locatienaam=replace(locatienaam, locatienaam == "Amsterdam Bijlmer", "Amsterdam Bijlmer (Zelfservice)"),
         locatienaam=replace(locatienaam, locatienaam == "Maarssen", "Maarssen (Zelfservice)"),
         locatienaam=replace(locatienaam, locatienaam == "Lelystad Centrum", "Lelystad Centrum (Zelfservice)"),
         locatienaam=replace(locatienaam, locatienaam == "Culemborg", "Culemborg (Zelfservice)"),
         locatienaam=replace(locatienaam, locatienaam == "Tiel", "Tiel (Zelfservice)"),
         locatienaam=replace(locatienaam, locatienaam == "Zandvoort Zilt-Bikes", "Zandvoort"),
         locatienaam=replace(locatienaam, locatienaam == "Enschede (Zelfservice)","Enschede"),
         locatienaam=replace(locatienaam, locatienaam == "Goes (Zelfservice)","Goes"))
save(dataset, file = "Dataset 2018.RData")

# integration of station-related information in booking-dataset
dataset$stationtype <- stations$Stallingtype[match(dataset$locatienaam,stations$locatienaam)]
dataset$Prorail <- stations$Prorail.typering[match(dataset$locatienaam, stations$locatienaam)]
dataset$bike_capa <- stations$maxtotaal[match(dataset$locatienaam, stations$locatienaam)]
dataset$region <- stations$RegioStations[match(dataset$locatienaam,stations$locatienaam)]
dataset$operator <- stations$Vervoerder.concessiehouder1[match(dataset$locatienaam,stations$locatienaam)]
dataset$KIS <- stations$Type.Kis[match(dataset$locatienaam,stations$locatienaam)]

# preliminary filtering to exclude bookings started before or after 2018 as well as disposition or maintenance
(aantal.verhuringen=0), stations out of NS service areas or unused (region=0, operator = "NS"), and include only staffed stations
with a bike capacity > 10

dataset_2 <- dataset %>%
  filter(booking_datetime >= startdate & booking_datetime < enddate) %>%
  mutate(booking_hour = as.numeric(booking_hour),
         return_hour = as.numeric(return_hour)) %>%
  filter(aantal.verhuringen > 0,
         region != "0",
         operator == "NS",
         bike_capa >= 10,
         stationtype == "Bemenste OV-fiets uitgifte" & bike_capa != 16 & bike_capa != 32)

### Summarising of rentals per hour (in the code referred to as "bookings") ####

# rentals summarised per hour and station
booking_hour_impro <- dataset_2 %>%
  select(locatienaam, booking_datetime, aantal.verhuringen,bike_capa) %>%
  group_by(locatienaam, booking_datetime) %>%
  summarise(bookings = sum(aantal.verhuringen)) %>%
  ungroup()

# data processing to fill hours no bikes were rented with 0 by creating empty array with all hours for the considered year, and
then filling in the hours for which information is available
timeslot <- seq.POSIXt(as.POSIXct(first(startdate)),
                       as.POSIXct(last(enddate)),
                       by = "hour") %>% as.data.frame()
names(timeslot)[1] <- "all_times"
booking_hour <- booking_hour_impro %>%
  dcast(booking_datetime ~ locatienaam, value.var = "bookings") %>%
  left_join(timeslot,., by = c("all_times" = "booking_datetime")) %>%
  replace(is.na(.),0) %>%
  rename(booking_datetime = all_times) %>%
  melt(.,id.vars = c("booking_datetime")) %>%
  rename(locatienaam = variable,
         bookings = value)
```

```r
### Import of additional datasets for all stations####

# Create list of stations where SBRT-data is available for further filtering processes
abbr <- stations %>%
  filter(locatienaam %in% unique(booking_hour$locatienaam)) %>%
  select(locatienaam, Verkorting)

# Import and preparation of hourly dataset including check-ins and -outs per train
load("D_cico_2018.rdata")
checkout <- inuit %>% # sorting and preparation of the imported dataset
  ungroup() %>%
  filter(station %in% abbr$Verkorting,
         uur != 24,
         in_of_uit == "U") %>%
  select(-in_of_uit) %>%
  left_join(.,abbr, by = c("station" = "Verkorting")) %>%
  select(-station) %>%
  mutate(checkouts = round(aantal_reizigers,0),
         datetime = ymd_hms(paste0(av_verkeersdatum,uur,":00:00"), tz = "")) %>%
  filter(!is.na(aantal_reizigers)) %>%
  select(-av_verkeersdatum, -uur, -aantal_reizigers)

# Import of holiday information for all stations
holidays = read.csv("D_Holidays.csv", sep = ";") %>%
  rename(date = ï..date,
         national = off_holiday_ZuidNL,
         school_south = school_holiday_SouthNL,
         school_middle = school_holiday_MiddleNL,
         school_north = school_holiday_NorthNL) %>%
  mutate(date = dmy(date))

# Import of weather information for all stations
weatherdata <- read.csv("D_Weatherdata_2018.csv",header=TRUE, sep = ";") %>%
  mutate(datetime = as.POSIXct(paste0(date,"",hour), format = c("%Y%m%d %H"))) %>%
  rename(weatherstation = ï..station)
colnames(weatherdata)[1] <- c("weatherstation")

# Import of table matching train/SBRT-stations to closest weather station
load("XX_Match Trainstation Weatherstation.RData")


# Join rentals and checkouts per hour
booking_checkout <- booking_hour %>%
  left_join(.,checkout, by = c("locatienaam", "booking_datetime" = "datetime")) %>%
  mutate(checkouts = ifelse(is.na(checkouts), 0, checkouts),
         abbr = stations$Verkorting[match(.$locatienaam, stations$locatienaam)])

# Combination of all separate datasets into one dataset, and additional definition of aggregated time-related determinants
complete_dataset <- booking_checkout %>%
  mutate(weatherstation = trein_weerstation$weerstation_nr[match(.$abbr,trein_weerstation$station)],
         bike_capa = stations$maxtotaal[match(.$locatienaam, stations$locatienaam)],
         rel_bookings = bookings/bike_capa,
         month = month(booking_datetime, label = TRUE),
         day = date(booking_datetime),
         weekday = weekdays(booking_datetime, abbreviate = TRUE),
         hour = hour(booking_datetime),
         timeofday = ifelse(hour >= 6 & hour < 10, "Morningpeak",
                            ifelse(hour >= 10 & hour < 16, "Daytime",
                                   ifelse(hour >= 16 & hour < 20, "Eveningpeak",
                                          ifelse(hour >= 20 | hour == 0, "Evening",
                                                 ifelse(hour >= 1 & hour < 6, "Night",0))))),
         season  = ifelse(month(booking_datetime) < 4, "Winter",
                          ifelse(month(booking_datetime) >= 4 & month(booking_datetime) < 7, "Spring",
                                 ifelse(month(booking_datetime) >= 7 & month(booking_datetime) < 10, "Summer",
                                        ifelse(month(booking_datetime) <= 12, "Autumn",0)))),
         weekend = ifelse(weekday == "Sat" | weekday == "Sun",1,0)) %>%
  left_join(.,weatherdata, by = c("weatherstation","booking_datetime" = "datetime")) %>%
  left_join(.,holiday_regions, by = c("abbr" = "Verkorting")) %>%
  left_join(.,holidays, by = c("day" = "date")) %>%
  select(-hour.y, -date) %>%
  rename(hour = hour.x) %>%
  filter(!is.na(temperature)) %>%
  filter(locatienaam != "Beverwijk") %>%
  distinct(.keep_all = TRUE)

# save overall patterns
write.csv(complete_dataset, file = paste0(path,"2018 complete hourpattern.csv"), row.names = FALSE)
```

C 2: Search algorithm and linear regression to identify significant determinants for 2018 using R

```r
# define environment and import libaries for data manipulation
Sys.setenv(tz="Europe/Amsterdam")
Sys.setlocale("LC_TIME","English")
library(dplyr)
library(tidyverse)
library(lubridate)
library(cowplot)
library(leaps)
library(car)
library(broom)
library(janitor)
library(Metrics)

# import of related datafile
data <- read.csv(paste0(path,"2018 complete hourpattern.csv"), sep = ",") %>%
  mutate(booking_datetime = ymd_hms(booking_datetime),
    weekday = weekdays(booking_datetime),
    hour = as.character(hour)) %>%
  distinct(.keep_all = TRUE)
```

```
### Identification of significant variables using backward search on entire dataset with rel_bookings as dependent variable ####

# No aggregation, no interaction
backward_unique <- regsubsets(rel_bookings ~ checkouts + hour + weekday +
                               month + windspeed + temperature + dewpoint +
                               sunshine_duration + rain_duration + cloudcover +
                               fog_dummy + rain_dummy + snow_dummy + thunder_dummy + ice_dummy +
                               national + school_middle + school_south + school_north,
                             data = data,
                             nvmax = NULL,
                             method = "backward",
                             really.big = FALSE)

# Aggregated, no interaction
backward_aggr <- regsubsets(rel_bookings ~ checkouts + timeofday + weekend +
                             season + windspeed + temperature + dewpoint +
                             sunshine_duration + rain_duration + cloudcover +
                             fog_dummy + rain_dummy + snow_dummy + thunder_dummy + ice_dummy +
                             national + school_middle + school_south + school_north,
                           data = data,
                           nvmax = NULL,
                           method = "forward",
                           really.big = FALSE)

# Aggregated, with interaction
backward_interact <- regsubsets(rel_bookings ~ checkouts*weekend*timeofday +
                                 checkouts*season +
                                 checkouts*national +
                                 checkouts*school_middle +
                                 checkouts*school_north +
                                 checkouts*school_south +
                                 season*windspeed +
                                 season*temperature +
                                 season*dewpoint +
                                 season*sunshine_duration +
                                 rain_duration + cloudcover +
                                 fog_dummy + rain_dummy + snow_dummy + thunder_dummy + ice_dummy +
                                 national + school_middle + school_south + school_north,
                               data = data,
                               nvmax = NULL,
                               method = "backward",
                               really.big = FALSE)

# No aggregation, with interaction
backward_uni_interact <- regsubsets(rel_bookings ~  checkouts*hour +
                                     checkouts*weekday +
                                     checkouts*month +
                                     checkouts*national +
                                     checkouts*school_middle +
                                     checkouts*school_north +
                                     checkouts*school_south +
                                     season*sunshine_duration +
                                     rain_duration + cloudcover +
                                     fog_dummy + rain_dummy + snow_dummy + thunder_dummy + ice_dummy +
                                     national + school_middle + school_south + school_north,
                                   data = data,
                                   nvmax = NULL,
                                   method = "backward",
                                   really.big = TRUE)

# Function to summarise and extract results of search methods
evaluation <- function (search_output) {
  eval <- summary(search_output)
  rs <- eval$rsq %>%
    as.data.frame() %>%
    rename("rsq" = ".")
  diff = diff(rs$rsq)
  diff= c(NA,diff)
  which = eval$which %>%
    as.data.frame()
  result <- rs %>%
    merge(.,which,by.x=0, by.y=0) %>%
    select(-Row.names)
  return(result)
}

# Application of dunction on all four backward searches
back_unique <- evaluation(backward_unique)
back_aggr <- evaluation(backward_aggr)
back_interact <- evaluation(backward_interact)
back_uni_interact <- evaluation(backward_uni_interact)
write.csv(back_unique, file = paste0(path, " backward unique result.csv"))
write.csv(back_aggr, file = paste0(path, " backward aggr result.csv"))
write.csv(back_interact, file = paste0(path, " backward interact result.csv"))
write.csv(back_uni_interact, file = paste0(path, " backward uni_interact result.csv"))

### Performance of MLR across all stations ####

# Function to be run across all stations (selection of variables discussed in report)
linreg_selected_determinants <- function(locatie) {
  data_locatie <- data %>% filter(locatienaam == locatie)
  linreg_locatie <- lm(rel_bookings ~ checkouts*hour + hour*weekend +  national*season +
                        checkouts*season + checkouts*windspeed + checkouts*sunshine_duration + season*sunshine_duration +
                        school_north + school_middle + school_south,
                      data = data_locatie, na.action = na.omit)
}

# Extract list of all stations to then run loop on them, as well as empty vectors to be filled by following loop
lm_results <- list()
locations <- unique(data$locatienaam)
R2 <- vector()
```

```
# run regression across all stations
for (i in locations) {
  lm_results[[paste0(i)]] <- linreg_selected_determinants(paste0(i))
}

# Save R² of all regressions for further sorting and then save as .csv
for (i in locations) {
  R2[[paste0(i)]] <- summary(lm_results[[i]])$r.squared
}
R2_output <- as.data.frame(R2)
R2_sorted <- R2_output %>%
  rownames_to_column(., var = "locatienaam") %>%
  arrange(.,-R2)
write.csv(R2_sorted,file = paste0(path, "R2_sorted_2.csv"))
```

C 3: Forecasting per station for the 'March'-period for Vlissingen based on 2018/19 data using R

```
# define environment and import libaries for data manipulation
library(dplyr)
library(tidyverse)
library(lubridate)
library(openxlsx)
library(Metrics)

# import and combination of related datasets
data_18 <- read.csv(paste0("C:/Users/Wilkesmann/NS/Team-Thesis Florian - General/R/NEW_Analysis/Fulldata/2018 complete
hourpattern.csv"), sep = ",") %>%
  mutate(booking_datetime = ymd_hms(booking_datetime),
         weekday = weekdays(booking_datetime),
         hour = as.character(hour)) %>%
  distinct(.keep_all = TRUE)
data_19 <- read.csv(paste0("C:/Users/Wilkesmann/NS/Team-Thesis Florian - General/R/NEW_Analysis/Fulldata/2019 complete
hourpattern.csv"), sep = ",") %>%
  mutate(booking_datetime = ymd_hms(booking_datetime),
         weekday = weekdays(booking_datetime),
         hour = as.character(hour)) %>%
  distinct(.keep_all = TRUE)
data <- data_18 %>% rbind(.,data_19) %>% as.data.frame()

# define station to be investigated and boundaries of training and test dataset
x = "Vlissingen"
start_train = as.POSIXct("2018-08-15")
end_train = as.POSIXct("2019-08-14")
start_test = as.POSIXct("2019-08-15")
end_test = as.POSIXct("2019-08-22")

# creating of training and test dataset
data_train <- data %>%
  filter(locatienaam == x) %>%
  select(booking_datetime, bookings, hour, weekend, season, school_north, school_middle, school_south, checkouts,
sunshine_duration, windspeed) %>%
  filter(booking_datetime >= start_train &
           booking_datetime <= end_train)
data_test <- data %>%
  filter(locatienaam == x) %>%
  select(booking_datetime, bookings, hour, weekend, season, school_north, school_middle, school_south, checkouts,
sunshine_duration, windspeed) %>%
  filter(booking_datetime >= start_test &
           booking_datetime <= end_test)


### MLR and Forecast assuming perfect information ####
# Reperform MLR (same as in

C 2, for consistency)
lm_x <- lm(bookings ~ hour*checkouts + season*sunshine_duration + school_north + school_middle + school_south +
             checkouts*windspeed + checkouts*sunshine_duration + season*sunshine_duration + hour*weekend, data = data_train)
# Perform forecast for test timeslot using the results of the previous MLR
predict_x <- predict.lm(lm_x, data_test, se.fit = TRUE, level = 0.95)
# Preparation of results
data_fc_all <- data_test %>%
  select(booking_datetime,bookings) %>%
  dplyr::rename(real = bookings) %>%
  mutate(forecast = predict_x$fit,
         forecast_low = predict_x$fit - predict_x$se.fit,
         forecast_high = predict_x$fit + predict_x$se.fit,
         diff = abs(real - forecast),
         forecast = replace(forecast, forecast < 0, 0)) %>%
  drop_na(.,forecast)
rmse <- rmse(data_fc_all$real, data_fc_all$forecast)
mse <- mse(data_fc_all$real, data_fc_all$forecast)


### MLR and Forecast assuming perfect information ####
# Reperform MLR (same as in

C 2, for consistency)
lm_x_selected <- lm(bookings ~ school_north + school_middle + school_south + hour*weekend + hour*season, data = data_train)
# Perform forecast for test timeslot using the results of the previous MLR
predict_x_selected <- predict.lm(lm_x_selected, data_test, se.fit = TRUE, level = 0.95)
# Preparation of results
data_fc_selected <- data_test %>%
  select(booking_datetime,bookings) %>%
  dplyr::rename(real = bookings) %>%
  mutate(forecast = round(predict_x_selected$fit,0),
         forecast_low = predict_x_selected$fit - predict_x_selected$se.fit,
         forecast_high = predict_x_selected$fit + predict_x_selected$se.fit,
         diff = forecast-real,
         forecast = replace(forecast, forecast < 0, 0)) %>%
```

```
  drop_na(.,forecast)

rmse <- rmse(data_fc_selected$real, data_fc_selected$forecast)
mse <- mse(data_fc_selected$real, data_fc_selected$forecast)


### Export of results of both forecasting methods into .xlsx
data_fc <- data_fc_all %>%
  left_join(., data_fc_selected, by = "booking_datetime") %>%
  select(-real.y, -forecast_low.x, -forecast_low.y, -forecast_high.x, -forecast_high.y,
         -diff.x, -diff.y) %>%
  rename(forecast_all = forecast.x,
         forecast_selected = forecast.y,
         real = real.x) %>%
  mutate(forecast_all = round(forecast_all,0),
         diff_all = forecast_all-real,
         diff_selected = forecast_selected-real)
write.xlsx(x = data_fc,
           file = paste0(path_result,"MLR_Summer",x,".xlsx"),
           sheetName = "Total")
```

C 4: Extraction of historical booking duration to estimate timesteps in which bikes are returned for 2018

```
# define environment and import libaries for data manipulation
library(dplyr)
library(tidyverse)
library(lubridate)
library(reshape2)

# import and additional preparation of dataset (first preparation already performed in C 1)
load("Dataset 2018.RData")
data <- dataset %>%
  filter(booking_date >= as.Date("2018-01-01") &
           booking_date <= as.Date("2018-12-31")) %>%
  select(locatienaam, booking_datetime, booking_weekday, booking_date, duration) %>%
  mutate(duration = as.numeric(duration),
         duration_grp = ceiling(duration/60),
         hour = hour(booking_datetime),
         month = month(booking_datetime)) %>%
  na.omit(.) %>%
  filter(duration_grp>0)

# count per station, month, weekday, and hour and export for further processing
durations <- data %>%
           group_by(locatienaam, month, booking_weekday, hour, duration_grp) %>%
  summarise(count = n_distinct(booking_datetime))
save(durations, file = paste0(path,"2018 durations.RData"))
```

C 5: Extraction of historical booking duration to estimate timesteps in which bikes are returned for 2018 using R

```
# define environment and import libaries for data manipulation
Sys.setenv(tz="Europe/Amsterdam")
Sys.setlocale("LC_TIME","English")
library(dplyr)
library(tidyverse)
library(lubridate)
library(reshape2)

# Definition of considered station as well as test time window for which the forecast is performed
x = "Amsterdam Zuid Mahlerplein"
start_test = as.POSIXct("2019-03-15")
end_test = as.POSIXct("2019-03-22")

# Import and combination of related datasets
data_18 <- read.csv(paste0("C:/Users/Wilkesmann/NS/Team-Thesis Florian - General/R/NEW_Analysis/Fulldata/2018 complete
hourpattern.csv"), sep = ",") %>%
  mutate(booking_datetime = ymd_hms(booking_datetime),
         weekday = weekdays(booking_datetime),
         hour = as.character(hour)) %>%
  distinct(.keep_all = TRUE)
data_19 <- read.csv(paste0("C:/Users/Wilkesmann/NS/Team-Thesis Florian - General/R/NEW_Analysis/Fulldata/2019 complete
hourpattern.csv"), sep = ",") %>%
  mutate(booking_datetime = ymd_hms(booking_datetime),
         weekday = weekdays(booking_datetime),
         hour = as.character(hour)) %>%
  distinct(.keep_all = TRUE)
data <- data_18 %>% rbind(.,data_19) %>% as.data.frame()
load("2018 durations.RData")

# preparation of test dataset to identify the corresponding duration distribution defined in C 4 based on station, month, weekday,
hour
dataset <- data %>%
  filter(locatienaam == x) %>%
  mutate(booking_date = date(booking_datetime)) %>%
  filter(booking_date >= date(start_test) & booking_date <= end_test) %>%
  select(locatienaam, booking_datetime) %>%
  mutate(m = month(booking_datetime),
         wd = wday(booking_datetime),
         h = hour(booking_datetime))
# filter durations for the selected station and prepare to fit previously defined dataset
dur <- durations %>%
  filter(locatienaam == x,
         month >= month(start_test) & month <= month(end_test)) %>%
  rename(m = month,
         wd = booking_weekday,
         h = hour) %>%
  dcast(m+wd+h ~ duration_grp) %>%
```

```
  replace(is.na(.),0) %>%
  mutate(wd = as.numeric(wd)
# calculation of relative rentals per hour to assess relative returns per following hour of each bike rented within one hour, then
extract as .csv
hourlyrentals <- dur %>%
  select(-m,-wd,-h) %>%
  rowSums(.)

dur_rel <- dur %>%
  mutate(across(c(4:length(dur)),
              .fns = ~./hourlyrentals))

joined <- dataset %>%
  merge(., dur_rel, by = c("m","wd","h"), all.x = True)

returns <- joined %>%
  mutate(across(c(7:143),
              .fns = ~.*bookings))

write.csv(dur_rel, file = paste0(path, x, " duration distribution month ", dur_rel$m[1],".csv"))
```

C 6: Forecast algorithm in Prophet using Python

```
# Import of libraries
from fbprophet import Prophet
from fbprophet.plot import add_changepoints_to_plot
import pandas as pd
import seaborn as sns
from pylab import rcParams
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import mean_squared_error
from math import sqrt

# Prevent SettingWithCopyWarning message from appearing
pd.options.mode.chained_assignment = None

# Import of both years and combination of datasets
df_18 = pd.read_csv("[…}/complete hourpattern.csv", delimiter = ",",
                parse_dates = ["booking_datetime"],
                index_col = "booking_datetime")
df_19 = pd.read_csv("[…]/ complete hourpattern.csv", delimiter = ",",
                parse_dates = ["booking_datetime"],
                index_col = "booking_datetime")
df_all = df_18.append(df_19)

### Data preparation ####

# Define city to analyse
x = "Rotterdam Centraal"

# Define training and testtime
startdate_train = pd.to_datetime("2018-03-15")
enddate_train = pd.to_datetime("2019-03-15")
startdate_test = pd.to_datetime("2019-03-15")
enddate_test = pd.to_datetime("2019-03-22")

# Filter for selected city
df = df_all[df_all["locatienaam"] == x]

# Eliminate last row as this is treated as January, 1st, 00:00 of the following year, leading to problems with plotting
df.drop(df.tail(1).index,inplace=True)

# Transform into prophet-suitable format
df_prophet = df[["bookings","national"]]
df_prophet = df_prophet.rename(columns = {"bookings":"y"})
df_prophet.reset_index(inplace = True)
df_prophet = df_prophet.rename(columns = {"booking_datetime":"ds"})

# Create train dataset
df_prophet_train = df_prophet[(df_prophet.ds >= startdate_train) & (df_prophet.ds <= enddate_train)]
df_prophet_train.drop(df_prophet_train.tail(1).index,inplace=True)

# Create test dataset
df_prophet_test = df_prophet[(df_prophet.ds >= startdate_test) & (df_prophet.ds <= enddate_test)]
df_prophet_test.drop(df_prophet_test.tail(1).index,inplace=True)

# Define upper and lower boundary of bookings
df_prophet_train["cap"] = df_prophet_train.y.max()
df_prophet_train["floor"] = df_prophet_train.y.min()

### Perform Prophet ####

# Definition and training of model
model = Prophet(growth = "linear",
                seasonality_mode = "multiplicative",
                weekly_seasonality = 7*12,
                daily_seasonality = False,
                yearly_seasonality = True)
model.add_country_holidays("NL")
model.fit(df_prophet_train)
```

```
# Create future horizon (on which prediction is performed)
future = model.make_future_dataframe(periods = 7*24, freq = "H", include_history = False)
future["morningpeak"] = future["ds"].apply(morningpeak)
future["cap"] = df_prophet_train.y.max()
future["floor"] = df_prophet_train.y.min()

# Perform forecast
Forecast = model.predict(future)

# Extract results from forecast
real =  df_prophet_test[["ds","y"]]
real.rename(columns = {"y":"real"}, inplace = True)

fc = forecast[["ds","yhat"]]
fc.rename(columns = {"yhat":"forecast"}, inplace = True)
fc.loc[(fc.forecast < 0), "forecast"] = 0
fc["forecast"] = fc["forecast"].round(decimals = 0)

future = real.merge(fc)
future = future.set_index("ds")
future.loc[(future.forecast < 0), "forecast"] = 0

# Calculate RMSE
mse = mean_squared_error(future.real, future.forecast)
rmse = sqrt(mse)

# Distribution of errors
future_mp["dif"] = future_mp["forecast"]-future_mp["real"]
future["dif"] = future["forecast"]-future["real"]

# Write .xlsx with results
path = "C:\\Users\\Wilkesmann\\NS\\Team-Thesis Florian - General\\R\\NEW_Prediction\\Results\\"
seq = (path,"Prophet_Summer_",x,".xlsx")
s = "".join(seq)
with pd.ExcelWriter(s) as writer:
    future.to_excel(writer, sheet_name = "Total")
    future_mp.to_excel(writer, sheet_name = "MorningPeak")
```

C 7: LSTM Forecast algorithm in Prophet using Python

```
# Import of libraries
import numpy as np
import time
import pandas as pd
import tensorflow as tf
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import register_matplotlib_converters
from pylab import rcParams
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from math import sqrt
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import LSTM
from matplotlib import rc

# Prevent SettingWithCopyWarning message from appearing
pd.options.mode.chained_assignment = None

# Set random seed
RANDOM_SEED = 21
np.random.seed(RANDOM_SEED)
tf.random.set_seed(RANDOM_SEED)

# Import of both years and combination of datasets
df_18 = pd.read_csv("[…}/complete hourpattern.csv", delimiter = ",",
                parse_dates = ["booking_datetime"],
                index_col = "booking_datetime")
df_19 = pd.read_csv("[…]/ complete hourpattern.csv", delimiter = ",",
                parse_dates = ["booking_datetime"],
                index_col = "booking_datetime")
df_all = df_18.append(df_19)

### Definition of used functions within LSTM ####

# Function to split into training and testing dataset; return of test and training datasets
def split_dataset(data):
    # split into standard weeks
    train = df_LSTM[startpoint_train:endpoint_train]
    test = df_LSTM[startpoint_test:endpoint_test]
    # restructure data to windows of daily data
    train = np.array(np.split(train, len(train)))
    test = np.array(np.split(test, len(test)))
    return train,test
```

```
# Function to calculate RMSE of results; return of overall RMSE (score) and vector with RMSE per predicted hour (scores)
def evaluate_forecasts(actual, predicted):
    scores = list()
    # calculate RMSE score per hour
    for i in range(actual.shape[1]):
        # calculate MSE
        mse = mean_squared_error(actual[:,i], predicted[:,i])
        # calculate RMSE
        rmse = sqrt(mse)
        # store result
        scores.append(rmse)
    # calculate overall RMSE
    s = 0
    for row in range(actual.shape[0]):
        for col in range(actual.shape[1]):
            s += (actual[row,col] - predicted[row,col]) **2
    score = sqrt(s / (actual.shape[0] * actual.shape[1]))
    return score, scores

# Function to evaluate a model; actual running and evaluation of the model (combines other functions)
def evaluate_model(train,test,n_input, n_output):
    # fit the model
    model = build_model(train,n_input, n_output)
    # create history as a list of weekly data
    history = [x for x in train]
    # walk-forward prediction over each week
    predictions = list()
    for i in range(len(test)):
        # predict the next week
        yhat_sequence = forecast(model, history, n_input)
        # store predictions
        predictions.append(yhat_sequence)
        # get real observation and add to history for predicting the then following week
        history.append(test[i,:])
    #evaluate predictions per hour for each week
    predictions =np. array(predictions)
    score, scores = evaluate_forecasts(test[:,:,0], predictions)
    return score, scores, predictions

# Function to summarise evaluation scores after running model evaluation
def summarise_scores(name, score, scores):
    s_scores = ','.join(['%.1f' % s for s in scores])
    print('%s: [%.3f] %s' % (name, score, s_scores))

# Function to convert training data into inputs and outputs; preparation of training dataset to be processable by LSTM
def to_supervised(train, n_input, n_out):
    # flatten data
    data = train.reshape((train.shape[0]*train.shape[1], train.shape[2]))
    X, y = list(), list()
    in_start = 0
    # step over the entire history one time step at a time
    for _ in range(len(data)):
        # define the end of the input sequence
        in_end = in_start + n_input
        out_end = in_end + n_out
        # ensure we have enough data for this instance
        if out_end <= len(data):
            X.append(data[in_start:in_end, :])
            y.append(data[in_end:out_end, 0])
        # move along one time step
        in_start += 1
    return np.array(X), np.array(y)

# Function for the actual building and training of the model
def build_model(train, n_input, n_output):
    # prepare the data
    train_x, train_y = to_supervised(train, n_input, n_output)
    # definition of parameters
    verbose, epochs, batch_size = 1, 30, 64
    n_timesteps, n_features, n_outputs = train_x.shape[1], train_x.shape[2], train_y.shape[1]
    # actual model definition
    model = Sequential()
    model.add(LSTM(units = 128, input_shape = (n_timesteps, n_features)))
    model.add(Dense(n_outputs))
    model.compile(loss = "mse", optimizer = "adam")
    # fit network
    model.fit(train_x, train_y, epochs = epochs, batch_size = batch_size, verbose = verbose,
             shuffle = False)
    return model

# Function to forecast using the built model; return of yhat, which can then be compared with real values of test data
def forecast(model, history, n_input):
    # flatten of data
    data = np.array(history)
    data = data.reshape(data.shape[0]*data.shape[1], data.shape[2])
    # retreive last observations for input data
    input_x = data[-n_input:, :]
    # reshape into [1,n_input,n]
    input_x = input_x.reshape((1, input_x.shape[0], input_x.shape[1]))
    # forecase next week
    yhat = model.predict(input_x, verbose = 0)
    # as we only want the vector forecase of the prediction
    yhat = yhat[0]
    return yhat

### Definition of input for model ####

# define city to analyse
x = "Amsterdam Zuid Mahlerplein"
```

```
# Definition of time windows to use
startpoint_train = pd.to_datetime("2018-08-15 01")
endpoint_train = pd.to_datetime("2019-08-15 00")
startpoint_test = pd.to_datetime("2019-08-15 01")
endpoint_test = pd.to_datetime("2019-08-22 00")

# filter for selected city
df = df_all[df_all["locatienaam"] == x]
df.drop(df.tail(1).index,inplace=True)# eliminate last row as this is treated as January, 1st, 00:00 of the following year, leading
to problems with plotting

# define which columns to keep for forecasting with LSTM and Prophet (latter only allows bookings and holidays)
var_LSTM = ["bookings",
            "hour",
            "national",
            "school_north",
            "school_middle",
            "school_south",
            "sunshine_duration",
            "checkouts"]

# filter to keep only these columns
df_LSTM = df[var_LSTM]
df_LSTM["weekday"] = df_LSTM.index.weekday

# scaling of non-binary variables
bookings = df_LSTM["bookings"].values.reshape((len(df_LSTM["bookings"]),1))
scaler_bo = MinMaxScaler(feature_range = (0,1))
scaler_bo = scaler_bo.fit(bookings)
df_LSTM["bookings"] = scaler_bo.transform(bookings)
#df_LSTM["bookings_inv"] = scaler_bo.inverse_transform(df_LSTM["bookings"].values.reshape((len(bookings),1)))

checkouts = df_LSTM["checkouts"].values.reshape((len(df_LSTM["checkouts"]),1))
scaler_co = MinMaxScaler(feature_range = (0,1))
scaler_co = scaler_co.fit(checkouts)
df_LSTM["checkouts"] = scaler_co.transform(checkouts)

hour = df_LSTM["hour"].values.reshape((len(df_LSTM["hour"]),1))
scaler_ho = MinMaxScaler(feature_range = (0,1))
scaler_ho = scaler_ho.fit(hour)
df_LSTM["hour"] = scaler_ho.transform(hour)

weekday = df_LSTM["weekday"].values.reshape((len(df_LSTM["weekday"]),1))
scaler_wd = MinMaxScaler(feature_range = (0,1))
scaler_wd = scaler_wd.fit(weekday)
df_LSTM["weekday"] = scaler_wd.transform(weekday)

### Actual running of LSTM ####

# Preparation of training and testing data as well as the preliminary hours used as input (24) and the hour predicted as output (1)
train,test = split_dataset(df_LSTM)
n_input = 24
n_output = 1

# Run of LSTM
score, scores, predictions = evaluate_model(train, test, n_input, n_output)

### Results ####

# Combination of forecast and observed values for later comparison
real =  pd.DataFrame(df_LSTM[startpoint_test:endpoint_test]["bookings"])
real.columns = ["real"]
real.reset_index(inplace=True)
fc = pd.DataFrame(predictions.reshape(predictions.shape[0]*predictions.shape[1]))
fc.columns = ["forecast"]
future = real.join(fc)
future = future.set_index("booking_datetime")
future.loc[(future.forecast < 0), "forecast"] = 0

# Inverse scaling
future["real_inv"] = scaler_bo.inverse_transform(future["real"].values.reshape((len(future["real"]),1)))
future["forecast_inv"] = scaler_bo.inverse_transform(future["forecast"].values.reshape((len(future["real"]),1)))
future["forecast_inv"] = future["forecast_inv"].round(decimals = 0)

# Calculation of MSE and RMSE
mse = mean_squared_error(future.real_inv, future.forecast_inv)
rmse = sqrt(mse)
```

Determinants of Station-Based Round-Trip Bikesharing

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***Abstract*— Around the world, authorities try to increase the attractiveness of multimodal public transport (PT)-related trips to reduce car usage. To achieve this, a seamless combination between the different modes is necessary. The Dutch train station operator NS tries to enhance the combination of the bike and train by providing a train station-based round-trip bikesharing (SBRT) scheme located at train stations throughout the country. This scheme allows users to rent a bike to connect the train station and their destination. The round-trip characteristic SBRT makes it unique in comparison to widely applied one-way bikesharing schemes. While on the latter a wide range of research exists, little research has been conducted on round-trip bikesharing, especially when being integrated into an existing public transport scheme. This paper aims to fill this gap by identifying potential temporal and weather-related determinants for SBRT-rentals of the Dutch SBRT-system OV-fiets using multiple linear regression (MLR). The results are compared with findings on one-way bikesharing schemes. It is found that for hourly rentals in an SBRT-system, the highest explanatory power achieved with the number of train travelers leaving the corresponding train station, followed by temporal and weather-related determinants. Further, the magnitude of the correlation between the determinants and the hourly demand differs across the stations in the system.**

***Keywords*— Round-Trip Bikesharing, Determinants, Multiple Linear Regression, Netherlands, Bike Train Combination**

I. Introduction

Urban areas all around the world face the challenge of a growing population, leading to increased traffic demand resulting in negative external effects such as road congestion and greenhouse-gas emissions [1]. One way to reduce the external effects caused by road traffic is by increasing the attractiveness of car-independent multimodal trips chains. These allow individuals to shift away from car usage towards alternative, resource-efficient modes of transportation. Multimodal trips often consist of one main mode (e.g., a rail service) and different modes used for the so-called first and last mile (sometimes referred to as access and egress leg, respectively) to connect the main mode with the travellers' origin and destination. To increase the attractiveness of multimodal trip chains, it is necessary to create a seamless travel experience between modes by making the access and egress modes easily accessible [2].

An increasing popular mode to be used for access and egress is bikesharing, which aims to encourage individuals for a use of active, environmentally friendly modes instead of relying on a car [3]. It emerged first in the Netherlands in 1965 [4], but service was soon stopped because of vandalism. With the rise of operational advancements such as electrical locks came the implementation of bikesharing-schemes around the world [5]. Another significant rise in the number of worldwide bikesharing schemes was caused by the rise of the internet, allowing for real-time availability information and mobile payments, supporting the worldwide spread of bikesharing schemes emerging from China in 2015 [6]. The existing bikesharing schemes can be classified into four different categories (see Fig. 1): One-way free-floating and station-based schemes account for most bikesharing schemes throughout the world [7].

Modern bikesharing generates a lot of data (real-time location, time of pick-up and drop-off, bike-identification numbers), which is either made available to scientists by operators or gathered by researchers through data mining [8]. The rise of one-way bikesharing all over the world throughout the last decade led to an increase in data accessible for scientific research. Multiple studies use the available data to identify potential determinants for the usage of bikesharing schemes, with the various findings being summarized within multiple reviews [6], [7], [9]–[11]. When it comes to round-trip bikesharing, limited research has been conducted [12]. This might be reasoned in the limited availability of these schemes, as, to the authors' knowledge, only two SBRT systems exist which allow users to do round-trip bookings to get around at their PT trip destination: OV-fiets in The Netherlands and Bluebike in Belgium [13], [14]. Different from one-way bikesharing, round-trip systems provide users with the certainty of having a bike available for a return trip, as a bike available exclusively for the user who rented it until being returned to its origin. So far, no research has been conducted on the determinants of demand for these SBRT-systems and the underlying usage patterns.

This paper aims to fill this gap by providing insights into the usage patterns of the SBRT-system OV-fiets in The Netherlands in comparison to existing findings on one-way bikesharing schemes. The identification of determinants for SBRT systems is done using booking data obtained from the world's largest SBRT system OV-fiets in The Netherlands. The booking data is complemented by further data sources

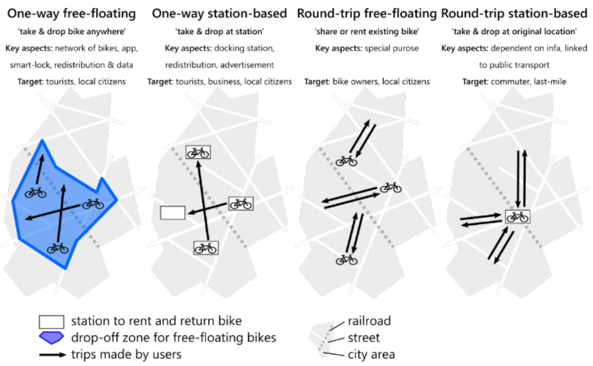

Fig. 1. Bikesharing typology based on Waes et al. [5]

This research was conducted as part of a master thesis at Delft University of Technology in cooperation with the national Dutch train station operator NS Stations.

such as historical passenger flows leaving the train stations next to the considered SBRT-stations and historical weather data to identify potential determinants for the number of bikes rented per hour. The identification of determinants of SBRT rentals is performed on an hourly level of aggregation using MLR and descriptive analytics. The results are then compared to the preliminary identified determinants for one-way bikesharing based on literature.

The focus of this paper lies on weather-related, train traveler-related and temporal determinants. Further factors such as land use and system accessibility are left out due to their location-specific characteristics [7]. Cycling infrastructure and topography are left out as the available data allows for an analysis of the Dutch context only, and both topography and cycling infrastructure are assumed to be similar amongst different Dutch cities. Socio-demographic characteristics cannot be investigated as the provided dataset does not provide any related information.

This paper is organized as follows: Section II identifies weather-, time-, and train travel-related determinants for bikesharing demand and assesses them based on their applicability on SBRT. Section III elaborates the data collection and the methods used for the analysis of SBRT demand. In section IV, the results of the performed MLRs and the descriptive analysis are provided and discusses. Sections V and VI discuss and conclude the findings of this paper. The final section VII provides recommendations for future research.

II. Determinants for Bikesharing Demand

Many weather-related determinants exist which are found to have an impact on one-way bikesharing demand according to various studies compared by Eren & Uz [7]: For one-way bikesharing, it is found that sunny weather results in a higher usage, while rain and wind have a negative impact on hourly rentals. Also, individuals tend to use one-way bikesharing more in moderate temperatures between 0°C and 30°C. The usage is identified to be highest between 20°C and 30°C, while scorching heat and temperatures below 0°C are found to have a negative correlation with the number of rented bikes [7]. Recent research also found that in cities with a higher share of young people and a high-quality cycling network, the bike usage is more robust to unfavorable weather conditions [15].

In terms of temporal differences, the usage of one-way bikesharing-schemes differs across seasons, with a higher usage in summer than winter [7]. Most studies investigating the usage throughout the week for specific systems see a clear difference in usage patterns between weekdays and the weekend [8], [9] The findings are confirmed by a cluster-analysis performed including 322 station-based free-floating systems [6]: According to the authors, the distribution throughout the day slightly differs between systems (e.g., different starting time of morning peak), but recurring patterns can be identified: Distinct morning and evening peaks on weekdays and a moderate usage during afternoons on weekends. Furthermore, it is found that during peak hours bikesharing is more competitive to cars in terms of travel time due to congestion, making the modal shift towards cycling more attractive [16].

It is to be investigated to what extent the described determinants for one-way bikesharing can be translated to SBRT systems. The temporal use might differ from one-way schemes, as users do not end a booking after reaching their destination. Instead, their booking continues until returning their bike at the same station.

Regarding the integration of bikesharing into existing PT services, one-way bikesharing is used to substitute PT trips involving transfers [17]. The proper integration of one-way bikesharing into the existing PT network is found to increase the added value of both modes for travellers instead of resulting in competition [18]. This is the case especially for longer trips [7] and in times of reduced PT services, i.e. at night and on weekends [19]. Further, the added value of round-trip bikesharing lies in the egress leg after travelling by PT as it allows users to cover a higher distance compared to walking, while also allowing to reach destinations which might have limited accessibility by PT [20].

While determinants of one-way bikesharing demand are thoroughly investigated, little is known about the determinants of SBRT-demand. Preliminary conclusions made for one-way schemes might be applicable for SBRT, but there is no scientific evidence supporting this to date. It is likely that the use case of SBRT differs from one-way schemes due to the requirement of ending a booking at the point where it started. This makes the SBRT especially suitable for the activity-end of multimodal trips [20]. This is supported by the rising number of rentals in the existing systems [14], [21].

III. Methodology

A. Data Preparation

Data is provided by the Dutch national train station operator NS Stations, which operates the world's largest fleet of SBRT-bikes. Weather data is extracted from the website of the Dutch Royal Meteorological Institute KNMI for countrywide weather measurement stations. The national holiday calendars are used to include the national and school holidays.

The provided SBRT dataset contains all individual bookings having the same origin and destination. Technically, trips between different SBRT stations are possible, but strongly discouraged by the operator by a fine if returning a bike at another station. These trips are excluded in this analysis for consistency. The rentals of the dataset are cleaned and aggregated on an hourly level per station for the year 2018. The resulting data is combined with a static dataset containing information per SBRT station on the related capacity, the corresponding PT station, and the provided service type. For further analysis, only staffed stations with a capacity of more than ten bikes are included. At these stations, bikes are handed out as the infrastructure of stations with other service types does not allow for a short-term change in the number of bikes[1].

Based on the corresponding PT station, information on the hourly number of travellers leaving the corresponding PT system is included. This information is based on the nationwide smartcard check-in/-out system. In this case, data is only available for stations that are served by the Dutch national rail operator NS Reizigers. Thus, SBRT stations located next to PT stations not served by NS Reizigers are excluded of this analysis. Information about national and school holidays is

[1]Within the SBRT-system provided by NS, multiple different service types can be distinguished: Staffed stations, in which service personnel takes care of the bikes, hands them out, and takes them back after a return; Different types of self-service stations with one main registration device, which after verification with a chipcard either provides access to a key box or automatically provides a bike; Self-service stations with separate boxes per bike, which each can be opened with a chipcard.[22]

added. All three different school holiday periods are included for all stations as SBRT users might use the service for their last mile in regions different form the one they live in. For example, users who have school holidays in their region might use SBRT in a city having no holidays.

The SBRT stations are connected to the closest KNMI weather stations to obtain weather-related information. It is emphasized that with a higher distance between weather stations and SBRT stations results in a lower accuracy on determinants such as rain duration per hour. SBRT stations for which no weather data is available for the closest weather stations in the reference year 2018 are excluded from the analysis.

The final filtered dataset contains 2,646,657 bookings across 48 SBRT stations. These are 75.5% of all bookings performed in 2018 at 15% of all stations, suggesting that the stations with a comparatively high usage are used for further analysis.

B. *Definition of determinants*

Based on research conducted for bikesharing forecasting, the meteorological and temporal factors are found to explain most of the variance in hourly one-way bikesharing rentals [23]. Other factors such as a SBRT stations accessibility, the surrounding cycling infrastructure, topography, and land use are defined by the circumstances in which a SBRT-station is located and thus are considered out of scope. The hourly travellers leaving the corresponding PT stations are included as the analysed SBRT system is integrated into the national train system. This allows for an assessment on whether hourly SBRT rentals depend on the number of train travellers leaving the corresponding train station, as identified for one-way bikesharing [24]. The specific variables used to represent the determinants are visualised in Fig. 2.

1) *Time-related determinants*

According to literature, temporal determinants play a significant role when assessing variance for hourly rentals in a bikesharing-system [6], [9]. To assess whether this is the case for SBRT-systems, different temporal determinants are translated into variables to be suitable for further analysis. While for determinants such as time of day, weekday, and month nominal scales exist (e.g., hour 1 to 24 for the time of day, or weekday 1 to 12 for months), these cannot be translated into numerical variables for further analysis as no order exists among the characteristics of the different determinants.

It is decided to represent each characteristic by a separate dummy variable to independently assess their explanatory power. Each of the dummy-variables becomes 1 if the characteristic is present in the related hour, and 0 otherwise. This is done for all temporal determinants, resulting in twenty-three dummy-variables to represent the hours, six to represent the weekdays, and eleven to represent the months. The reference variables were selected arbitrary, with the first variable in alphabetical order to be the reference variable.

To reduce the number of variables, an aggregated representation of the temporal determinants is added: Hours are aggregated into five different times of day (namely Night, Morning peak, Daytime, Evening peak, Evening). The definition of the aggregated times of day is based on the definition of peak hours by NS: The morning peak occurs between 6:30am and 9:00 am, while the evening peak occurs between 4:00am and 6:30pm. As this analysis is performed on hourly basis, it was decided to include the hours 6am to 9am in the morning peak and 4pm to 7pm in the evening peak, respectively. The weekdays are reduced into one dummy-variable indicating whether it is weekend or a weekday, and the months are aggregated on a seasonal level (Spring, Summer, Autumn, Winter). Holidays, national and school in the three holiday regions, are represented by one dummy-variable each. In total, this results in forty temporal variables on a non-aggregated level, and eight on an aggregated level.

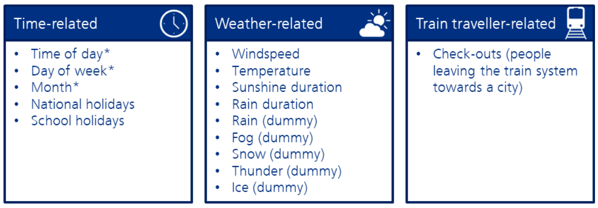

Fig. 2. Grouping of determinants considered for analysis (*exist on an aggregate and disaggregate level)

2) *Weather-related determinants*

As discussed, weather-related determinants are assumed to have a significant impact on the number of rentals of one-way bikesharing schemes [25]. To see to what extent these determinants can explain variance in hourly SBRT-rentals, they are included in the dataset based on the closest KNMI weather station providing suitable data for further analysis. Based on literature [7] and the available data by the KNMI, multiple determinants are selected for further analysis: Windspeed, Temperature, Sunshine Duration, and Rain Duration. These determinants are translated into variables using the interval scales defined by the KNMI: Windspeed and Temperature are assessed using averages for the last hour in in 0.1 m/s and 0.1°C, respectively. Rain and Sunshine Duration are indicated based on their occurrence, measured in tenths of an hour. Additionally, dummy variables are included indicating whether Rain, Fog, Snow, Thunder, or Ice occurred within an hour. Together, this results in nine different weather-related variables. It needs to be emphasized that this analysis only includes the weather within the hour a bike was rented. This assumes that the choice for a bike is based on the weather in that hour, leaving out the potential impact of weather forecasts for later hours.

3) *Train traveller-related determinants*

According to literature it is likely that a link exists between the usage of PT and bikesharing [18], [26]. This is especially relevant in this research as it analyses a train station-based SBRT-system, suggesting a high volume of combined train and SBRT users. Therefore, the number of train travellers leaving a train station is used to assess its explanatory power on the hourly rentals of a SBRT-system. As the focus of this research lies on the distribution of rentals only, this determinant is included as nominal variable, i.e. the number of checkouts per hour. The assessment of the other side of train station-based SBRT-trips, namely the potential correlation between bikes being returned at a train station and the number of train travellers entering the train system, is considered out of scope due to additional complexity.

In total there are fifty different independent variables to assess their explanatory power regarding hourly SBRT-rentals. This number can be reduced to eighteen when using aggregated time-related variables instead of determining each temporal component independently. Both approaches are used to assess to which variable is able to capture most of the variance in the hourly rentals.

C. Identification of significant determinants

To assess the explanatory power of the different variables defined above, a MLR is used, an established statistical method which is conducted in the programming language R based on preliminary research [27]. The basic mathematical formulation is shown below:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \qquad (1)$$

In (1), Y represents the dependent variable (in this case the number of SBRT-rentals per hour), while X_1 to X_n represent the independent variables, and β_0 to β_n the corresponding weights of the independent variables. n represents the total number of considered independent variables, as described in the previous section. ε represents the error term of the equation.

The considered selection of variables results in up to fifty unique variables. When adding interaction effects between different variables, this is expected to result in an excessive number of variables n to be considered in the MLR. To limit the number of variables while keeping as much explanatory power as possible, a backward search algorithm is applied [28]. This method begins with a regression model including all considered variables, and then removes the least significant variables one after another based on a defined criteria until a predefined threshold is met. When comparing with other stepwise search methods, the backward search is considered in favour of the forward search as within the given dataset it can be expected that among variables collinearity might exist. The identification of relevant determinants is based on the relative decrease of the R^2 per removed variable. The magnitude of this decrease R^2 represents the reduction of the ability of the remaining model to explain the variance in the data. Thus, the higher the decrease after removing a variable, the higher its explanatory power in the model [29].

The backward search is performed on the dataset containing all filtered stations. It is chosen to conduct the search across all stations to identify variables which can explain variation existing across the entire system. To make the stations comparable, the dependent variable is normalised using each stations' bike capacity as shown in (2). The relative number of rentals RR_{sh} is calculated using the number of rentals R_{sh} at SBRT-station s in hour h divided by the bike capacity C_s at the corresponding SBRT-station s.

$$RR_{sh} = R_{sh} / C_s \qquad (2)$$

Multiple combinations of variables are used as input for four separate backward search iterations to reduce computational complexity. Across the different iterations, the time-related variables are included on an aggregate or disaggregate level and to consider interaction effects between the different variables. A visualisation of the four combinations is shown in Fig. 3.

The selection of included interaction effects is based on the results of a preliminary conducted test for correlations among the different variables (see Fig. 4). It is found that the weather-related variables Dewpoint and Temperature are highly correlated. Additional correlations are found between

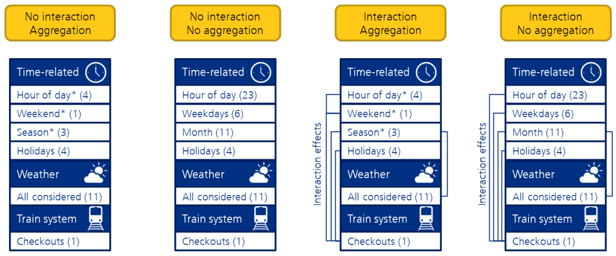

Fig. 3. Four different scenarios considered for backward search application (*Aggregated variables)

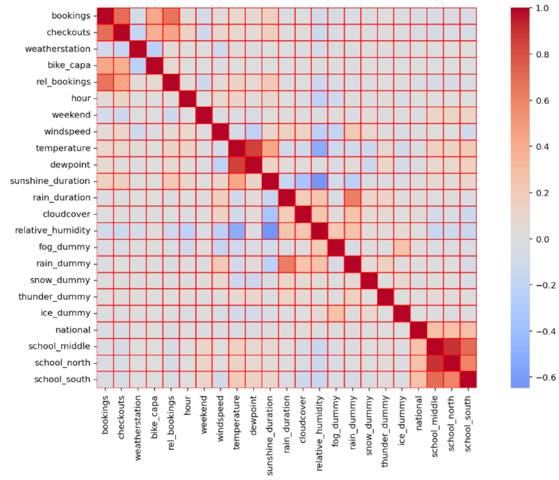

Fig. 4. Indication of correlations between the different variables (red indicates positive correlation, blue negative correlation)

Sunshine Duration, Relative Humidity, Cloud Coverage, and Rain Duration. These weather-related variables might have a different impact on the hourly rentals depending on the time of the year (for example rain in winter might be perceived worse for cyclists compared to summer). To assess this, in the aggregated backward search all these weather-related variables are assessed for potential interaction effects with the seasons.

In the disaggregated backward search, only the interaction between Season and Sunshine Duration is included due to limited computational power. On a temporal level, interactions between Checkouts and Hour/Time of Day, Weekend, and the four different holiday types are included as it is expected that the number of travellers in the corresponding PT system differs across these different temporal variables. This in return is likely to have an impact on the number of rentals in the SBRT-system according to literature [26]. Further two- and multi-variable interaction variables might be interesting to investigate but are considered out of scope for this thesis to reduce computational complexity.

D. Performance of identified determinants per station

The variables contributing to a change of R^2 higher than 0.001 within the previously described backward searches are selected for a further analysis on station level. Station-specific MLRs are performed to examine whether differences exist in terms of the identified determinants' ability to explain the variance in the dependent variables across different stations. This is done as stations are found to have different usage patterns when it comes to the bike-train combination [12], [30].

In the station specific MLR performances, instead of RR_{sh} the absolute number of bikes rented per hour is used as the

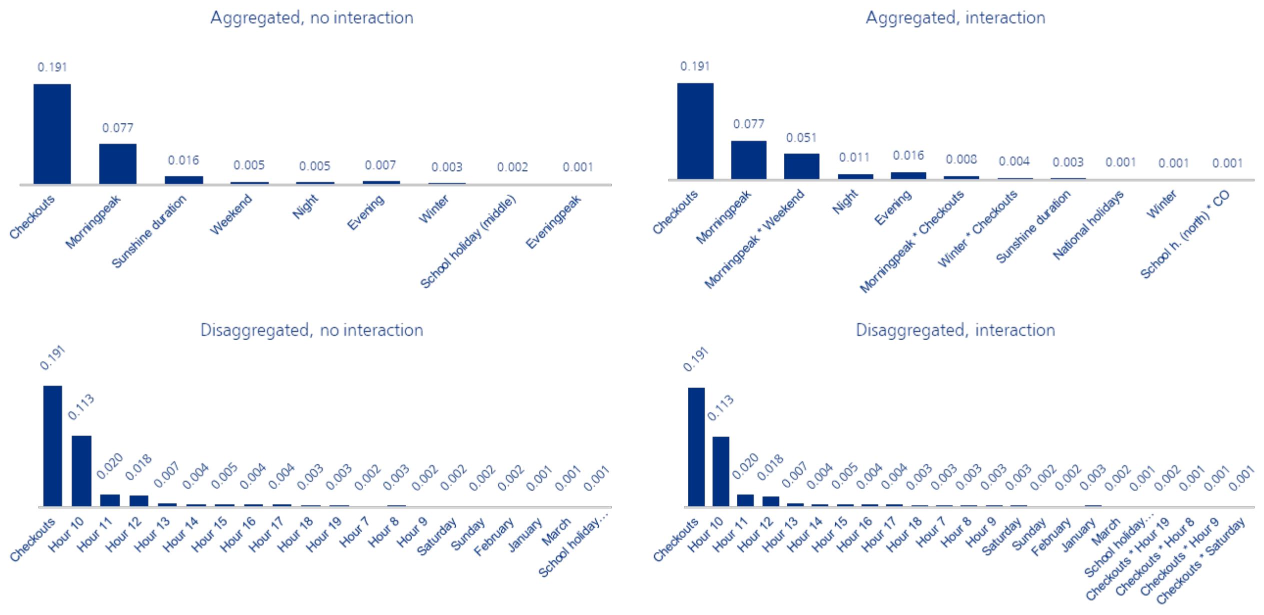

Fig. 5. Backward search –Change in R^2 per removed variable for the four different search methods

dependent variable to allow for an easier interpretation of the model's outcome. While this adaptation is expected to change the magnitude of the weights per variable, it neither has an impact on the significance of variables nor on their sign. The results of these MLRs are compared using the number of significant variables per station to assess how well the previously conducted variable selection explains the variance at a specific station. Also, the resulting R^2-value from each MLR-application is used to examine to what extent the noise in the data can be explained by using the identified variables. This indicator is used as a high R^2-value suggests that the selected variables can capture most noise within the hourly bookings throughout the assessed dataset [29].

E. *In-depth analysis*

Based on the performance of the different stations in the station-specific MLRs, to reduce complexity eight exemplary stations are selected and investigated in more detail to generate a further understanding of the determinants. The station selection is based on the distribution of the R^2-values of the station-specific MLRs. The selection of exemplary stations involves two stations with a low and a high remaining noise, selected using the highest and lowest R^2-value across all stations, respectively. Additionally, the stations being closest to the mean, the median, as well as the 25% and 75% quantile are selected to provide a wide range of exemplary stations. This is only a small selection of both the forty-eight stations filtered for analysis and the in total 313 SBRT-stations in the system, but is deemed sufficient to provide first insights into the data and reduces complexity of the research. The selected stations are then compared using a visual representation of the average hourly rentals across days and weeks in combination with the identified determinants. The aim of this descriptive analysis is to assess whether the determinants have a similar impact across different stations, or whether the patterns are so different that no overarching findings can be concluded.

IV. Results

A. *Identification of significant determinants*

The backward searches using the previously described selection of variables is applied on the dataset to identify the most significant variables. The results for the different backward searches are visualised in Fig. 5, with each bar indicating the magnitude of drop in R^2 caused by the backward search removing the corresponding variable.

The number of hourly checkouts is found to have the highest explanatory power across all backward searches when determining the relative number of bookings per station, as 19% of the variance in the hourly rentals across all stations can be explained using this variable. Further, the multiple time-related variables are found to together allow for an explanation of 22% of the variance. The explanatory power is mostly covered by the disaggregated Hours 8-18 and the aggregated variables Morningpeak, Evening, Eveningpeak, and Night. Other considered variables are the time-related variables Saturday, Sunday and weekends, respectively, as well as both national and school holidays. The weather-related variables allow for an explanation of the variance in the data of around 5%, while the only weather-related variable resulting in a change of R^2 of more than 0.001 is the sunshine duration.

All variables causing a drop of R^2 of more than 0.001 across all four different backward search applications are jointly shown in Fig. 6. The colour of the variables indicates

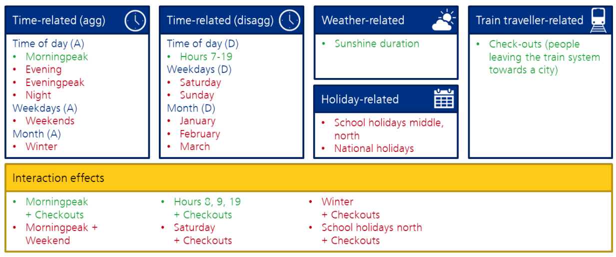

Fig. 6. Indication of correlations between the different variables (red indicates positive correlation, blue negative correlation)

the positive or negative correlation with the hourly bookings in relation to the reference variable. For example, when looking at the time-related variables on an disaggregate level, the hourly rentals in Hour 7-19 show a positive significant difference from the reference Hour 0. When aggregated, the reference variable is Daytime, to which hours in Morningpeak show a significantly higher number of rentals compared to the reference. The other three, Evening, Eveningpeak, and Night show significantly fewer hourly rentals. The interaction effects are read as a combination of two variables: For example, the negative significant interaction between Morningpeak and Weekend indicates that in weekend morning peaks fewer bikes are rented out per hour in comparison to morning peak hours during the week.

B. *Performance of variables across all station-specific MLRs*

While the findings are identified on a dataset across all stations providing general tendencies of the determinants, they provide limited information on which determinants are able to explain the variance of the hourly rentals on an individual station level. To assess to what extent the identified variables are suitable to explain the variance in hourly rentals per station, station-specific MLRs are performed using the previously identified significant variables.

The following decisions are made regarding the level of aggregation for the time-related variables allowing for an appropriate representation. It is decided to keep the time of day on a disaggregate level and include all hours as dummy variables, while weekdays and months are aggregated. For the latter two variables the aggregate versions include the corresponding non-aggregated variables: Winter includes the months January, February, and March, while Weekend includes both Saturday and Sunday.

48 separate MLRs are performed using the defined variables, one per station. For each station, the reference variables for the dummy variables consist of the time-of-day Hour 0 (midnight), the season Autumn, and a day being not on a Weekend. Fig. 7 provides results of the station-specific MLRs, aggregating the significant levels per variable. The significance levels are counted separately based on their value using the following upper boundaries of the corresponding p-value: 0.0001, 0.001, 0.01, 0.05, 0.1. An additional overflow-category is included for p-values > 0.1 to indicate the number of stations for which a variable remains insignificant.

For five variables (Interaction between Checkout (CO) and Hour), less than 48 occurrences were counted. This is a result of multiple stations having neither checkouts nor SBRT-rentals in the corresponding hours. It needs to be emphasized that the following analysis of the results shown in Fig. 7 is solely based on the significance levels of the station-specific MLRs, leaving out information about the positive or negative correlation of the variables with the hourly rentals as well as their magnitude. In the following, the different groups of variables will be analysed in more detail.

1) *Train-traveller related variables*

For checkouts, in Fig. 7 it becomes clear that the variable itself shows a high significance level on few stations only, while many stations show interaction variables including checkouts on a high significance level. The interaction effects will be further analysed in the following research.

2) *Weather-related variables*

Sunshine Duration as the only weather-related variable included in this analysis is significant on a 95%-level (i.e., a p-value below 0.05) for 44% of all stations. A similar result is shown by the interaction between Sunshine Duration and Checkouts (50% of stations on 95%-level). The interaction variables representing Sunshine Duration and Seasons is found to have a high significance across 36% and 39% of all stations for Spring and Summer on a 95%-significance level, respectively. This translates to spring being less different in terms of hourly rentals when interacting with sunshine duration compared to the reference level autumn. In Winter, 54% of all stations indicate the related interaction variable to be significant on a 95% significance level compared to the reference level:

3) *Time-related variables*

When investigating the independent hour-of-day variables and the interaction variables combining hour-of-day and checkouts, it becomes visible that the timeslots of Hour 22, 23, and 1-5 are insignificant even on a 90%-significance level. It is important to mention that this does not necessarily translate to unreliable data for these timeslots, but instead means that the data does not provide sufficient information to distinguish the rentals in these timeslots from the rentals in the reference-timeslot Hour 0. This can be reasoned in the number of hourly rentals in these hours being similar, and much lower compared to the remainder of the day. In addition, for some

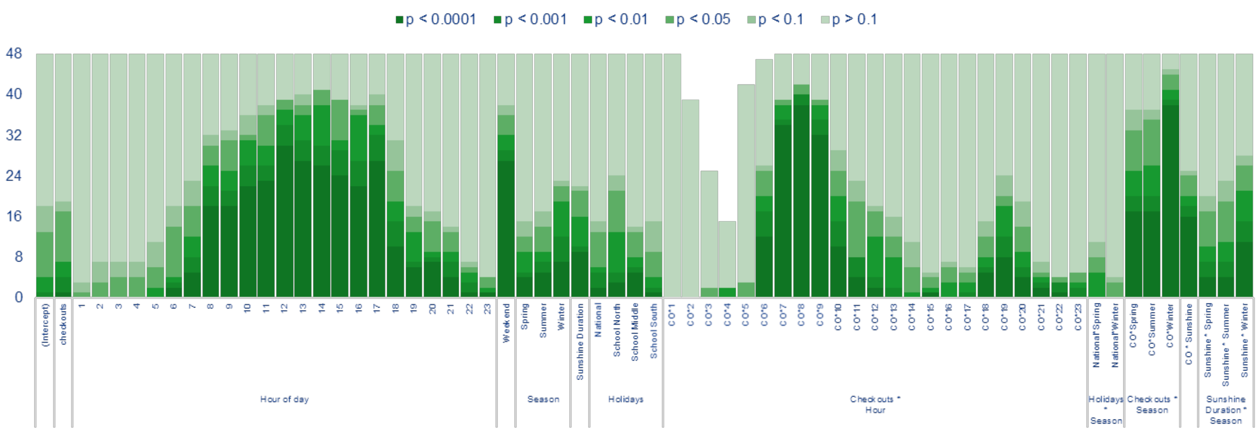

Fig. 7. Number of significant variables across significance levels and stations per variable (reference levels: Autumn, midnight, no weekend)

stations no interaction variables could be assessed for the timeslots between Hour 1 and Hour 6, as either no checkout and/or no SBRT-booking data is available for these timeslots. This can be caused by the corresponding facilities being closed during that time. The timeslots in the morning peak (Hour 7-9) show a high significance among most stations when interacting with Checkouts in that timeslot compared to their independent counterparts. The opposite effect can be seen for Hours during Daytime (Hour 12-18), which are mostly significant on an independent level and thus seem to be less explainable by an interaction with Checkouts. An exception can be seen for the evening timeslots (Hour 18-20), where up to 42% of the stations indicate a high significance of interaction variables with Checkouts. A further analysis on this is done in the following section.

The fact of a timeslot being on a weekend has significant correlation with the hourly rentals across most stations, with 75% of the stations having a significance level >95%, and 56% even higher than 99.99%.

The variables representing the seasons are found to be significant across few stations when considered separately but show a higher interaction when being combined with sunshine duration and checkouts (for the interaction with the sunshine duration, see above). The interaction with Checkouts is prominent for Winter, as for 92% of the stations this variable is significant on a >95%-level.

Lastly, the variables representing the national and school holidays are found to be significant on a 95%-level for at least nine stations, but none of the variables is significant across more than 50% of the stations. Also, the interaction variables combining National Holiday and Seasons are found to be insignificant on a 95%-level for at least 83% of the stations, suggesting that the presence of holidays is only relevant for a small number of stations. There is no interaction variable between summer and national holidays as no national holidays take place in the summer period.. An investigation on whether the correlation of the explanatory variables with the hourly rentals differs between negative and positive across the different stations or is the same across all stations is considered out of scope due to the expected extensiveness. Nevertheless, such an analysis could provide additional understanding in the similarities and differences among the different stations.

C. Performance of variables per station-specific MLR

While the aggregated analysis of the MLR-results provides first insights into the significance of different

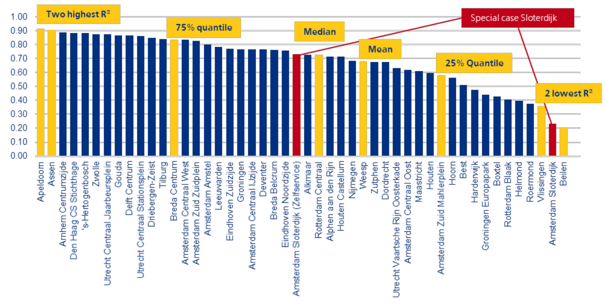

Fig. 8. R^2 of the station-specific MLR, descending order

variables regarding the hourly number of rentals, it lacks information on the magnitude of the correlation between the independent and dependent variables. To further investigate this, a descriptive analysis of selected SBRT-stations is provided in the following section.

Among the forty-eight stations analysed in the previous sections, a selection of exemplary stations is done to represent the dataset in an in-depth analysis. The selection is done using the R^2-values resulting from the MLRs performed per station in the previous section. The stations with the two best and worst performing R^2-values are selected to investigate why the station-specific MLR is able or unable to capture variance in the corresponding data. In addition, four stations are selected to assess whether stations performing comparatively good/bad (25%- and 75%-quantile, respectively) and those providing the middle of the dataset (median and mean) show significant differences compared to the best/worst performing stations and between one another.

Amsterdam Sloterdijk is a special case as there is an overlap of the datasets for these SBRT-stations at the corresponding train station. This is caused by a temporary self-service facility installed alongside the staffed station for a limited period in 2018. As the two stations cannot be analysed independently due to potential interdependencies, it is decided not to include them in the in-depth analysis conducted in the next section.

Fig. 8 shows that the selected variables can explain more than 92% of the variance in the hourly bookings for stations like Apeldoorn and Assen, and in 75% of the stations the MLR is able to explain more than 58% of the variance. When assessing the R^2-performance of the different stations in combination with the number of significant variables per station in Fig. 9, it is remarkable that some stations achieve a

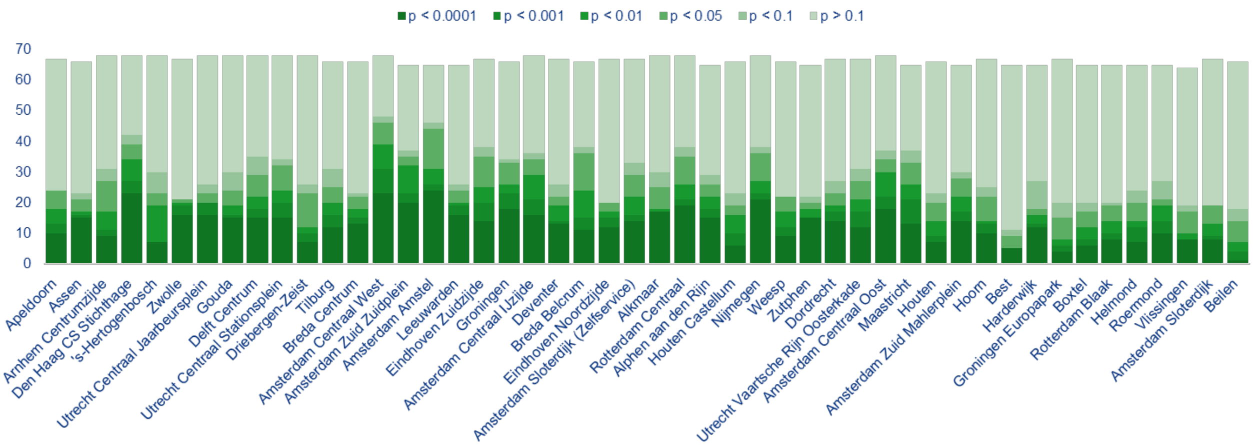

Fig. 9. Number of significant variables across significance levels and stations per station (stations sorted by R^2-performance, descending)

high R^2-value with a comparatively low number of significant variables (Apeldoorn, Assen). For other stations a higher number of variables is significant (e.g., Den Haag CS Stichthage, Amsterdam Centraal West, Nijmegen) to explain the variance in the hourly rentals, while their overall R^2-value is comparatively low. When investigating stations with a lower R^2-value, the visualisation should be read with caution as it only considers the preselected variables. While the high significance level of some variable suggests that the variance in the hourly rentals might be explainable by the selected variables, the low R^2-value suggests much uncaptured noise in the data.

Therefore, it can be concluded that while there are variables which are significant across most stations, there are differences in terms of the number of significant variables per station. These discrepancies in the performance of the MLR per station suggest separate models for the different stations when comparing their performance using the identified significant variables. It might require further research to investigate whether for some stations, a lower number of variables and/or additional variables can provide an added value to the models, which is considered out of scope for this research for complexity reasons. Instead, this researches further investigates to what extent the different variables influence the hourly/ weekly/ monthly rentals in the following section, using eight selected stations as examples. To limit the required space in some cases instead of all eight stations only exemplary stations are provided within the report. In this case, a visualisation of all eight can be found in the Appendix.

D. *Descriptive analysis*

The following section provides a descriptive in-depth analysis of different determinants using selected exemplary stations. This includes a discussion on potential causes when identifying recurring patterns among multiple stations. The exemplary stations are selected based on the performance of the station-specific MLRs. Then, the determinants are descriptively analysed to unravel their potential dependency with the rental patterns, which are aggregated or averaged on a monthly, daily, and hourly level. Per determinant and level of aggregation, only a selection of the eight selected stations is shown to reduce the report's complexity. The selected stations are shown in Fig. 9: *Beilen*, *Vlissingen*, *Weesp*, *Rotterdam Centraal*, *Amsterdam Zuid Mahlerplein*, *Breda Centrum*, *Assen*, and *Apeldoorn*.

The selection of determinants considered for comparison differs per level of aggregation: On a monthly and daily level, the aggregated rentals and checkouts are compared, while on an hourly level further time- and weather-related variables are analysed. This is reasoned in the time- and weather-related variables which cannot be compared on a daily or monthly level due to the potential loss of hour-specific information.

First, the monthly, daily, and hourly levels will be compared to identify recurring patterns across multiple stations. The aim is to investigate whether usage patterns are similar enough to allow for a generalisation of the previous findings across multiple stations. If it is found that the patterns are unique per station across multiple variables, distinct models per station would be required. The interpretation of the differences amongst stations were discussed with and confirmed by individuals working for the operational department of the SBRT-scheme. While the performed MLRs provide insights into these causalities allowing for a visual high-level analysis, the following results should be read with caution, as a descriptive analysis lacks the scientific foundation to confirm visually identified causalities.

1) *Monthly patterns*

When comparing the distribution of rentals per month (see blue lines in Fig. 10), all selected stations apart from *Beilen* and *Vlissingen* show an increase in rentals throughout the first

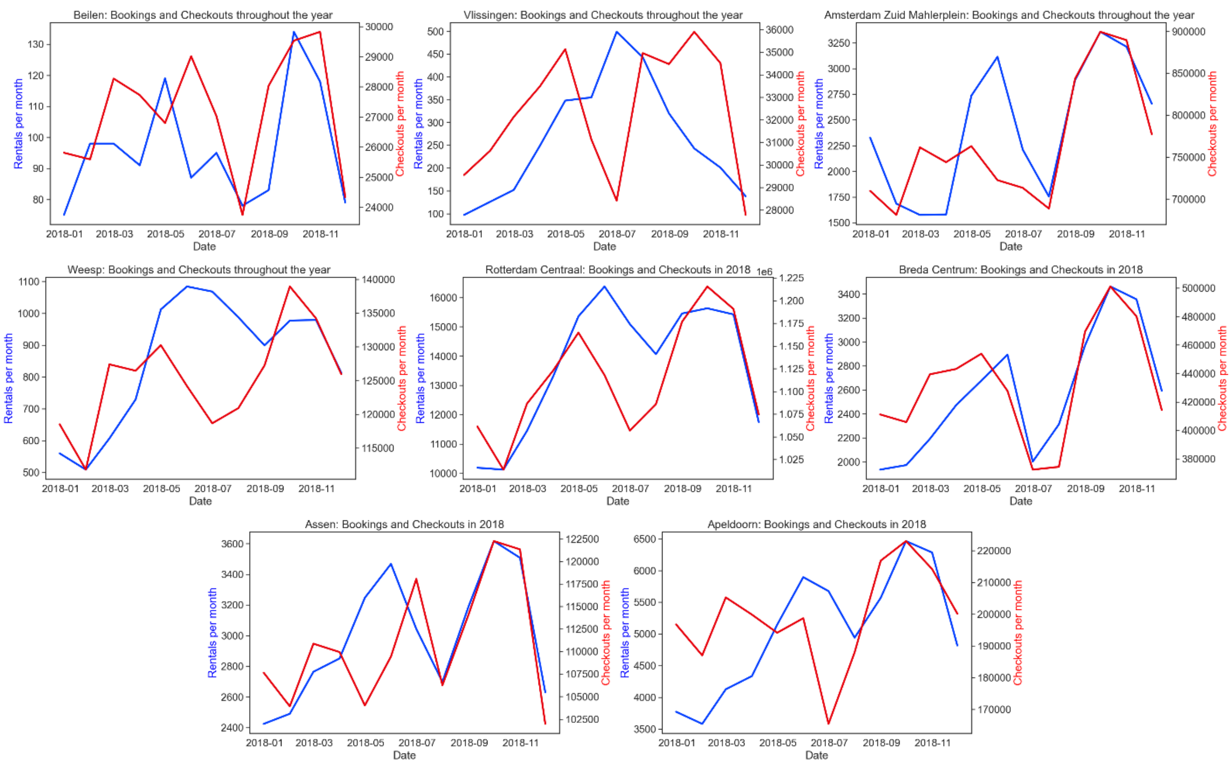

Fig. 10. Aggregated monthly rentals and checkouts in 2018 for the exemplary stations

half of the year, followed by a decline in July and August in which the school summer holidays fall. This is in line with the decrease in the total number of checkouts at the corresponding train stations, visualised by the red lines in Fig. 10. In Autumn, the number of rentals rises again, which is in line with the increasing number of checkouts (with *Weesp* being an exception). This confirms the previous finding that checkouts can explain a high share of the variance in the hourly rentals.

The patterns of the other two stations, *Beilen* and *Vlissingen*, show limited similarity with the other stations. Due to the low amount of bike rentals (on average 3-4 a day) there is too much noise in the data for *Beilen* to look for patterns. For *Vlissingen*, the station being located close to outdoor recreation areas might suggest a higher usage throughout summer compared to winter. To conclude, the patterns of the stations themselves and in combination with the monthly checkouts provide little potential for generalisation.

2) Daily patterns

To compare the average number of rentals per weekday throughout the week, two different patterns occur at multiple stations (see Fig. 12 for three exemplary stations and App. 1 for all eight stations). The first pattern (*Beilen*, *Weesp*, *Breda Centrum*, *Assen*, *Apeldoorn*) follows a stable level or rentals throughout working days Monday to Thursday, with a small drop on Wednesdays and a sharp decrease from Friday to Sunday. The checkouts of these stations follow a similar pattern, suggesting that the dips in rentals on Wednesdays and Fridays might be caused by less commuters on these days, which use the SBRT to overcome the trip between workplace and train station. *Vlissingen* follows a similar tendency, but the high width of the confidence interval does not allow for an interpretation of an explicit pattern.

The second pattern occurs at both *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein*, showing an increase in rentals from Monday to Friday followed by a sharp decrease towards the end of the week. When comparing these daily rentals with the daily checkouts , checkouts show a similar pattern across all selected stations, with a stable level throughout the week and a drop towards the weekend. The difference between the two patterns might thus be reasoned in location-specific characteristics of the stations. For example, *Amsterdam Zuid Mahlerplein* and *Rotterdam Centraal* are located in the two biggest Dutch cities which attract both tourists and nightlife visitors using bikes to reach their destination [31]. An investigation of hourly rentals and the comparison between weekends and weekdays can provide additional insights.

3) Hourly patterns

Two recurring patterns become visible when analysing the average hourly rentals per day, with *Vlissingen* being an exception (see Fig. 12 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen* as examples, and App. 2 for all stations): While *Weesp*, *Breda Centrum*, *Assen*, and *Apeldoorn* show a high number of rentals in the morning peak hours, they remain low throughout the rest of the day. This pattern is different from the hourly checkouts throughout the day, which have an increase in the evening peak (4-7pm). These evening peak checkouts are mainly train commuters on their way back home. While the SBRT-system is mainly used on the activity-end of a trip and not on the home-end, this probably explains the difference between rentals and checkouts in the evening.

The high number of SBRT-rentals in the morning peak could be reasoned in commuters travelling by train to the corresponding city for work, using the SBRT-system for their last mile to reach their workplace. The second pattern occurs at *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein* showing a less steep decrease after the morning peak compared to the first pattern. Instead, the number of hourly rentals remains on an elevated level before displaying a second increase in the evening peak. Remarkably, for these two stations the hourly SBRT-rentals are following a pattern roughly following the hourly checkouts. This suggests that SBRT-bikes are rented out for different purposes throughout the day. For example, the evening peak in rentals might be reasoned in a higher attraction of the corresponding cities to serve recreational purposes. This finding would be in line with previous findings on a daily level.

To test for the findings obtained from the daily and weekly patterns, the daily patterns are analysed based on the time-

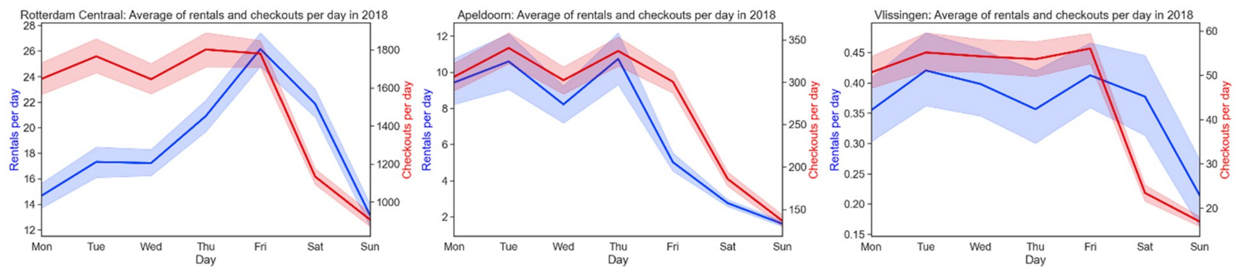

Fig. 12. Average hourly rentals and checkouts per day throughout the year 2018 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen* (light filled areas indicate 95%-variance interval)

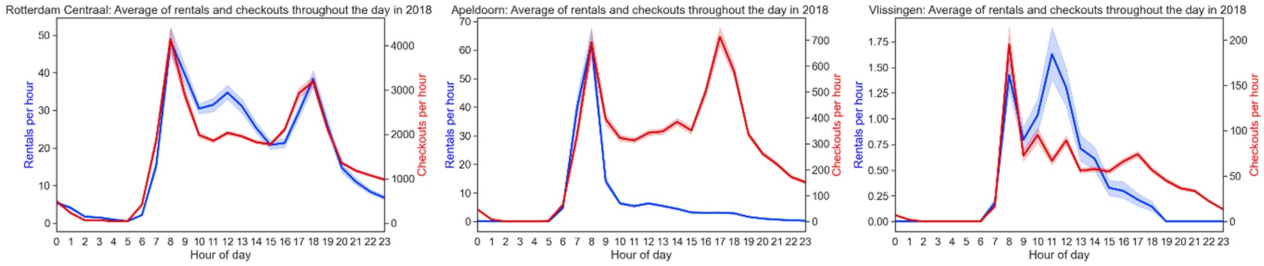

Fig. 12. Aggregated hourly rentals throughout the year 2018 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen* (light filled areas indicate 95%-variance interval)

related determinants 'weekend', 'national holiday', and 'school holiday'. The results are visualised in Fig. 13 for *Rotterdam Centraal* and *Apeldoorn*, and in App. 3-App. 5 for all stations. It is found that weekend and national holiday have a similar effect on the daily pattern, with morning and evening peaks being replaced by an increase in rentals around noon and the early afternoon. While this new peak is more elevated in stations located in big cities (*Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein*), for stations located in smaller cities such as *Breda Centrum*, *Apeldoorn*, and *Assen*, the peak is less distinct. The potential causality with school holidays in at least one of the three holiday regions is less severe, with only a small decrease in the morning peak. This might be reasoned in the fact that, different to weekends and national holidays, the overall mobility behaviour remains unchanged, with only those having holidays (pupils) or taking holidays (employed people) changing their mobility behaviour.

In addition to the temporal determinants, the impact of the annual seasons is assessed. The results are shown in App. 6. For the station *Beilen* no conclusion can be made due to the high variance in rentals per hour and season. *Amsterdam Zuid Mahlerplein*, *Weesp*, *Rotterdam Centraal*, *Breda Centrum*, *Assen*, and *Apeldoorn* show similar effects of the different seasons, with an overall higher level of rentals per hour in Summer and Autumn and a lower level in Winter. An exception, again, is *Vlissingen*. There, in Spring and Summer an increase of rentals can be seen around noon, supporting the interpretation that in warmer seasons people are likely to use the SBRT for recreational purposes.

Also, the impact of rain occurring within an hour is analysed and shown in App. 7. It is found that at *Amsterdam Zuid Mahlerplein*, *Rotterdam Centraal*, and *Vlissingen* the presence of rain has almost no effect on the number of rentals within the morning peak among the selected stations, while leading to a slight decrease in other hours of the day. The other exemplary stations show no significant impact of occurring rain at all. This might be reasoned in the lack of other options to reach the destination. The rain-related results should be read with caution, as they lack information on how long rain lasted or how heavy it was.

It can be summarised that while there are similar patterns among some exemplary stations, the determinants differ too much across them to allow for a generalisation of effects. Instead, to capture the local differences between the stations, it is recommended to apply models separately per station to allow for an appropriate representation of the local context.

V. Discussion

In the following, the identified determinants and their impact are compared to preliminary scientific findings.

A. Weather conditions

The lack of impact of the occurrence of rain on hourly rentals in the morning peak differs from the negative impact of rain for one-way bikesharing systems [25]. This might be caused by commuters relying on the SBRT-system for the egress leg of their trip as there might be no or few (less attractive) alternatives to reach their destination. Thus, they might be less sensitive to occurring rain. Additionally, when renting an SBRT-bike the users are assured to also have it available for their return trip to the station. This results in a certainty of availability which differs from one-way bikesharing systems in which users cannot be certain that a bike will be available at a certain time and location when they need it.

Regarding the positive correlation between hourly rentals and sunshine duration, this is in line with findings for one-way bikesharing [7]. This finding is supported by the national train operator NS using a separate model to forecast train traveller demand for stations with a high recreational attraction in times of sunshine and elevated temperature, especially for destinations close to the beach. This finding can be translated to the analysed SBRT-system OV-fiets: An additional MLR performed for the station Vlissingen indicates that both sunshine duration and temperature have a positive correlation with hourly rentals. The same holds for the combination of a day being on a weekend, suggesting that most SBRT-rentals at this station are done on sunny, warm days on weekends (see App. 8).

B. Temporality

The findings for patterns within the rentals throughout the year, aggregated on a monthly basis, are to a certain extent in line with literature findings [7]. Different from preliminary conclusions for one-way bikesharing, the present research identifies the highest number of monthly rentals during autumn, while the authors identify a peak of rentals during summer for one-way bikesharing. In the given case, the

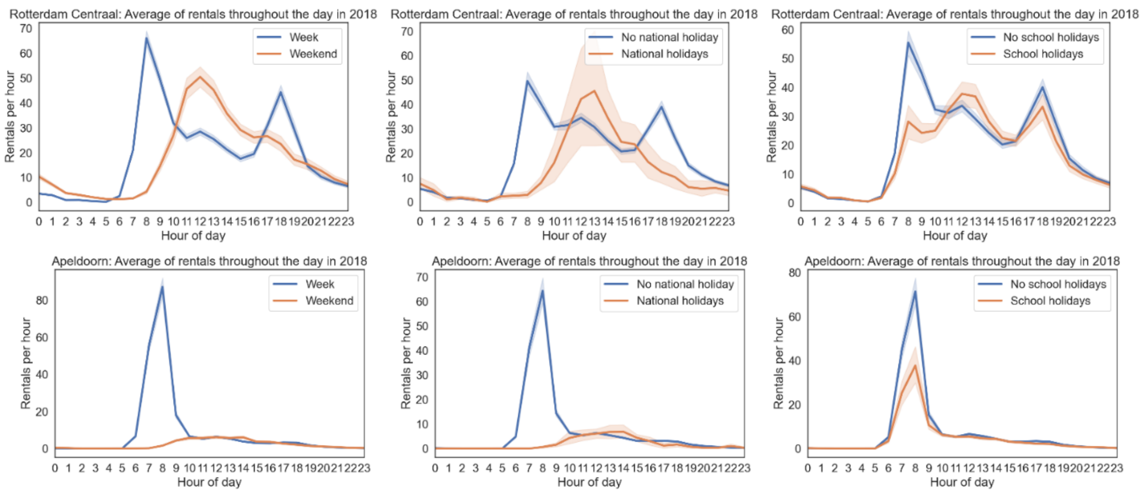

Fig. 13. Aggregated hourly rentals throughout the year 2018 for *Ro* and *Ap*, compared regarding the related days being on a weekend or a national holiday, or in school holidays (light filled areas indicate 95%-variance interval)

SBRT-system has a smaller number of rentals during summer months compared to autumn and spring, which is reasoned in the holiday season and lower numbers of commuters and train travellers according to the operator and supported by the provided results. A special case, again, are SBRT-stations located at destinations with a high attraction for recreational trips: For example, Vlissingen has the highest number of rentals in summer, which is more in line with findings for one-way bikesharing. This might be reasoned in a similar trip purpose, namely recreation. Regarding winter, this season shows the lowest number of monthly rentals for the analysed SBRT-system and, according to literature, for one-way bikesharing.

Regarding rental patterns aggregated per day throughout the week, some of the SBRT-patterns selected for the in-depth analysis are in line with preliminary findings [6]: Both SBRT- and one-way bikesharing show a higher number of rentals on weekdays compared to weekends. Among the different one-way bikesharing schemes identified by the authors, they defined a cluster of systems they named *inefficient systems with low occupancy numbers*, which show a similar number of rentals per hour as two of the selected stations, namely *Beilen* and *Vlissingen*. This connection between the systems needs to be read with caution, as it is unsure whether the lower usage at the mentioned stations is caused by a dissatisfying system design or a lack of a sufficient user potential. Another pattern identified among the selected stations has no similar counterpart in one-way bikesharing literature: The peak of rentals at bigger stations such as *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein* between Thursday and Saturday. This might be caused by the 24-hour pricing scheme of the OV-fiets making long-term bookings cheap in comparison to one-way bikesharing systems. Another reason might be the round-trip nature of the system, making it more attractive to book a bike overnight and/or for an entire weekend in comparison to one-way bikesharing.

When comparing the literature findings for the distribution of rentals throughout the day, the distinct morning peak is in line with literature for one-way schemes. Contrasting one-way schemes, the evening peak is less distinct. A potential reason is that the individuals renting the bikes in the morning still have their rented bikes available to return to the station in the evening. In the one-way-schemes discussed in literature, these return-trips are separately booked, thus leading to distinct evening peaks [6]. Still, evening peaks exist in the SBRT-systems across some stations, but they occur later compared to one-way schemes and only at stations located in bigger cities such as *Ro* and *AZM*. On weekends, the hourly patterns throughout the day show peaks in the early afternoon, which is in line with findings for one-way schemes.

Thus, while there exist determinants with similar effects on both SBRT- and one-way bikesharing schemes like sunshine duration, temperature and time of the year, other determinants show noteworthy differences between the two schemes such as the higher number of rentals on Fridays or the differences and/or the lack of evening peaks at SBRT-stations. It therefore can be concluded that SBRT-usage requires research independent from one-way bikesharing schemes in terms due to its distinct characteristics.

VI. Conclusion

To identify significant determinants for bike rentals at SBRT-stations, the rentals done in 2018 throughout the Dutch SBRT-system OV-fiets are aggregated on an hourly level per station. The results are then filtered, normalised using the total capacity per station, and combined with information on national and school holidays as well as hour-specific information about the weather conditions. The latter is gathered from the national weather stations closest to each SBRT-station. The resulting dataset is used to perform MLRs across the entire dataset as well as per individual SBRT-station to identify significant weather- and time-related determinants. For some stations a high explanatory power can be achieved using few variables only, while others achieve a lower explanatory power even when having more significant variables. Thus, there is no clear set of variables being able to explain variance across the entire set of stations

To further investigate whether the available data can be used to identify temporal usage similarities and differences among SBRT-stations, a descriptive analysis is done using eight selected stations. The hourly rentals per station are then aggregated on a monthly, daily, and hourly level and compared with the previously identified determinants. When comparing the patterns of the different stations, it is found that while the patterns mostly differ across the stations, a number of general trends can be identified: For example, on average all stations have their highest number of hourly rentals in the morning peak between 7-9 am, and the two selected SBRT-stations located in bigger cities also experience a second peak in the afternoon between 5-7 pm. The latter suggests a different use case of the SBRT-system in the evening peak compared to the morning peak. Another identified difference becomes visible between the patterns of hourly rentals on weekends and weekdays, as on weekends neither morning nor evening peaks appear. Instead, the rentals either stay on a low level throughout the day or experience a peak during the early afternoon between 12-2 pm. Another finding is that the occurrence of rain is unlikely to impact the number of rentals in the morning peak, while the number of rentals throughout the rest of the day slightly drops when rain occurs.

For operators, the provided information on the determinants of a SBRT-system in combination with suitable demand forecasting methods might allow for an increase in efficiency in terms of staff scheduling, maintenance of bikes, and a potentially higher user satisfaction due to an improved match of supply and demand.

VII. Recommendations

The present research does assess weather- and time-related determinants, while leaving out further location-specific and other external determinants such as events. The included determinants are also focussing on causalities and two-dimensional causalities only, while a higher dimensionality of interaction between determinants might be required to accurately explain the variance in the data. Further, the in-depth analysis only covers eight exemplary stations to provide a first insights into the system, while missing insights on the remaining forty stations included in the analysis and into the 265 SBRT-stations not included in this analysis. Furthermore, this research was conducted using data from 2018 to avoid the impact of COVID-19 related travel restrictions.

To conclude, this research provides new insights into a new, barely researched type of bikesharing. The learnings provide a first indication on where SBRTs have similarities and differences with the widely known one-way bikesharing and provides existing and potential operators new insights on how these learnings can be used to forecast the occupancy of their services to improve the service availability and efficiency. Further research can deepen the understanding of the system and help SBRT-systems to gain a wider acceptance by raising awareness on the added value of the system. Additionally, an investigation into whether the results of this work might be reproducible for different SBRT-systems or data for different timeslots, e.g. post-COVID-19 might be interesting to verify or neglect the present findings.

Acknowledgment

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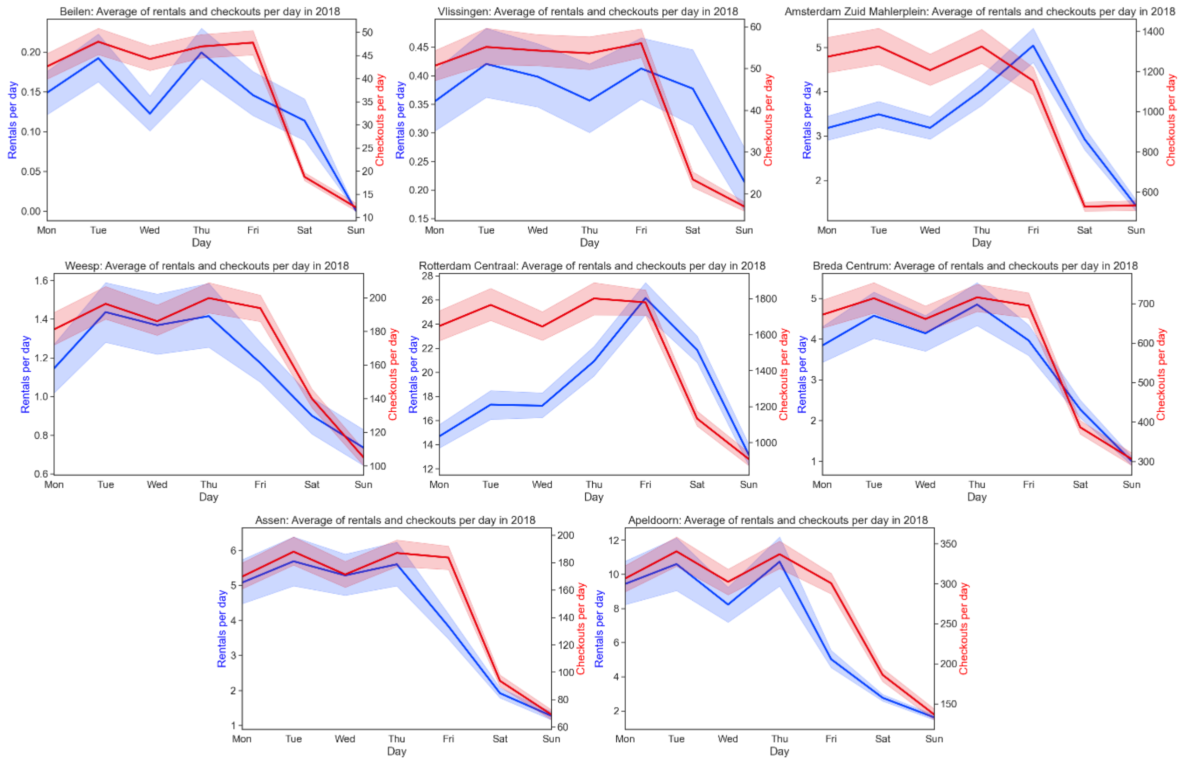
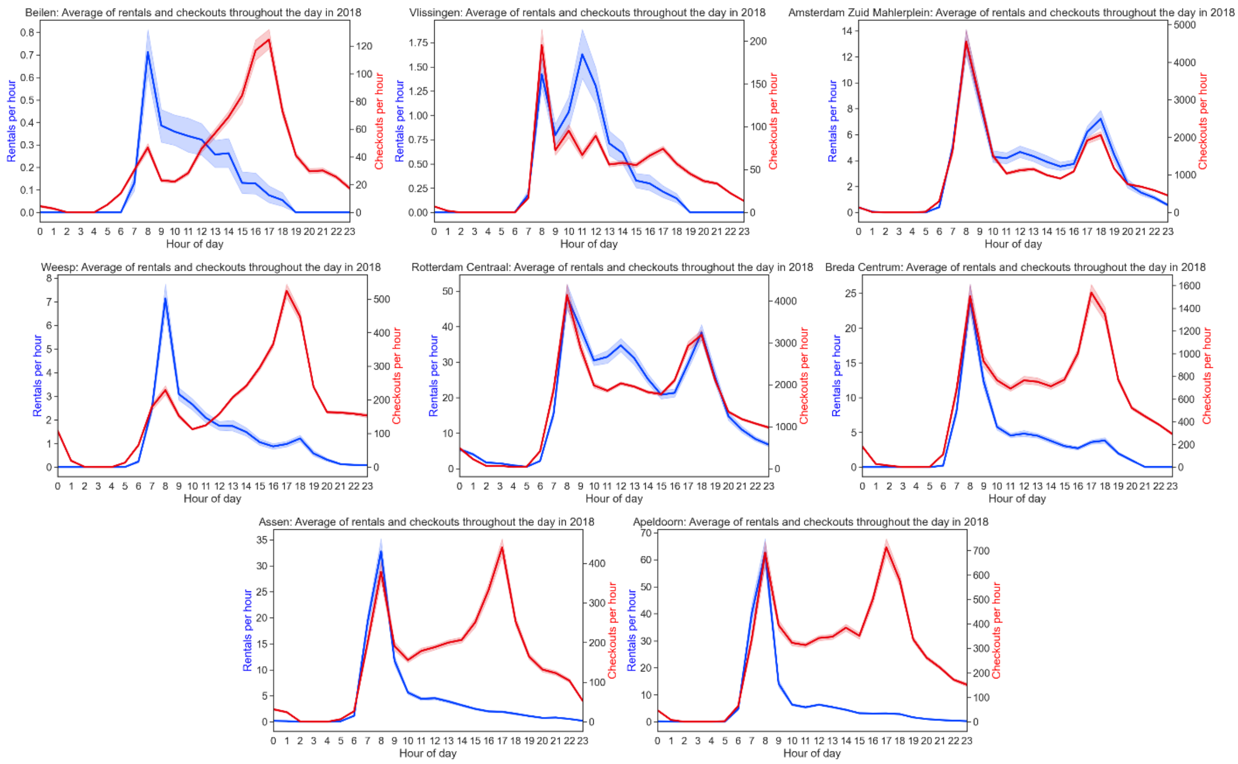
APPENDIX

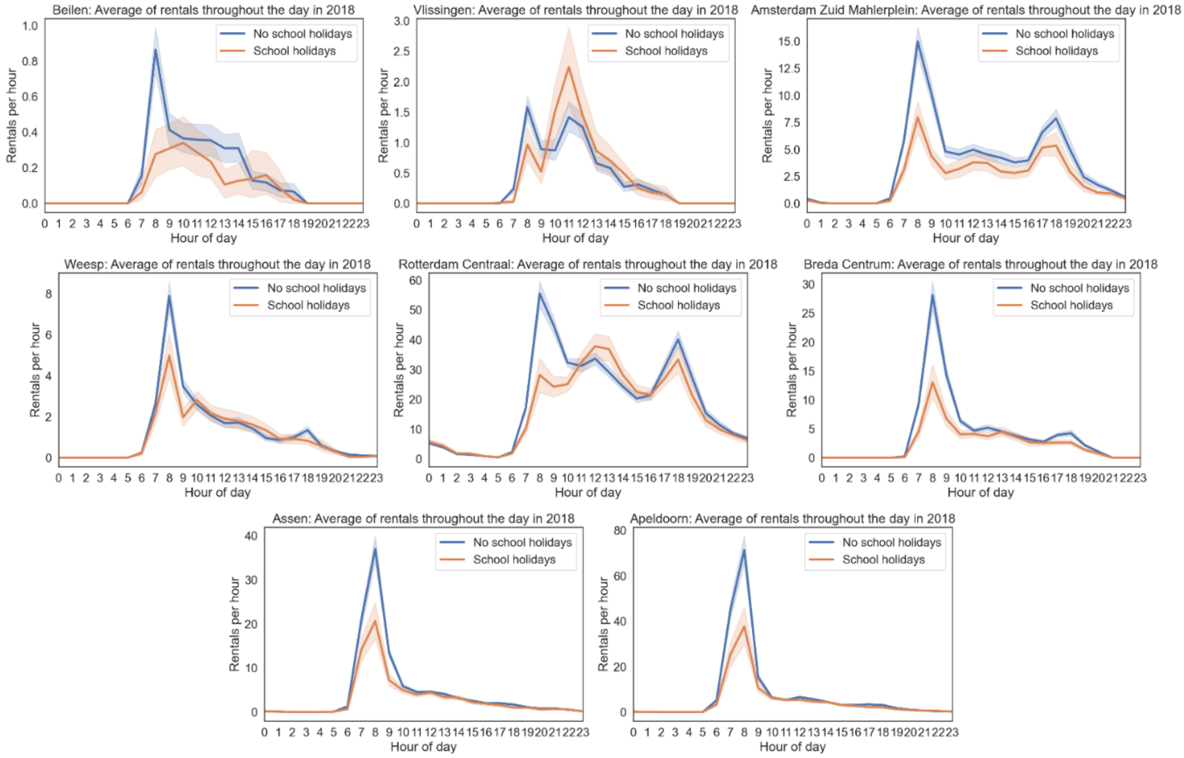
App. 1: Average daily rentals and checkouts per week in 2018 for the exemplary stations (light filled areas indicate 95%-variance interval)



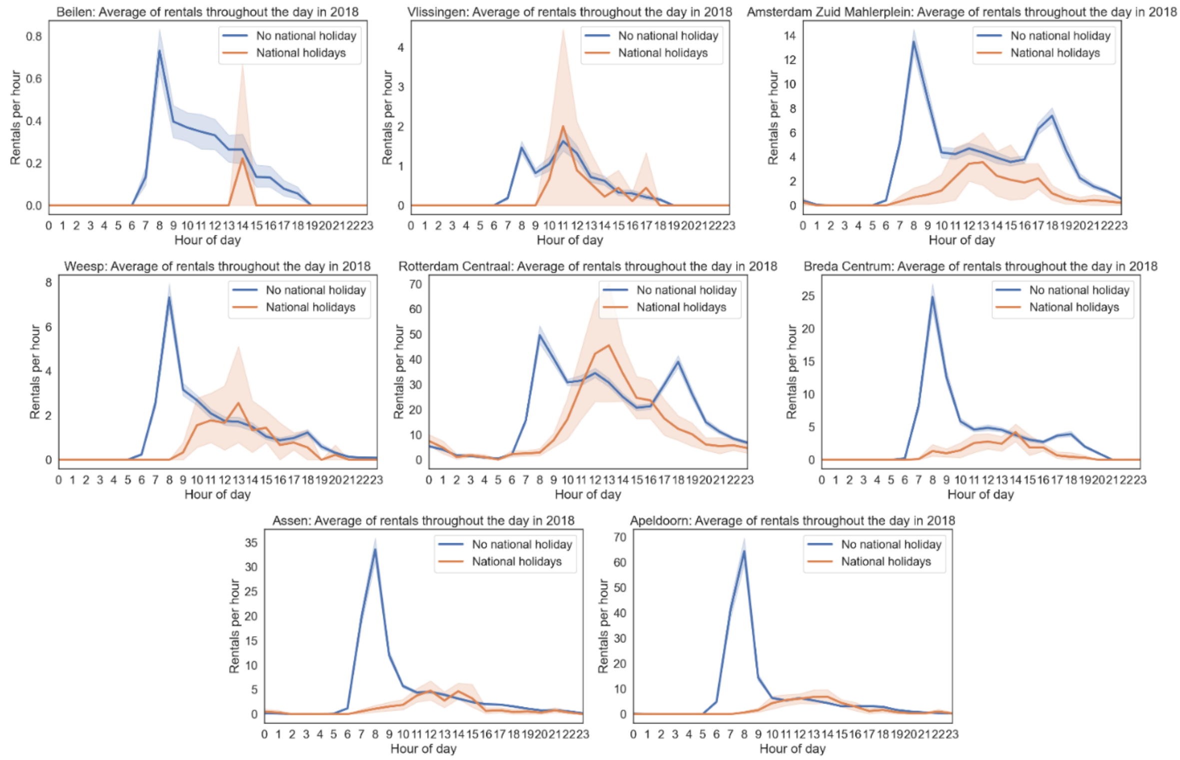
App. 2: Average hourly rentals and checkouts per day in 2018 for the exemplary stations



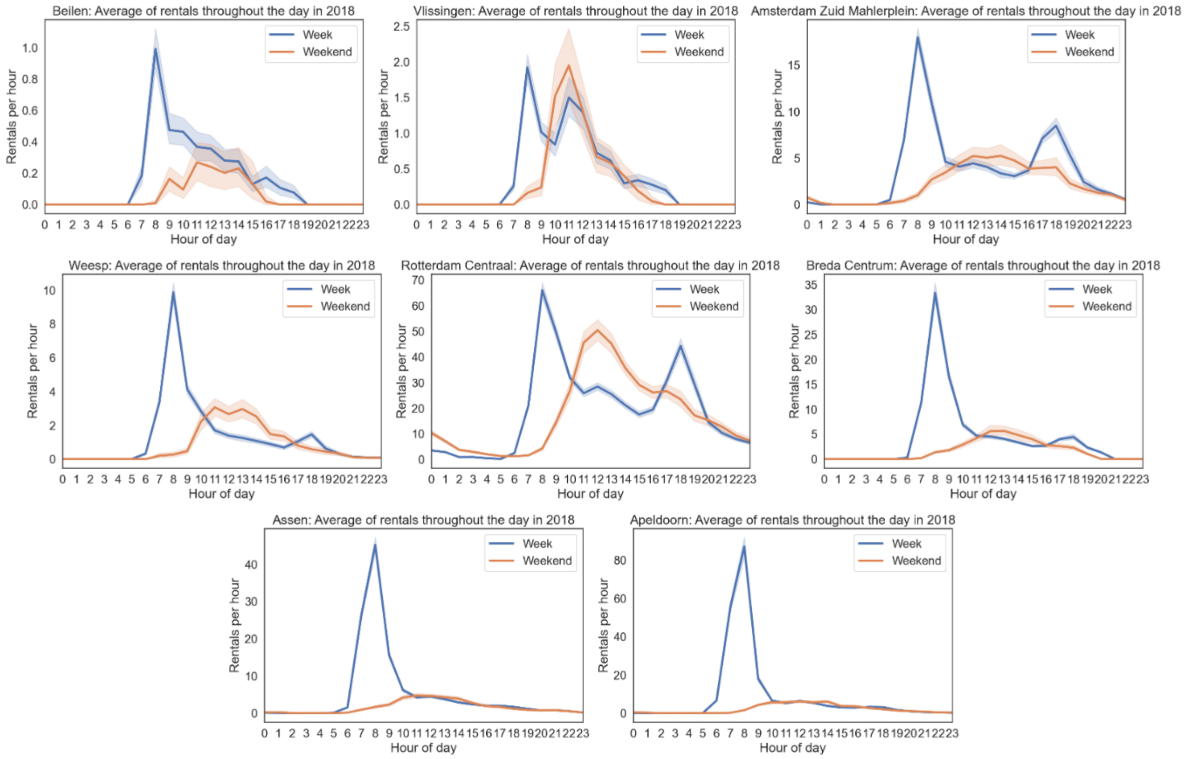
App. 3: Average hourly rentals per day in 2018 on school holidays and non-school holidays for the exemplary stations



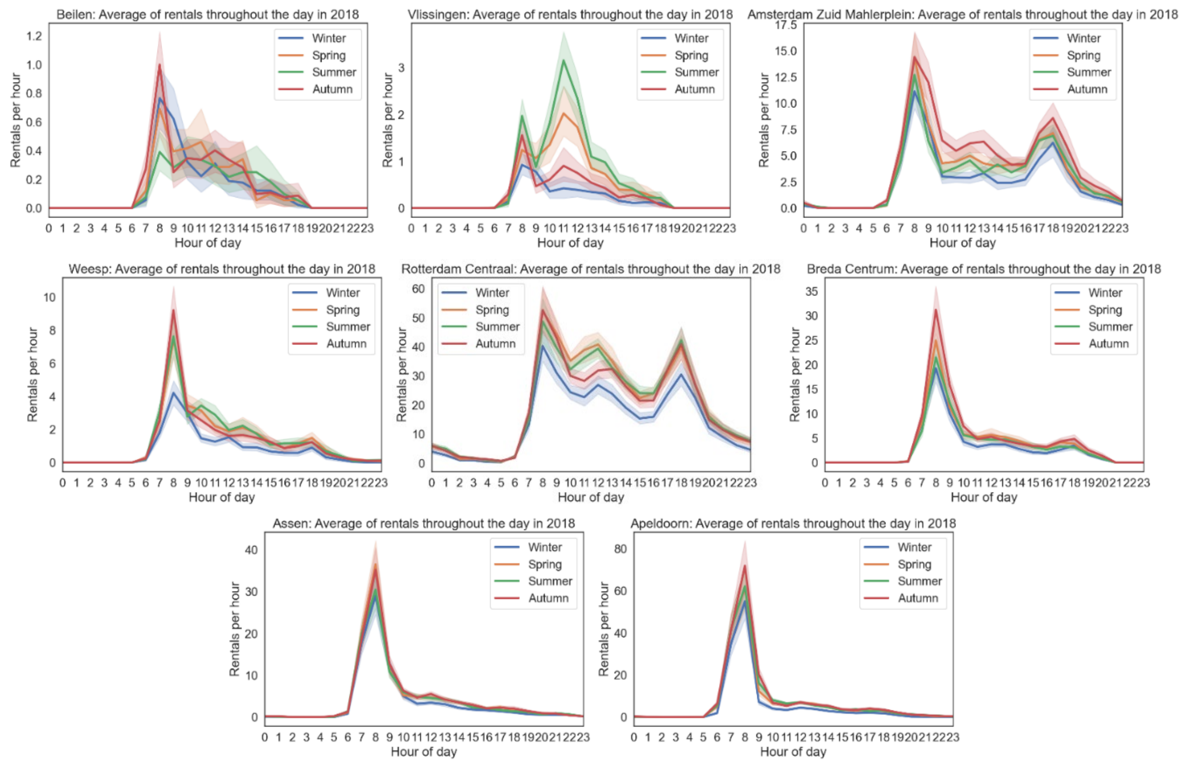
App. 4: Average hourly rentals per day in 2018 on national holidays and non-national holidays for the exemplary stations



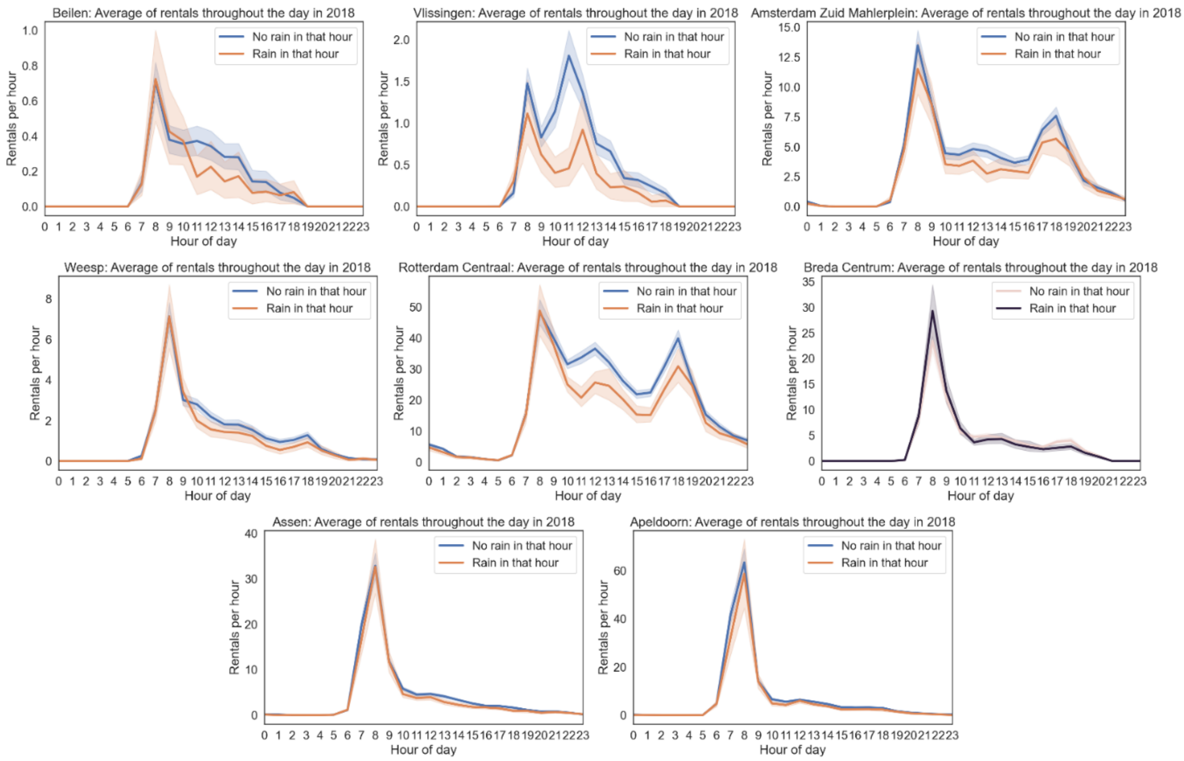
App. 5: Average hourly rentals per day in 2018 on weekends and weekdays for the exemplary stations



App. 6: Average hourly rentals per day in 2018 across the seasons Winter, Spring, Summer, Autumn for the exemplary stations



App. 7: Average hourly rentals per day in 2018 for hours in which rain did and did not occur for the exemplary stations



App. 8: MLR results for Vl considering checkouts, time of day, sunshine duration, and temperature (Time of day Daytime is reference)

	Model 1
(Intercept)	-0.5227***
	(0.0502)
checkouts	0.0061***
	(0.0004)
timeofdayEvening	0.5269***
	(0.0682)
timeofdayEveningpeak	0.3812***
	(0.0802)
timeofdayMorningpeak	0.4471***
	(0.0673)
timeofdayNight	0.5282***
	(0.0636)
sunshine_duration	0.0212***
	(0.0048)
temperature	0.0065***
	(0.0003)
weekend	-0.0274
	(0.0426)
checkouts:timeofdayEvening	-0.0059***
	(0.0013)
checkouts:timeofdayEveningpeak	-0.0022*
	(0.0009)
checkouts:timeofdayMorningpeak	-0.0004
	(0.0004)
checkouts:timeofdayNight	-0.0062
	(0.0154)
timeofdayEvening:temperature	-0.0067***
	(0.0004)
timeofdayEveningpeak:temperature	-0.0064***
	(0.0005)
timeofdayMorningpeak:temperature	-0.0049***
	(0.0005)
timeofdayNight:temperature	-0.0067***
	(0.0004)
timeofdayEvening:sunshine_duration	-0.0273
	(0.0368)
timeofdayEveningpeak:sunshine_duration	-0.0160*
	(0.0078)
timeofdayMorningpeak:sunshine_duration	0.0006
	(0.0077)
timeofdayNight:sunshine_duration	-0.0248
	(0.0232)
temperature:weekend	0.0007*
	(0.0003)
sunshine_duration:weekend	0.0146*
	(0.0057)
R^2	0.3079
Adj. R^2	0.3061
Num. obs.	8759

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$