MASTER

Proactive vehicle relocation in free-floating car sharing systems

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Proactive vehicle relocation in free-floating car sharing systems

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Master Thesis

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Abstract

This thesis introduces a proactive relocation strategy for free-floating car sharing (FFCS) systems. While existing studies, aiming to design a proactive relocation strategy for FFCS systems, design a standalone proactive relocation model with the aim to reach the forecasted vehicle distribution for a single target period, this thesis approached the development of a proactive relocation strategy for FFCS systems by integrating the proactive relocation strategy in a reactive relocation model. In this way we ensure that proactive relocations are only executed when there is unused capacity and the marginal costs of proactive relocations are minimized. To estimate the demand in a FFCS system, the FFCS system is transformed to a station-based system by virtually dividing the service area into smaller zones. The zone categorization method uses zones that consists of a set of clustered hexagons. An ARIMA model is derived to estimate the short-term demand over the zones. Then, a rule-based method is used that translates the over- and undersupplied zones on individual vehicle level and a list of pick-up vehicles and drop-off hexagons is derived. The transportation of a pick-up vehicle to all the drop-off spots results in the optimal vehicle distribution over the zones based on the output of the ARIMA model. With the use of a real-life scenario analysis, we were able to gain insights in the added value of the proactive relocation strategy. We proved that the proactive relocation strategy can be used to prepare the FFCS system for the peak periods. Furthermore, the scenario analysis proved that proactive relocations are only executed when there is unused capacity and that priority is always given to the reactive relocations. In addition, we showed that there is room to include the proactive relocations in the relocation model without deploying additional operators.

Executive summary

Problem statement

This Master Thesis is conducted at Amber Nederland B.V. (Amber). Amber is a young electric car sharing (CS) company based in Eindhoven. The service areas in the network of Amber operate as free-floating car sharing (FFCS) systems. A FFCS system can be seen as a flexible way of car sharing, where there are no stations and users can pick up and drop off the vehicles freely within a predefined service area. Amber provides the service of bringing the car within 300 meters (as the crow flies) of the customer if the reservation is made a certain time in advance, this is called the guaranteed mobility proposition. The problem of unbalanced vehicle inventories arises through this guaranteed mobility proposition and because cars are not necessarily returned to the same place after each ride. Therefore, periodic relocation of vehicles becomes necessary to ensure that there are sufficient vehicles spread geographically to serve user demands. The usage of electric vehicles (EVs) in the FFCS system leads to the additional challenge of charging the vehicles. The planning strategy of Amber is currently fully reactive and transfers are only planned when rides are booked. To mitigate the problem of unbalanced vehicle inventories in the FFCS systems of Amber it is important that there are sufficient vehicles spread geographically to serve the user demands. If Amber knows where they can expect to have demand they can be better prepared for the peak moments by using the unused capacity of fleet operators during the off-peak moments to relocate their cars. Therefore demand prediction and proactive relocation can be very useful for Amber.

Research objective

The objective of this thesis is to develop a proactive vehicle relocation strategy for the FFCS system of Amber in Eindhoven through the integration of proactive relocations in their existing reactive relocation model. The development of this proactive vehicle relocation strategy is divided into three different phases. First, the service area has to be partitioned into smaller zones that are approached as artificial stations. Thereafter, a forecasting instrument is to be derived to predict short-term demand per zone in the service area. Lastly, once the demand is predicted, a relocation model is needed to plan the transfers of cars from oversupplied zones to undersupplied zones in an efficient way.

Approach and results

While existing studies, aiming to design a proactive relocation strategy for FFCS systems, design a standalone proactive relocation model with the aim to reach the forecasted vehicles distribution for a single target period, this thesis approached the development of a proactive relocation strategy for FFCS systems by integrating the proactive relocations in a reactive relocation model. In this way, we ensure that proactive relocations are only executed when there is unused capacity and the marginal costs of proactive relocations are minimized.

To estimate the demand in a FFCS system, the FFCS system is transformed to a station-based system by virtually dividing the service area into smaller zones. The zone categorization method uses zones that consists of a set of clustered hexagons. An ARIMA model is derived to estimate the short-term demand over the zones. Then, a rule-based method is used that translates the over- and undersupplied zones on individual vehicle level and a list of pick-up vehicles and drop-off hexagons is derived. The transportation of a pick-up vehicle to all the drop-off spots results in the optimal vehicle distribution over the zones based on the output of the ARIMA model. However, not all proactive relocations have to be executed since proactive relocations are only executed when there is capacity of operators and vehicles left. The proposed proactive relocations for a target period are provided to the relocation model.

With a real-life scenario analysis, we were able to gain insights in the added value of the proactive relocation strategy. One week of data was analyzed. The peak moments were discussed individually and visual results of the relocation tour without and with the inclusion of the proactive relocation strategy were analyzed. First of all, we proved that with the help of a proactive relocation strategy the FFCS system is more prepared for the peak period. Furthermore, the scenario analysis proved that proactive relocations are only executed when there is unused capacity and that priority is always given to the reactive relocations. In addition, we showed that there is room to include the proactive relocations in the relocation model without deploying additional operators.

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1 Introduction

In the last decades, changes have taken place in the urban transportation (Jorge et al., 2014). Increases in congestion, pollution and nonproductive time for travelers, particularly in peak hours represent an undesired outcome (Lomax et al., 2011). Given its promise of a scalable sustainable business model, the sharing economy has received a lot of attention. The advantage of sharing is a higher utilization of goods by replacing permanent individual ownership by temporary on-demand access (Botsman and Rogers, 2010). A prime example of the sharing economy is car sharing (CS). CS is a service that provides members with access to a fleet of vehicles (Millard-Ball, 2005). The members of such a system can reserve the car by phone or online, walk to the nearest car that is available and open the car with an electronic key card. To explain the advantages of sharing over owning and exploiting underutilized assets, CS is often used as a first example (Botsman and Rogers, 2010). It has been observed that CS has a positive impact on urban mobility, mainly by using each car more efficiently (Litman, 2000). Furthermore, CS can result in a decrease of needed parking spaces in urban areas. In the USA, for example, automobiles spend around 90% of their time parked (Hu and Reuscher, 2004). In practice, there are different types of CS systems based on several characteristics. An overview of these different characteristics for CS systems is illustrated in Table 1.

<table>
<tr><th>Dimension</th><th colspan="3">Characteristics</th></tr>
<tr><td>Vehicle ownership</td><td colspan="2">B2C</td><td>P2P</td></tr>
<tr><td>Vehicle types</td><td colspan="2">EV</td><td>Gasoline</td></tr>
<tr><td>Operating type</td><td>Round-trip</td><td>One-way</td><td>Free-float</td></tr>
<tr><td>Vehicle relocation</td><td colspan="2">Operator-based</td><td>User-based</td></tr>
<tr><td>Relocation algorithm</td><td colspan="2">Proactive</td><td>Reactive</td></tr>
</table>

Table 1: CS system classification

There are two types of vehicle ownership in CS systems: Business to Consumer (B2C) and Peer-to-Peer (P2P). B2C is the most common form of CS, where a private company or organization owns a fleet of vehicles that are rented out to users (Münzel et al., 2019). In the P2P service model consumers rent out their own cars to other consumers using a two-sided platform operated by a coordinating CS organization (Shaheen et al., 2016).

Generally, there are three operating types in CS systems: a round-trip station-based CS system, a one-way station-based CS system and a free-floating CS (FFCS) system (Ait-Ouahmed et al., 2018). A FFCS system can be seen as a flexible way of CS, where there are no stations and users can pick up and drop off the vehicles freely within a predefined service area (Ciari et al., 2014). Using electric vehicles (EVs) in a FFCS system results in lowering emissions but leads to the additional challenge of charging the vehicles. Staff needs to be used to relocate a vehicle to a charging station when the battery level drops below a given threshold (Folkestad et al., 2020). Station-based models provide less flexibility because the user has to pick up and drop off the vehicles at a certain station. In a round-trip station-based CS system the user must bring the vehicle back to the same departure station (Ait-Ouahmed et al., 2018). This CS system simplifies the task of the operators because stocks can be planned on the demand of each station (Jorge and Correia, 2013). However, it is less convenient for the users because they have to pay for the time that the vehicles are parked (Jorge et al., 2014). Better suited for the user are one-way station-based CS systems. In a one-way station-based CS system the user can pick up a vehicle and drop off the vehicle at a chosen station among all the available stations (Ait-Ouahmed et al., 2018). This process should allow to use vehicles more often since the user does not occupy the car when they are parked.

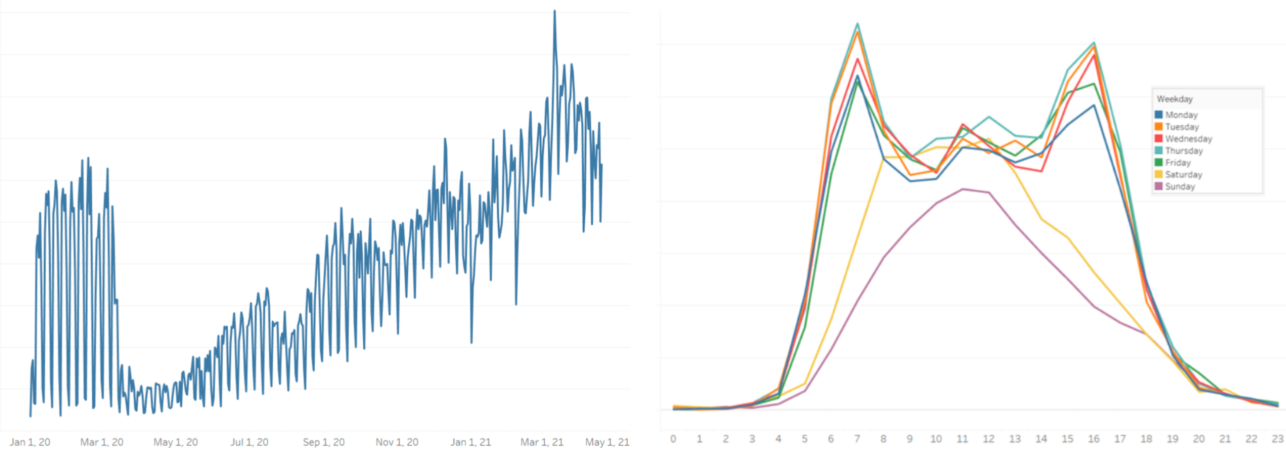
In a station-based model with one-way trips or in a FFCS system, the problem of unbalanced vehicle inventories arises as the vehicle is not necessarily returned to the same place after each ride. (Alfian et al., 2017). This vehicle relocation problem can lead to excess and shortages of vehicles at different stations or in different areas, potentially leading to poor service levels and low customer satisfaction (Illgen and Höck, 2019). As a result, periodic relocation of vehicles becomes necessary to ensure that there are sufficient vehicles spread geographically to serve user demands (Kek et al., 2009). The relocation of vehicles can be done with a user-based or an operator-based system. In a user-based system, the users are encouraged to leave the vehicle in a different location than they intended for an incentive (e.g. in the form of a discount) (Di Febbraro et al., 2018). In an operator-based system, the CS organization employs operators that relocate the vehicles in order to re-balance the system (Ait-Ouahmed et al., 2018).

The current operation practices for relocation strategies are mainly reactive, meaning that the vehicles are only dispatched based on observed demand (Lei et al., 2020). Reactive relocation works well when demand and supply are aligned. Nevertheless, real world observations suggest that such systems are highly imbalanced leading to inefficiencies (Qian et al., 2015). Instead of waiting for observed demand to make relocation decisions, proactive relocation takes effect whenever a vehicle is empty (Lei et al., 2020). The operator plans the relocation of the vehicle to the next location based on the prediction of future demand. In the late '90s, Powell (1996) and Barth and Todd (1999) already concluded that proactive relocation outperforms reactive relocation.

1.1 Problem statement and current situation

This Master Thesis is conducted at Amber Nederland B.V. (Amber). Amber is a young electric CS company based in Eindhoven. The network of Amber consists of service areas and hubs. The service areas operate as FFCS systems and the hubs operate as one-way station-based CS systems. Amber launched their FFCS system in September 2020 in the city of Eindhoven to trigger the consumer market as a reaction to the COVID-19 pandemic and their fallen business market. Amber provides the service of bringing the car within 300 meters (as the crow flies) of the customer if the reservation is made a certain time in advance, this is called the guaranteed mobility proposition. The problem of unbalanced vehicle inventories arises through this guaranteed mobility proposition and because cars are not necessarily returned to the same place after each ride. Therefore, periodic relocation of vehicles becomes necessary to ensure that there are sufficient vehicles spread geographically to serve user demands. Amber even guarantees the availability of a car when a reservation is made on time. Although the service areas are really in their infancy for Amber, the development of the service areas has received full focus from Amber. Especially the operational aspect in the service areas is a challenge as the time to get the car to the user is limited.

Figure 1a shows the total demand in different days and Figure 1b shows the mean of user demand in different hours of a day. From Figure 1a, it can be observed that the total demand drops to a abnormally low level at the start of the COVID-19 pandemic. From then on, the total demand slowly increases over the days. From Figure 1b, it can be observed that the user demand in weekdays demonstrates a double-peak nature while the user demand in weekends shows a single-peak property. Besides, it can be observed that the user demand in weekends is lower than the user demand in weekdays.



(a) Demand in different days

(b) Mean of hourly demand

Figure 1: Temporal variations of the Amber service

The planning strategy of Amber is currently fully reactive, transfers are only planned when trips are booked. However, trips are not always booked far in advance and sometimes the customer even wants to leave "here an now". In order to offer a good user experience, Amber wants to give customers the option to book as short as possible in advance. Ideally, there is hardly any difference between using your own car and an Amber. To mitigate the problem of unbalanced vehicle inventories in the FFCS systems of Amber it is important that there are sufficient vehicles spread geographically to serve the user demands. Bookings come in peak moments during the day and show a pattern over the days. If Amber knows where they can expect to have demand they can be better prepared for the peak moments by using the unused capacity of fleet operators during the off-peak moments to relocate their cars. Therefore demand prediction and proactive relocation can be very useful for Amber.

This chapter aimed to give an introduction to the overall topic of this thesis. In the next chapter a literature review will be conducted to have an understanding of the existing works in the literature regarding proactive vehicle relocation in FFCS systems. Thereafter, the research objective and research design will be further explained.

2 Literature review

This section presents the results of a literature review that was conducted to have an understanding of the existing works in the literature regarding proactive vehicle relocation in FFCS systems. In Section 2.1, it is discussed how a FFCS system can be partitioned into multiple zones for which the short-term demand can be be predicted. Thereafter, Section 2.2 discusses the literature on the demand prediction, while Section 2.3 discusses literature on the proactive relocations once the demand is known. Section 2.4 summarizes the findings and draws conclusions of the complete literature review.

2.1 Free-floating car sharing system

FFCS systems can be transformed to station-based systems by theoretically dividing the service area of a FFCS system into smaller units referred to as blocks (Barrios and Godier, 2014) or zones (Weikl and Bogenberger, 2013). The size of these zones is determined by the distance a user might find acceptable to walk (Paschke et al., 2016). In this literature review this theoretical division of a service area is called zone categorization, in which a zone thus represents an artificial station. This paragraph will discuss the existing literature about zone categorization in FFCS systems.

2.1.1 Zone categorization

Stations in station-based systems have strict capacity limits based on the number of parking spaces. In contrast, those defined zones in FFCS systems do not have strict capacity limits. The capacity limit is the space limit of the zone (Weikl and Bogenberger, 2015). As these zones represent artificial stations, the size of the zone is a critical element to determine if a relocation is needed. According to experts, a FFCS user is willing to walk a maximum distance of 500 meters to the next vehicle (Seign and Bogenberger, 2013; Barrios and Godier, 2014). If the zones are too big, a vehicle that is typically placed anywhere within the zone, might still not be accessible to a particular user (Paschke et al., 2016). However, aggregate forecasts tend to have a smaller standard deviation of error relative to the mean (Wang et al., 2010). In other words, it is easier to forecast the demand for a larger zone than to forecast the demand for a smaller zone. A trade-off has to be made in satisfying the maximum willingness to walk of users, while still being able to predict the demand with a small standard deviation of error.

Static zone categorization

In the paper of Weikl and Bogenberger (2015) a relocation model for a mixed FFCS system with traditional (i.e. gasoline) and EVs is proposed. According to the authors, vehicle movements between large zones are not precise enough and do not satisfy local demand. Meanwhile, vehicle movements between smaller zones are pseudo exact and vehicle movements of very small distance might be suggested. Therefore, the authors propose a method that combines macroscopic and microscopic zones. To achieve the desired macro level relocation an optimization model is used. Then, rule-based methods are used to make intra zone relocations on the individual vehicle level and charging decisions. The macroscopic zones reflect dynamics and booking patterns of the FFCS system to reduce the re-occurrence of imbalances subsequent to vehicle relocations. For finding optimal macroscopic zones, a GIS-based approach similar to the one proposed by García-Palomares et al. (2012) is used. García-Palomares et al. (2012) propose a P-median solution as it covers the whole service area relatively uniformly, resulting in homogeneous zones. The stations are located such that the weighted costs between the demand points and solution facilities are minimized. These solution facilities build the centers of the macroscopic zones. This P-median approach is solved iteratively for a different number of zones. The final number of zones is chosen, such that it results in appropriately sized and homogeneous zones spread over the service area. The macroscopic zones are covered with non-overlapping hexagons with a diameter of 500 meters and an area of 0.16km^2 based on the maximal distance a FFCS user is willing to walk. The authors propose to execute this zone categorization method periodically (e.g. monthly based on the historical booking data).

In a study of Kypriadis et al. (2020) a fixed zone categorization method is proposed. The service area is partitioned into a number of non-overlapping hexagonal cells like the microscopic zones from Weikl and Bogenberger (2015). In comparison to the hexagonal cells of Weikl and Bogenberger (2015) these hexagonal cells have a side of 500 meters and a diameter of 1000 meters, resulting in an area of 0.65km^2. In the hexagonal cells of Weikl and Bogenberger (2015) the vehicle can be parked anywhere and is still within the maximum walking distance of 500 meters of the user, while in the hexagonal cells of Kypriadis et al. (2020) the vehicle have to be parked in the middle of the hexagon to be sure it is within the maximum walking distance of any user. Paschke et al. (2016) partitioned the service area in which the FFCS system is available into non-overlapping polygons. The vehicle density near the city is higher and therefore the dimensions of these polygons are about equivalent to the maximum walking distance a user finds acceptable. However, they might be larger in the suburbs where fewer vehicles are available. The studies of Müller and Bogenberger (2015); Zhang et al. (2019b) do not take users maximum willingness to walk into account but just calculate the forecast for every zip code to include spatial differences. However, this approach might lead to unsuccessful relocations when the area covered by a zip code is too large (i.e. a relocated vehicle is still not in reach of the user according to the maximum willingness to walk).

Dynamic zone categorization

The zones in the previously discussed methods are assumed to be fixed and unchangeable during the day. The zone categorization is executed in the network design phase or periodically (e.g. once a month based on historical booking data). In comparison to these methods, Caggiani et al. (2017) suggest a dynamic zone clustering methodology for the FFCS systems. The authors make the assumption that static zones lead to an excess of relocations during the day, with the (misleading) idea of actually improving the systems overall performance and satisfying a greater number of users. The zero-vehicle-time (ZVT) of Kek et al. (2009) is used as a performance indicator. When ZVT occurs in a zone, there are no available vehicles in the zone and customer requests will be rejected. The authors divide the service area into square zones with a side length of 0.2km and make the assumption that the maximum walking distance to the next vehicle is 630 meters. According to this assumption, the square zones can be clustered to four possible configurations that satisfy the maximum walking distance in any scenario, these configurations can be seen in Figure 2.

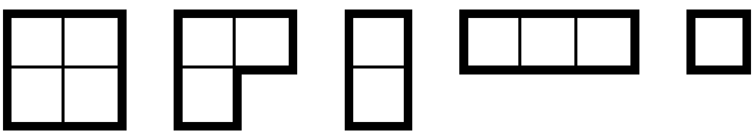


Figure 2: Cluster configuration (Caggiani et al., 2017)

The dynamic clustering method runs each time interval that ZVT occurs and tries to minimize the ZVT. In that way, the operator finds out when the system needs a proper vehicle relocation or when a relocation is unnecessary. The authors explain the associated benefits from their proposed dynamic clustering with an example that can be seen in Figure 3. The service area in the example is composed of 36 square zones of 0.2km^2, therefore the cluster configurations shown in Figure 2 can be used to satisfy the assumption of maximum walking distance. The numbers in the square zones represent the vehicles available. In Test(1) the service area is equally divided into 9 square clusters, each one made by 2x2 square zones. ZVT occurs in a cluster in Test(1), therefore the dynamic clustering method is executed. Although, the number of vehicles in every square zone remains the same, there is no cluster with zero vehicles anymore in Test(3), so the system does not need a vehicle relocation. The reduction of the ZVT obtained by using the dynamic clustering method does not derive from any relocation. It only represents a strategy to look from a different point of view, (maybe) fewer users experience a drawback from the unbalanced system than expected. In the Amber case ZVT occurs when the demand for a cluster is not met instead of when there are no available vehicles in a cluster, for each square zone the demand will be predicted.

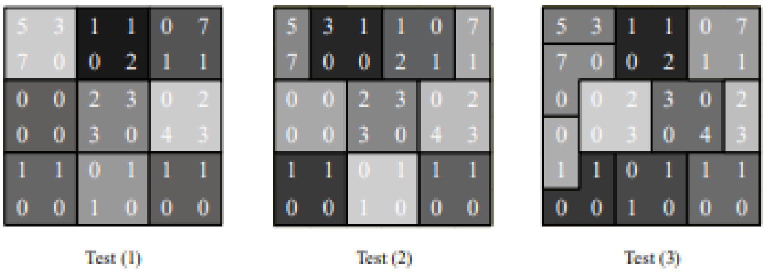


Figure 3: Clustering example (Caggiani et al., 2017)

2.1.2 Conclusions on the zone categorization problem

The zone categorization method has to minimize the number of times there is unmet demand in a zone to avoid unnecessary relocations, while still satisfying the maximum willingness to walk of users. It is interesting to test the effectiveness of the dynamic approach of Caggiani et al. (2017) in comparison to the static zoning methods to estimate the reduction in times of unmet demand, taking into account the loss in accuracy through the smaller zones in the dynamic approach. As previously discussed, aggregate forecasts tend to have a smaller standard deviation of error relative to the mean as previously discussed (Wang et al., 2010). In the next chapter literature of demand prediction for the zones will be discussed.

2.2 Estimating free-floating car sharing demand

The operational aspect of CS systems is complex because of the imbalance of demand and supply, which leads to inefficiencies in the CS systems. Therefore, one must be able to accurately model the demand and supply of these CS systems to optimize their operations (Jorge and Correia, 2013). Instead of waiting for observed demand to make relocation decisions, the operator can plan the relocation of a vehicle to the next location based on the prediction of future demand. The trips in FFCS systems are usually shorter and the number of trips is higher than in station-based systems. Therefore, imbalances might occur more often and relocations have to be performed multiple times throughout the day (Weikl and Bogenberger, 2015). This implicates that future demand in FFCS systems also has to be predicted more often than once a day.

Barth and Todd (1999) were the first to classify three relocation algorithms that determine when and how a relocation is executed:

1. **Static relocation** - A threshold triggers the relocation when the number of vehicles at the station ends up lower or higher then the determined threshold. The static relocation algorithm is based on immediate needs of a particular station.
2. **Historical predictive relocation** - The historical predictive relocation algorithm is based on an estimation of future demand using historical data.
3. **Exact predictive relocation** - In the exact predictive relocation algorithm the assumption is made that there is perfect knowledge about the future demand, therefore the relocation events can be optimally scheduled. However, exact knowledge of future demand is impossible to achieve in real-world.

Barth and Todd (1999) implemented these algorithms in a simulation model to minimize the total average wait time and compared them to each other. Obviously, the exact predictive relocation algorithm performed the best. More interesting is that the historical predictive relocation method performed better than the static relocation method in all cases. The static and historical predictive relocation algorithms described by Barth and Todd (1999) correspond to the reactive and proactive relocation algorithms as described in Section 1 respectively.

This paragraph will discuss the existing literature about proactive relocation algorithms in which a distinction is made between traditional forecasting methods and more sophisticated Machine Learning methods (i.e. Artificial Intelligence (AI)).

2.2.1 Traditional forecasting methods

In this paragraph existing literature is discussed of traditional forecasting methods used to predict the demand in CS systems. A distinction is made between the studies that make use of demand matrix techniques and the studies that make use of different time series techniques. These demand matrix techniques are not real forecasting techniques but more a similarity analysis to find corresponding demand patterns.

Demand matrix techniques

Historical data can be organized in an origin/destination (O/D) matrix. These matrices are indexed by time of day, day of week and week during the year. The number of trips taken from an origin node to a destination node in a specified period of time are contained by the matrix (Barth and Todd, 1999). Then, an estimation of the demand can be given at a particular node for a specified time.

A similar approach is provided by Weikl and Bogenberger (2013). They propose an offline demand module that is carried out periodically (e.g. once a year), with the idea to find repeating spatio-temporal demand patterns within the FFCS system. Demand is represented by demand indicators in a demand matrix and with a two-dimensional cluster method various days with similar demand patterns are combined. Demand patterns could be daily (time of the day, peak hours), weekly (weekend or weekday), seasonal or based on events (e.g. football matches, festivals). Vehicle positioning and booking data of the FFCS system is analyzed, to identify so-called spatio-temporal 'hot spots' and 'cold spots', for which the number of bookings is used as demand indicator. For the identification of demand patterns, days are divided into six three-hour time slices from 6 a.m. to 12 p.m. and one six-hour time slice from 12 p.m. to 6 a.m. The clusters vary significantly for the different time slots, which underlines the importance of the time of the day for CS usage. The authors indicate that this offline demand module has to be automated in the future.

Weikl and Bogenberger (2015) made use of an historical data analysis that is executed periodically to estimate the demand as well. They did a data analysis for different combinations of target time slices of length l_{tp} (in hours, e.g. 0-3 a.m., 6-9 a.m., etc for $l_{tp} = 3$) and target periods (all Mondays, mean values of all weekdays, etc.). This time interval's length is set according to the dynamics of the FFCS system (e.g. the time intervals are set to the average time span within which demand patterns are relatively homogeneous). Two indicators are calculated and based on these indicators, zones with historical vehicle surplus and zones with historical shortage are identified for all target periods. Zones with historical vehicle shortages have a short idle time and low vehicle balance and zones with historical vehicle surplus have a long idle time and high vehicle balance.

Time series techniques

The work of Müller and Bogenberger (2015) focuses on short times prediction of FFCS bookings. Their forecasts provide hourly based predictions of a future week for every zip code area. Booking data of DriveNow in Berlin is used for their forecast. Müller and Bogenberger (2015) used two methods of time series analysis to compare their performance: A seasonal autoregressive integrated moving average (ARIMA) model and exponential smoothing with Holt-Winters-Filter. These two methods are realized based on data of a whole year, a half-year, a quarter or just a month, the results are compared regarding their precision and practicability. Exponential smoothing with Holt-Winters-Filter with a training data set of a quarter proves to be the best working method with better results and distinct less computation time.

Wang et al. (2010) propose an inventory management model to forecast and relocate CS vehicles. Their model consists of three main components: focus forecasting, inventory replenishment and microscopic traffic simulation. In the focus forecasting phase several time series techniques (e.g. Selective moving average, Holt's model, Winter's model, Tabu Search heuristics) are deployed and compared. The forecasting technique that would have been the most accurate for the previous time period is then used to forecast the next period.

Conclusion on traditional forecasting methods

Several demand matrix and time series techniques are discussed in Section 2.2.1. The demand matrix techniques are not considered as typical traditional forecasting methods but are more like a similarity analysis technique to find corresponding demand patterns. The studies of Barth and Todd (1999); Weikl and Bogenberger (2013, 2015) belong in this category. Disadvantages of these techniques are the periodically data analysis that has to be executed and the manually workload that comes with it. Besides, these demand matrix methods are more case specific and less easily transferred to other service areas. The second category makes use of time series techniques. The studies of Müller and Bogenberger (2015); Wang et al. (2010) belong in this category. Advantages of time series techniques are that they are widely usable and can easily be transferred to other service areas. Besides, they are less time costly and have no particular need for periodical execution.

2.2.2 Machine learning methods

Deep learning (DL) algorithms have been more and more utilized in shared based vehicle mode prediction over the past three years, due to their ability to capture complex relationships from large amounts of data (Yu et al., 2020). These algorithms are capable of learning by trial and error and improving their performance over time (Makridakis et al., 2018). In this section the existing literature about the practice of machine learning methods to predict CS demand is discussed.

In the paper of Moein and Awasthi (2020) different methods of customer demand forecasting are compared against each other based on a monthly prediction basis. According to the authors, an accurate forecast for different times of the year can increase customer satisfaction and help to reach business performance targets. Causal methods (regression forecast with or without seasonality adjustments), time series (exponential smoothing, moving average) and neural networks are evaluated for forecasting the demand on monthly basis for a specific station. In the case study of Moein and Awasthi (2020) a 90:10 (90% training, 5% validation and 5% test) neural network performed best. Alfian et al. (2017) propose a forecasting relocation method to solve imbalances for one-way station-based CS systems on a daily prediction basis. A multilayer perceptron (MLP) is used as forecasting model. MLP is used to predict the number of cars needed at each station for the next day. The study focuses on static relocation at the end of the day and therefore the variable demand during the day (e.g. peak moments and off peak moments) is not considered in the study. The MLP was trained for a particular month using data from the previous three months, the training set comprised the oldest two months and the most recent month was used as the validation set. The performance of the MLP used in the study of Alfian et al. (2017) is shown in Figure 4. The mean absolute error of the forecasting model is 2.9 trips and the root mean squared error is 3.5 trips.

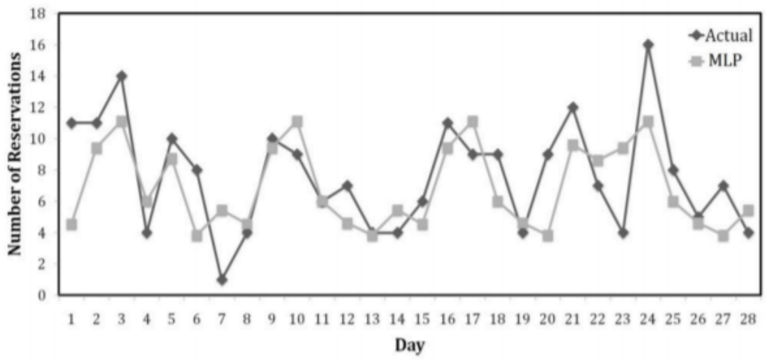


Figure 4: Predicted total number of reservations using MLP (Alfian et al., 2017)

The studies of Moein and Awasthi (2020) and Alfian et al. (2017) forecast the demand on monthly and daily prediction basis, respectively. However, for the Amber case more short-term prediction (i.e. smaller time steps than 24h) is necessary as discussed in Section 2.2.

Xu and Lim (2007) propose an evolutionary neural network (ENN) for predicting the net flow (i.e. difference between demand and supply) of a CS system. They build a model that can capture the trend of the net flow and predict the change for next period, in which the forecasting period is one hour in advance. The ENN is tuned and optimized by means of a mixed genetic algorithm with back-propagation method. In the work of Xu and Lim (2007), the proposed method is compared with three other neural networks, the results show that their ENN can achieve the best forecasting performance.

In a study of Luo et al. (2019) it is assumed that the station network is not static but dynamically evolving. In that case, state of the art forecasting methods for station-level demand will fail because they rely to heavily on historical data to make predictions. To address this challenge, they propose a novel dynamic demand prediction approach based on graph sequence learning. A multi-scale prediction network is used to estimate the demand of stations, which forecasts both the long-term expected demand and the instant future demand of the system.

Wang et al. (2018) present a GPS-data-driven method to dynamically predict the user destinations in order to support decisions on dynamic fleet management. The study presents a procedure based on GPS trajectory similarity, historical GPS data can match the user's current trajectory and infer its possible destination. Based on an experiment of 96,821 valid test tracks is proven that the positive prediction rate can be above 92% if the test trip has been completed over 70%, which proved the feasibility of the method.

Long short-term memory

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) that has emerged as an effective and scalable model for several learning problems related to sequential data (Greff et al., 2016). The idea behind the LSTM architecture is a memory cell in which the state over time can be maintained. Therefore, LSTM can not only process single data points, but also entire sequences of data.

LSTM is validated to be an appropriate tool of addressing the time-series predicting problem in transportation problems (Tian et al., 2018; Xu et al., 2018). In addition, LSTM showed better performance than ARIMA and support vector machine (SVM) regression in terms of traffic speed prediction and could easily capture issues like incident patterns under different road conditions on hourly basis (Ma et al., 2015; Yu et al., 2017). Furthermore, LSTM models were also proposed to solve the traffic flow predictions. (Wu and Tan, 2016; Zhao et al., 2017)

In a study of Zhang et al. (2019a) hourly variation in short-term traffic characteristics including travel demand and travel distance is modelled in a FFCS system on basis of an LSTM recurrent neural network. The performance of LSTM is compared with ARIMA and SVM regression. Results show that LSTM performs better in terms of statistical analysis and tendency precision based on limited data sample.

In a paper of Yu et al. (2020) demand management of station-based CS systems is analyzed. To help perceive the vehicle usage behaviors, a discrete event model is established and an LSTM structure is formulated to forecast station-based CS demand. The LSTM structure of Yu et al. (2020) includes historical data such as numbers of vehicle pick-up/drop-off, arbitrary time, and weather variables, to predict the number of vehicle pick-ups and drop-offs on hourly basis. The LSTM structure of Yu et al. (2020) is compared with a CNN capturing spatial correlation and with an ANN which only considers temporal features. Resulting in the LSTM structure outperforming both the CNN and ANN.

Ai et al. (2019) propose a deep learning approach that is employed to address the spatial dependencies and temporal dependencies for short-term distribution forecasting in a dockless bike-sharing system. Experiments show that their convolutional long short-term memory network (conv-LSTM), in which a CNN is combined with an LSTM, outperforms LSTM on capturing spatio-temporal correlations.

Following Ke et al. (2017) this is because both CNN and LSTM lack in addressing spatio-temporal forecasting problems. CNN fails to capture the temporal dependencies and LSTM is incapable of characterizing local spatial correlations. The conv-LSTM can learn complicated spatio-temporal characteristics by the convolutional and recurrent structure of the model. Nevertheless, short-term passenger demand is also dependent on other explanatory variables. Ke et al. (2017) propose a similar DL approach as Ai et al. (2019) for the short-term passenger demand forecasting under an on-demand ride service platform. In the model of Ke et al. (2017) spatial, temporal and exogenous dependencies can be addressed at the same time. Their fusion conv-LSTM (FCL-NET) is fed with a variety of explanatory variables including the historical passenger demand, travel time rate, time-of-day, day-of-week and weather conditions. Two FCL-Nets are trained, one with full variables and the other with selected variables. Furthermore a conv-LSTM is trained that only includes historical passenger demand as explanatory variable. These three models are compared with several benchmark algorithms (e.g. HA, MA, ARIMA, XGBoost, ANN, LSTM, CNN). Results show that the two FCL-nets outperform the benchmark algorithms which indicate that they are better at capturing the spatio-temporal characteristics. The FCL-net with selected variables reduce the training time by 24.4%, while only suffering 1.8% in loss of RMSE. Furthermore the results show that the inclusion of exogenous variables is important since the FCL-net achieves a 48.3% lower RMSE compared to the conv-LSTM that only includes historical passenger demand.

Conclusion on machine learning methods

The majority of the existing literature uses a type of neural network as a learning method to predict demand in shared vehicle systems. Within the proposed neural networks, the LSTM is the most promising for its capability to process entire sequences of data. Besides, LSTM is validated to be an appropriate tool for addressing time-series prediction problems in transportation problems. In the studies of Ai et al. (2019) and Ke et al. (2017) the LSTM is combined with a CNN. The authors of both studies state that the combined version outperforms the LSTM on capturing spatio-temporal problems.

2.2.3 Conclusion on estimating free-floating car sharing demand

In the discussed studies that compared machine learning methods with traditional forecasting methods, the machine learning methods outperform the traditional forecasting methods based on prediction performance in all cases (Moein and Awasthi, 2020; Ma et al., 2015; Yu et al., 2017; Zhang et al., 2019a; Ke et al., 2017). This is in all probability through their ability to capture complex relationships from large amounts of data. However, machine learning methods involve a certain complexity in terms of interpretation, which raises the following question: is the gain in predictive power from using machine learning methods over traditional forecasting methods worth the loss of interpretation? It could be that for the Amber case a sophisticated machine learning method like LSTM is overkill and a traditional forecasting method will do the job. Further conclusions are that future demand in FFCS systems has to be predicted multiple times a day (Weikl and Bogenberger, 2015) and that the inclusion of exogenous variables significantly improves the forecast (Ke et al., 2017).

2.3 Relocation models for free-floating car sharing systems

Following Kypriadis et al. (2020), the objective of a relocation strategy in CS systems is to meet user demand with minimum relocation cost, taking into account the distance traveled by the vehicle and the fatigue of the operators. In order to meet the user demand, vehicles have to be dispatched from oversupplied to undersupplied stations/areas. While it is possible to relocate multiple bikes with one truck in bike-sharing systems (Forma et al., 2015; Zhang et al., 2017; Pal and Zhang, 2017; Jia et al., 2019), the relocation of one car requires one operator in CS systems (Paschke et al., 2016; Weikl and Bogenberger, 2015; Bruglieri et al., 2014).

Relocation strategies for station-based systems can not directly be applied for FFCS systems since FFCS sytems have different dynamics than the station-based systems. The relocation in FFCS systems takes place among much more different positions in the service area, instead of a set of selected stations, which increases the size of the vehicle relocation and staff scheduling problem (Kypriadis et al., 2020). Besides, EVs have to be relocated to a charging station in FFCS systems when the battery level drops below a given threshold (Folkestad et al., 2020). Furthermore, the operation in FFCS systems is more based on spontaneous or 'on demand' usage than on user reservations (Kypriadis et al., 2020).

According to several studies (Nourinejad and Roorda, 2014; Kypriadis et al., 2019, 2020; Repoux et al., 2019), two possibilities exist for the time when operator-based relocation activities are executed. In static vehicle relocation, vehicles are mainly relocated during the idle periods of the system (e.g. during the night or before peak moments) and in dynamic vehicle relocation, the relocation process takes place while the system is fully functional. Different system aspects have to be taken into account for static and dynamic vehicle relocation. In static vehicle relocation the variation of demand throughout a certain time period is excluded from the model. A target number of required vehicles for a zone is determined for the next time period and the aim of the static relocation strategy is to reach this target number in each zone before the next time period begins. In contrast, dynamic vehicle relocation takes into account the variation of demand throughout a time period, therefore the state of the system changes dynamically. The aim of a dynamic vehicle relocation strategy is to have the required number of vehicles at the right moment in time throughout a time period taking into account possible user movements (e.g. vehicles entering the zone during the time period). Furthermore, a static relocation strategy is executed on fixed moments in time and a dynamic relocation strategy is executed whenever the current vehicle distribution across the service area significantly mismatches the user demand (Wang et al., 2019; Kek et al., 2009; Cao et al., 2016; Kypriadis et al., 2019). Note that a relocation strategy can be executed multiple times a day (i.e. including when the system is fully functional) without taking into account the variation of demand through the time period, in these cases the relocation strategy is considered as static. The existing literature on static and dynamic relocation strategies in FFCS systems will be discussed in Section 2.3.1 and Section 2.3.2, respectively.

2.3.1 Static relocation models

In a study of Weikl and Bogenberger (2015) a relocation model for FFCS systems with the following six steps is proposed:

1. (Re-) initialization of the model input data
2. Historical data analysis and zone categorization

3. Macroscopic inter-zone relocation (optimization)
4. Microscopic inter-zone relocation on the vehicle level (rule-based)
5. Microscopic intra-zone relocation on the vehicle level (rule-based)
6. Service trip planning on the vehicle level (rule-based)

The first and second step of this relocation model are previously discussed in Section 2.1.1 and Section 2.2.1, respectively. The relocation itself is executed in step three to six, the vehicles are distributed in proportion to the historical booking distribution of the target period. A mathematical model is used to find the optimal relocation between macroscopic zones in step three and in the next steps rule-based methods are used to find relocations on microscopic level including service trips like the charging of EVs. The paper does not describe detailed movements of relocation operators and cost estimates. The model was applied to a FFCS system in Munich to test the performance. From the results, it can be concluded that proactive vehicle relocations make sense for FFCS systems. However, the model still has some weaknesses. The authors admit that a planning module should be integrated in the future that assigns relocations and service trips to specific operators and generate schedules. Furthermore the relocation part of the model (i.e. steps three to six) are build upon step one and two including the zone categorization with macroscopic and microscopic zones. This makes it hard to adapt the relocation part of the model proposed by Weikl and Bogenberger (2015) to another zone categorization method discussed in Section 2.1.

Paschke et al. (2016) describe the implementation of relocation operators within a MATSim framework as an extension to previous work on CS (Ciari et al., 2014). A relocation strategy is proposed for a FFCS system, in which the day is split into six three-hour time slices. Once the desired numbers of vehicles for each relocation zone are determined for a specific time interval, relocations can be dispatched. The zones in the service area are ordered by the number of required vehicles. The zones with the largest number of required vehicles are placed on top of the list. Vehicles from zones at the bottom of the list are transferred to zones that are on top of the list.
Once a necessary relocation is identified, an operator is selected to move the vehicle. The operator travels to the vehicle (e.g. using a bicycle), drives the vehicle to the destination zone and returns to the original location immediately. Thus, a relocation operator executes only one relocation per time interval. The authors wanted to show that operators are actually able to relocate vehicles in a given way and order but admit that the relocation strategy is very simple (e.g. no relocations are combined). The method of Paschke et al. (2016) is tested in a FFCS system in Zurich. The study does not describe detailed movements of relocation operators and cost estimates.

In the study of Folkestad et al. (2020) a mathematical model is proposed for the problem of charging and repositioning a fleet of shared electric cars. CS systems with electric cars require charging when battery levels fall below a given level. The authors combine charging with repositioning from the idea that repositioning cars, rather than simply moving them to the closest charging station, might provide a better distribution of cars, which consequently leads to increased revenue and customer service while the operational costs are only marginally increased.
Folkestad et al. (2020) assumed in their model that operators are transported to the vehicles in need of charging by service vehicles with fixed capacity. After being dropped off, the operator drives the rental car to the selected charging station, where the operator is picked up by a service vehicle that transports the operator to the next vehicle to be handled. This leads to a complex routing problem

were multiple decisions have to be made: the routes of the service vehicles, the routes of the service operators, which vehicle to charge/reposition and to which charging station to bring the vehicle. The authors developed a Mixed Integer Programming (MIP) model. However, the MIP model is computationally too hard to solve and therefore a Hybrid Genetic Search with Adaptive Diversity Control (HGSADC) is proposed for practice. The authors choose the HGSADC because is has proven to perform well on a number of vehicle routing problems. Using the HGSADC for the charging in repositioning problem in FFCS systems produces high quality solutions within reasonable computational time for realistic problem sizes (i.e. instances up to 200 vehicles solved in an average computational time of less than 2400s.)

Following Haider et al. (2019), the EVs in Folkestad et al. (2020) are moved to charging stations rather than actual demand points. In situations with plenty of charging stations the EVs can still be moved close to actual demand points. However, in areas with a lack of charging stations, postponement of charging is considered. This will make the relocation model of Folkestad et al. (2020) similar to the one for station-based CS systems rather than FFCS systems, especially when charging station in the infrastructure is insufficient (Haider et al., 2019). Besides, the model of Folkestad et al. (2020) is more charging based than repositioning as only EVs with low battery level are relocated.

In the paper of Haider et al. (2019) the focus lies on the relocation, recharging and routing decisions to serve the given demand for the next day in the static environment during the night. A typical relocation operation for FFCS systems is carried out with shuttles to transport the drivers. Following the authors, most current approaches make the relocation and shuttle routing decisions sequentially. In the study of Haider et al. (2019) these two levels of decisions are combined in what the authors call a synchronized approach. Their synchronized approach reveals much enhanced performance in terms of solution quality and computation time in comparison to the sequential approach. For small-scale problems the authors propose a MIP formulation. However, this exact solution method cannot provide feasible solutions for large-scale problems. Therefore the authors developed a heuristic algorithm named Exhange-Based Neighborhood-Search Method (EBNSM). This method improves the solution obtained from the sequential method by an iterative procedure of adding neighborhood paths and updating the shuttle routes. The EBNSM method is tested on a real-life FFCS system. For the largest instance solved, 155 EVs were relocated while increasing the system wide average battery level from 42% to 90%. For a comprehensive overview of the EBNSM used, see Haider et al. (2019).

Kypriadis et al. (2020) propose a method for operator-based static repositioning in FFCS systems. The car relocation takes place at night and tries to perfectly rebalance the system. The Minimum Walking Car Repositioning Problem (MWCRP) is defined, whose primary objective is to compute a relocation tour with minimum walking distance, as the walking part is more time consuming than the driving part.

In the method of Kypriadis et al. (2020) the service area is divided into a number of non-overlapping hexagonal cells and the assumption is made that for each cell the desired number of cars in the morning is known. The cells are categorized as undersupplied or oversupplied taking into account the desired and current occupancy. Furthermore, the EVs with low battery level are transferred to charging points. An operator should follow a relocation tour defined as follows: Starting from a depot, the operator moves to the first car and moves the car to the proposed place, then the operator moves to the next car and moves that car to the proposed place, and so on, until the operator completes the

set of assigned relocations and returns to the depot. An operator can use an auxiliary car to initially move from the depot to the first car, after relocating the set of assigned cars the operator takes the auxiliary car back to the depot.
The objective of the method of Kypriadis et al. (2020) is to determine a minimum walking distance relocation tour, such that a complete rebalancing is achieved. With complete rebalancing the authors mean an optimal number of available cars per cell at the start of the next day, with minimum possible total relocation time as a secondary objective, considering also the battery level of EVs and moving all the cars with battery level below a certain threshold to charging points.

The MWCRP can be extended to an k-MWCRP when more than one driver is available. Given the k drivers, k relocation tours are determined that cover disjoint subsets of car relocations. A flowchart of the static relocation procedure can be seen in Figure 5.

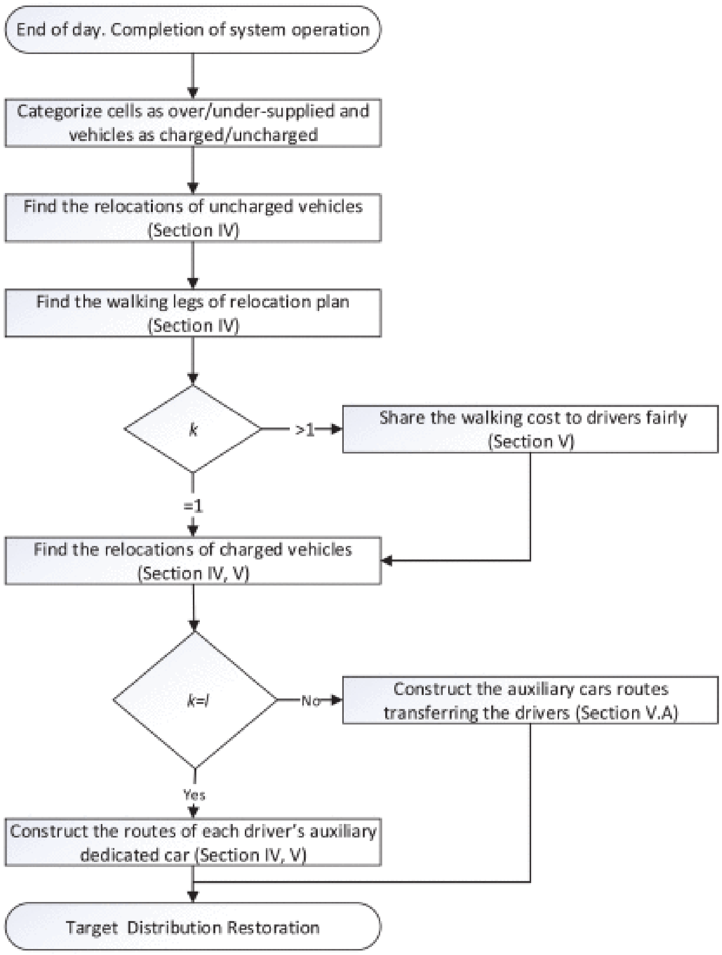


Figure 5: Flowchart of relocation procedure (Kypriadis et al., 2020)

The algorithm for the MWCRP problem is applied to the set of cars that should be relocated to the set of available parking places/charging points, an example is shown in Figure 6. Each edge in the MWCRP is associated with two different costs, one corresponding with the walking costs and one with the driving costs. The objective is to minimize the walking costs first. In Figure 6 can be seen that it is possible to form more than one cycle, the cycles are connected with driving edges that an operator will cross using an auxiliary car, resulting in a Generalized Traveling Salesman Problem (GTSP). This can be more efficient when the operator needs to cross large areas walking, instead the operator can drive to another area using an auxiliary car.

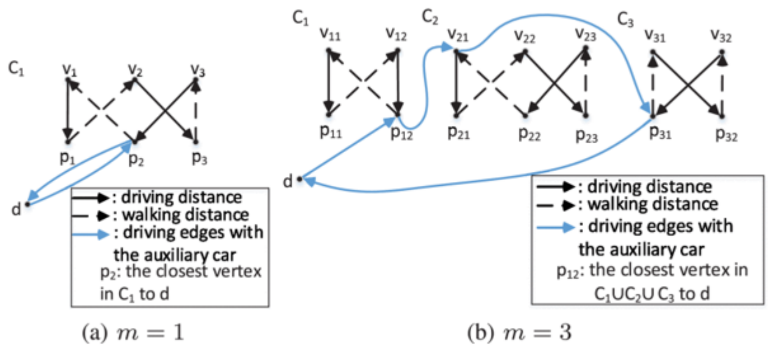


Figure 6: Vehicle relocation plan (Kypriadis et al., 2020)

Kypriadis et al. (2020) tested their approach using data from an existing FFCS, which operates in several cities such as Rome and Florence. The main conclusion from the simulations is that several drives are needed for feasible relocations plans to complete in reasonable time. Furthermore, walking time is reduced with the use of more auxiliary cars at the expense of increasing the driving distance traveled by those cars. Still, using more auxiliary cars results in lower total completion time of the relocation plan most of the time, which supports the technique of minimizing the walking distance. The purpose of this paragraph is to provide an understanding of the method Kypriadis et al. (2020) use to solve the MWRCP, for a comprehensive explanation of the algorithm used, see Kypriadis et al. (2020).

2.3.2 Dynamic relocation models

In Kypriadis et al. (2019) a dynamic relocation strategy for FFCS systems is proposed. The main task remains to move cars from oversupplied to undersupplied areas as in the static relocation models. However, there is a time limit defined in which the operation has to be completed as cars cannot be rented to the user while they are in the relocation process. Therefore, the goal is to have the car distribution as close to the optimal car distribution as possible. Since the relocation is carried out when the system is fully functional, users may intervene in the on-going relocation either supportively or against the system. In a supportive way by making a trip from an oversupplied to an undersupplied area or against the system with a trip in the opposite direction. These user movements affect the balance of the system. Therefore, Kypriadis et al. (2019) included dynamic adjustment of the relocation plan, which is able to change an ongoing relocation route depending on users' movements. The operator follows the same kind of relocation route as described in Kypriadis et al. (2020).

According to Kypriadis et al. (2019), a dynamic repositioning process is associated with a starting time T_0 and an ending time T_1. During the relocation process users may pick-up/drop-off cars from/to any parking place within a certain area. If the current car distribution is known and an estimation is made of the optimal number of cars per cell at times T_0 and T_1, it is known which cells are oversupplied or undersupplied in which time periods. Through the limited time all relocations have a certain priority that is based on the current car distribution at time T_0 and the optimal distribution scenario at time T_0 and T_1. Then, the objective of the algorithm is to find a relocation tour so that the sum of the priorities is maximized while the relocation tour is completed within the specified time period.

Kypriadis et al. (2019) evaluated their algorithm on an existing FFCS system operating in the city of

Rome. A test case was solved by their algorithm and an exact Linear Programming (LP) approach. The results showed that the algorithm of Kypriadis et al. (2019) performed slightly worse or as good as the exact LP approach, demanding however significantly less computation time.

2.3.3 Conclusion on relocation models for free-floating car sharing systems

The discussed studies on relocation models for FFCS systems can be classified on four characteristics as can be seen in Table 2. The first characteristic is whether the relocation model is static or dynamic. In dynamic relocation the state of the system changes dynamically as variation of demand throughout a time period is taken into account. In static relocation this variation of demand is excluded. The second characteristic determines whether the charging of EVs is taken into account. The third characteristic is about the routing of multiple relocations in a tour to achieve a higher efficiency and the fourth characteristic is whether a complete rebalancing is achieved (i.e. all proposed relocations are executed). A general learning is that it is computationally too hard to solve large-scale relocation models exactly, therefore all the discussed studies propose algorithms to solve the case.

Study	**Static/Dynamic**	**Charging**	**Routing**	**Complete rebalancing**
Weikl and Bogenberger (2015)	Static	Yes	No	Yes
Paschke et al. (2016)	Static	No	No	Yes
Folkestad et al. (2020)	Static	Yes	Yes	No
Haider et al. (2019)	Static	Yes	Yes	Yes
Kypriadis et al. (2020)	Static	Yes	Yes	Yes
Kypriadis et al. (2019)	Dynamic	No	Yes	No

Table 2: Classification of relocation models for FFCS systems

From the discussed studies on static relocation models for FFCS systems, the relocation models proposed by Weikl and Bogenberger (2015); Paschke et al. (2016); Folkestad et al. (2020) can be considered as the most basic models. The model of Weikl and Bogenberger (2015) proposes proactive relocations but does not contain a routing module and therefore does not plan a relocation tour. The relocation model of Paschke et al. (2016) is inefficient as all relocations are executed apart from each other and no relocations are combined in a tour. Furthermore, the model of Folkestad et al. (2020) is only working optimal in an infrastructure with plentiful charging stations as the vehicles are relocated to charging stations close to actual demand points. Besides, only EVs with low battery are relocated, while the first goal in a proactive relocation strategy is to meet random demands at the right place and time.

Both Haider et al. (2019) and Kypriadis et al. (2020) combine relocation, recharging and routing decisions to serve the given demand for the next day and are proven to be applicable for large-scale problems. Although the papers cover the same aspects in their static relocation strategy, the papers differ in their operational approach to relocate the cars. In Haider et al. (2019) the operators are transported with shuttles to the vehicles that have to be relocated and picked up again by the shuttle after they relocated the car. While in Kypriadis et al. (2020), operators are able to use an auxiliary car to initially move from the depot to the first car. From there, the operator follows a relocation tour and when the relocation tour is completed, the operator takes the auxiliary car back to the depot. During the relocation tour the operator has to walk from the relocated car to the next car the operator has to relocate. While, in the model of Haider et al. (2019), the operator is picked up through a shuttle and brought to the next car the operator has to relocate. The walking time in the model of Kypriadis et al. (2020) could be reduced by using folding bicycles to transport the operator between cars.

Although, limited research has been done on dynamic relocation strategies for FFCS systems, Kypriadis et al. (2019) managed to come up with a model. The relocation strategy is executed while the FFCS system is fully functional and variation of demand throughout a time period is taken into account. Furthermore, dynamic adjustment is included to change an ongoing relocation route depending on user movements and the authors set a time limit on the operation as cars cannot be rented while they are in the relocation process. Complete rebalancing of the system is not achieved in all cases through the time limit and the charging of EVs is not included in the model.

2.4 Conclusion on literature review

This literature review started with an introduction, which introduced Amber and the research context. In specific, the introduction described the fast growing interest in the sharing economy, the different CS systems in the market and the CS characteristics of the Amber case. This literature review focuses on proactive vehicle relocation in FFCS systems, which consist of the following three main components: zone categorization of service areas, estimating demand in the different zones and a relocation strategy to reposition the cars when the demand is known.

The first step is to theoretically divide the service area in which the FFCS system is operating into zones that represent artificial stations. This step is discussed in Chapter 2.1 and is referred to as zone categorization. The size of these zones is based on the maximum willingness to walk of users. If the zones are too big, a vehicle that is typically placed anywhere within the zone, might still not be accessible to a particular user (Paschke et al., 2016). However, when the zones are too small it is harder to forecast the demand as aggregate forecasts tend to have a smaller standard deviation of error relative to the mean (Wang et al., 2010).
Static and dynamic zone categorization methods are both applicable to the Amber case. The dynamic approach will lead to a reduction in unnecessary relocations. However, it will lead to a loss in prediction accuracy as well through the smaller zone size. This results in a difficult trade-off between the static and dynamic zone categorization methods and the performance of both methods has to be tested on the Amber case.

Different methods for estimating FFCS demand are discussed in Chapter 2.2. Following several studies machine learning methods outperform traditional forecasting methods based on prediction performance. However, traditional forecasting methods are easier to understand than the complex machine learning methods. This trade-off raises the following question: is the gain in predictive power from using machine learning methods over traditional forecasting methods worth the loss of interpretation? Further conclusions are that future demand in FFCS systems has to be predicted multiple times a day and that the inclusion of exogenous variables significantly improves the forecast.

The final chapter in the literature review presents different relocation strategies for FFCS systems once the demand is predicted. A distinction in made between static and dynamic relocation models. In static relocation a target number of required vehicles for a zone is determined for the next period and the aim of the static relocation strategy is to reach this target number in each zone before the next time period begins. Haider et al. (2019) and Kypriadis et al. (2020) combine relocation, recharging and routing decisions to serve the given demand for the next day and are proven to be applicable for large-scale problems. In contrast, dynamic relocation takes into account the variation of demand throughout a time period. Limited research has been done on dynamic relocation strategies for FFCS sytems. However, Kypriadis et al. (2019) came up with a model that is proven on an existing FFCS system.

3 Research objective

The goal of this research is to develop a proactive vehicle relocation strategy for the FFCS system of Amber in Eindhoven. Relevant literature regarding proactive vehicle relocation in FFCS systems is identified in Chapter 2. The identified literature will be the input in the development of the proactive vehicle relocation strategy, which can be divided into three different phases. First, the service area has to be partitioned into smaller zones that are approached as artificial stations. Thereafter, a forecasting instrument has to be derived to predict short-term demand per zone in the service area. Once the demand is predicted, a relocation model is needed to plan the transfers of cars from oversupplied zones to undersupplied zones in an efficient way.

The problem Amber is currently facing fits in the broad field of Supply Chain Management (SCM). In general, there are three different planning levels within SCM. Strategic planning, which considers the network design, including prescribing facility locations, production technologies and plant capacities. Tactical planning, which prescribes flow management policies, processing and distributing products. At last, operational planning schedules operations to assure in-time delivery of products to customers (Schmidt and Wilhelm, 2000). The management of CS systems addresses all three planning levels. The location of stations and/or service areas relates to strategic decisions. Sizing problems of fleet or staff are related to tactical and operational decisions. Rebalancing incentives are mainly related to operational decisions and vehicle relocation is related to tactical and operational decisions. For a comprehensive review on these three planning levels, see Laporte et al. (2018). As a result, the proactive vehicle relocation problem can be classified as a tactical and operational planning problem within the context of SCM.

3.1 Research design

This section introduces the main research question and supporting research questions. These questions are defined using the problem definition in Section 1.1 and the conducted literature review presented in Section 2. The main research question is defined as follows:

How can a proactive vehicle relocation strategy in FFCS systems be used to improve the operational aspect of the car sharing service?

Three supporting research questions that correspond to the different sections in the literature review are proposed to formulate an answer to the main research question. The first supporting research question is defined as follows:

1. *How can the service area in which the FFCS system is operating be best partitioned into smaller zones (i.e. artificial stations)?*

To answer the first supporting research question a zone categorization method is required. Multiple zone categorization methods are reviewed in Section 2.1. Ideally, the zones have a size that satisfies the maximum walking distance from a user to the car (set by Amber to 300m) in all cases and a dynamic zone categorization method is used to avoid unnecessary relocations as explained by Caggiani et al.

(2017). However, this method results in relatively small zones. As the demand intensity is lower in smaller zones, the forecasts tend to have a higher standard deviation of error relative to the mean (Wang et al., 2010). If the demand intensity in the zones is too low, the size of the zones needs to be increased while still satisfying the maximum walking distance. This could be possible by swapping the dynamic categorization method of Caggiani et al. (2017) with a static categorization method. Another possibility is to use the method of Kypriadis et al. (2020) where the cars have to be parked in the middle of the zone to be sure that they are within the maximum walking distance of the user in any case. These methods will be investigated in Chapter 5 and on basis of the demand intensity in the zones of the service area it will be determined which zone categorization methods can be used.

2. *What type of forecasting instrument is best suited to predict short-term demand in FFCS systems capturing spatio-temporal correlations?*

To answer the second supporting research question a forecasting instrument has to be derived that predicts the short-term demand per zone. Vehicle positioning and booking data will be analyzed to identify so-called spatio-temporal 'hot spots' and 'cold spots', for which the number of bookings is used as demand indicator. The overall goal of the forecasting instrument is to achieve a high predictive performance while taking into account the interpretability of the forecasting instrument. In Section 2.2, studies were discussed that compared machine learning methods with traditional forecasting methods. It was found that machine learning methods usually outperform traditional forecasting methods based on prediction performance. However, machine learning methods involve a certain complexity in terms of interpretation and result in larger computation times. Especially the larger computation times can form a problem when the forecasting instrument has to run multiple times a day. To illustrate, in the study of Ke et al. (2017) several forecasting instruments are compared. Their most sophisticated FCL-Net achieves the best predictive performance but also has a computation time of more than 200 minutes, while the very simple moving average method has a computation time of 0.01 minute. Both traditional forecasting and machine learning methods will be tested in Chapter 6. The best forecasting instrument will be chosen in terms of a trade-off between predictive performance, interpretability and computational burden.

3. *What is the most efficient way to relocate the cars from the oversupplied zones to the undersupplied zones?*

Once the demand is predicted, the cars need to be relocated from oversupplied zones to undersupplied zones. To do this in the most efficient way a relocation strategy has to be derived. As Amber does not have separate operators to execute reactive and proactive relocations, the 'uncertain' proactive relocations have to be integrated into the tour of the 'certain' reactive relocations. Ideally, proactive relocations are executed when there is unused capacity of operators and vehicles. In that way the unused capacity can be used and the marginal costs of proactive relocations is minimized. In Figure 1b it is observed that bookings come in peak moments. Relocations will be executed before the peak moments (i.e. during the idle time of the system). Therefore a static relocation strategy has to be implemented. In a static relocation strategy a target number of required vehicles for a zone is determined for the next period by the forecasting instrument. The aim of the relocation strategy is to reach this target number in each zone before the next period begins. The charging of cars is included in the proactive relocation strategy. The proactive relocation strategy is discussed in Chapter 7.

4 Available data

The available data at hand at Amber is presented in this section. Amber launched their FFCS system in September 2020 in the city of Eindhoven to trigger the consumer market as a reaction to the COVID-19 pandemic and their fallen business market. Figure 7 shows the total demand over time for the SA of Eindhoven since its origin.

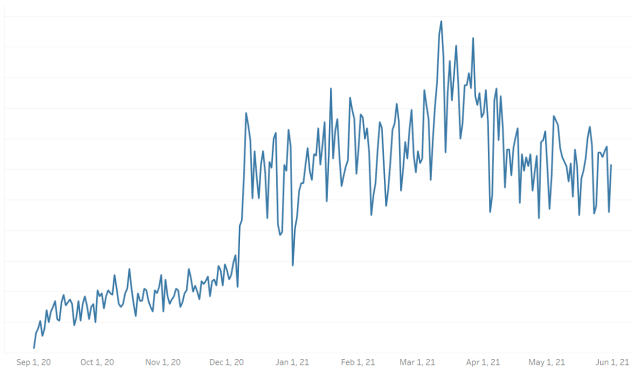


Figure 7: Total demand over time for the SA of Eindhoven

From the figure it can be observed that the demand more than doubles from one day to the next in December. Before this moment, Amber had some hubs situated in the city of Eindhoven, besides the already existing SA. However, in December they decided upon removing these hubs. The demand that was generated in these hubs shifted to the SA from that moment onwards. Therefore, it is concluded that the data of the months in 2020 is not representative for the FFCS system of Eindhoven and only data of the months January until May of 2021 is used in the study.

It should be noted that the Netherlands was still highly affected by several measures as a consequence of the COVID-19 pandemic during these months. As earlier explained in Chapter 1, the COVID-19 pandemic had a huge impact on the demand of Amber and therefore a substantial increase of demand is expected in the period after the COVID-19 pandemic. This can affect the performance of the proactive relocation strategy. However, the methodology used in the thesis remains valid and the proactive relocation strategy may be revised when the travel needs of people are recovered.

As previously discussed in Chapter 2.3, a distinction can be made between a static and dynamic relocation model. In static relocation the demand is aggregated into periods. A target number of required vehicles for a zone is determined for the next period and the aim is to reach this target number in each zone before the next period begins. In contrast, dynamic relocation takes into account the variation of demand throughout a time period. Amber wants to use the unused capacity during the off-peak period to prepare the system for the peak period. The proactive relocations will be executed before the peak period begins and therefore a static relocation model suits best for the Amber case. From Figure 1b, it can be observed that the user demand in weekdays demonstrates a double-peak nature while the user demand in weekends shows a single-peak property. The single weekend peak is found to be at 10-13 a.m. and the peak moments for the weekdays are found to be at 6-9 a.m. for the morning peak and at 15-18 p.m. for the afternoon peak.

4.1 Description of variables

In this section a description of the variables that are used in this thesis is given.

(1) Demand intensity.

The demand intensity is defined as the total number of orders within a specified hexagon during the peak intervals

(2) Time-of-day, day-of-week and working-day.

As discussed, the peak-hour demand is aggregated. A dummy variable is introduced based on the time-of-day during which these peak-hours take place:

$$Peaks = \begin{cases} 0, & \text{if peak belongs to single weekend peak (10-13 a.m.)} \\ 1, & \text{if peak belongs to morning peak for weekdays (6-9 a.m.)} \\ 2, & \text{if peak belongs to afternoon peak for weekdays (15-18 p.m.)} \end{cases} \tag{1}$$

Further, the variable day-of-week is designed, which distinguishes properties between different days.

$$Day-of-week = \begin{cases} 0, & \text{if peak belongs to a Monday} \\ 1, & \text{if peak belongs to a Tuesday} \\ 2, & \text{if peak belongs to a Wednesday} \\ 3, & \text{if peak belongs to a Thursday} \\ 4, & \text{if peak belongs to a Friday} \\ 5, & \text{if peak belongs to a Saturday} \\ 6, & \text{if peak belongs to a Sunday} \end{cases} \tag{2}$$

Finally, we denote another dummy variable to working-day, which catches up the distinguished properties between weekdays and weekends.

$$Working-day = \begin{cases} 0, & \text{if peak belongs to weekdays} \\ 1, & \text{if peak belongs to weekends} \end{cases} \tag{3}$$

5 Zone categorization in free-floating car sharing systems

This chapter addresses the zone categorization of a FFCS system, as discussed in Section 2.1. More specifically, this chapter introduces different grids that can be used to partition the service area (SA) in a FFCS system. The zones in the grid serve as artificial stations for which the short-term demand will be predicted. Section 5.1 discusses the general principles of the zone categorization problem in the FFCS system of Amber. Section 5.2 evaluates the fit of particular grids for the Amber case. To determine the most appropriate grid for the Amber case a trade-off needs to be made between the size of the zones, the average demand per zone and the forecasting errors. As the forecasting errors are not yet known for a specific grid, the final decision about which grid to use for further analysis is done in Chapter 6. This chapter results in a general answer to the first research question:

1. *How can the service area in which the FFCS system is operating be best partitioned into smaller zones (i.e. artificial stations)?*

5.1 Introduction to zone categorization problem

FFCS systems can be seen as a flexible way of CS, where users can pick up and drop off the vehicles freely within a predefined SA. Customers can access the vehicles in two ways in the SA of Amber: they can either make a reservation to book a vehicle or they can access a vehicle spontaneously without reservation. If a reservation is made, Amber provides the extra service of bringing the car within 300 meters (as the crow flies) of the customer. An order is considered as a "reservation" when the customer makes a booking a certain time in advance. This time can vary and is called the service level agreement (SLA). The SLA was 60 minutes in the SA of Eindhoven until 18 may 2021 and is from then on shifted to 180 minutes. So, for every reservation that is made in advance that satisfies the SLA, a car is guaranteed within 300 meters of the user's location. On the other hand, an order is considered as an "instant" when the time between the booking of the car and the user's departure time is shorter than the set SLA. In Figure 8, the distribution of the vehicle request types in the SA of Eindhoven is shown. The percentage of instant bookings (i.e. customers spontaneously pick a vehicle without a reservation) is interesting as it reflects the part of demand that is not reserved in advance and for which the vehicle was on the right place at the right time. This part of the demand is only generated when vehicles are placed on the right spots, which enhances the added value of proactively relocating vehicles.

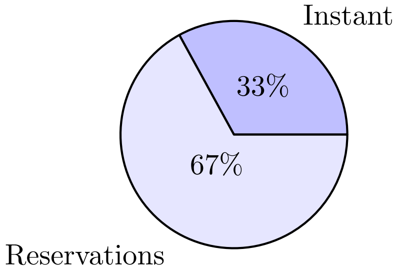
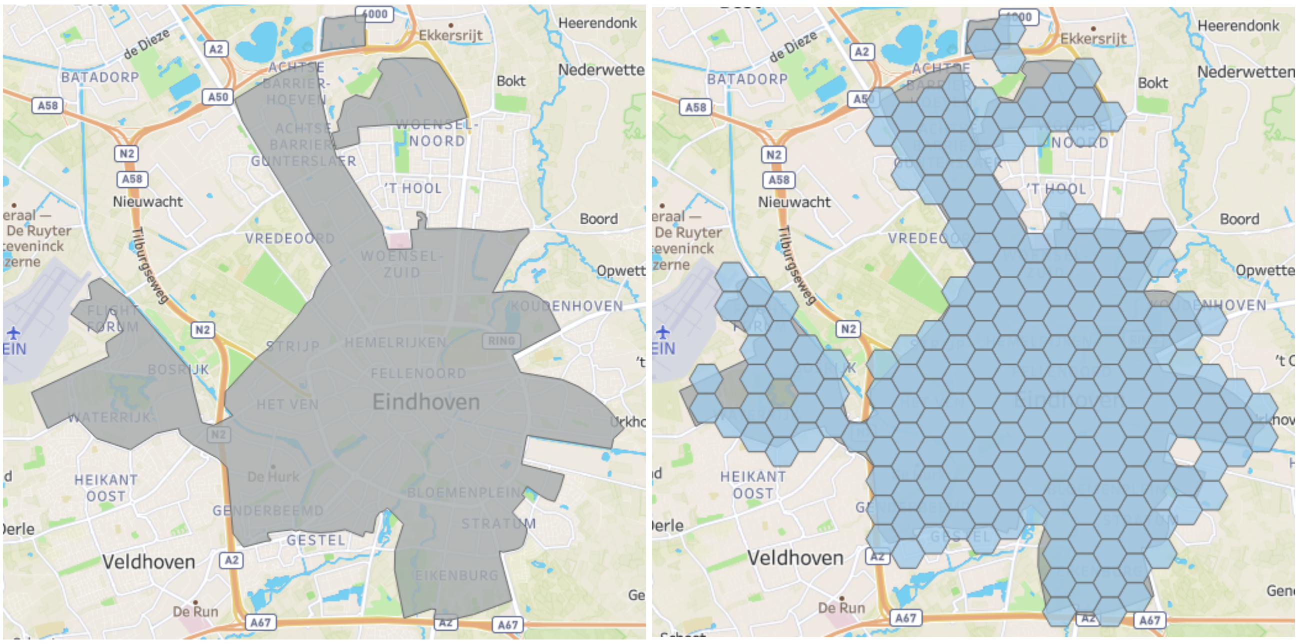


Figure 8: Distribution of vehicle request types in SA Eindhoven

In order to predict the user behavior in FFCS systems, the FFCS system has to be transformed to a station-based system by virtually dividing the service area into smaller zones. The size of these zones is a critical element to determine whether a relocation is needed, as previously discussed in Chapter 2.1. According to experts, there is a maximum willingness to walk to the vehicle of 500 meters (Seign and Bogenberger, 2013; Barrios and Godier, 2014). As previously explained, Amber set the maximum willingness to walk to 300 meters as the crow flies. The maximum distance between a user and the car should therefore not exceed the above-mentioned threshold. If zones are too big, a vehicle that is placed anywhere within the zone, might still not be accessible to a particular user in terms of the user's maximum willigness to walk (Paschke et al., 2016). However, if the zones are too small, there may be too little demand within a zone to make an accurate forecast. That is, if demand is aggregated, forecasts tend to have a smaller standard deviation of error relative to the mean (Wang et al., 2010), which is exactly why smaller zones are more difficult to forecast. The final decision is therefore a trade-off between the size of the zones, the average demand per zone and the corresponding forecasting errors.

5.2 An 'Ideal' grid for the relocation model of SA Eindhoven

Ideally, the zones in the SA of Eindhoven should be made as large as possible while still satisfying the threshold of 300 meters walking distance set by Amber, as explained in Section 5.1. In the method of Kypriadis et al. (2020), cars have to be parked in the middle of the zone to be sure that they are within the maximum walking distance of the user in any case. Using this method, zones can be defined as circles with a diameter of 600 meters. As it is not possible to cover the whole SA with a grid of non-overlapping circles, hexagons with a diameter of 600 meters (across corners) should be used. Figure 9a shows the SA of Eindhoven while Figure 9b shows the grid of hexagons with a diameter of 600 meters on the SA of Eindhoven.



(a) SA Eindhoven

(b) Grid with hexagons of 600 meters

Figure 9: Visualizations of SA Eindhoven and grid of hexagons with a diameter of 600 meters

As previously discussed, demand is aggregated into periods that correspond to the peak moments. These peak moments are three hour periods for which the average hexagon demand per peak is 0.18 measured from January until May 2021. This average hexagon demand has to be increased to ensure that there is sufficient demand in the zones to execute the forecasting model. Increasing the time slices directly results in a higher demand intensity and could therefore be used to increase the average hexagon demand per peak. However, the time slices are already as long as the duration of the peaks and increasing the time slices is therefore not considered as an option. To deal with these low amounts of demand per hexagon we follow the idea of macroscopic and microscopic zones of Weikl and Bogenberger (2015). They use an optimization model for the macroscopic zones and then use rule-based methods to make intra zone relocations on the individual vehicle level. According to the authors, vehicle movements between larger zones are not precise enough and do not satisfy local demand. Meanwhile, vehicle movements between smaller zones are pseudo exact and vehicle movements of very small distance might be suggested.

The forecasting model will be executed for the macroscopic zones. In this way we can make sure that there is sufficient demand in the zones to execute a forecasting model. The microscopic zones in the Amber case will be hexagons with a diameter of 600 meters as these hexagons are as large as possible while still satisfying the threshold of 300 meters walking distance set by Amber. In further readings of this thesis, macroscopic zones are referred to as zones and microscopic zones are referred to as hexagons. Weikl and Bogenberger (2015) determine the zones by clustering the bookings with a p-median method to ensure that the zones should be homogeneous and should cover the whole operating area. The p-median method calculates the distances with the taxicab distance (i.e. manhatten distance). In comparison to Weikl and Bogenberger (2015), the hexagons are clustered in the Amber case rather than the bookings to ensure that the entire hexagons fall within a zone. As bookings are already clustered within the hexagons it does not make sense to use the 'more precise' p-median clustering method and the k-means clustering method is used to cluster the hexagons. K-means clustering calculates the distances with the euclidean method. The k-means clustering method is solved iteratively for different values of k, *i.e.*, the number of microscopic hexagons per macroscopic zone is varied. The more zones k there are, the fewer the number of hexagons included in each zone. Less zones directly results in less demand per zone. The results of this iterative method are visualized in Figure 10. In Section 6.1, a simple traditional moving average method is used to derive forecasting errors for the different number of zones, such that the average demand is large enough to make a proper forecast and the zones are appropriately sized and spread over the SA.

(a) 3 zones (b) 4 zones (c) 5 zones

(d) 6 zones (e) 7 zones (f) 8 zones

Figure 10: Results of k-means clustering method of hexagons for SA Eindhoven

6 Estimating free-floating car sharing demand

This chapter presents different forecasting models to estimate the short-term demand in FFCS systems. More specifically, a forecasting instrument is derived that predicts the demand per zone for the coming peak hours. Multiple forecasting models used by other studies to predict short-term demand in FFCS systems are discussed in Section 2.2. Promising traditional forecasting models and more sophisticated machine learning models are executed and compared for the Amber case, with the overall goal to derive a forecasting instrument to achieve high predictive performance while taking into account the interpretability of the forecasting instrument. First, a final number of zones for SA Eindhoven is chosen with the use of a traditional moving average (MA) method in Section 6.1. Subsequently, the autoregressive integrated moving average (ARIMA) model is tested and evaluated in Section 6.2. Thereafter, the long short-term neural network (LSTM) is executed as machine learning method for the Amber case in Section 6.3. The effect of weather variables is tested for the LSTM as well. Finally, an overall comparison of the different forecasting models is given in Section 6.4. This chapter provides a general answer to the second research question:

2. *What type of forecasting instrument is best suited to predict short-term demand in FFCS systems capturing spatio-temporal correlations?*

6.1 Determination number of zones in SA Eindhoven

A final number of zones for SA Eindhoven needs to be chosen which will be used for further analysis in the thesis. To determine the final number of zones for the Amber case, a trade-off needs to be made between the forecasting errors per zone, the average demand per zone and the size of the zones. As previously explained, smaller zones are more difficult to forecast. With this reasoning, the ratio between the forecasting errors and the average demand per zone will probably increase when the number of zones is increased. To provide better insights in how this ratio may change and how the forecasting errors are affected for smaller or bigger zones, the traditional moving average (MA) method is used to derive forecasting errors for the different number of zones. The provided insights are used to choose the final number of zones. The MA method predicts the future value by the mean of various nearest historical values. The number of historical values averaged is called the window size. With common sense we derived four moving averages, as listed below, in which a distinction is made between some variable's properties as indicated in definitions 1, 2 and 3. The window size is denoted as x.

1. *MA-x (standard)*: Moving average in which the next peak is predicted by last x peaks, no distinction is made between different peaks.
2. *MA-x (specific period)*: Moving average in which the next peak is predicted by the same last x peaks.
3. *MA-x (work weekend)*: Moving average in which the next peak is predicted by last x peaks on the same type of day (i.e. working days or weekends)
4. *MA-x (period day)*: Moving average in which the next peak is predicted by same last x peaks on the same day of week.

These four MA methods are executed for the different number of zones, as defined in Chapter 5. The dataset is divided into two consecutive parts, 80% for training (i.e. January-April) and 20% for prediction/test (i.e. May) respectively. For each of the four different types of MA models, a grid search is executed. This grid search is performed for all the different zone sizes defined in section 5.2. For each zone size and MA type, the grid search aims to find the MA-x model with its corresponding optimal window size x. The grid search is executed from window size one to the maximum window size that is possible with the current training set for that MA. To illustrate, the maximum window size for the standard MA is larger than for the specific period MA, as it does not make a distinction between different peaks and therefore has more historical periods at its disposal.

6.1.1 Results of moving average method

Table 16 in the Appendix shows the performance metrics on the test set of the four moving average methods for the different number of zones shown in Figure 10. The forecasting models are evaluated via the following two performance metrics: root mean squared error (RMSE) and mean absolute error (MAE), which are computed with Equations 4 and 5, respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| \tag{5}$$

To provide a better overview of the results in Table 16, the RMSE and MAE for the different number of zones are plotted in Figure 11. The results show that both the RMSE and MAE decrease when the number of zones increase. This is expected as the average demand per zone decreases as well when the number of zones is increasing. It can also be observed that the RMSE has a steeper slope when the number of zones is increased from three to five than from five to eight and the MAE has a steeper slope when the number of zones is increased from three to four than from four to eight. Furthermore, the standard MA method can be viewed as the best performing MA method as the standard MA method is performing best on RMSE and MAE in all cases.

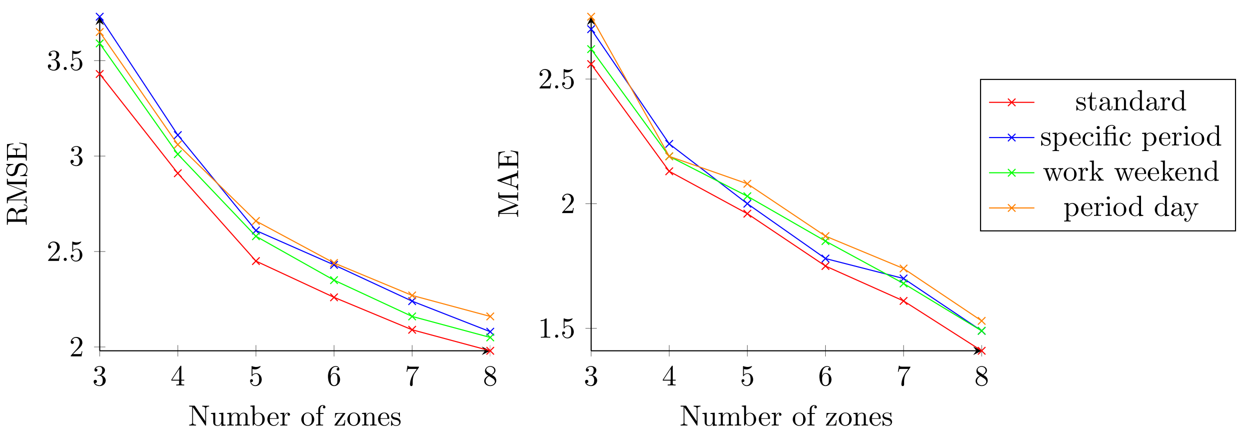


Figure 11: Performance metrics for different number of zones

The results of this best performing MA method are provided in Table 3. From this table it can be seen that the standard MA method takes a window size close to 50 for all different number of zones. As there are 12 peaks in a week, the optimal window size is close to four weeks of data. That a large window size results in the best performance of the MA method could be due to high statistical noise in the data, since an advantage of taking a large window size is a decreased effect of this noise (Shinzawa et al., 2006).

Model	Zones	RMSE	MAE	Average demand	SD
MA-50 (standard)	3	3.41	2.56	10.09	7.54
MA-50 (standard)	4	2.91	2.13	7.57	6.14
MA-50 (standard)	5	2.52	1.96	6.05	4.36
MA-50 (standard)	6	2.31	1.75	5.04	4.02
MA-49 (standard)	7	2.12	1.61	4.32	3.34
MA-48 (standard)	8	1.89	1.41	3.78	3.44

Table 3: Best results moving average method for each number of zones

However, looking at the RMSE and MAE alone is not enough as it should always be viewed in relation to the average demand. The ratio between the error and the average demand is an interesting metric to determine the number of zones in the SA. The ratio between the error X, i.e. either RMSE or MAE, and the average demand is therefore visualised in Figure 12. It can be observed that the slope of both the RMSE and MAE flattens from seven to eighth zones. Therefore, it could be an argument to choose eighth zones above seven as the ratio between the error and the average demand stays the same while the prediction is more precise. Nevertheless, the average demand per zone is a deciding factor to choose the number of zones in the SA as we are dealing with low volume data and the average demand per zone is getting too low for seven or eighth zones.

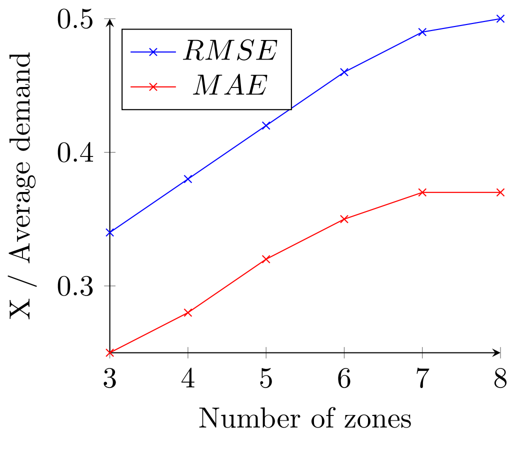


Figure 12: Ratio between MAE/RMSE and the average demand per number of zones

As previously explained, a trade-off needs to be made between the forecasting errors per zone, the average demand per zone and the size of the zones to determine the final number of zones for the Amber case. When taking only the forecasting errors and the average demand in consideration, the SA with 3 zones should be chosen since the ratio between error and the average demand is the lowest in this case (see Figure 12). On the other side, if only the size of the zones is taken into consideration, the SA with eighth zones should be chosen since proactive relocations can be executed with more precision. After consultation with the personnel of Amber it is decided that using three or four zones results in macroscopic zones that are too large, which eventually results in vehicle relocations that may still not be accessible for all users within the zones. The visuals of the different zones per number of zones as presented in Figure 10 are taken into account when making this decision. As we are dealing with low volume data we want to pick the lowest number of zones that will result in appropriately sized zones spread over the SA of Eindhoven. This is the case for a minimum number of zones of five as concluded with the personnel of Amber. In Figure 11 it was observed that the RMSE dropped faster from three to five zones than afterwards which is also an argument in favor of choosing five zones. Therefore, the number of zones for SA Eindhoven is set to five for further analysis in this thesis. Note that this decision is made as we are dealing with a low volume data set which is a consequence of the COVID-19 pandemic. As the demand is expected to increase in the upcoming period, the number of zones can easily be increased to a higher number. Besides, the clustering method used can also be easily transferred to other cities as no demographic or geographic variables are used.

6.2 Traditional time-series forecasting model

A visualisation of the five zones in the SA of Eindhoven is shown in Figure 13. A forecasting model will be derived for these five zones, in which a particular forecast is executed for each of the zones. As previously discussed, a short-term forecast should be used to estimate the demand in the upcoming peak and bookings are aggregated for these peaks per zone.

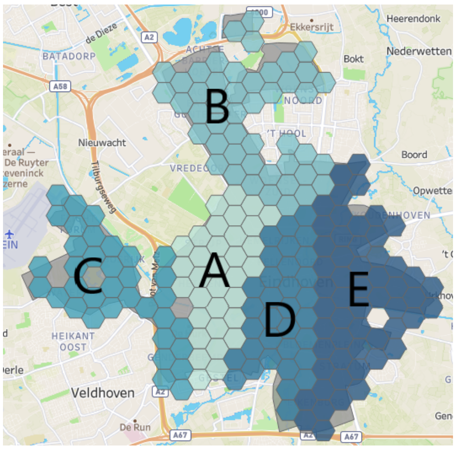
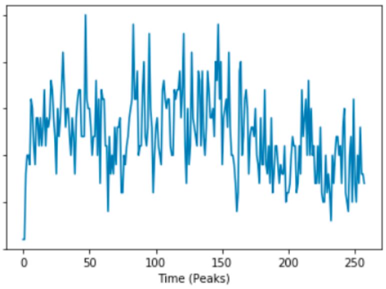
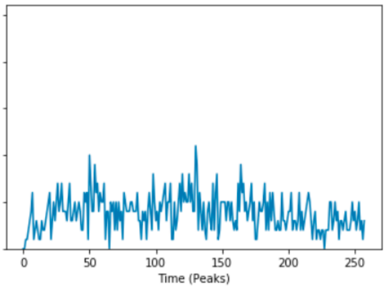


Figure 13: Visual result of 5-means clustering method of SA Eindhoven

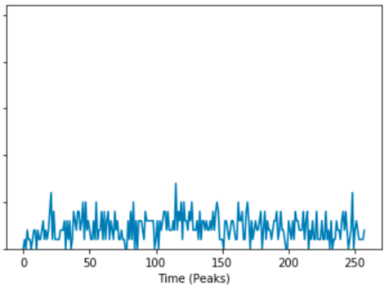
The time series of each zone are shown in Figure 14. It can be observed that the volume of demand in the zones differs. The demand intensity in zone A and D is higher than in zone B, C and E, which makes sense as zone A and D cover more of the centre of Eindhoven and zones B, C and E cover more of the suburbs of Eindhoven.



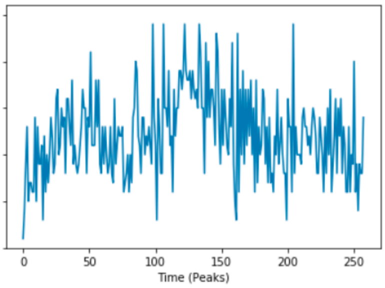
(a) Zone A



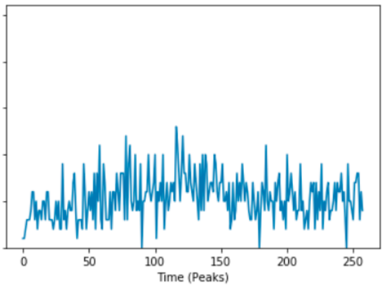
(b) Zone B



(c) Zone C



(d) Zone D



(e) Zone E

Figure 14: Time series of defined peaks for each zone of January-May

The results of the best performing MA method for each individual zone are provided in Table 4. The average demand and standard deviation that can be observed are derived from the test set for comparison reasons as the RMSE and MAE are calculated over the test set as well. It can be observed that the value of the MAE is lower than the value of the standard deviation for all cases, meaning that the MA method explains a part of the variation of the data set. The results provided in Table 4 of the standard MA method will be used as benchmark for the other forecasting models executed in this thesis.

Zone	RMSE	MAE	Average demand	SD
A	3.53	2.99	9.40	3.62
B	1.44	1.18	2.92	1.38
C	1.31	1.06	1.94	1.30
D	3.38	2.84	10.94	3.40
E	2.07	1.73	5.06	2.05

Table 4: Results standard MA method (window size of 50) per individual zone

6.2.1 Autoregressive Integrated Moving Average model

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used time series forecasting model. In the ARIMA model the autoregressive (AR), integrated (I), and moving average (MA) parts are integrated. The ARIMA model considers trends, cycles and non-stationary characteristics of a dataset simultaneously. The three parts in the ARIMA model have a corresponding parameter that should be specified: the auto-regressive parameter (p), the integrated parameter (d) and the moving average parameter (q). In further analysis the standard notation of ARIMA(p,d,q) will be used in which p, d and q will refer to the parameters used in that ARIMA model. The classical approach for fitting an ARIMA model is to follow the Box-Jenkins methodology (Box et al., 2015). The Box-Jenkins approach uses time series analysis and diagnostics to discover the parameters for the ARIMA model. Instead of using the Box-Jenkins method to select the parameters in the ARIMA model for the Amber case, grid search is used. Computationally this is harder to solve than the parameter estimation that is used in the Box-Jenkins approach. However, grid search will lead to the optimal parameter values and is therefore used. The ARIMA(1,1,2) model was found to be optimal and the results of this ARIMA model are shown in Table 5.

Zone	**RMSE**	**MAE**	**Average demand**	**SD**
A	3.68	3.21	9.40	3.62
B	1.43	1.12	2.92	1.38
C	1.34	1.09	1.94	1.30
D	3.28	2.67	10.94	3.40
E	2.09	1.73	5.06	2.05

Table 5: Results ARIMA method per individual zone

When you compare the results of the ARIMA model with the results of the MA method, it can be observed that there is not one forecasting model in which the performance metrics for all zones is better and which model performs best differs per zone. The performance of the different forecasting instruments is further discussed in Section 6.4.

6.3 Long short-term memory neural network

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) that has emerged as an effective and scalable model for several learning problems related to sequential data (Greff et al., 2016). The idea behind the LSTM architecture is a memory cell in which the state over time can be maintained. Therefore, the LSTM can not only process single data points, but also entire sequences of data. As discussed in Section 2.2.2, the machine learning methods usually outperform the traditional forecasting methods based on prediction performance. This is due to their ability to capture complex relationships from large amounts of data. Within the proposed machine learning methods that are discussed in Section 2.2.2, the LSTM is most promising for its capability to process entire sequences of data. In addition, the LSTM is validated to be an appropriate tool for addressing time-series prediction problems in transportation problems. Furthermore, Ke et al. (2017) concluded that the inclusion of exogenous variables significantly improves the forecast. Therefore, the LSTM will be executed for the Amber case and the addition of weather variables will be tested and evaluated.

6.3.1 Model configuration and parameter tuning of the LSTM

The configuration of neural networks is a difficult task as there is no 'best working' method on how to do it. The tutorial of Brownlee (2018) is used to configure the LSTM for the Amber case. First, a few data preparation steps need to be executed, followed by some general choices for the model configuration. Finally, the parameters need to be tuned for the LSTM.

There are mainly two important data preparation steps for the LSTM:

- Transform the time series into a supervised learning problem. The observations of the previous x time steps are used as input to forecast the observation at the current time step, where x is the number of lag observations used as input time steps. For now, x is set to one.
- Transform the observations with the use of min-max normalization.

The forecasts are inverted to their original scale before calculating the performance scores. For the Amber case a three layered multivariate LSTM is used, in which the three variables are included as denoted in Equations 1, 2 and 3. Different numbers of layers for the LSTM are tested and with three layers the best and most constant predictive performance for the Amber case was achieved. A few scenarios are tested to determine the initial parameter values for parameter tuning process, this resulted in the following values: *Number of epochs: 250, Batch size: 64, Number of neurons: 50, Number of lag observations: 1.*

Random initial conditions for an LSTM can result in different outcomes each time a given configuration for the LSTM is trained (Brownlee, 2018). Therefore, each configuration has to be run multiple times for each parameter value in order to compare the mean performance. For the Amber case, ten runs were completed (as recommended by Brownlee (2018)) for each parameter value and the performance metrics are calculated for the test set. The first parameter that is tuned is the number of epochs. The number of epochs is the number of times that the algorithm will work through the entire dataset. In general, the performance of the LSTM will increase when the algorithm is trained additional times until the algorithm will result in overfitting. The values 50, 100, 250 and 500 are used for the tuning process of the number of epochs. The distribution of the results for each parameter is shown on a box and whisker plot in Figure 15. The RMSE is taken as performance measure and corresponds to the y-axis of the graph. From this figure it can be seen that the average performance is best when the number of epochs is set to 100. The performance with 250 epochs is close to the performance with 100 epochs, however the mean and the best value achieved is lower with 100 epochs. Therefore, the number of epochs in the LSTM is set to 100.

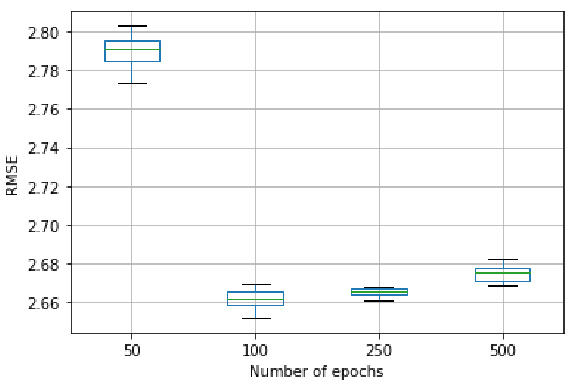


Figure 15: Box and whisker plot summarizing epoch results

Next, the batch size parameter is tuned, the batch size refers to the number of samples trained from the training set each iteration. The values 32, 64 and 128 are used for the tuning process of the batch size parameter as these are commonly used batch sizes following Brownlee (2018). The distribution of the results for each parameter is shown on a box and whisker plot in Figure 16. It is clear from this figure that with a batch size of 64 the best performance is achieved. Therefore, the batch size in the LSTM is set to 64 for further analysis.

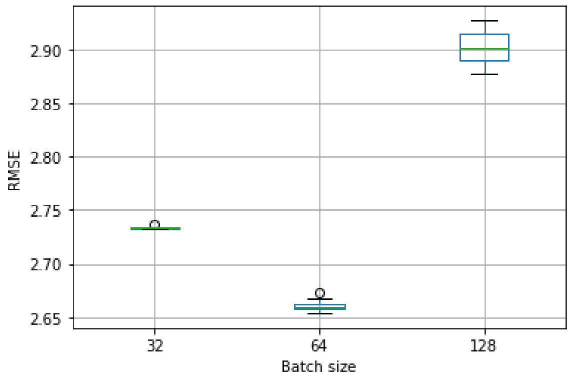


Figure 16: Box and whisker plot summarizing batch size results

The number of neurons in the LSTM is the next parameter to be tuned. Overall, more neurons would be able to learn more structure from the problem. However, it will take longer to train the model and more learning capacity can potentially lead to overfitting the training data (Brownlee, 2018). For the number of neurons the following values are tested: 25, 50, 100 and 200. The distribution of the results is shown on a box and whisker plot in Figure 17. From the results can be observed that the LSTM with 50 and 100 neurons reach about the same performance in the best cases. However, the distribution of the results for 50 neurons is much more spread while the results for 100 neurons are more constant and on average better. Therefore, the number of neurons in the LSTM is set to 100.

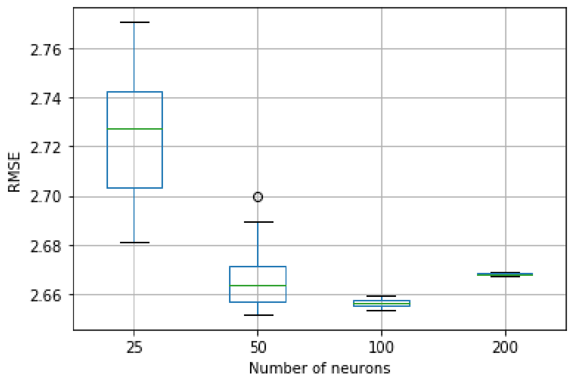


Figure 17: Box and whisker plot summarizing neuron results

The final parameter that is tuned for the LSTM is the number of lag observations. This parameter is is used to test whether a different number of lag observations as input feature can improve the predictive capability of the LSTM. The distribution of the results is shown on a box and whisker plot in Figure 18. From this plot, it can be concluded that the lowest RMSE is achieved with two lag observations. Thus, the number of lag observations parameter is set to two.

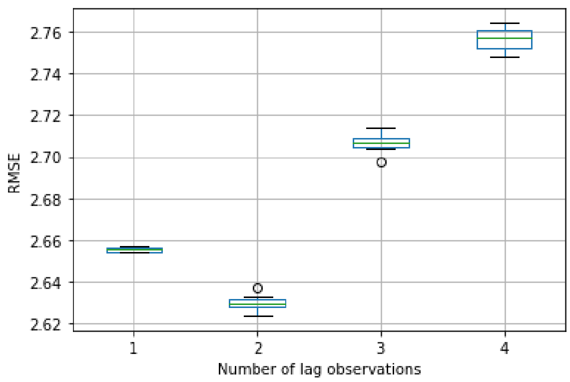


Figure 18: Box and whisker plot summarizing lag observations results

The results of the tuned LSTM are provided in Table 6 per individual zone. Again, all values are calculated over the test set. The inclusion of weather variables for the LSTM is tested in next section to improve the predictive performance. The performance of the different forecasting instruments is discussed in Section 6.4.

Zone	RMSE	MAE	Average demand	SD
A	3.69	3.11	9.40	3.62
B	1.61	1.40	2.92	1.38
C	1.53	1.19	1.94	1.30
D	3.52	2.87	10.94	3.40
E	1.94	1.60	5.06	2.05

Table 6: Results LSTM per individual zone

6.3.2 Including weather variables in LSTM

The studies of Ke et al. (2017) and Yu et al. (2020) both prove the effect of weather variables for forecasting the demand in an on-demand ride service platform. In the study of Ke et al. (2017) the following five categories of weather variables are considered: temperature, relative humidity, weather state, wind speed and visibility. In which weather state could contain one of the following categories: sunny, cloudy, light rain, moderate rain and heavy rain. Ke et al. (2017) show that all weather variables have only few contributions (less than 5%) to the prediction, except for the temperature variable. In the study of Yu et al. (2020) similar weather variables are included. They used temperature, wind speed, visibility and weather condition. The weather condition in their study can take the values: sunny, cloudy, light rain, light snow, moderate snow, moderate rain, heavy rain, heavy snow and snow storm. Unfortunately, Yu et al. (2020) do not explain the contribution of the individual weather variables on the LSTM.

For the Amber case weather data is retrieved from the weather station of the KNMI in Eindhoven (KNMI, 2021). Three weather variables are individually tested on the LSTM to see whether the performance metrics of the LSTM would increase as a result of the inclusion of the weather variable.

The following weather variables are tested based on the studies of Ke et al. (2017) and Yu et al. (2020):

- Temperature - The average temperature for the peak is calculated from the individual measurements for each hour in the peak
- Duration of precipitation - The total duration (in hours) of precipitation during the peak.
- Rain - If it rained within an hour the value one is given and otherwise zero. For the peak the values of the corresponding hours are summed. So, if it rained in two of the three hours the variable has the value two.

The inclusion of the above defined weather variables in the LSTM did not result in any improvement for the Amber case. Therefore, the weather variables are not included in the LSTM and the final results of the LSTM are the results that were defined in Table 6. In next section, the different forecasting instruments are compared and a forecasting instrument is chosen for further analysis.

6.4 Conclusions on estimating free-floating car sharing demand

This section summarizes and concludes on the dilemma of estimating free-floating car sharing demand. Thereby, the section formulates an answer to the second research question.

The overall goal of the forecasting instrument is to achieve high prediction performance while taking into account the interpretability of the forecasting instrument. In Section 2.2, forecasting models were discussed that proved to be helpful in the prediction of short-term demand in FFCS systems. In the current chapter, these models were tested and evaluated for the Amber case. The following three forecasting instruments are tested and evaluated:

1. Moving average method, which predicts the future value by the mean of various nearest historical values.
2. ARIMA model, which considers trends, cycles and non-stationary characteristics of a dataset simultaneously.
3. LSTM, an effective type of recurrent neural network for sequential data problems. The inclusion of weather variables in the LSTM is tested as well.

The results of the three forecasting instruments are previously provided separately for each forecasting instrument. However, to provide a better overview of the results between the different forecasting instruments, the results of these three forecasting instruments can be observed in Table 7.

First of all, it can be observed that the performance of the three forecasting instruments is close to each other. To illustrate, there is not one forecasting instrument that performs best in comparison to the other forecasting instruments on all zones and the maximum difference in MAE for a zone is 0.28.

Zone	MA		ARIMA		LSTM	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
A	3.53	2.99	3.68	3.21	3.69	3.11
B	1.44	1.18	1.43	1.12	1.61	1.40
C	1.31	1.06	1.34	1.09	1.53	1.19
D	3.38	2.84	3.28	2.67	3.52	2.87
E	2.07	1.73	2.09	1.73	1.94	1.60
Average	**2.35**	**1.96**	**2.36**	**1.96**	**2.46**	**2.03**

Table 7: Results of the different forecasting instruments per individual zone

The averaged forecasting errors are provided as well in Table 7. From these averaged errors it is observed that the MA and ARIMA model perform better than the LSTM. This is against expectations as machine learning methods usually outperform the traditional forecasting methods based on prediction performance according to the discussed studies in Section 2.2. Makridakis et al. (2018) published a study as a response to the increasing number of claims that machine learning and deep learning methods offer superior results for time series forecasting. In the study, the performance of many classical and modern machine learning and deep learning methods is compared and evaluated on a large and diverse set of more than 1,000 univariate time series forecasting problems. The results of the study suggest that simple classical methods outperform complex and sophisticated methods. Cerqueira et al. (2019) responded on the study of Makridakis et al. (2018) by showing that machine learning methods only systematically present a lower predictive performance relative to simple statistical methods under an extremely low sample size. Furthermore, their results suggest that machine learning methods improve their relative performance as the sample size grows. These studies explain why the MA and ARIMA method perform better than the LSTM, as we are dealing with extremely low volume data in the Amber case. In addition, the MA and ARIMA model are preferred over the LSTM in terms of interpretation.

Then, the final choice has to be made between using the MA or ARIMA model. This decision is based on the mathematical characteristics of the models since both models reach similar performance. The MA method predicts the future value by the mean of various historical values. Thus, the MA method indicates trends in the data. The ARIMA model considers trends, cycles and non-stationary characteristics of a dataset simultaneously and is therefore more comprehensive than the MA method. As previously discussed, a substantial increase of demand is expected in the period after the COVID-19 pandemic. Through this increase of demand it is possibly that more patterns emerge in the data. Therefore, the more comprehensive ARIMA model is preferred over the MA method since the ARIMA model also considers cycles and non-stationary characteristics.

Given the low volume dataset the forecasting itself is definitely not perfect. Still, it can be used to better know the over/under supplied zones during the peak hours in the SA of Eindhoven. The overall goal is not to forecast for the beauty of forecasting, but to make a forecast on which a useful decision can be made. In the next Chapter, the derived forecasting instrument will be used to propose proactive relocations as an extension on the reactive relocation model of Amber.

7 Proactive relocation strategy

This chapter presents the proactive relocation strategy. As explained in Section 5.2, we make use of the idea of macroscopic and microscopic zones of Weikl and Bogenberger (2015) to deal with the low volume data in the Amber case. They use an optimization model for the macroscopic zones (i.e. zone level) and rule-based methods to make inter-zone relocations on the individual vehicle level (i.e. hexagon level). In Section 7.1, zones are labelled as balanced, oversupplied or undersupplied based on the output of the forecasting model derived in Chapter 6 and real-life information of the system. Section 7.2 defines inter-zone relocations on the individual vehicle level with a rule-based method. Subsequently, in Section 7.3 it is discussed how the proactive relocation strategy is integrated into the reactive relocation model of Amber. Thereafter, in Section 7.4 a scenario analysis is executed to evaluate the proactive relocations. Eventually, this chapter provides a general answer to the third supporting research question:

3. *What is the most efficient way to relocate cars from the oversupplied zones to the undersupplied zones?*

7.1 Optimization model on zone level

This section will determine for each zone in a particular period whether the zone is balanced, under- or oversupplied, and if under- or oversupplied with how many vehicles. To do this, an optimal vehicle distribution over the zones for the target period will be determined based on the output of the forecasting model derived in Chapter 6 and real-life information of the CS system of Amber. The aim of a static relocation strategy is to balance the vehicles based on this optimal vehicle distribution over the zones before the target period begins.

An arbitrary target period is used as an example, for which the input data is shown in Table 8. This example will be used for further explanation of the proactive relocation strategy in this chapter. The input data is defined as follows. The *Requests* are the bookings that are already made at the moment that the proactive relocation strategy is executed. These requests satisfy the SLA as earlier defined in Section 5.1. *Requests assigned* are requests for which a car has already been assigned as part of the reactive relocation strategy. *Vehicles* is the total number of vehicles in that zone. If a car is assigned to a request, the car is not available anymore. The *Vehicles available* in a zone corresponds therefore to the number of vehicles minus the requests assigned in that zone. The *Estimated demand* for the target period is provided by the forecasting model derived in Chapter 6.

Zone	Requests	Requests assigned	Vehicles	Vehicles available	Estimated demand
A	2	0	3	3	8.9
B	0	0	3	3	3.2
C	0	0	1	1	2.2
D	1	1	8	7	13.5
E	0	0	5	5	5.3

Table 8: Example of input information for target period

Algorithm 1: Pseudocode generate optimal vehicle distribution over the zones

```
Data: Number of requests; Number of requests assigned; Number of vehicles available;
      Number of vehicles; Estimated demand; (all data is aggregated per zone)
Result: Vehicle distribution over the zones
1  #Check if there is room for proactive relocations;
2  if sum of Number of requests in SA < sum of Number of vehicles in SA then
3      #Generate vehicle distribution in proportion to the estimated demand;
4      Factor = sum of Number of vehicles in SA / sum of Estimated demand in SA;
5      for zone in zones do
6          vehicleDistribution(zone) = Estimated demand * Factor;
7      end
8      round vehicleDistribution per zone with the largest remainder method;
9      #Check if number of requests for a zone is higher than vehicleDistribution;
10     while Number of requests > vehicleDistribution for one of the zones do
11         for zone in zones do
12             if Number of requests > vehicleDistribution then
13                 set vehicleDistribution(zone) to Number of requests;
14                 add zone to list fixedZones
15         end
16         #Generate vehicle distribution again for the unfixed zones;
17         Factor = (sum of Number of vehicles in SA - vehicleDistribution(fixedZones)) /
            Estimated demand(flexibleZones);
18         for zone in zones do
19             vehicleDistribution(zone) = Estimated demand * Factor;
20         end
21         round vehicleDistribution per zone with the largest remainder method;
22     end
23     return vehicleDistribution;
```

In Algorithm 1, the pseudocode for determining the optimal vehicle distribution of a particular target period is shown. As previously explained, the aim is to balance the number of vehicles with the estimated demand over the zones before the target period begins. Note, however, that proactive relocations are only executed when there is unused capacity of vehicles and operators. Priority will always be given to the bookings that are already made (i.e. reactive relocations). Therefore, there are no proactive relocations proposed if there are already more requests in the SA for the target period than vehicles in the SA at the moment that the relocation strategy is executed. As one can see in the pseudocode, this requirement is checked in *line 2*. It is common to have less vehicles in the SA at the moment that the proactive relocation strategy is executed than the estimated demand in the SA for the target period. This is a consequence of the 3-hours target period since vehicles can arrive in the SA during the target period and vehicles may be dispatched multiple times in the target period. The algorithm makes sure that the vehicles are distributed over the different zones in proportion to the estimated demand per zone. To do this, a factor is calculated which is equal to the number of vehicles in the SA divided by the estimated demand in the SA, as can be seen in *line 4* of the pseudocode. This factor is multiplied with the estimated demand of each zone to derive the vehicle distribution over the zones, as can be seen in *line 6* of the pseudocode. Because of this, the number of vehicles in a zone is at least equal to the zone's share in estimated demand times the number of vehicles in the SA. Since it is not possible to assign a part of a vehicle to a zone the vehicle distribution per zone is rounded with the largest remainder method as can be seen in *line 8* of the pseudocode. In *line 10* it is checked that the minimum number of vehicles assigned per zone is at least equal to the number of requests in that zone since priority is given to the reactive relocations. As a result, the optimal vehicle distribution over the zones is provided.

7.1.1 Oversupplied and undersupplied zones

If the current vehicle distribution in a zone deviates from the optimal vehicle distribution, the zone is labelled as oversupplied or undersupplied. In Table 9, an example is provided for the same target period as used in Table 8. It can be observed that zone B and zone E are oversupplied with one and two vehicle(s), respectively. Zone A is undersupplied with three vehicles and zone D and zone E are already balanced.

Zone	Vehicles	Optimal vehicle distribution	Oversupplied / undersupplied
A	3	6	-3
B	3	2	+1
C	1	1	0
D	8	8	0
E	5	3	+2

Table 9: Overview of oversupplied and undersupplied zones

It can happen that an undersupplied zone is (partly) undersupplied through bookings that are made in that zone. In Table 10, an example is provided for two fictional zones X and Y. The number of vehicles and optimal vehicle distribution in both zones is the same. However, there is one request in zone X, whether there are five requests in zone Y. Since the requests will be served by the reactive relocation strategy, zone Y is undersupplied with only one vehicle while zone X is undersupplied with three vehicles. Therefore, the total number of surplus may be higher than the total number of shortage of all zones in the SA. In that case, the proactive relocation strategy has more choice for picking a vehicle to relocate. In the next section, these oversupplied and undersupplied zones will be detailed on individual vehicle level.

Zone	Requests	Vehicles	Optimal vehicle distribution	Oversupplied / undersupplied
X	1	3	6	-3
Y	5	3	6	-1

Table 10: Example of undersupplied case through requests

7.2 Rule-based method on individual vehicle level

This section presents a rule-based method to translate the over- and undersupplied zones on individual vehicle level. In Algorithm 2, pseudocode is provided to explain this rule-based method. The ultimate goal is to determine which vehicles to take away from oversupplied zones and where to place them in the undersupplied zones. Intuitively, vehicles should be taken away from the hexagons of the oversupplied zones that have the lowest booking frequency and brought to the hexagons of the undersupplied zones that have the highest booking frequency. These booking frequencies are derived per target period to include temporal variability (e.g. some hexagons are more likely to have demand during the morning than the evening). A set of drop-off hexagons is generated for each undersupplied zone as can be seen in *lines 2-6* of the pseudocode. The vehicle shortage is distributed in proportion to the historical booking frequency over the hexagons. The set of pick-up vehicles is generated for each oversupplied zone as can be seen in *lines 8-13* of the pseudocode. First, vehicles that are not charging and have low battery are selected, as can be seen in *line 11* of the pseudocode. After consultation with the personnel of Amber it is decided to set this threshold at a battery level of 40%. As we want to decrease the marginal costs of proactive relocations it makes more sense to proactive relocate cars that have to be relocated to a charging point anyway. Then, the remaining number of pick-up vehicles are selected in proportion to the historical booking frequency over the hexagons.

Algorithm 2: Pseudocode inter-zone relocations on individual vehicle level

```
   Data: System information on hexagon level; Historical booking information per target period
         on hexagon level; Oversupplied zones; Undersupplied zones
   Result: List of proposed pick-up vehicles; List of proposed drop-off hexagons
 1 #Generate set of proposed drop-off hexagons for each undersupplied zone;
 2 for zone in Undersupplied zones do
 3 |   Create list of hexagons in zone and sort descending on booking frequency for target period;
 4 |   Distribute vehicles in proportion to the historical booking frequency (descending) over the
 |     hexagons;
 5 |   Add selected hexagons with number of assigned vehicles to list of proposed drop-off
 |     hexagons
 6 end
 7 #Generate set of proposed pick-up vehicles for each oversupplied zone;
 8 for zone in Oversupplied zones do
 9 |   Create list of hexagons with available vehicles in zone and sort ascending on booking
 |     frequency for target period;
10 |   #Select first vehicles with low battery level that are not charging;
11 |   if batteryLevel < 40% and charging == False for available vehicles then
12 |   |   Add vehicle to list of proposed pick-up vehicles unless number of pick-up vehicles in
 |   |     zone is reached
13 |   Distribute remaining number of pick-up vehicles in proportion to the historical booking
 |     frequency (ascending) over the hexagons;
14 end
15 return list of proposed pick-up vehicles and list of proposed drop-off hexagons;
```

In Table 11, an example is provided to select the drop-off hexagons in the undersupplied zone A. As determined in Section 7.1, zone A is undersupplied with three vehicles for the arbitrary target period used as an example. In Table 11, the first five hexagons of zone A can be seen. The hexagons are ranked descending on their historical booking frequency. The current vehicles available in the hexagons can be seen as well. As we want to distribute the three vehicles over the hexagons in proportion to the historical booking frequency, the ratio in booking frequency between different hexagons is checked. For example, the ratio between hexagon 317 and hexagon 337 is $395/192 = 2.06$. Therefore, two vehicles will be placed in hexagon 317 before we assign a vehicle to hexagon 337. With this reasoning, the three vehicles that need to be distributed over the hexagons are assigned as follows: one vehicle will be assigned to hexagon 317, hexagon 337 and hexagon 296.

Zone A	**Historical booking frequency**	**Vehicles available**
Hexagon 317	395	1
Hexagon 337	192	0
Hexagon 297	186	1
Hexagon 296	141	0
Hexagon 318	52	1
...	...	...

Table 11: Example of undersupplied zone A in target period

As determined in Section 7.1, there are two oversupplied zones in the target period that is used as an example. Table 12 provides a list of all available vehicles in the oversupplied zone E. Zone E has an oversupply of two vehicles. The vehicles are ranked ascending on the historical booking frequency of the hexagon in which they are placed. As defined in Algorithm 2, first it is checked if vehicles can be selected that are not charging and have a battery level below 40%. Afterwards, the vehicles are selected based on the lowest historical booking frequency. With this reasoning, the two vehicles that need to be relocated are the vehicles in hexagon 477 and 418. In Table 13, the available vehicles in the oversupplied zone B are shown. Zone B had an oversupply of one vehicle and therefore the vehicle in hexagon 322 is selected as pick-up vehicle.

Zone E	**Historical booking frequency**	**Battery level**	**Charging**
Hexagon 477	13	74%	False
Hexagon 418	21	75%	False
Hexagon 434	45	61%	False
Hexagon 417	48	39%	True
Hexagon 459	53	61%	False

Table 12: Example of oversupplied zone E in target period

Zone B	**Historical booking frequency**	**Battery level**	**Charging**
Hexagon 322	0	100%	True
Hexagon 341	6	85%	False
Hexagon 408	6	41%	False

Table 13: Example of oversupplied zone B in target period

In Figure 19, a visual result of the over- and undersupplied hexagons in the target period is provided. The green hexagons are the oversupplied hexagons in the target period and the red hexagons are the undersupplied hexagons in the target period. In the next section is explained how these proposed proactive relocations can be integrated into the reactive relocation model Amber is using.

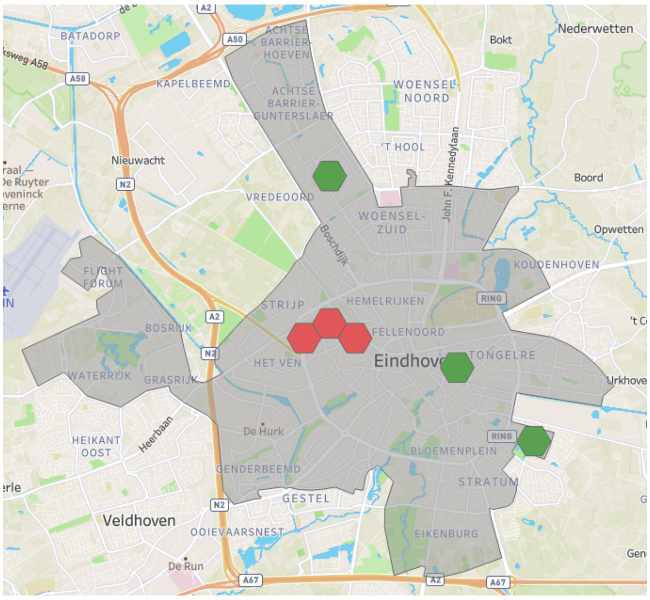


Figure 19: Visual result of over- and undersupplied hexagons in target period

7.3 Relocation model

This section provides an explanation of the relocation model Amber is currently using and explains how the proactive relocation strategy is integrated into the reactive relocation model of Amber. As previously discussed, Amber does not have separate operators to execute reactive and proactive relocations. Therefore, the 'uncertain' proactive relocations have to be integrated into the tour of the 'certain' reactive relocations. Priority will always be given to reactive relocations. Therefore, proactive relocations are only executed when there is unused capacity of operators and vehicles.

7.3.1 Reactive relocation strategy

To provide a better understanding of the reactive relocation strategy Amber is currently using, a description of the relocation strategy is given. For confidentiality reasons, the reactive relocation strategy is not described in full details. However, the description of the reactive relocation strategy should provide enough insights to understand the integration of the proactive relocation strategy.

The reactive relocation model solves a routing problem to deliver cars on time to the request locations by one or multiple operators. Costs are assigned to the movements of operators and penalties are given to requests that are not planned. This results in a linear programming (LP) model that minimizes the total costs. The penalty for requests that are not planned in the route depends on the estimated departure time of the trip. Trips that start sooner will have a higher penalty than trips that start later. The penalty for not planning a request with a departure time in less than 30 minutes is set to an infinite value and therefore the model gives an error when it cannot serve all requests on time. The operators use folding bikes to move between the drop-off location of one particular car to the pick-up location of the next car. More weight (i.e. in terms of cost) is assigned to the cycling part than the driving part as cycling is more tiresome and takes more time than the driving part.

In practice, this routing problem is solved online. The input information used for the reactive relocation strategy is updated every few minutes and the routing problem is solved again if the input information is changed. For example, the input information may change because a new request is made or a car is returned from another booking. If a new request is made, it will always have a departure time of three hours at the earliest since it has to satisfy the earlier defined SLA. It cannot happen that a car that is planned to use for a request is taken by an instant order as the reactive relocation model blocks the cars it is planning to use. Since a simulation framework is out of the scope of this thesis and Amber does not have one for their relocation model, it is decided to treat the relocation model as an offline model. The relocation tour generated as output by the relocation model is assumed to remain the same and executed by the operators.

7.3.2 Proactive relocation strategy

In Section 7.2, a list of pick-up vehicles and drop-off spots is derived. The transportation of a pick-up vehicle to all the drop-off spots will result in the optimal vehicle distribution over the zones based on the output of the forecasting model. However, not all proactive relocations have to be executed since proactive relocations are only executed when there is capacity of operators and vehicles left.

The drop-off spots selected in Section 7.2 are provided as request locations in the relocation model. As previously explained, the aim of a static relocation strategy is to balance the vehicles over the zones before the target period begins. Therefore, the drop-off spots have a fictional departure time that is set to the start of the target period. The relocation model cannot select all available vehicles for these drop-off spots but only the pick-up vehicles selected in Section 7.2 as part of the proactive relocation strategy. Because of this, it is not a matter of serving the 'request' but moving the car from the oversupplied zone to the undersupplied zone. Since the pick-up vehicles and drop-off spots are not linked to each other, each drop-off spot can be served by all pick-up vehicles, and it is up to the reactive relocation model to optimize this choice in terms of costs.

To ensure that priority will always be given to the reactive relocations, lower penalties are given for the proactive relocations. First of all, there is no penalty for not executing proactive relocations as is the case for the reactive ones. Therefore, it is not required for the relocation model to execute all the proactive relocations. In addition, it is not obligated for a proactive relocation to be executed on time and it is allowed to be one hour late. Penalties for not planning the proactive relocations are set based on empirical analysis.

The proactive relocation strategy is executed one hour before each target period begins. This choice is based on the duration of the peaks and the planning schedule of the relocation model. Because the relocation model is planning four hours in advance and the duration of the peaks is three hours, the whole peak period is included in the planning of the relocation model when the proactive relocation strategy is executed one hour before the target period begins. The FFCS system of Eindhoven is down at night from 19:00 - 7:00h, the hours during this time window are therefore excluded from the previous defined SLA. For example, a request with a departure time at 8:00h has to be made at 17:00h the previous day to satisfy the SLA since the SLA is set to three hours. With this reasoning, the execution time of the proactive relocation strategy for the different peaks is as follows:

- 9:00h, single weekend peak (10-13 a.m.)
- 18:00h the previous day, morning peak for weekdays (6-9 a.m.)
- 14:00h, afternoon peak for weekdays (15-18 p.m.)

In the next section, a scenario analysis is provided in which the integration of the proactive relocations is discussed per scenario.

7.4 Scenario analysis proactive relocations

This section presents a scenario analysis to provide insights in how the proactive relocations are integrated into the reactive relocation model. One week of data is used for this scenario analysis which comes down to twelve peak moments. These peak moments are discussed individually and visual results are shown for the reactive relocation model without and with the inclusion of the proactive relocation strategy.

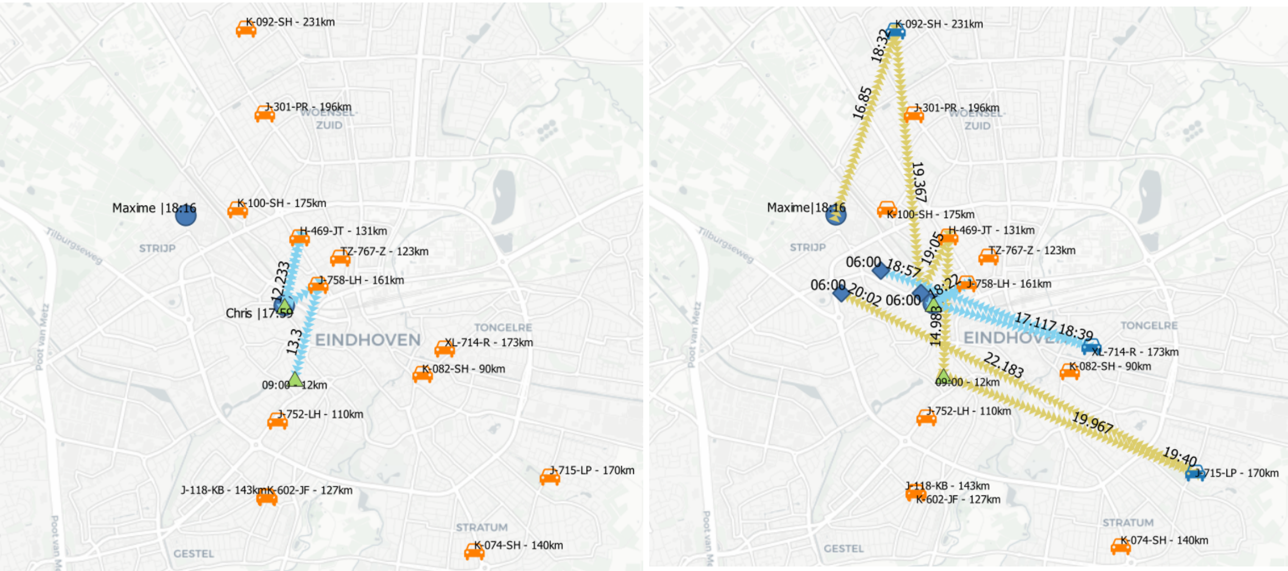
In Table 14, an overview is provided of the peaks that are discussed in the scenario analysis. As previously discussed in Section 7.1, there is no room for proactive relocations when there are more requests than vehicles in the SA at the moment the proactive relocation strategy is executed. Therefore, it can be concluded that there is no room for proactive relocations in the afternoon of May 25 and May 28. In Section 7.1.1 is explained that zones are labelled as oversupplied or undersupplied if the current vehicle distribution in a zone deviates from the optimal vehicle distribution. Note, however, that it is possible to have all zones balanced and that the current vehicle distribution equals the optimal vehicle distribution. In that case, there are no proactive relocations proposed. In Table 14, it can be observed whether the vehicle distribution in the peaks is balanced or unbalanced. Proactive relocations are proposed in the case the vehicle distribution is unbalanced. So, proactive relocations are proposed for seven of the twelve peaks. These seven scenarios are discussed individually to understand how and if the proposed proactive relocations are included in the reactive relocation model.

Peak number	**Requests**	**Vehicles**	**Room for proactive relocations**	**Vehicle distribution**
24/05 morning	3	20	True	unbalanced
24/05 afternoon	7	20	True	unbalanced
25/05 morning	14	32	True	unbalanced
25/05 afternoon	23	18	False	-
26/05 morning	22	23	True	balanced
26/05 afternoon	19	20	True	balanced
27/05 morning	14	19	True	unbalanced
27/05 afternoon	19	24	True	unbalanced
28/05 morning	14	27	True	unbalanced
28/05 afternoon	29	19	False	-
29/05 weekend	40	42	True	unbalanced
30/05 weekend	29	28	False	-

Table 14: Overview of scenarios

Morning peak on May 24

The morning peak on May 24 is the first period discussed. The output of the reactive relocation model is shown in Figure 20a. It can be observed that two operators are working, Chris and Maxime. In the solution obtained by the reactive relocation strategy, Chris *'blue line'* handles both requests and Maxime is idle. Note, in Table 14, it was observed that there are three requests in the morning peak on May 24. One of the requests already has a car assigned and can therefore not be seen in Figure 20a. Clearly, there is unused capacity in this case. The inclusion of the proposed proactive relocations can be observed in Figure 20b.



(a) Reactive relocations

(b) Proactive relocations integrated

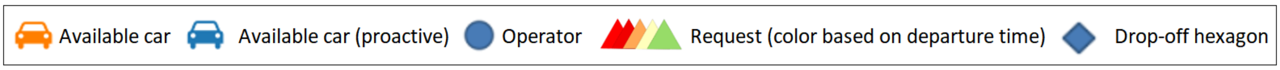


Figure 20: Morning peak of 24 May

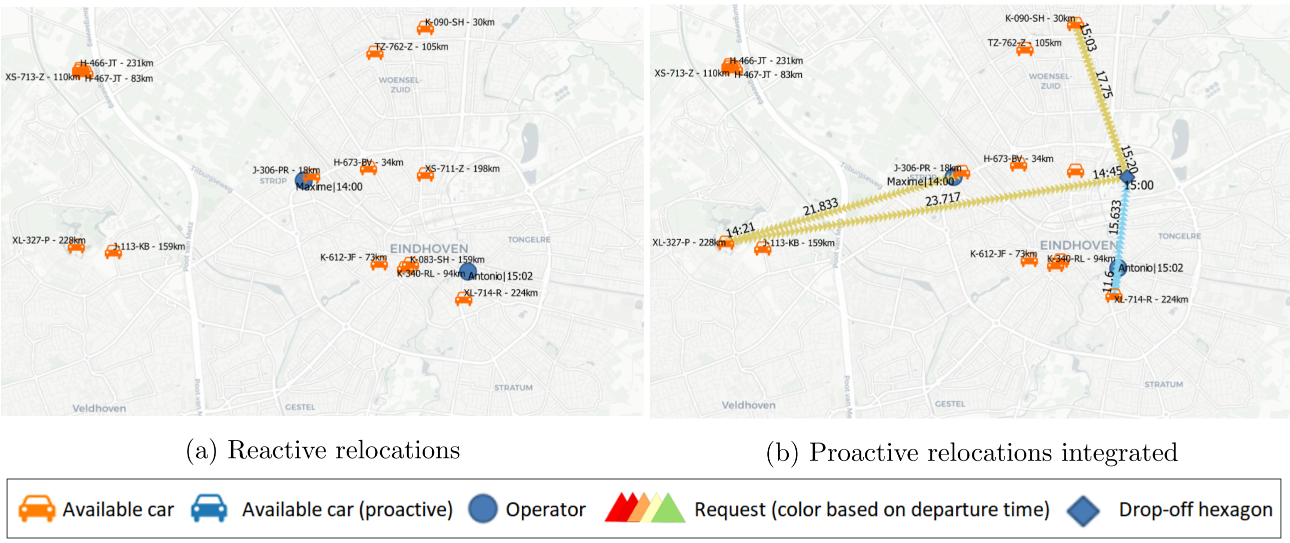
Three proactive relocations are proposed for this period. The drop-off hexagons can be observed as blue diamonds and the pick-up vehicles that are selected for these proactive relocations are coloured blue. All three drop-off hexagons are served by a pick-up vehicle and thus all three proactive relocations have been executed. Since all three proactive relocations are executed, the vehicle distribution over the five zones is as determined by Algorithm 1. Then, with the use of Algorithm 2 logical pick-up vehicles and drop-off hexagons are selected. As explained, vehicles should be taken away from the hexagons of the oversupplied zones that have the lowest booking frequency and brought to the hexagons of the undersupplied zones that have the highest booking frequency. The following proactive relocations are executed:

- K-092-SH from hexagon 322 (frequency of 0) to hexagon 337 (frequency of 192)
- K-604-JF from hexagon 447 (frequency of 13) to hexagon 296 (frequency of 141)
- XL-714-R from hexagon 418 (frequency of 21) to hexagon 357 (frequency of 395)

As can be noticed, the vehicles are taken away from low demand hexagons and brought to high demand hexagons. The execution of these three proactive relocations takes an additional time of 113 minutes, with equals 37.7 minutes per proactive relocation. In comparison to the 25.5 minutes per reactive relocation in this period, the proactive relocations cost on average more than ten additional minutes to execute than the reactive ones. Note, however, that a car that is selected for a proactive relocation is not the closest car to the drop-off hexagon but a car that is moved from an oversupplied zone to an undersupplied zone. Therefore, it makes sense that the execution of these proactive relocations takes a longer time. Besides, be aware that the operator is paid anyway and the car in a low demand hexagon will probably not be booked otherwise.

Afternoon peak on May 24

The second period discussed is the afternoon peak on May 24. The output of the reactive relocation model is shown in Figure 21a. It can be observed that both operators are idle since there are no unassigned requests.



(a) Reactive relocations

(b) Proactive relocations integrated

Figure 21: Afternoon peak of 24 May

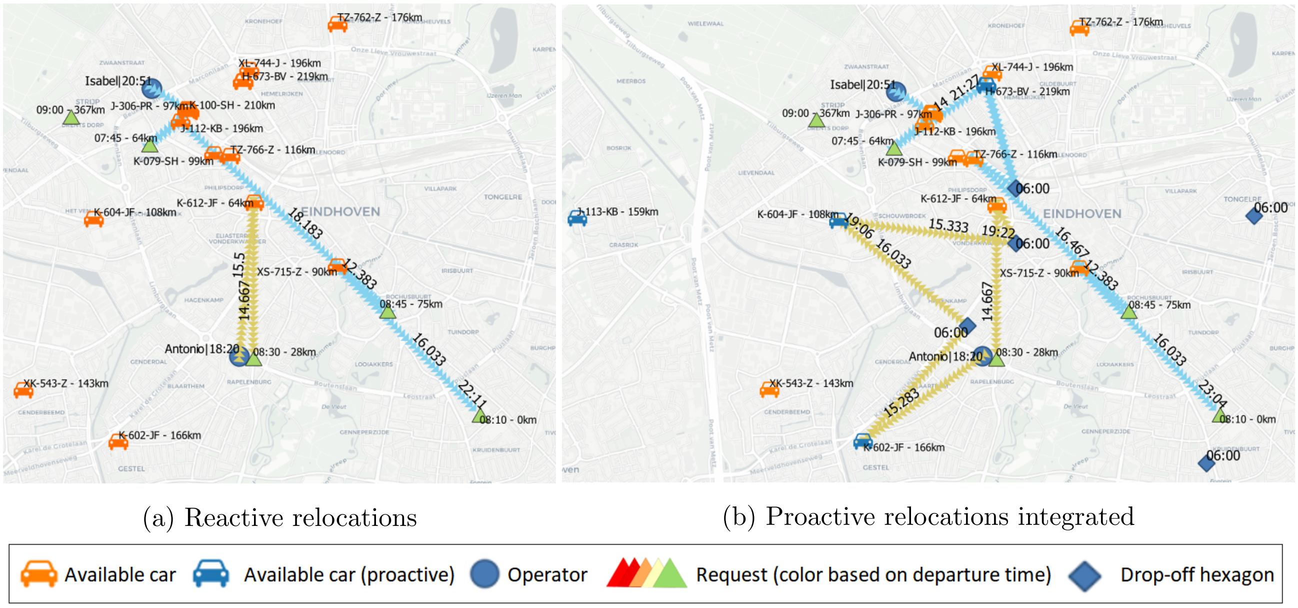
Three proactive relocations are proposed for this period and all three proactive relocations have been executed. The following proactive relocations are executed:

- K-090-SH from hexagon 383 (frequency of 27) to hexagon 420 (frequency of 126)
- XL-327-P from hexagon 396 (frequency of 20) to hexagon 420 (frequency of 126)
- XL-714-R from hexagon 131 (frequency of 3) to hexagon 420 (frequency of 126)

All three vehicles are brought to the same drop-off hexagon. Hexagon 420 covers the Eindhoven University of Technology and is the most popular hexagon for the afternoon peak in zone E. As previously explained in Algorithm 2, vehicles are distributed in proportion to the historical booking frequency (descending) over the hexagons. Therefore, all three vehicles are allocated to hexagon 420.

Morning peak on May 25

The morning peak on May 25 is the next period discussed. The output of the reactive relocation model is shown in Figure 22a. It can be observed that again two operators are working, Isabel and Antonio.



(a) Reactive relocations

(b) Proactive relocations integrated

Figure 22: Morning peak of 25 May

Isabel *'blue line'* handles three requests for which she travels from one side to the other side of the ring of Eindhoven. Antonio *'yellow line'* handles one request. There is a request left to Isabel which is not handled by the reactive relocation strategy. This is because the reactive strategy is currently only serving requests for which a car can be selected with a higher range than the expected travel distance of the request. As can be seen in Figure 22a, there is no car with a range of more than 367km and therefore this request is not served. Amber is aware of this bug and it will be solved in a coming update of the reactive relocation strategy.

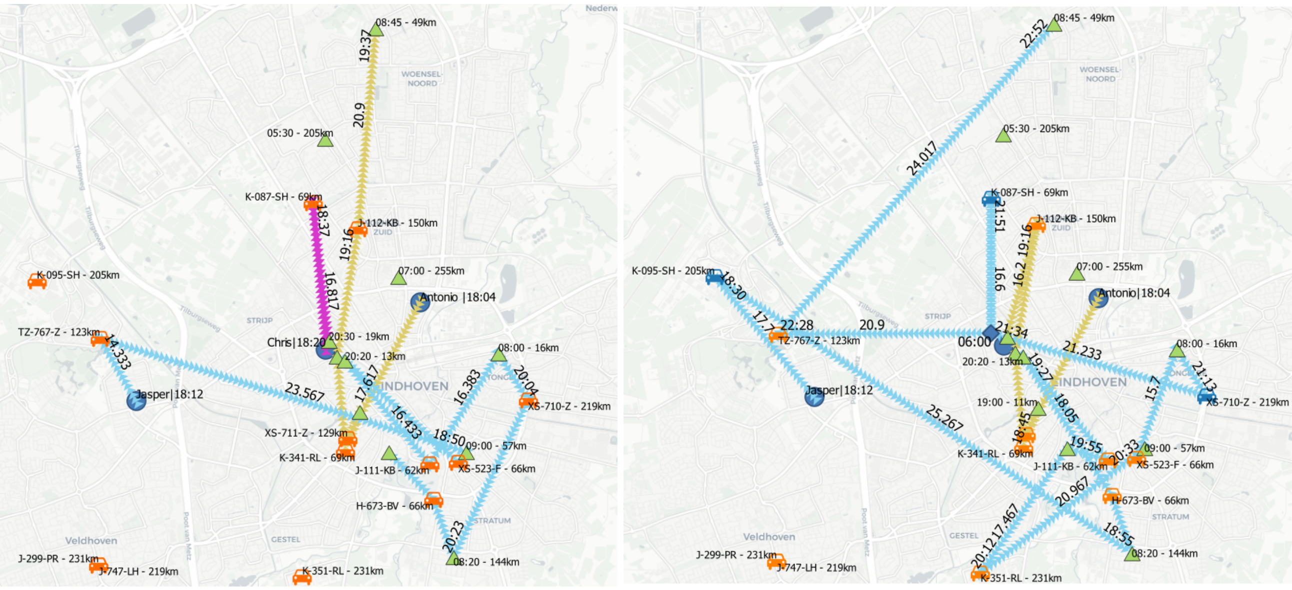
The inclusion of the proposed proactive relocations can be observed in Figure 22b. Antonio handles two proactive relocations for which he takes a vehicle from outside the ring of Eindhoven and transports it to a drop-off hexagon within the ring of Eindhoven. After handling both proactive relocations he handles the request he was also handling in the reactive relocation strategy. It is not obligated to execute the reactive relocations first as long as they are executed on time. In this case, the costs are minimized if the proactive relocations are executed first. As previously explained Isabel has to travel from one side to the other side of the ring of Eindhoven to handle the requests. With a rather small extension to her reactive relocation route, she can serve two proactive relocations. It is hard to see in Figure 22b, but Isabel moves two cars from the same spot to the same drop-off hexagon. Therefore the following proactive relocations are executed in this case:

- K-602-JF from hexagon 291 (frequency of 5) to hexagon 334 (frequency of 109)
- K-604-JF from hexagon 274 (frequency of 4) to hexagon 356 (frequency of 82)
- H-673-BV & K-351-RL from hexagon 338 (frequency of 42) to hexagon 357 (frequency of 315)

Note that two drop-off hexagons are not handled by the proactive relocation strategy. The execution of these proactive relocations apparently cost too much time and is therefore considered not worth it. The proactive relocations that were relatively closest to the reactive relocation tour are executed which makes sense as the marginal costs of proactive relocations is minimized in this way. The average additional time per proactive relocation is 27.5 minutes in this case.

Morning peak on May 27

The output of the reactive relocation strategy for the morning peak on May 27 is shown in Figure 24a. It can be observed that three operators are working. Furthermore, it can be seen that two requests are not handled by the operators since the expected driving distance exceeds the range of the available cars. The inclusion of the proposed proactive relocations can be observed in Figure 24b. It is interesting to observe that the relocation model is now solved with the use of two operators instead of three. Apparently, with the inclusion of the proactive relocations, the costs are minimized if two operators rather than three operators are used. In some scenarios an operator can be sent home and then it makes sense to execute the relocation tour with two instead of three operators as it will lead to minimal costs. Note, however, that new requests can be expected and therefore an additional operator might be of help. It would be a good idea to add an additional penalty in the relocation model Amber is using whenever an operator is idle.



(a) Reactive relocations (b) Proactive relocations integrated

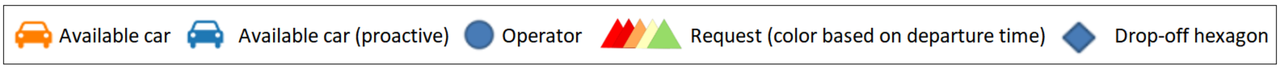


Figure 23: Morning peak of 27 May

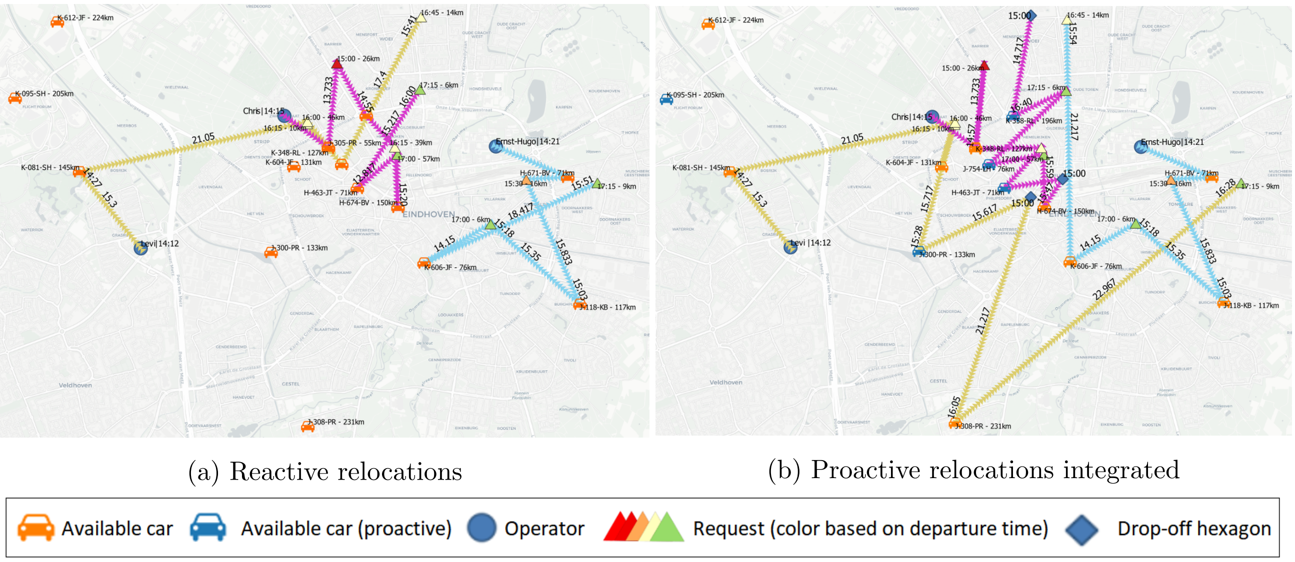
Jasper *'blue line'* transports two vehicles to the same drop-off hexagon since there is a shortage of two vehicles in this drop-off hexagon. Therefore, the following proactive relocations are executed in this case:

- XS-710-Z from hexagon 479 (frequency of 4) to hexagon 317 (frequency of 395)
- K-087-SH from hexagon 321 (frequency of 1) to hexagon 317 (frequency of 395)

The average additional time per proactive relocation is 41.5 minutes in this case. Which is quite high in comparison with the earlier mentioned additional times in other scenarios. It can also be observed in Figure 24b that the distances from the blue coloured cars to the drop-off hexagon are not that long. The additional time is higher in this scenario since the selected cars for the proactive relocations were used for reactive relocations in the relocation tour of the reactive relocation model as can be observed in Figure 24a. The relocation model selects two other vehicles for the reactive relocations through the inclusion of the proactive relocations. These are cars, K-095-SH and K-351-RL. Since the cars in the centre of the SA are already in use the relocation model has to pick two cars from more low demand zones.

Afternoon peak on May 27

The afternoon peak on May 27 is the next period discussed. The output of the reactive relocation model is shown in Figure 24a and the inclusion of the proposed proactive relocations can be observed in Figure 24b.



(a) Reactive relocations

(b) Proactive relocations integrated

Figure 24: Afternoon peak of 27 May

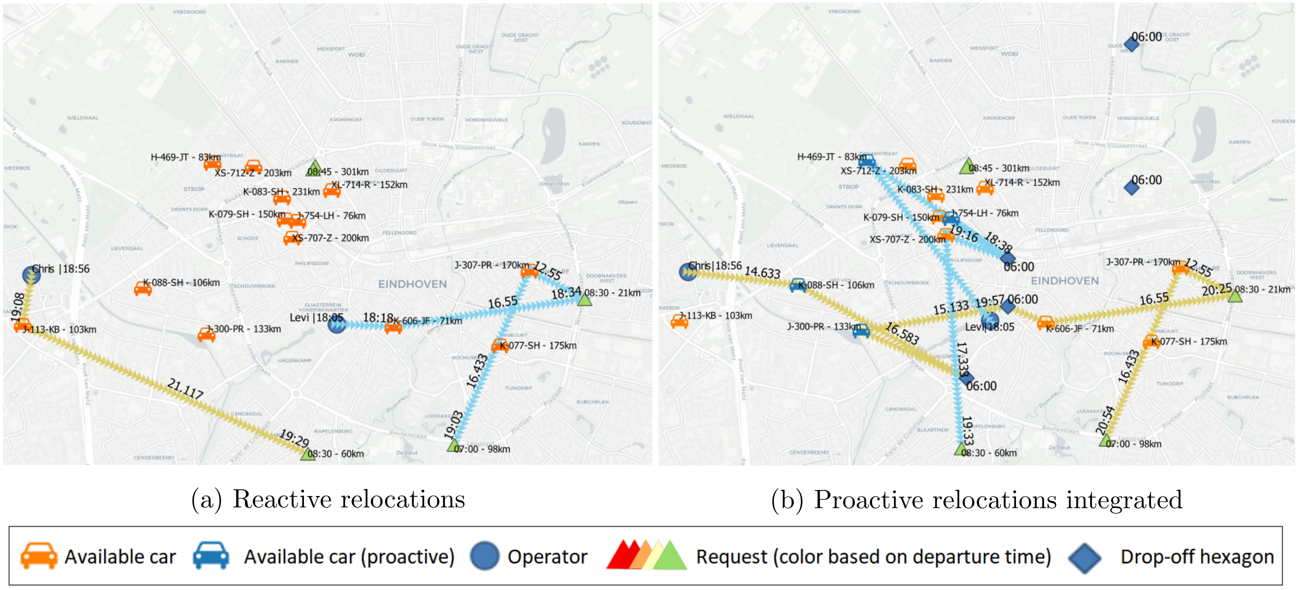
Three proactive relocations are proposed and all three are planned by the relocation model. Therefore, the following proactive relocations are executed in this case:

- J-300-PR from hexagon 294 (frequency of 14) to hexagon 357 (frequency of 297)
- H-463-JT from hexagon 337 (frequency of 197) to hexagon 378 (frequency of 67)
- K-358-RL from hexagon 339 (frequency of 45) to hexagon 362 (frequency of 44)

It should be noted that two of these three proposed proactive relocations result in a decrease of frequency from one hexagon to the other. Car H-463-JT is selected as pick-up vehicle due to the low battery level of the car. As previously explained in Algorithm 2, vehicles that are not charging and have a battery level below 40% are selected first since these vehicles have to be relocated to a charging point anyway. In this specific case, hexagon 337 is the outer hexagon of a zone and therefore it is possible that a vehicle relocation of a small distance is proposed. In addition, car K-358-RL is selected as pick-up vehicle. In this case, zone A is the oversupplied zone and zone B is the undersupplied zone. Note, however, that the demand intensity in zone A is higher than the demand intensity in zone B as was observed in Figure 14. Therefore, it can happen that the historical booking frequency of a low demand hexagon in a high demand zone is higher than a high demand hexagon in a low demand zone.

Morning peak on May 28

The morning peak on May 28 is the next period that is discussed. The output of the reactive relocation model is shown in Figure 25a and the inclusion of the proposed proactive relocations can be observed in Figure 25b.



(a) Reactive relocations

(b) Proactive relocations integrated

Figure 25: Morning peak of 28 May

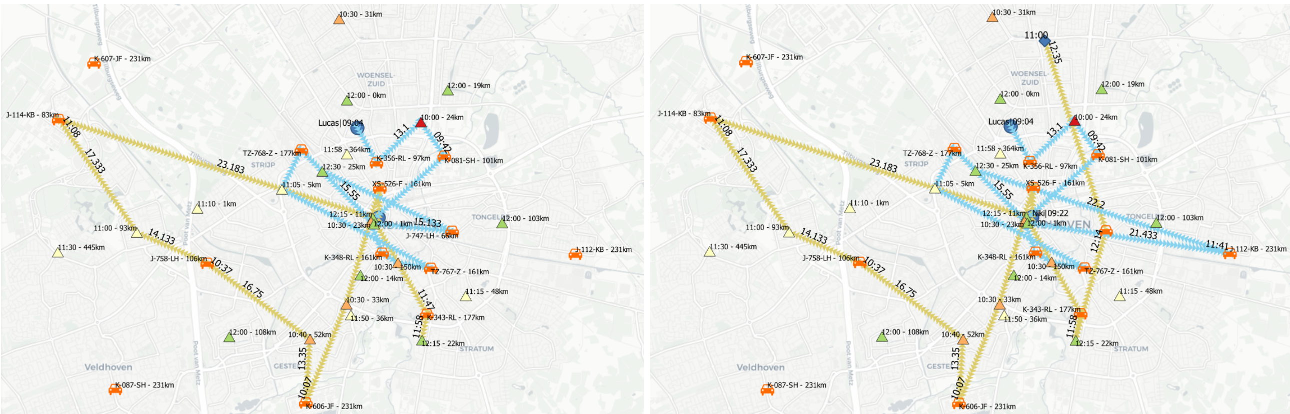
Six proactive relocations are proposed in this period of which four are planned by the relocation model. Both operators handle two proactive relocations. Chris *yellow line* executes the proactive relocations while travelling from the left to the right side of the SA, where after the execution of the proactive relocations he handles two reactive relocations. Levi *blue line* brings two cars to the same drop-off hexagon. Therefore, the following proactive relocations are executed in this case:

- K-088-SH from hexagon 254 (frequency of 4) to hexagon 334 (frequency of 109)
- J-300-PR from hexagon 294 (frequency of 2) to hexagon 356 (frequency of 82)
- H-469-JT from hexagon 277 (frequency of 25) to hexagon 357 (frequency of 315)
- J-754-LH from hexagon 337 (frequency of 192) to hexagon 357 (frequency of 315)

Two proactive relocations are not planned by the relocation model, the execution of these proactive relocations apparently costs too much time and is therefore considered not worth it. The proactive relocations that were closest to the requests are executed. The average additional time per proactive relocation is 27.5 minutes in this case.

Weekend peak on May 29

The last period discussed is the weekend peak on May 29. The output of the reactive relocation model is shown in Figure 26a. Two operators are working, Niki and Lucas. Although both operators serve multiple requests it can be observed that numerous requests are not included in the planning. This is because the operators cannot serve all requests on time. As previously explained penalties are given to requests that are not planned and the penalty for not planning a request with a departure time in less than 30 minutes is unlimited. Since there are no requests with a departure time in less than 30 minutes, the relocation model gives a solution. Note, however, that it is not possible to serve all requests on time with two operators in this case. It should be a nice extension for the relocation model of Amber to notice these insoluble cases in an earlier phase. The inclusion of the proactive relocations can be observed in Figure 26b. One proactive relocation is proposed and this one is planned by the relocation model. Note, that priority should be given to the unplanned reactive relocations. However, it is allowed to arrive too late in the drop-off hexagon for a proactive relocation and therefore, the proactive relocation is planned. In practice, this proactive relocation will not be executed as the model will give an error for the reactive relocations.



(a) Reactive relocations (b) Proactive relocations integrated

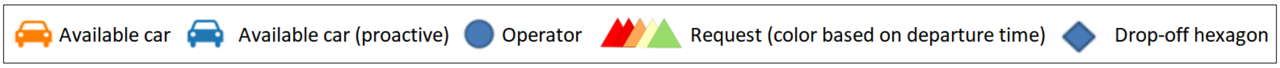


Figure 26: Weekend peak of 29 May

7.5 Conclusions on the proactive relocation strategy

This section summarizes and concludes on the proactive relocation strategy. Thereby, the section formulates an answer to the third research question.

First of all, an optimization model on zone level and a rule-based method on individual vehicle level have been implemented. The optimization model derives an optimal vehicle distribution over the zones for a certain target period. This is based on the output of the forecasting model and real-life information of the FFCS system. Then, the optimal vehicle distribution is compared with the current vehicle distribution to label zones as oversupplied or undersupplied. The rule-based method translates the over- and undersupplied zones on individual vehicle level. The aim of this rule-based method is to determine which vehicles to take away from oversupplied zones and where to place them in the undersupplied zones. Intuitively, vehicles should be taken away from the hexagons of the oversupplied zones that have the lowest booking frequency and brought to the hexagons of the undersupplied zones that have the highest booking frequency. In addition, vehicles that are not charging and have low battery are selected first since it makes more sense to proactive relocate cars that have to be relocated to a charging point anyway. This results in a set of pick-up vehicles and drop-off hexagons.

The drop-off hexagons are provided as request locations in the relocation model with a fictional departure time that is set to the start of the target period. The relocation model can select one of the pick-up vehicles to serve the drop-off hexagons. A scenario analysis is executed to provide insights in how the proactive relocations are integrated in the reactive relocation model. One week of data is used for this scenario anlaysis which comes down to twelve peak moments. In five scenarios there was either no room for proactive relocations (i.e. less vehicles than requests) or the vehicle distribution was already balanced (i.e. current vehicle distribution equals optimal vehicle distribution). In seven of the twelve scenarios, however, proactive relocations were proposed. In one of these seven scenarios the proposed proactive relocations was not executed as previously explained. Therefore there were proactive relocations executed in six out of the twelve scenarios. Table 15 presents the percentage of cars distributed across the zones in the desired car distribution without and with the inclusion of proactive relocations. For each zone, the number of vehicle surplus or vehicle shortage is computed and the percentage of surplus and shortage of the total number of vehicles is listed in Table 15.

Peak	No proactive relocation	Proactive relocation
24/05 morning	85%	100%
24/05 afternoon	85%	100%
25/05 morning	81%	94%
27/05 morning	89%	100%
27/05 afternoon	88%	100%
28/05 morning	78%	93%

Table 15: Improvement in balance percentage through proactive relocation strategy

It can be observed that in four of the six cases complete rebalancing was achieved and that the average increase of cars that are distributed across the zones in the desired distribution is 13.5%. On average there were 3.8 proactive relocations proposed per scenario from which 3.2 proactive relocations were planned. The average historical booking frequency of the hexagons from which the pick-up vehicles were taken is 30.7 which is equal to 0.29 bookings per peak period. In comparison, the average historical booking frequency of the drop-off hexagons was 207.7 which is equal to 1.94 bookings per peak period. Furthermore, the average additional execution time of a proactive relocation is 35 minutes. It should be noted that demand can emerge through the correct execution of proactive relocations. Therefore, it is hard to quantify the added value from a economic perspective without a real-life testing phase or the use of a simulation framework. Still, we proved that with the help of a proactive relocation strategy the FFCS system is more prepared for the peak period. In the next Chapter, final conclusions on this thesis and further research suggestions on this topic are provided.

8 Conclusion and further research

The objective of this thesis was to design a proactive relocation strategy for the free-floating car sharing system of Amber in Eindhoven through the integration of proactive relocations in their existing reactive relocation model by using the unused capacity. This chapter briefly summarizes the main findings of this thesis in Section 8.1, after which recommendations for further research are discussed in Section 8.2.

8.1 Conclusions

We approached the development of a proactive relocation strategy for FFCS systems by integrating the proactive relocations in a reactive relocation model. In this way, we ensure that proactive relocations were only executed when there was unused capacity and the marginal costs of proactive relocations was minimized. In comparison, existing studies, aiming to design a proactive relocation strategy for FFCS systems, design a standalone proactive relocation model with the aim to reach the forecasted vehicle distribution for a single target period. This thesis provides a general answer to the main research question:

How can a proactive vehicle relocation strategy in FFCS systems be used to improve the operational aspect of the car sharing service?

To estimate the demand in a FFCS system, the FFCS system was transformed to a station-based system by virtually dividing the service area into smaller zones. The zone categorization method uses zones which consists of a set of clustered hexagons. An ARIMA model was derived to estimate the short-term demand over the zones. In this way we made sure that there was sufficient demand in the zones to execute the ARIMA model. Then, a rule-based method was used that translates the over- and undersupplied zones on individual vehicle level and a list of pick-up vehicles and drop-off hexagons was derived. The transportation of a pick-up vehicle to all the drop-off spots results in the optimal vehicle distribution over the zones based on the output of the ARIMA model. However, not all proactive relocations have to be executed since proactive relocations were only executed when there was capacity of operators and vehicles left. The proposed proactive relocations for a target period were provided to the relocation model.

With a real-life scenario analysis, we were able to gain insights in the added value of the proactive relocation strategy. One week of data was analyzed. The peak moments were discussed individually and visual results of the relocation tour without and with the inclusion of the proactive relocation strategy were analyzed. First of all, we proved that with the help of a proactive relocation strategy the FFCS system was more prepared for the peak period. Furthermore, the scenario analysis proved that proactive relocations are only executed when there was unused capacity and that priority was always given to the reactive relocations. In addition, we showed that there was room to include the proactive relocations in the relocation model without deploying additional operators.

8.2 Further research suggestions

We suggest four directions for further research into this topic. First of all, the proactive relocation strategy is executed one time per peak period in this research. Instead of only using a proactive relocation strategy to be better prepared for the peak moments it can be used to be better prepared during the whole day. Therefore, additional periods over the day can be defined and used in the proactive relocation strategy. Thereby, proposed proactive relocations are based on the output of the forecasting model and real-life information of the FFCS system. Since the real-life information of the system changes, new proactive relocations could be proposed if the proactive relocation strategy is executed multiple times per peak period. In this way, the proactive relocation strategy acts more as an online decision making tool that planners can access any time to check the expected demand and suggested proactive relocations to balance the CS system.

Furthermore, service trips should be included in the relocation model since it makes more sense to proactive relocate cars that have to be relocated anyway. In this research we proved that additional tasks can be included in the relocation model by giving the additional task a lower penalty than the primary tasks (i.e. reactive relocations). Service trips such as the cleaning of cars but also the mandatory charging of cars can be included. In our developed proactive relocation strategy, cars with low battery level are selected first as pick-up vehicle in an oversupplied zone. Note, however, it can also be the case that a car with low battery level is not selected for charging since it is placed in a balanced or undersupplied zone.

The proactive relocation strategy developed in this research does not include the number of vehicles entering the zones during the target period. Since the errors of the forecasting model are not that accurate as a consequence of the low volume dataset we did not want to include additional variance by including an estimation of another parameter. However, the entering of vehicles during the target period might increase the vehicle surplus in a zone or decrease the vehicle shortage of a zone. Therefore, the inclusion of entering vehicles should be considered in future versions.

Lastly, a scenario analysis is executed to evaluate the proactive relocations. Note, however, that demand can emerge through the correct execution of proactive relocations. Therefore, the real added value of the proactive relocation strategy is hard to quantify in this scenario analysis. It would be a nice addition to develop a simulation framework that is able to realistically capture the dynamics in a FFCS system. In that way, the relocation model and future implementations can be easier analyzed and evaluated.

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Appendix

Model	Zones	RMSE	MAE	Average demand	SD
MA-50 (standard)	3	3.41	2.56	10.09	7.54
MA-10 (specific period)	3	3.72	2.70	10.09	7.54
MA-4 (work weekend)	3	3.57	2.62	10.09	7.54
MA-4 (period day)	3	3.64	2.75	10.09	7.54
MA-50 (standard)	4	2.91	2.13	7.57	6.14
MA-28 (specific period)	4	3.11	2.24	7.57	6.14
MA-4 (work weekend)	4	3.01	2.19	7.57	6.14
MA-4 (period day)	4	3.06	2.19	7.57	6.14
MA-50 (standard)	5	2.52	1.96	6.05	4.36
MA-15 (specific period)	5	2.62	2.00	6.05	4.36
MA-8 (work weekend)	5	2.65	2.03	6.05	4.36
MA-4 (period day)	5	2.72	2.08	6.05	4.36
MA-50 (standard)	6	2.31	1.75	5.04	4.02
MA-29 (specific period)	6	2.41	1.78	5.04	4.02
MA-6 (work weekend)	6	2.42	1.85	5.04	4.02
MA-4 (period day)	6	2.49	1.87	5.04	4.02
MA-49 (standard)	7	2.12	1.61	4.32	3.34
MA-29 (specific period)	7	2.23	1.70	4.32	3.34
MA-8 (work weekend)	7	2.20	1.68	4.32	3.34
MA-5 (period day)	7	2.28	1.74	4.32	3.34
MA-48 (standard)	8	1.89	1.41	3.78	3.44
MA-8 (specific period)	8	2.04	1.49	3.78	3.44
MA-8 (work weekend)	8	1.98	1.49	3.78	3.44
MA-4 (period day)	8	2.10	1.53	3.78	3.44

Table 16: Results different moving average models