

AGENT-BASED MODELING AND SIMULATION OF PUBLIC TRANSPORT TO IDENTIFY EFFECTS OF NETWORK CHANGES ON  
PASSENGER FLOWS

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# Agent-based modeling and simulation of public transport to identify effects of network changes on passenger flows

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## ABSTRACT

This research looks at the application of an agent-based model to assess the effects of changes in public transport on passenger flows. Data from public transport company GVB was provided by the municipality of Amsterdam. A baseline model was created based on domain knowledge, literature and data. This model was used to simulate a baseline scenario and a scenario with a malfunctioning tram line. The simulations show that the malfunctions result in different occupancy levels of several lines and cause an increase in waiting time for a lot of people. Future research should be aimed at implementing the model for the complete transport network in Amsterdam and expanding the behaviour of the different agent types.

## KEYWORDS

public transport, route choice behaviour, agent-based simulation, Amsterdam, GVB

## 1 INTRODUCTION

In a big city, malfunctions, delays or constructions can often lead to problems in public transport. In these situations passengers might have to take different routes or wait longer, which can result in crowdedness in different places than usual. The municipality of Amsterdam has a data set from the public transport company GVB. This data set contains travel information from bus, tram and metro lines in the city of Amsterdam. The municipality wants to be able to assess the effects of possible malfunctions or changes in public transport, so it is possible to take action. The effects of malfunctions need to be compared to a similar scenario without malfunctions to draw any conclusions. This calls for a model which is representative of real public transport flows in Amsterdam. This model will serve as a baseline for regular travel behaviour. When a scenario with malfunctioning transport lines is simulated, this can be compared to the baseline model.

This research is aimed at creating a baseline with a simulation of public transport flows in the city of Amsterdam. The baseline will be created with the help of agent-based modeling (ABM). ABM has been used at the municipality before to asses the impact of quay-wall renovations on the nautical traffic in the city [10]. In this research, ABM was chosen because it is able to give insight into the effects of the renovations. It shows where congestion might occur and also why it will occur based on route decisions of boats in the canals. With the use of ABM, complex behaviour can be accounted for and high explainability is also ensured. For these reasons, the municipality wanted to explore the use of this approach to model and simulate public transport flows in the city. In the context of public transport, ABM makes it possible to model and simulate route choice behaviour. This behaviour produces the flows through

the public transport network in the city. If route choice behaviour can be simulated correctly, it will also be possible to analyse the effects of any malfunctions or delays in the future as was done for nautical traffic. The simulation can also have benefits for decision making processes in public transport companies, because an understanding of route choice behaviour can help in designing new platforms or transport lines. The challenge of creating a model for this research is the lack of data. There is no data on travel preferences or route choice behaviour specifically for Amsterdam. This brings us to the main research question, which is defined as follows:

**RQ:** How can an agent-based model be used to assess the effects of changes in public transport on passenger flows?

In order to answer the main research question, one sub-question is formulated:

**RQ1:** To which extent can a baseline model be created to simulate passenger flows in public transport with limited data?

A combination of domain knowledge at GVB, related work and GVB data will be used to create a population and behaviour for the baseline model for RQ1. The model will be evaluated with data from GVB. The baseline model will then be used to simulate the effects of malfunctions as well. The baseline scenario and a scenario with malfunctions will be compared to answer the main research question.

## 2 GVB DOMAIN KNOWLEDGE

Every year, GVB creates around two thousand new schedules. This ranges from a complete new schedule every December to small schedule changes for a short period of time. There are situations like construction work, in which GVB is informed about the issue and is able to prepare an alternative schedule in time. Some situations like delays, accidents and malfunctions in the infrastructure are not planned. In these cases, passengers can be informed directly by civil servants on site or via digital boards at the stops. If the inconvenience is severe, alternative transport options will be provided to the passengers. In most cases however, it is just a matter of communicating the situation as soon as possible to passengers. Often, no further action is taken because doing so would take longer than waiting for the next bus/tram/metro to arrive. This does, however, result in additional crowdedness at certain stops or in lines that provide an alternative.

Another reason to change the schedule might be patterns in the occupancy of certain lines. The occupancy of every line is measured for every thirty minutes. If this occupancy is above a certain threshold that is based on the actual capacity of the vehicles,

the data will be analysed in more detail by GVB. Sometimes the high occupancy can be a sign that people are missing a certain connection. Bart Maters, transport developer at GVB, mentioned an example of this that arose when a new location for the University of Amsterdam, Science Park, was opened in 2010. This resulted in very high occupancy for certain lines. The problem here was that the connections to Science Park were insufficient. The schedule was changed in response to the situation.

GVB has identified different passenger groups, but these groups are used mostly for marketing purposes. In the context of route choice behaviour there are no predefined groups. To accommodate the needs of different types of people, the most important source of data are the memberships and products that are linked to a person's transport chip-card. Even though the memberships can not be linked to the routes a person takes, it is possible to make some assumptions about the type of traveller. For example, people with a business membership who travel mostly during rush hours are probably going to work. A few people at GVB with a lot of experience and domain knowledge use this information to get a picture of the different passenger groups. There are certain places, like hospitals and retirement homes, where the stops and lines will not be altered (or as little as possible) due to the passenger groups. People at hospitals and retirement homes that take public transport need to be able to get to a near stop. These groups also prefer little waiting time and no transfers. A difficult passenger group to work with are tourists. A lot of tourists take routes that might not be the obvious choice. This might be because tourists generally prefer to take trams, because they can look outside and go straight through the city. An example of this is tram 2, which is a very popular line for tourists since National Geographic has named it their top 10 Trolley Rides Worldwide<sup>1</sup>. Tourists are also hard to track in data because most tourists use throw away cards in public transport. Even though it is mandatory to check in and out in every mode of transport, there is no incentive to check out if the card will be thrown away afterwards. As a result of this, there might be more people checking in than out in the data.

### 3 RELATED WORK

#### 3.1 Route choice behaviour

Research has been done on route choice behaviour and traveller preferences, but because of big differences in transport networks in different cities, it is not possible to take these findings and apply them directly to the city of Amsterdam. This is because comfort, prices and speed of certain types of transport vary across different cities and countries. A survey on satisfaction with public transport in different cities in Europe showed that there are some overlapping factors for all cities, but local conditions also need to be taken into consideration [3]. Some cities show exceptions that need to be researched further to find the underlying reason. Research has shown however, that some general features influence route choice behaviour.

Several important factors for route choice behaviour are on-board travel time, cost, frequency, waiting time and the number of transfers [2, 4, 7]. The parameter cost is not really interesting for this

research, because the difference in cost for the modes of transport in Amsterdam is very minimal. The busses, trams and metros in Amsterdam all have the same boarding rate and the rest of the costs are very close as well. If trains and regional transport are included as well, it becomes a bigger factor. Earlier research often uses the shortest path approach, because it is assumed this is also the fastest and cheapest route [5]. When there are common lines between two stations, other factors also become important. Common lines means there are two lines between a certain origin-destination pair. When this is the case, waiting time becomes more important [5]. The problem here is not necessarily having to wait, but the uncertainty regarding the arrival of the next transport option [2]. Modes of transport with a high frequency and reliability have a higher guarantee of a fast transfer, which is why a lot of people have a preference for this type of transport [1]. In Amsterdam this might be the case for certain lines. Metro line 52 is the most frequent metro line and according to GVB currently the most stable one. Since the line has only been running since the end of July 2018, it has not been researched if this has an influence on personal travel preferences yet. The importance of different variables largely depends on the type of passenger [7]. A regular commuter, like work commuters or students, have a slight preference for the fastest route. Elderly people usually prefer trips without any transfers and dislike waiting time relatively more than on-board travel time compared to other groups.

Cognitive processes also play a part in the decision making process [8]. Spears et al. have combined factors into a theoretical framework which takes into account factors like personal preferences and perceived control. Based on all these factor the current travel behaviour arises. The model also includes a feedback loop with long and short term adaptations. This model was tested and the results showed that factors like personal safety and personal attitude toward the transit type play a large role in the decision making process. This research shows that there are a lot of personal aspects that can be taken into account when analysing route choice behaviour. It is hard to include these parameters in a model for public transport of Amsterdam, because these parameters are very specific for a certain place. The perceived control correlates with the reliability of the mode of transport. The personal preferences and safety in different modes of transport should also be researched specifically for the city of Amsterdam as well to include this in any type of model.

#### 3.2 Agent-based modeling

In agent-based modeling (ABM), the model represents a system with many individual agents who act in a specific environment. The agents can have properties from position and speed to age and wealth. ABM is a good method to discover why people, in public transport for example, make certain decisions and what happens in the system based on these decisions [11]. The agents can interact with the environment they are in and it is also possible to model interaction between agents. There is not one single definition of an agent, but there are a few things that most research agrees on. Macal & North define it as follows [6]:

- (1) An agent is a discrete individual with characteristics and rules that governs its behaviour and decision-making.

<sup>1</sup><https://www.nationalgeographic.com/travel/top-10/trolley-rides/>

- (2) An agent is situated in an environment where it can interact with other agents.
- (3) An agent can have certain goals to achieve, with respect to the behavioural rules. In these situations the agent can compare several outcomes of its behaviour.
- (4) An agent is autonomous.
- (5) An agent is flexible and able to learn and adapt based on experience.

In the context of route choice behaviour, agents are a good way to represent travellers and their behaviour. An agent as a traveller in the environment of public transport can choose several modes of transport based on their position. Based on their personal rules (1) they make a decision for a certain mode of transport. Someone travelling to work might prefer the fastest route. This can be formulated then as a rule for this particular agent. The environment (2) it acts in here is the whole public transport network, in which other agents act as well. It can be possible for agents to see behaviour of the agents around them, so if a certain mode of transport is very busy this might influence an agent's behaviour as well. The goal to achieve for every agent (3) is to get from point A to B with respect to their rules (1). To make a decision on how to get to B from point A, several options might be compared with respect to their personal rules. The agent is autonomous in this network (4), meaning that the agent makes its own decisions. Finally, the agent is able to adapt and learn (5). If a certain mode of transport is always delayed, the agent might try another mode of transport and see if this is an improvement.

When analysing travel behaviour, a distinction is made between static (pre-planning) and dynamic (within a trip planning) route choice behaviour [11]. With respect to route choice behaviour, most people travelling in public transport will have planned their trip before entering the public transport network. Malfunctions and delays will either be known before arriving at the origin of their trip or when arriving. This means the route choice has to be altered. Even though the route is changed, it is still considered static as the decision is being made before the start of travelling. Dynamic planning might occur when an accident happens during a trip or there are delays, but this is less common.

Since GVB has no clear behaviour model, the most useful information is the product type of a passenger. There is some domain knowledge about the product types and the behaviour that is expected. As mentioned, business membership probably correlate with travelling during rush hours and preference for the shortest route. For this group of people, the trip duration is very important. For other groups, like elderly people, waiting time and the number of transfers are prioritised. Duration, waiting time and the number of transfers will be used as variables in the model. These three variables can be used to create a variety of route choice decisions and it is also possible to represent different types of people. All variables are supported by research and GVB to have an impact on route choice decisions and they can be calculated without additional data. Additional data would be needed for example to include variables like personal preference, reliability and comfort. Choosing a small set of parameters also ensures high explainability and provides a good start point for the model. The behaviour can easily

be increased in complexity or altered when more information is available.

The agents in the model will have different rule sets to make a decision about the route they want to take. It is possible to let agents adapt their behaviour, but this needs additional information about reliability and personal preferences in public transport. Since this is not available for this research, the behaviour will not be adaptable. The behaviour of other agents will also not be taken into account. The possible routes for every agent will be calculated statically. This means the routes are generated before departure and will not change over time. This is a good way to represent actual behaviour, because most people will look at their route before entering the public transport system. All vehicles and passengers will be agents moving through the network. The passengers should be able to access the schedules of the vehicles and analyse the network to make their decisions. The vehicles need static behaviour of the standard schedule. It should then be possible to alter this schedule to simulate delays or malfunctions. The behaviour of the agents will not be altered when simulating delays or malfunctions. It is assumed that all agents will not choose a mode of transport other than public transport like a car, bike or taxi to get to their destination.

## 4 METHODOLOGY

To speed up the simulation process and ensure high explainability, only a sub-set of the public transport network was used. The lines for the sub-network needed some overlapping stations and good coverage of the city. This makes it possible to simulate routes different parts of the city and also simulate different types of routes for every origin-destination pair. The lines that were selected for the simulation are tram lines 12 and 24 and metro lines 50, 52 and 53. This results in a network with 67 different stations. To further reduce the computation all simulations were made for a weekday (aggregation of Monday through Thursday) and a weekend day (Saturday) for only a few hours of the day. The hours that were simulated were 08:00 - 09:00, 11:00 - 12:00, 14:00 - 15:00, 17:00 - 18:00 and 20:00 - 21:00. These hours have diverse distributions over the day and include both morning and evening rush hours. By doing this, the effects of malfunctions can still be analysed in different situations in an acceptable time frame.

### 4.1 Data exploration and preparation

The data of GVB contains information about complete trips and sub-trips that people have taken. A sub-trip is a part of the complete trip in one mode of transport without any transfers. A trip can consist of several sub-trips. An example trip can be someone travelling from metro station *Noord* to tram stop *Muntplein*. To complete this trip, a transfer is needed between the metro and tram. This trip is therefore made up of a sub-trip from *Noord* to *Centraal Station* in metro line 52 and a sub-trip from *Centraal Station* to *Muntplein* in tram 24.

In the GVB data, only the origin and destination of the sub-trips are matched. There are strict privacy regulations that make it impossible to match the complete trip. The risk of matching all data is that in some situations it might be able to deduce whom this travel data belongs to. This could happen, for example, if the GVB data were to be matched with different data sets. It is also due

to privacy concerns that travel streams per hour of less than ten people are not available in the data. If there are less than ten people arriving at or departing from a particular station, the station is set to *Overig* (other). This was also done for sub-trips that were made less than ten times in an hour. Because of this, it is not possible to correctly match all data to derive the trips and their sub-trips. Figure 1 shows a sample of the trip origin data. This data shows how many trips were made per hour from which station. This data is also available for all destination stations. Figure 2 shows the sub-trip data, where the origin and destination are matched. This shows sub-trips per hour for all origin-destination pairs.

Date	Hour	OriginCode	OriginName	Trips
1/1/2018 12:00:00 AM	09:00 - 09:59	00005	Muiderspoortstation	10
1/1/2018 12:00:00 AM	09:00 - 09:59	00017	Linnaeusstraat	15
1/1/2018 12:00:00 AM	09:00 - 09:59	00020	Beukenveld	12
1/1/2018 12:00:00 AM	09:00 - 09:59	00029	Oostpoort	10
1/1/2018 12:00:00 AM	09:00 - 09:59	00076	Brinkstraat	12

Figure 1: Trip data

Date	Hour	OriginCode	OriginName	DestinationCode	DestinationName	Trips
1/1/2018 12:00:00 AM	09:00 - 09:59	02158	Adm. de Ruijterweg	05011	Centraal Station	10
1/1/2018 12:00:00 AM	09:00 - 09:59	02361	Station Sloterdijk	07006	Museumplein	10
1/1/2018 12:00:00 AM	09:00 - 09:59	03010	Witte de Withstraat	05069	Nieuwezijds Kolk	11
1/1/2018 12:00:00 AM	09:00 - 09:59	03060	Bos en Lommerplein	05025	Centraal Station	11
1/1/2018 12:00:00 AM	09:00 - 09:59	03130	Plein '40 - '45	05025	Centraal Station	11

Figure 2: Sub-trip data

The data sets also contain coordinates for the stops along with a stop code. With this information it is possible to derive the type of stop (e.g. tram or metro) and what lines stop here. Most stops are used as a stop by different transport lines. Since not every transport line is included in the simulation, all trip numbers were recalculated. If a certain stop is used by three transport lines and only one of these lines is in the sub-network, the number of trips was divided by three. The time interval that was chosen is August 6th 2018 - March 25th 2019. This gives us an even distribution of weekdays and all dates are after the opening of the Noord/Zuid line. The opening of the line had a big impact on a lot of public transport lines in the city and the use of public transport. Combined with the opening, a new schedule was made and a lot of lines were changed or stopped. For this reason data before the opening is not used.

Since the simulation will be used to show public transport flows, it is important to simulate routes that are taken in a way that represents reality. As mentioned the complete routes were not available in the data. To generate routes, the passenger distribution per hour and the probabilities of all origins and destinations per hour were analysed. Figure 3 shows the passenger distribution for all days of the week. This shows that the weekdays are quite similar, but the weekends differ quite a bit. All weekdays show clear peaks during the rush hours 08:00 - 09:00 and 17:00 - 18:00. Wednesday and Friday seem to have slightly fewer passengers, which could suggest these are popular part-time working days. Saturday and Sunday follow a completely different pattern from weekdays. There is no morning or evening rush hour and the busiest hours are actually

midday, Saturdays being busier than Sundays. The average number of passengers per hour was used as a base for the simulation. An overview of the distribution over all hours can be found in Appendix A.

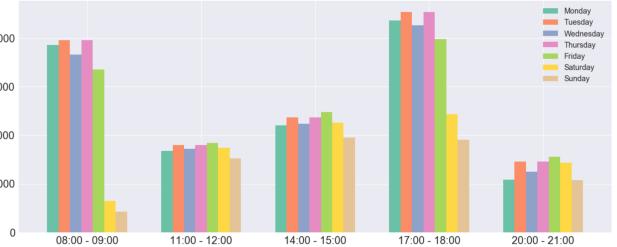


Figure 3: Passenger distribution

For all people in the simulation, a route has to be calculated. Even though complete route information is unavailable, the GVB data was used as a base. For every hour, the probability was calculated of departing from and arriving at a particular station. These probability distributions were also compared for all days of the week. Since the probability distributions of Monday through Thursday were relatively similar, these days were aggregated. By aggregating, noise like past malfunctions and delays will have less impact on these distributions. Figure 4 and 5 show examples of the distribution over several stations. Figure 4 shows a heat map for all origin stations on a weekday and weekend day from 17:00 - 18:00. Figure 5 shows the same information for destination stations. A complete overview of all hours can be found in Appendix B.

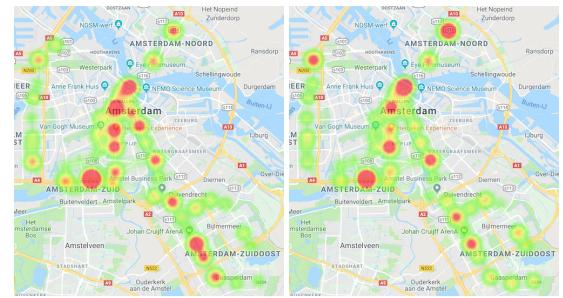


Figure 4: Origin and destination for weekday (17:00 - 18:00)

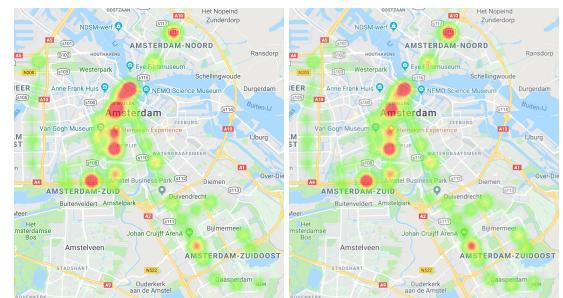


Figure 5: Origin and destination for Saturday (17:00 - 18:00)

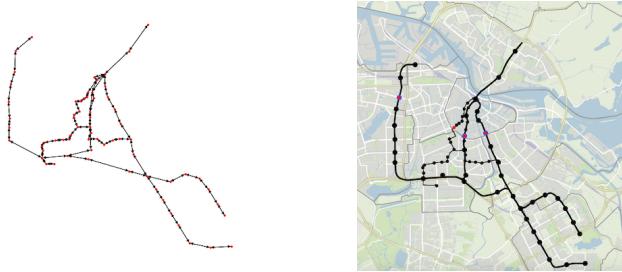
The GVB data can be used to create a distribution that is somewhat similar to reality, but there is no guarantee that the resulting routes are actually correct. Generating correct routes is out of scope for this research, because there is no way to evaluate the routes with the (incomplete) data. The model was built so that when the real distributions and complete routes are known, this can be given as input to the model.

## 4.2 Simulation

For earlier research on ABM at the municipality, the *Transport Network Analysis* package from TU Delft was used<sup>2</sup>. The code on GitHub of the TU Delft was used as the base code for this research. The model provided was written in python, using simply, networkx and a custom package of TU Delft to simulate agent-based behaviour.

### 4.2.1 Network

The sub-network of the transport lines in the city was created in networkx. Each node represents a station and each edge is a connection between two stations. Each edge has a duration weight in minutes and a line attribute which is the name and direction of the transport line. Figure 6 shows the network that was created and the real transport network on a map. The network in networkx does not completely follow the same shape, because all edges are straight lines, but the locations of the stops are matched correctly.



**Figure 6: Transport lines in networkx (left) and on maps.amsterdam.nl (right)**

### 4.2.2 Simulation process

The agents in the simulation are the vehicles and the passengers. The vehicles have a name, route and start node. The *Transport Network Analysis* package provides classes to make it possible for the vehicles to move over the network and pick up passengers. At every node the vehicle will check for passengers. If there are passenger that want to take this mode of transport, they will be loaded into the vehicle. At every node it is also checked if any passengers want to get off the vehicle and they are removed from the vehicle. After the (un-)loading process, the vehicle drives over the network edge to the next node in their route. The duration in minutes between two stops is stored as an attribute for that edge. The generation of the vehicles is based on the scheduling of every line. The frequency of metro 52 is six minutes, so every six minutes a new vehicle with the right attributes for this line is generated at both ends of the line.

<sup>2</sup><https://github.com/TUDelft-CITG/Transport-Network-Analysis>

The passengers were generated based on the average number of passengers for that hour. An arrival rate is calculated based on this number, to evenly distribute all passengers over the whole hour. The probability distribution is used to generate an origin and destination for each passenger. Between these two stations, all possible routes are generated with networkx. The possible routes do not include any loops or double nodes, which reduces computation. A route scoring function was created to calculate all route information. This function creates a dictionary for each route with the duration, waiting time and the number of transfers. The duration was calculated by adding all time in transport and the time for any transfers. The time for a transfer includes the waiting time on the platform and a time for the actual transfer. For each transfer, five minutes were added to the total duration to account for walking from one stop to another. The waiting time is calculated as the time before entering the first mode of transport. The number of transfers is calculated by keeping track of the different lines in a route that are stored with the edges. From all possible calculated routes, one will be chosen based on the passenger class. To reduce the amount of unrealistic routes as a result of using a sub-network, only routes with less than three transfers were considered. There are three different classes:

- **Class 1:** the preferred trip is the one with the shortest duration. This time is calculated from the moment the passenger is in a mode of transport until the end. This class represents people that regularly travel and want to get from their origin to their destination as fast as possible. People in this class are probably going to work/class and are familiar with the public transport system. If there are trips that have the same duration, the trip with the least amount of waiting time is chosen because this is the trip with the earliest arrival time at the destination.
- **Class 2:** the preferred trip is the one with the least amount of transfers. The amount of transfers outweighs the total duration of a trip for certain people. Generally disabled and elderly people will prefer a trip with no transfers if possible. Other people that might fall into this class are tourists. They want an easy trip where they will not have too much trouble finding a transfer. If there are trips that have the same number of transfers, the trip with the least amount of waiting time is chosen because this will decrease the uncertainty within the trip even further.
- **Class 3:** the preferred trip is the one with the least amount of waiting time. The waiting time before entering the first mode of transport outweighs the total duration of the trip, because the trip starts earlier. Elderly and disabled people might also prefer this type of transport, because this means they will be seated sooner. If there are trips that have the same amount of waiting time, the trip with the least amount of transfers is chosen.

One of the parameters of the simulation, is a probability distribution for the three different classes. Each simulation can be executed with a different distribution of people, and it can be altered for every hour if needed.

Two different scenarios will be simulated to represent different situations and answer the main research question. All simulations

will be run for a weekday (aggregation of Monday - Thursday) and a weekend (Saturday). As mentioned before, five hours are selected for every day to reduce computation. All simulations were run with an even probability distribution for all classes (all 0.33), because the real population is unknown. To make sure the results converge, each simulation will be run ten times. The scenarios are as follows:

- **Scenario 1:** all lines in the network run according to the normal schedule.
- **Scenario 2:** line 12 will fail for 30 minutes during every hour. This can be used to assess the effects of failures/delays.

The first scenario was simulated to produce a baseline to answer RQ1. The second scenario was simulated to assess the effects of malfunctions and answer the main research question. Tram 12 was chosen as a malfunctioning line because the stations Centraal Station, Dam, Roelof Hartplein, De Pijp and Amstel Station can also be reached by using other transport lines. This provided a lot of passengers with the choice to either wait for the next tram 12 or choose a different option.

#### 4.2.3 Evaluation

The results of every simulation round were split into separate files. The files contain information about the origin, destination, sub-trips, vehicle occupancy and passenger information for each iteration of the simulation. The passenger information contains their unique id, class, creation time, departure time, arrival time, origin, destination, trip duration, route, transfers, transfer stations, waiting time and the different transport lines they used. For the vehicles, their id, departure time, arrival time, line name, route and occupancy is stored. The occupancy is stored between all stations.

To evaluate the results of the baseline model, GVB data was used. The results that were possible to evaluate with the data were the origin, destination and sub-trips from all passengers. To compare simulation data with measurement data, the *goodness of fit* is often used. This measure indicates in what capacity the simulation data represents the actual data (the GVB data in this case) [9]. The root mean square error (RMSE) is a popular metric to asses the goodness of fit. The downside of the RMSE is that the squaring of deviations puts more emphasis on points that do not fit well [10]. Another metric that can be used for evaluation is the mean average error (MAE). This metric is an absolute number which represents the average of absolute differences between the simulation data and measurement data. If the MAE is 5, this means the simulation is on average 5 people off from the measurement data. To evaluate the results, the MAE is used because this metric is easy to interpret and understand [10]. To answer the main research question, the results of the baseline model and the alternative scenario were compared. The metrics that were evaluated were waiting time, transfers, trip duration and vehicle occupancy.

## 5 RESULTS

This section will discuss the simulation results about origin stations, destination stations, sub-trips, trip data and vehicle occupancy. Heat maps of all origin and destination distributions throughout the city are available in Appendix B and can be compared to GVB data. All heat maps show that the distribution is almost the same. The heat maps are a visual representation of the results, but do not

show nuances like the MAE calculations below, which is why they are not included in this section and were only used to check the distribution.

### 5.1 Origin

Table 1 and table 2 show the MAE for both scenario 1 and 2 for weekdays and Saturdays. The MAE represents the average difference between the amount of people with a certain origin in the simulation and in the GVB data. The results show that during the rush hours on weekdays the MAE is highest, where the predictions are between 20 and 23 people off on average.

Hour group	MAE scenario 1	MAE scenario 2
08:00 - 09:00	22.59	22.72
11:00 - 12:00	4.67	5.57
14:00 - 15:00	6.13	6.68
17:00 - 18:00	19.57	20.55
20:00 - 21:00	3.94	3.65

Table 1: Origin weekday

Hour group	MAE scenario 1	MAE scenario 2
08:00 - 09:00	3.01	3.07
11:00 - 12:00	6.33	5.80
14:00 - 15:00	6.99	8.20
17:00 - 18:00	7.70	7.17
20:00 - 21:00	3.90	4.45

Table 2: Origin Saturday

### 5.2 Destination

Table 3 and table 4 show the MAE for both scenario 1 and 2 for weekdays and Saturdays. The MAE is higher in every case than the MAE for the origin stations, with a highest value of 45 people.

Hour group	MAE S1	MAE S2
08:00 - 09:00	25.75	25.80
11:00 - 12:00	5.92	6.10
14:00 - 15:00	17.76	17.79
17:00 - 18:00	44.98	45.17
20:00 - 21:00	6.93	7.23

Table 3: Destination weekday

Hour group	MAE S1	MAE S2
08:00 - 09:00	5.29	5.23
11:00 - 12:00	7.98	7.63
14:00 - 15:00	9.05	8.82
17:00 - 18:00	14.10	14.11
20:00 - 21:00	7.09	6.59

Table 4: Destination Saturday

### 5.3 Origin/destination sub-trip

Table 5 shows the MAE for scenario 1 for weekdays and Saturdays. Scenario 2 was not included, because trips made in this scenario will differ as a result of malfunctions and should not be compared to GVB data. The MAE is a lot higher than for the origins and destinations, ranging from 13 to 36 people.

Hour group	MAE Weekdays	MAE Saturdays
08:00 - 09:00	36.26	12.66
11:00 - 12:00	18.18	18.69
14:00 - 15:00	20.46	20.51
17:00 - 18:00	32.51	22.01
20:00 - 21:00	16.12	16.73

Table 5: MAE of sub-trips, scenario 1

### 5.4 Trip metrics

For all simulations the average waiting time, average amount of transfers and average duration were calculated. This was done for scenario 1 and 2 for weekdays and Saturdays. Figure 7 and 8 show a box plot of the results from 08:00 - 09:00 (the other hour groups showed similar results). The plots show the spread of the waiting time is larger in scenario 2. The mean duration and mean waiting time do not seem to be affected. Figure 9 shows the counts of the number of transfers. There seems to be no difference between the two scenarios in the amount of transfers.

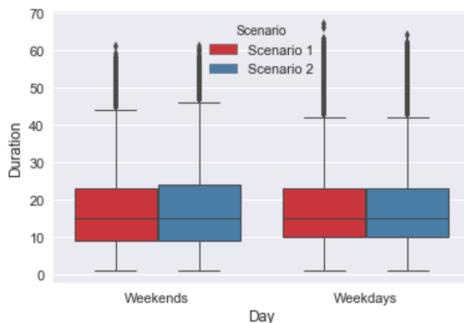


Figure 7: Box plot of duration

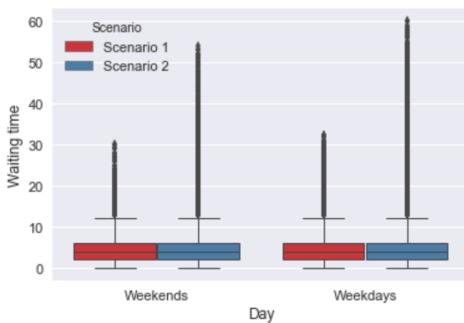


Figure 8: Box plot of waiting time

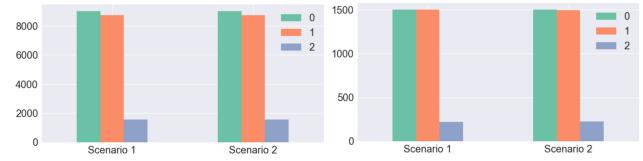


Figure 9: Weekdays (left) and Saturdays (right) frequency count of transfers

### 5.5 Vehicle occupancy

For each vehicle there are some differences in occupancy between all hours and between weekdays and weekends. The subsections will show examples for each vehicle in both directions where scenario 1 and scenario 2 can be compared. Since the patterns between all hours and days were similar, only vehicles between 08:00 - 09:00 on weekdays are shown as examples. The number corresponding to a station on the x-axis represents the number of people in the vehicle to this particular station. For example, if this value is 50 at station De Pijp this means that 50 people were in the vehicle while driving to station De Pijp. Since there are no people travelling to the origin station of a vehicle, this station is not included in the plot. Explanations for differences between the two scenarios will be given in section 6.

#### 5.5.1 Tram 12

In scenario 2, tram 12 had a malfunction problem for 30 minutes. The first trams to run again depart at 08:35 and 08:33. The results clearly show a much higher number for the occupancy of this tram in scenario 2 than in scenario 1.

#### 5.5.2 Tram 24

Tram 24 to Centraal Station shows a higher occupancy for scenario 2, but tram 24 in the other direction shows the opposite. Most vehicles of tram 24 show a little peak in scenario 2 between Roelof Hartplein and De Pijp, but overall the two scenarios show few differences.

#### 5.5.3 Metro 50

Metro line 50 shows very similar results for both scenarios, which indicate that this line is not affected by the malfunctions of tram 12.

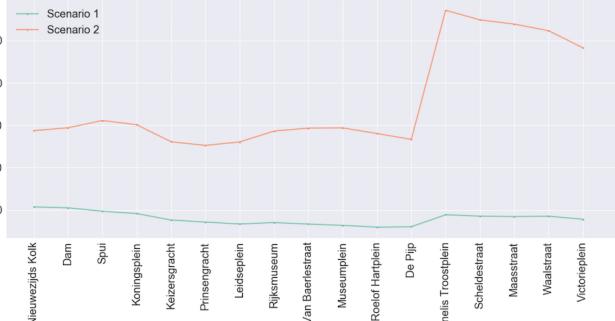
#### 5.5.4 Metro 52

Metro line 52 to Zuid shows a clear peak from station De Pijp to station Zuid. The line in the other direction to station Noord does not follow the same pattern, but does have a slight increase in passengers from De Pijp to Vijzelgracht and Rokin.

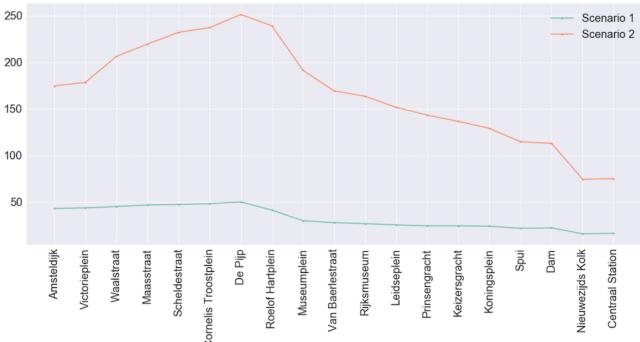
#### 5.5.5 Metro 53

Metro line 53 to Centraal Stations shows an increase in passengers from Amstelstation to Centraal Station. The line in the other direction to Gaasperplas shows a similar increase from Centraal Station to Amstelstation as well as a decrease in passengers from Amstelstation to Spaklerweg and Van der Madeweg.

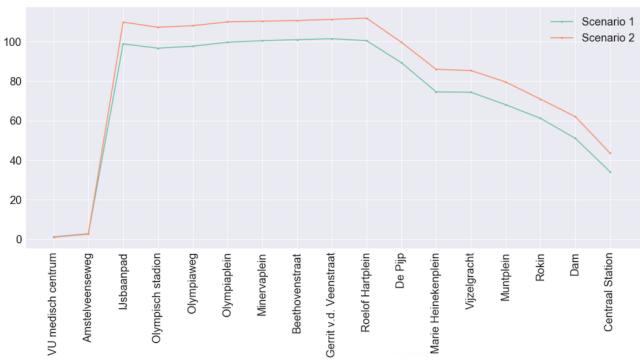
**Figure 10: Tram 12 to Amstelstation (08:35)**



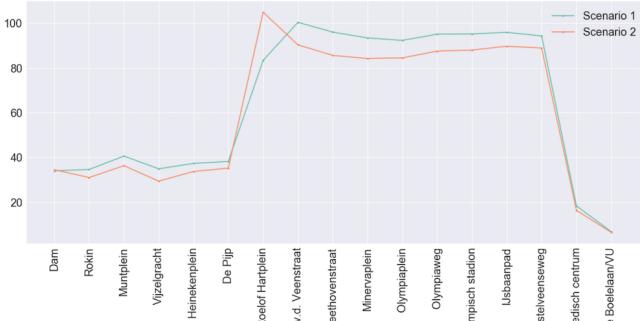
**Figure 11: Tram 12 to Centraal Station (08:33)**



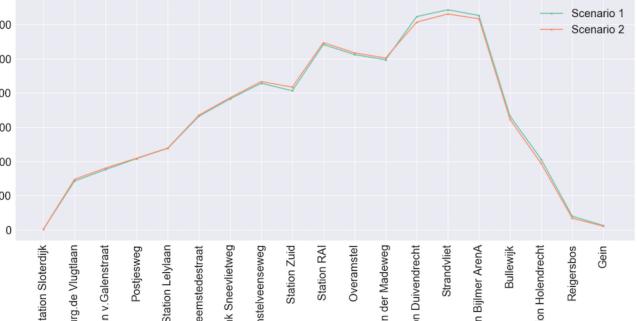
**Figure 12: Tram 24 to Centraal Station (08:25)**



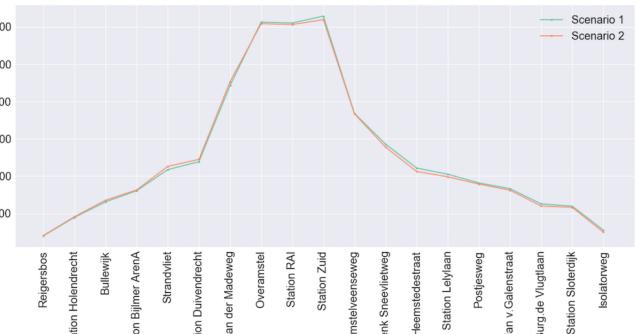
**Figure 13: Tram 24 to Boelelaan/VU (08:24)**



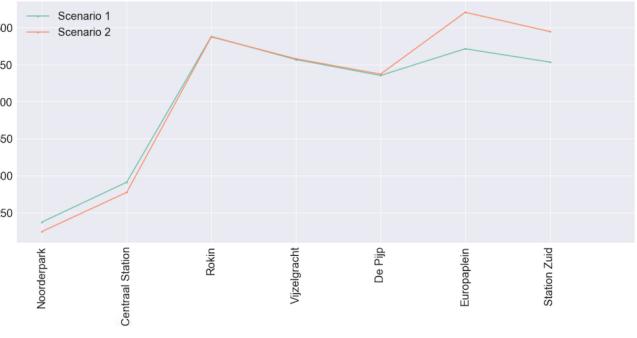
**Figure 14: Metro 50 to Centraal Station (08:01)**



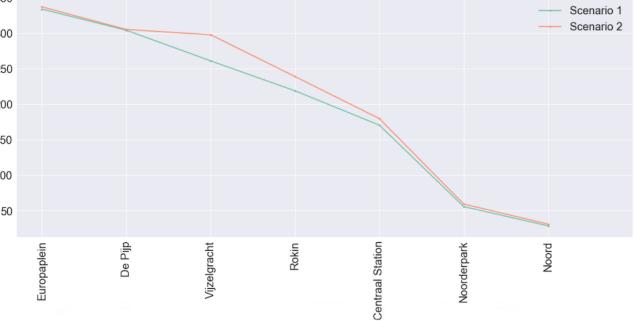
**Figure 15: Metro 50 to Isolatorweg (08:00)**



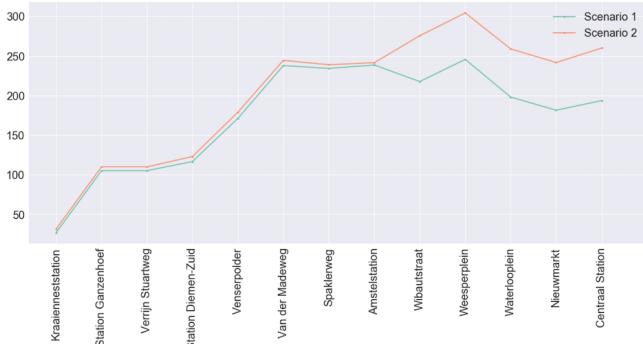
**Figure 16: Metro 52 to Zuid (08:36)**



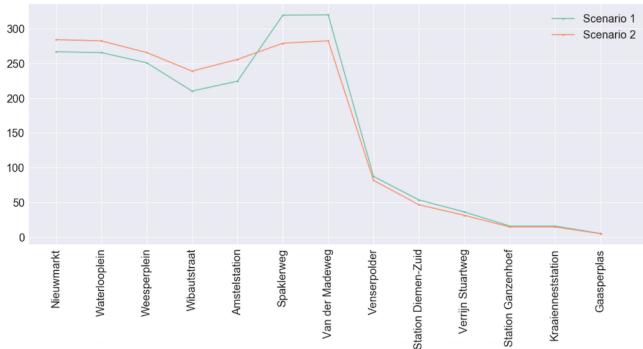
**Figure 17: Metro 52 to Noord (08:41)**



**Figure 18: Metro 53 to Centraal Station (08:03)**



**Figure 19: Metro 53 to Gaasperplas (08:33)**



## 6 DISCUSSION

### 6.1 Data

The simulations that were run all used the GVB data for probability distributions of the number of passengers per hour and the origin/destination of their route. The number of passengers per hour might differ a bit from reality because all data was normalised for the stations and lines that were included in the model. The distribution of the origin and destination stations were calculated independently. It might work better to match these stations and calculate origin/destination pair probabilities. To do this, additional data with matched origin and destination pairs for complete trips needs to be made available by GVB.

Since the sub-trips are not matched, it is also hard to analyse what types of trips have been taken in the past. If they were matched it would have been possible to calculate average trip lengths and number of transfers. This information could be used to improve the passenger behaviour in the model as well.

### 6.2 Origin and destination

Overall the busy hours show a larger MAE. Since there are a lot of passengers during these hours, it might take more iterations of the simulation for the results to converge and thereby decrease the MAE. The higher errors for the destination stations can be assigned to the fact that the probability distributions are derived

from a single hour. The problem with this is that a lot of destination stations within an hour are destination from a trip that was started in the previous hour and a lot of actual destinations will fall within the next hour. Since the GVB data was aggregated by hour, it is not possible to correctly assign the destinations to the hour the trip was started in. This has not been taken into account when creating a population and explains the higher errors for the destinations.

### 6.3 Origin/destination sub-trip

Some origin-destination pairs that were generated in the simulation, might result in sub-trips that people do not generally use in reality. The simulation used a subset of the whole transport network, so the most used option to get from a certain origin to a destination might not be available in the simulation. As a result some sub-trips will not be representative of someone travelling between certain origin-destination pairs.

Another factor could be the time penalty for transfers. Since the time it takes to make a transfer really depends on the person, the two modes of transport and the locations of the stops, it is hard to apply a general rule here. A penalty of five minutes was given to any transfer, but this can not be accurate for every situation. Since the transfer time is included into the total duration of a trip, some trips might have been either longer or shorter than they are in reality due to the time penalty. A longer or shorter trip duration can lead to passengers either choosing a route more or less than in reality.

### 6.4 Trip metrics

The trip metrics show that there are more outliers for waiting time and the trip duration and amount of transfers are not really affected by the malfunctions in scenario 2. The increase in waiting time can be explained by people who are waiting for tram 12 and do not change their route. Naturally the waiting time for a lot of people increases.

### 6.5 Vehicle occupancy

The vehicle occupancy figures show the most interesting results. These results show the effects of a malfunctioning tram line in the public transport network. The results show that most people who are affected by the malfunctions choose to wait for tram line 12. This number is probably a lot higher now, due to the fact that some stations simply can not be reached by any other line in the network. In other cases, it might still be the preferable route if this means there is no need to transfer or the trip duration is still a lot shorter. Tram 24 has two overlapping stations, Roelof Hartplein and De Pijp, that show some fluctuations that are probably a result of the malfunctioning line. Metro line 50 was not affected by the malfunction, because there are no overlapping stations with tram 12 and it does not provide a solution for people who use tram 12. Metro line 52 shows an interesting result. In both directions, the stations after De Pijp show a clear peak after tram 12 has resumed running. During the malfunctions the same parts in the route actually show a slight decrease. The explanation for this is that some people who need to use tram 12 to get to station De Pijp to transfer to metro 52 cannot do this during the malfunctions. For metro 53, only the metros in the direction of Centraal Station seem to be affected.

From Amstelstation to Centraal Station the occupancy is higher for scenario 2. This is also the case for the metro line in the other direction. This metro line also shows a decrease from Amstelstation to the next two stops. This is similar to the decrease in metro 52, where people simply can't reach Amstelstation until the trams are running again.

## 6.6 Contribution and future work

The baseline model provides a good starting point for agent-based modeling of public transport for both the municipality and GVB. It enables the municipality to further monitor crowdedness in the city and analyse how it is affected by changes in public transport. An application for GVB could be the identification of critical lines in the network. The results showed that tram 12 was a critical line in the network, because the failure resulted in a lot of people that were forced to wait at their stop. It could also be used to see what influence the new schedules might have on the passenger flows in the network, by editing the network structure in the model. Even though this research is focused on Amsterdam, it provides a methodology that can be applied for other cities as well. If there is little data available about passenger behaviour, the baseline model can still produce interesting insights.

There are three main directions for future work based on the baseline model. The first one could be aimed at expanding the network and using a similar method for the entire network. This will give better insights into the performance of the model, since all options that are available in real life will be represented.

Second, the behaviour of the passengers can be increased in complexity. The baseline model uses three classes to base route choice decisions on and the classes are evenly distributed over all passengers. This is a simplification of reality and the behaviour should be altered step-wise to assess the effect on the performance of the model. Survey data or extra data from GVB could serve as a base for this.

The third direction is most important for the team at the municipality. Before any action can be taken, it should be researched when certain places and certain vehicles are overcrowded. A clear definition of crowdedness is needed to assess whether places are too crowded as a result of malfunctions or delays. For now the results clearly show differences between the two scenarios, but an increase of fifty people is not the same for every type of station and vehicle. To accurately interpret these results in the context of crowdedness, future research is recommended.

## 7 CONCLUSION

Agent-based modelling provides a good methodology to simulate passenger flows in a public transport network. With limited data about passenger behaviour, research and domain knowledge have provided a basis for the model. Three different classes were used in a subset of the public transport network in Amsterdam to create a baseline model. The results show that even though the model needs improvement to represent reality, it is able to generate passengers and routes that are somewhat similar to reality. To accurately assess the model, it should be further tested on the complete public transport network. After this, the behaviour of the passenger groups can be altered as well to further improve the model.

To answer the main research question, two scenarios were simulated. The results show clear differences between a normal scenario and a scenario with malfunctions in the network. All differences are easy to interpret as they are a result of the available transport lines, the malfunctioning lines and the passenger groups. This shows that the simulations produce adequate results to assess the effects of malfunctions in public transport. To accurately quantify the impact of certain malfunctions, further research is needed within the crowdedness team of the municipality. An accurate definition and understanding of crowdedness in Amsterdam is needed to use the results in any decision making process.

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## A FULL PASSENGER DISTRIBUTION

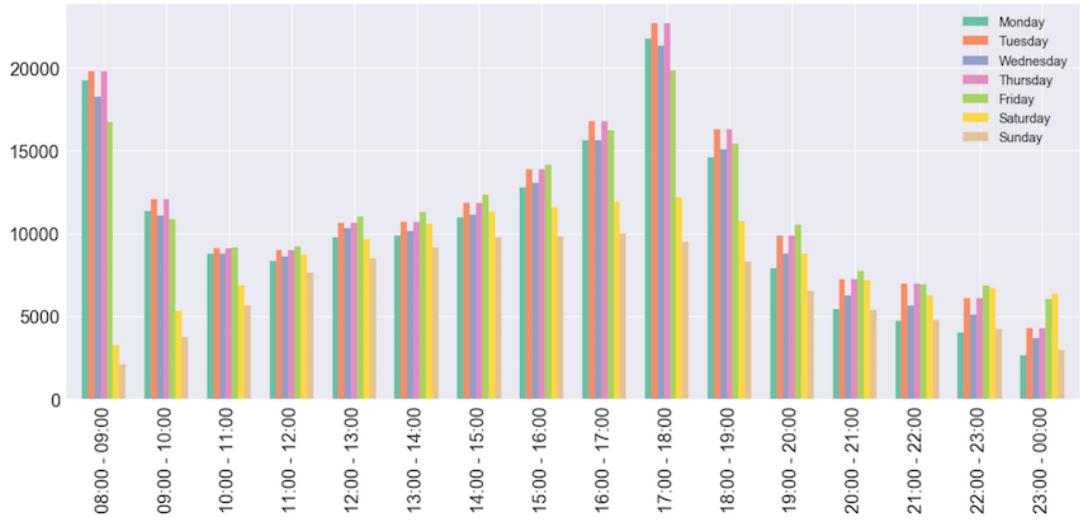


Figure 20: Full passenger distribution for all days

## B HEATMAPS

### B.1 Weekdays

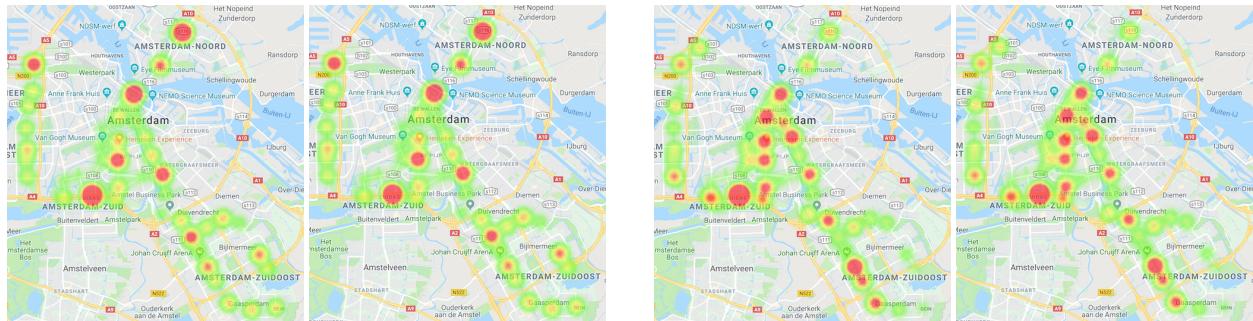


Figure 21: GVB origin, simulation origin, GVB destination, simulation destination (08:00 - 09:00)

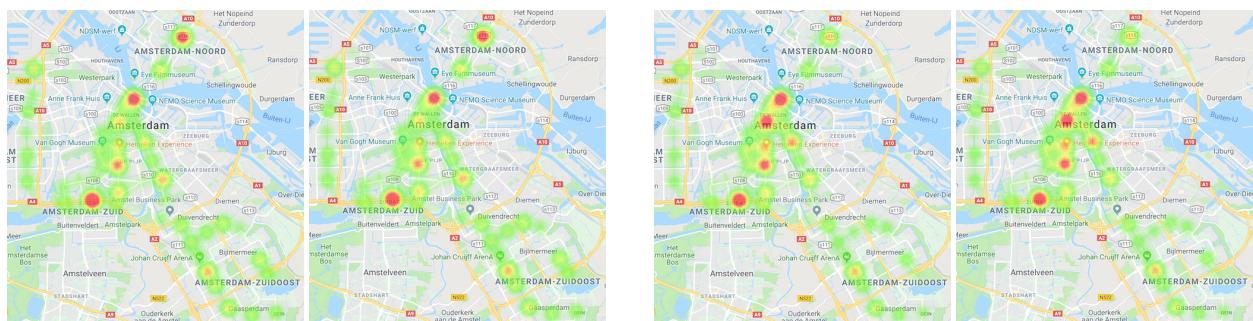
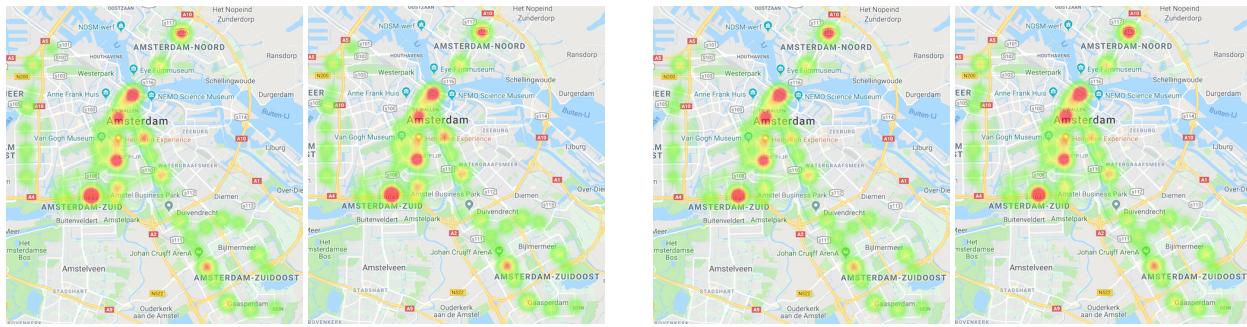
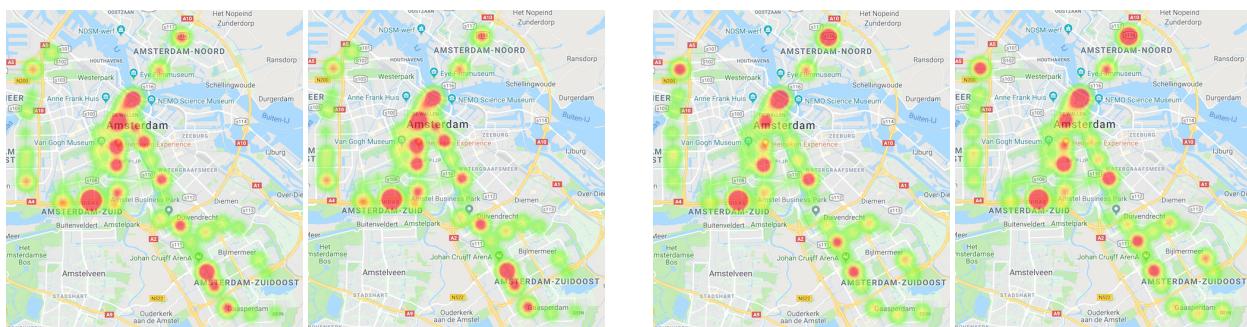


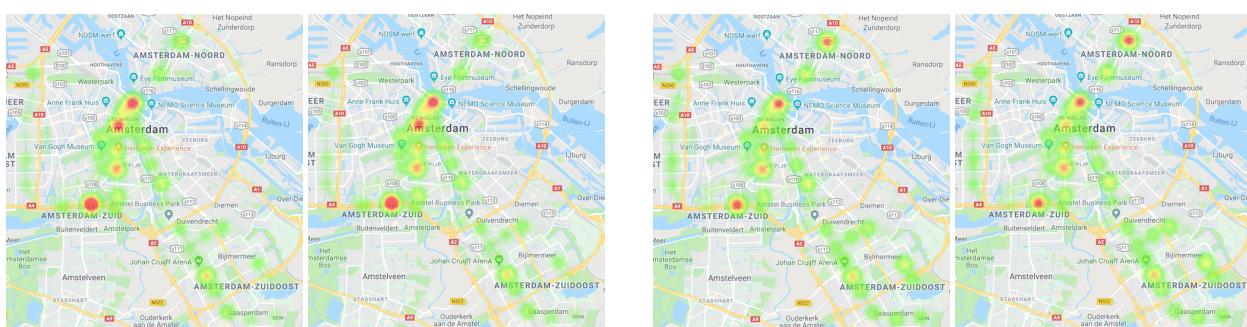
Figure 22: GVB origin, simulation origin, GVB destination, simulation destination (11:00 - 12:00)



**Figure 23: GVB origin, simulation origin, GVB destination, simulation destination (14:00 - 15:00)**

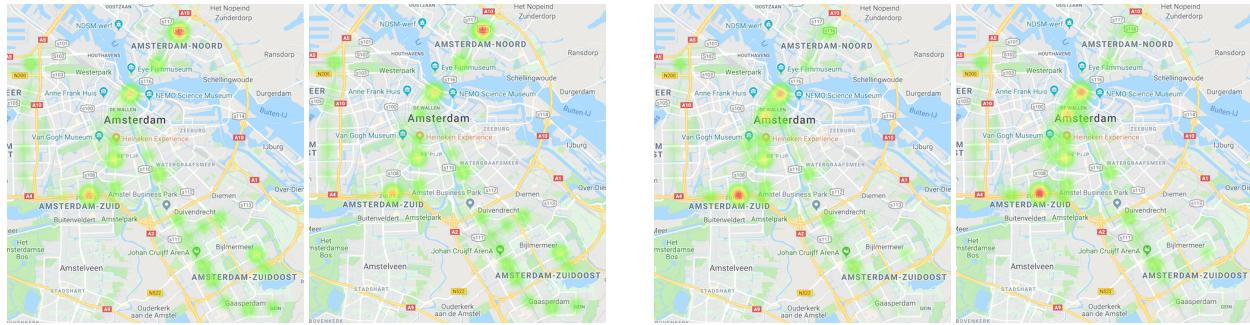


**Figure 24: GVB origin, simulation origin, GVB destination, simulation destination (17:00 - 18:00)**

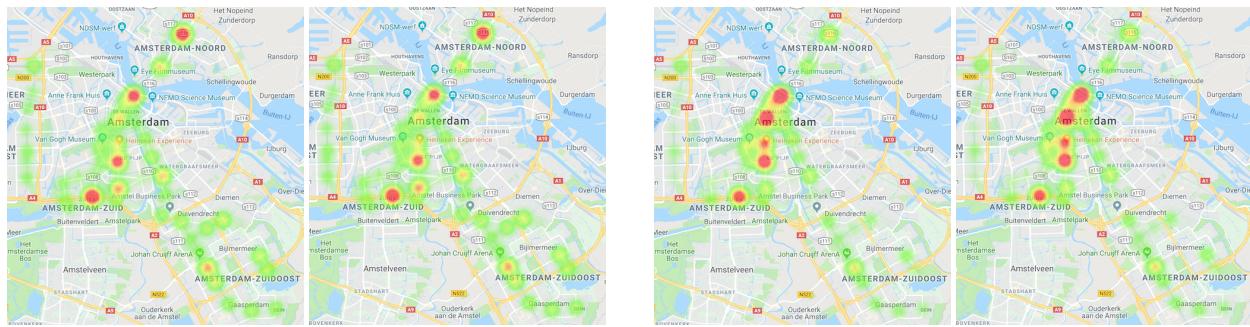


**Figure 25: GVB origin, simulation origin, GVB destination, simulation destination (20:00 - 21:00)**

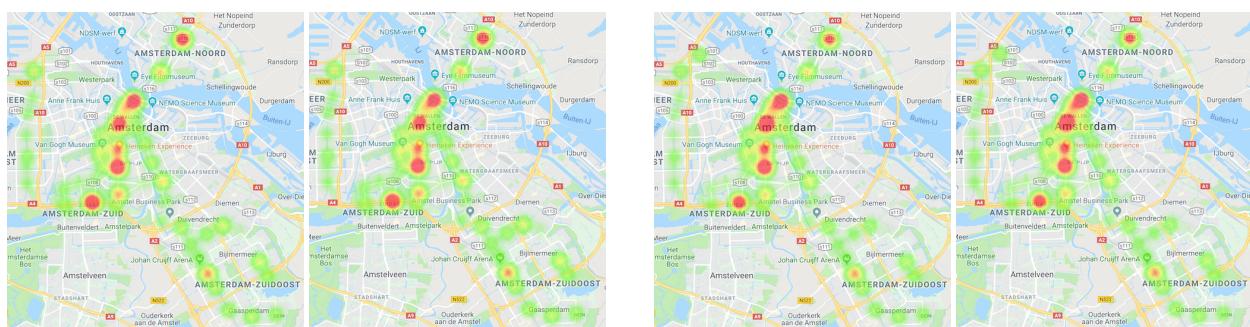
## B.2 Weekend



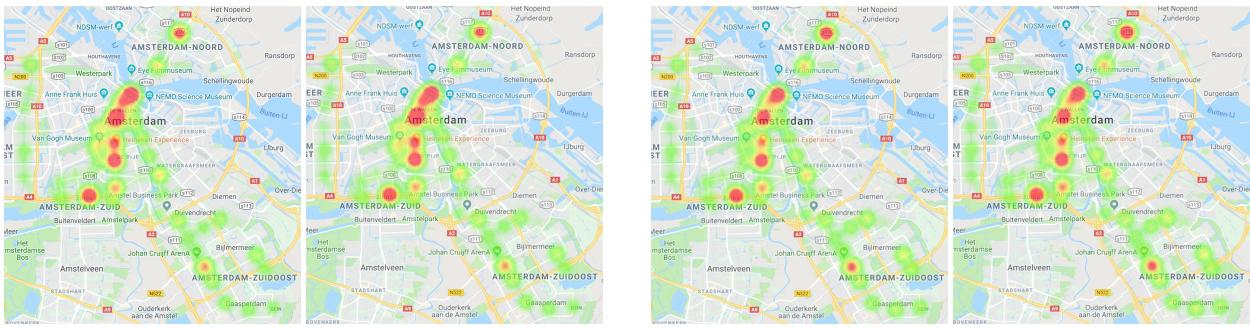
**Figure 26: GVB origin, simulation origin, GVB destination, simulation destination (08:00 - 09:00)**



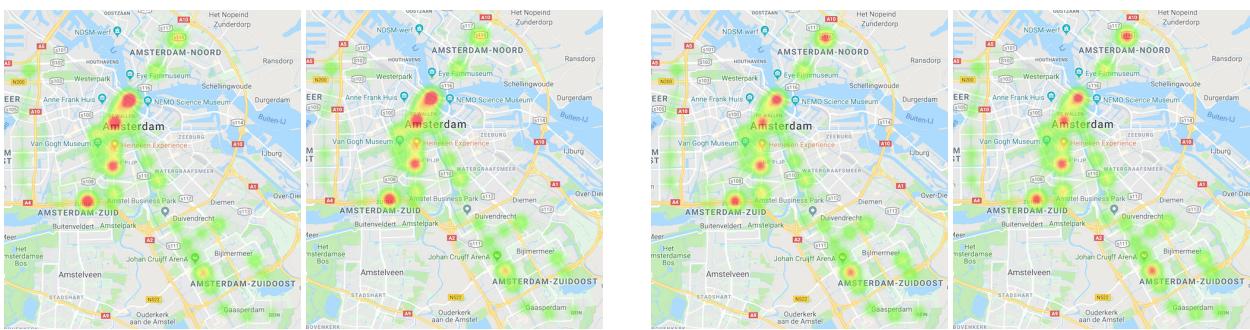
**Figure 27: GVB origin, simulation origin, GVB destination, simulation destination (11:00 - 12:00)**



**Figure 28: GVB origin, simulation origin, GVB destination, simulation destination (14:00 - 15:00)**



**Figure 29: GVB origin, simulation origin, GVB destination, simulation destination (17:00 - 18:00)**



**Figure 30: GVB origin, simulation origin, GVB destination, simulation destination (20:00 - 21:00)**