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Automatic bottleneck detection using AVL data: a case study in Amsterdam

Ties Brands · Niels van Oort · Menno Yap

Abstract In daily practice, public transport authorities and operators are constantly searching for improvements in public transport operations. To this end, it is necessary to identify inefficiencies and bottlenecks in the current public transport services. In this paper, we propose a method to automatically detect bottlenecks in the public transport network, using Automatic Vehicle Location data. A tool is developed to automatically process AVL data to identify bottlenecks for the current situation. This tool is applied to Amsterdam, capital of the Netherlands, where a new metro line will come into operation in the summer of 2018. The results show that bottlenecks are mainly found on radial lines and in the inner city. Therefore we expect that the operations of the tram network will improve in terms of operating speed and reliability due to the opening of the metro line, since the tram lines are expected to become less crowded and fewer lines will traverse the inner city.

Keywords: AVL data · Bottleneck detection · Performance indicators · Service reliability

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1 Introduction

Service reliability is considered to be one of the most important quality aspects of public transport. Peek and Van Hagen (2002) consider it as one of the basic elements of good services. Several passenger choices (such as mode and route choice) are affected by the level of service reliability (see for instance Bates et al. 2001; König and Axhausen 2002; Li et al. 2010; Van Oort 2016). In addition to increasing service quality (and expected ridership growth accordingly), improving service reliability also positively affects the costs of operations, since buffer times might be reduced. It is therefore not surprising that improving service reliability received much attention last decade, both in academia and in practice (see for instance Delgado et al. 2012; Xuan et al. 2011; Nesheli and Ceder 2017; Yap et al. 2018).

Service reliability, which is a result of variability in operations, is the certainty of service aspects (such as travel time) compared to the schedule as perceived by the user. Unreliability causes longer and uncertain passenger journeys, due to longer average waiting time. In case of crowded PT operations, also due to longer dwell times. It also causes more crowded vehicles and therefore higher perceived in-vehicle time. In numerous studies, reliability-related attributes have been found among the most important service attributes. In earlier work, Van Oort et al. (2015) provide an overview of unreliability causes and impacts on passengers (see Figure 1). Multiple internal and external causes are identified and proper analyses are required to find and understand them.

1.1 Service reliability and AVL data

Van Oort et al. (2015) also illustrate possible applications of AVL (Automatic Vehicle Location) data analysis, focusing on the Dutch situation and based on the basic principles of AVL data analysis as were established by Furth et al. (2006) and Hickman (2004). AVL data remains a valuable data source to assess service reliability. In this paper it is used to assess the current state (before opening of the new metro line) of the tram network in Amsterdam. This enables assessing the impacts of opening the new metro line on service reliability.

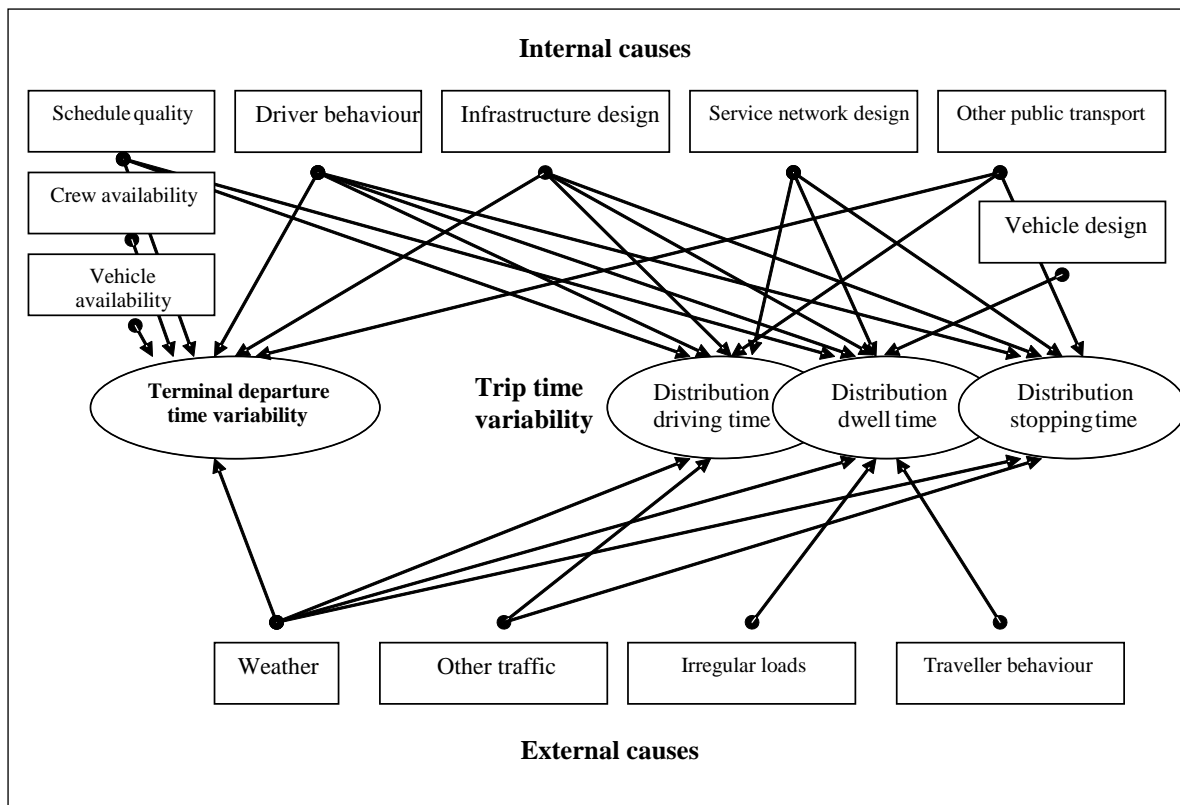


Fig. 1: Main causes of service variability in urban public transport

1.2 Paper objective

The objective of this paper is to develop a method to automatically detect bottlenecks in the public transport network, using Automatic Vehicle Location data as data source for analysing service reliability. As mentioned, a lot of literature exists on applications of AVL data in the past 15 years. The novelty of our approach is the ability to automatically identify bottlenecks in a systematic way. We develop a tool to translate the data into valuable information about quality of service. We will apply and demonstrate our method by providing an overview of unreliability causes in the current tram network of Amsterdam, using AVL data. The data and tool are applied to assess the quality of the tram network in Amsterdam in terms of operating speed and reliability. This may act as a starting point for before and after comparison analyses after opening of the new metro line.

1.3 Case study: Amsterdam network

Amsterdam has about 850,000 inhabitants within its municipality borders. Including the surrounding areas the number of inhabitants is about 1,350,000, covering an area of about 250 km². Currently, the area served by 13 train stations, 4 metro lines with 51 metro stations, 15 tram lines and 25 urban bus lines. The broad river IJ divides the city into two parts, where the city centre is situated in the larger southern part. The northern part of the city is only served by buses, but it is also connected to the rest of the city by 6 ferry connections.

A new metro line will come into operation in Amsterdam in the summer of 2018. The new metro line is to connect the north, central and south parts of the city, adding a large amount of capacity to the public transport (PT) network, especially in the busiest areas of the city (i.e. the monumental, dense city centre). The northern part of the city will be served by the metro network and buses will feeder on the metro line. In the southern part of the city the line ends at the main business district of Amsterdam (“Zuidas”).

Until now, the city centre is mainly served by tram lines, suffering from low speeds and unreliable operation. In the situation with the new metro line, the tram network will be redesigned to feeder on the new metro line (see Figure 2). It is expected that the operation of the tram network will improve in terms of operating speed and reliability, for two reasons. First, existing tram lines are expected to become less busy, leading to shorter dwell times, less bunching and therefore faster and more reliable operation. Second, in the redesigned tram network less lines are needed to serve the central train station and have a (partly) tangential route instead. It is expected that these tangential routes have less intersecting traffic (pedestrian, cycle and car), which also may results in faster and more reliable operations.

All PT vehicles in Amsterdam are equipped with GPS devices, so that AVL data can be collected. Table 1 shows an example of the data as available in Amsterdam. For each trip basic data is available like date, line number, direction, trip ID and vehicle ID. Within a trip each stop is included using both stop order numbers and stop names and numbers. For each combination of trip and stop, both the planned and realised arrival and departure times are available.

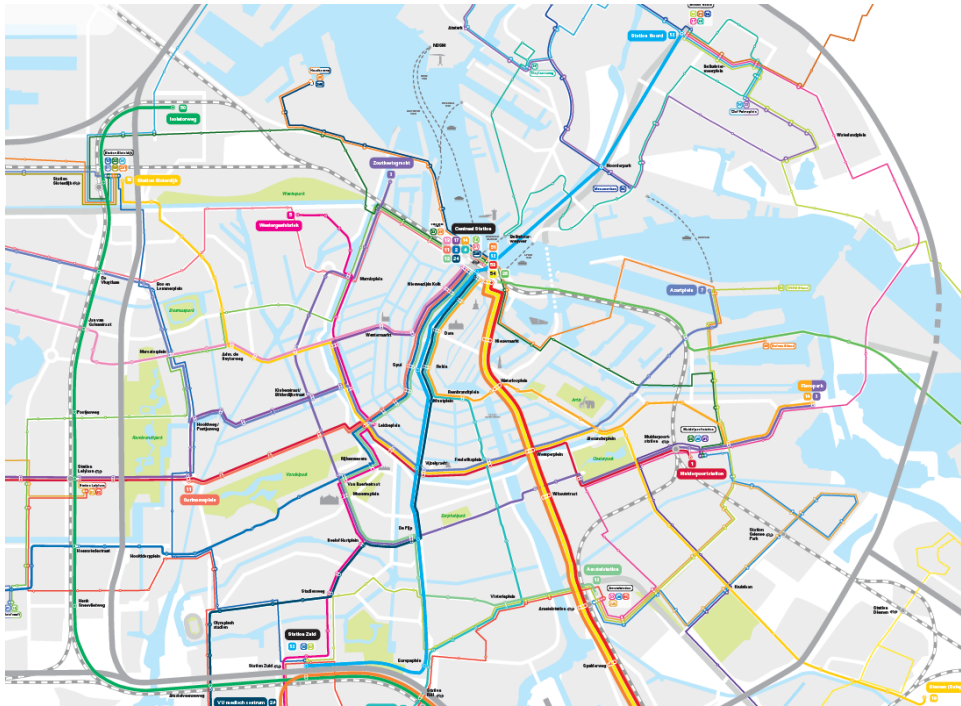


Fig. 2 The PT network of Amsterdam after opening of the new north south metro line. The new metro line is shown in light blue. Thick lines are metro lines and thin lines are tram lines.

Table 1 Example of AVL data in Amsterdam

Date	Line number	Direction	Trip ID	Stop order number	Stop name	Stop number	Vehicle ID	Planned arrival time	Planned departure time	Realized arrival time	Realized departure time
1-11-2017	2	1	355	1	Oudenaardeplantsoen	4314	574	18:54:00	18:54:00	18:54:34	18:54:34
1-11-2017	2	1	355	2	Kasterleepark	4278	574	18:55:17	18:55:35	18:55:48	18:56:02
1-11-2017	2	1	355	3	Laan v. Vlaanderen	4276	574	18:56:25	18:56:43	18:56:47	18:57:08
1-11-2017	2	1	355	4	Louwesweg	4089	574	18:57:31	18:57:49	18:58:31	18:58:56
1-11-2017	2	1	355	5	Johan Huizingalaan	4113	574	18:58:50	18:59:08	19:00:04	19:00:32
1-11-2017	2	1	355	6	Heemstedestraat	4116	574	19:01:09	19:01:27	19:01:59	19:02:44

1.4 Paper outline

The remainder of the paper is structured as follows. In chapter 2 the method of automatic bottleneck detection is described, starting with the introduction of notations and definitions. After that, the bottleneck criteria are mathematically described and a short description of the implementation in a software tool is given. In chapter 3 the results of the bottleneck detection for the case study in Amsterdam are described, including a sensitivity analysis with respect to the parameter values. Finally, chapter 4 provides conclusions and recommendations.

2 Systematic bottleneck detection

In this section the process to detect bottlenecks is described. After defining the notation, it is described how the data is processed to aggregated numbers. Next, the definitions of bottlenecks are given. Finally, the tool in which this method is implemented is shortly described.

2.1 Notation

The following notation is based on Gentile and Noekel (2016); it is extended where necessary. It is used in subsequent sections to define the criteria for bottleneck detection.

- $S_{l,d} \subseteq S$ Stop sequence of line $l \in L$ in direction d ; an ordered set with no repetitions.
- $S_{l,d}^- \in S_l$ First stop of line l in direction d .
- $S_{l,d}^+ \in S_l$ Last stop of line l in direction d .
- $s_{l,d}^- \in S_l$ Previous stop of stop $s \in S_{l,d} - S_{l,d}^-$ of line l in direction d .
- $s_{l,d}^+ \in S_l$ Successive stop of stop $s \in S_{l,d} - S_{l,d}^+$ of line l in direction d .
- $R_{l,d} \subseteq R$ (Scheduled) runs sequence of line $l \in L$ in d ; ordered set with no repetitions.
- P Set of time periods P .
- $R_{l,d,p} \subseteq R_l$ Runs of line $l \in L$ in direction d that fall into time period p .
- $K_p \subseteq K$ Days that fall into time period p .
- $\theta_{l,d,k,r,s}^{sched}$ Scheduled departure time for run r , line l direction d , at stop s , on day k .
- $\tau_{l,d,k,r,s}^{sched}$ Scheduled arrival time for run r , line l direction d , at stop s , on day k .
- $\theta_{l,d,k,r,s}^{real}$ Realised departure time for run r , line l direction d , at stop s , on day k .
- $\tau_{l,d,k,r,s}^{real}$ Realised arrival time for run r , line l direction d , at stop s , on day k .
- $L_{l,d,s}$ Length of line segment s on line l in direction d .
- α^1 to α^8 Threshold values for bottleneck detection.

2.2 Data processing

The following data is generated from the AVL data, and aggregated.

- Realised dwell time is calculated (difference between actual arrival time and departure time, see equation 1) for each r, l, d, s, k .

$$t_{l,d,k,r,s}^{dwell} = \theta_{l,d,k,r,s}^{real} - \tau_{l,d,k,r,s}^{real} \quad (1)$$

The average values are calculated for each time period P (see equation 2).

For each time period the 15, 50 and 85 percentile values $t_{l,d,s,p}^{dwell,p15}$, $t_{l,d,s,p}^{dwell,p50}$ and $t_{l,d,s,p}^{dwell,p85}$ are also calculated.

$$t_{l,d,s,p}^{dwell,av} = \frac{\sum_{k \in K_p, r \in R_{l,p}} t_{l,d,k,r,s}^{dwell}}{|k \in K_p| * |r \in R_{l,p}|} \quad (2)$$

- Realised punctuality is calculated (difference between actual departure time and planned departure time, see equation 3) for each r, l, d, s, k .

$$\pi_{l,d,k,r,s}^{real} = \theta_{l,d,k,r,s}^{real} - \theta_{l,d,k,r,s}^{sched} \quad (3)$$

Similar with dwell time, also for punctuality for each time period the average value $\pi_{l,d,s,p}^{av}$ is calculated, as well as the 15, 50 and 85 percentile values $\pi_{l,d,s,p}^{p15}$, $\pi_{l,d,s,p}^{p50}$ and $\pi_{l,d,s,p}^{p85}$.

- For each r, l, d, k , for each line segment $s \in S_{l,d} - S_{l,d}^-$ (from previous stop $s_{l,d}^-$ to current stop s , i.e. the segment before stop s), realised run time (difference between actual departure time at the previous stop and actual arrival time at the current stop, see equation 4) is calculated.

$$t_{l,d,k,r,s}^{run} = \tau_{l,d,k,r,s}^{real} - \theta_{l,d,k,r,s_{l,d}^-}^{real} \quad (4)$$

Similar with dwell time, also for run time for each time period the average value $t_{l,d,s,p}^{run,av}$ is calculated, as well as the 15, 50 and 85 percentile values $t_{l,d,s,p}^{run,p15}$, $t_{l,d,s,p}^{run,p50}$ and $t_{l,d,s,p}^{run,p85}$.

- Using the length of each segment $L_{l,d,s}$ these travel times are converted into speeds $v_{l,d,s,p}^{run,p15}$, $v_{l,d,s,p}^{run,p50}$, $v_{l,d,s,p}^{run,p85}$ and $v_{l,d,s,p}^{run,av}$.

Each of these values is calculated for 6 different time periods $p \in P$:

1. AM peak (7AM-9AM) on work days;
2. Inter peak period (9AM-4PM) on work days;
3. PM peak (4PM-6PM) on work days;
4. Evening period (6PM-midnight) on work days;
5. Saturdays;
6. Sundays.

These time periods represent the relevant distinctions between several situations to analyse. In both peak periods, the largest delays and travel time variations are expected to occur due to high traffic volumes: in many cases only in the peak direction. However, there is a difference: in the AM peak most traffic is commuter traffic, while in the PM peak traffic is more mixed with other purposes. The inter peak period on work days generally has moderate traffic volumes with a lot of leisure/shopping traffic, comparable with Saturdays. Evening periods on work days are usually less busy, just like Sundays. In a city like Amsterdam, with many

visitors coming to the city, also on Sundays and evenings busy times occur on a non-regular basis.

2.3 Bottleneck definition

Based on these aggregated data, the following definitions are used to identify bottlenecks. The parameter values used in the case study are based on expert judgement of the authors and of Dutch PT operators and authorities. In section 3.4 a sensitivity analysis on these values is included.

1. Large dwell time: $t_{l,d,s,p}^{dwell,av} > \alpha^1$. In the case study $\alpha^1 = 60$ seconds.
2. Large variation in dwell time: $t_{l,d,s,p}^{dwell,p85} - t_{l,d,s,p}^{dwell,p15} > \alpha^2$. In the case study $\alpha^2 = 120$ seconds.
3. Early departure: $\pi_{l,d,s,p}^{p50} < \alpha^3$. α^3 should be a negative value; in the case study $\alpha^3 = -60$ seconds.
4. Late departure: $\pi_{l,d,s,p}^{p50} > \alpha^4$. α^4 should be a positive value; in the case study $\alpha^4 = 180$ seconds.
5. Large variation in departure time: $\pi_{l,d,s,p}^{p85} - \pi_{l,d,s,p}^{p15} > \alpha^5$. In the case study $\alpha^5 = 300$ seconds.
6. A punctuality change compared to the previous stop: $|\pi_{l,d,s,p}^{p50} - \pi_{l,d,s_l^-,p}^{p50}| > \alpha^6$.
If this is the case, a structural delay occurs at the stage between those stops, that is not included in the schedule. In the case study $\alpha^6 = 60$ seconds.
7. Low speed: $v_{l,d,s,p}^{run,av} < \alpha^7$. In the case study $\alpha^7 = 15$ km/h.
8. Large travel time compared to free flow (the 15th percentile of the travel time on Sundays): $t_{l,d,s,p}^{run,av} - v_{l,d,s,p=6}^{run,p15} > \alpha^8$. In the case study $\alpha^8 = 60$ seconds.

If at least one of these criteria is met for a specific stop on a specific line and direction, a bottleneck is added to the list. This list is made for each time period p . For each criterion and time period, a top list can be created based on the indicator values.

2.4 Software tool

The data is processed using two tools in MS Excel (using VBA). First, the AVL data for each line is processed using the equations in section 2.2, resulting in aggregated data per line and time period. For one month of AVL data, the calculation time is approximately 5 minutes per line, on a regular laptop (Intel® Core™ i5-6200U CPU@2.30GHz). In the second tool, the aggregated data of all lines is put together in one database. The bottleneck detection rules (as defined in section 2.3) are applied to this database, with a bottleneck list as a result. An example screenshot of a resulting bottleneck list in the tool is shown in Figure 3.

Line	Direction	Period	Stop	Stop number	Average dwell time	Dwell time variation	Punctuality 50%	Variation departure time	Punctuality change wrt previous stop	Average speed	Difference with free flow travel time
10	Back	Evening	14Elandsgracht	6028	20	13	-28	217	65	30	18
10	Back	Saturday	13Leidseplein	6061	31	25	66	182	18	14	17
10	Back	Sunday	13Leidseplein	6061	29	22	32	163	14	15	14
10	Back	Sunday	14Elandsgracht	6028	20	17	-42	177	73	32	12
2	Forth	AM peak	09Hoofddorpplein	7049	25	18	73	199	45	13	39
2	Forth	AM peak	10Amstelveenseweg	7034	22	15	95	223	22	15	28
2	Forth	AM peak	13Van Baerlestraat	7322	23	11	50	303	2	18	37

Fig. 3 The resulting bottleneck list in the bottleneck detection tool

3 Results

3.1 Case study

The method for automatic bottleneck detection has been applied to the tram network of Amsterdam, consisting of 14 lines. In total, 617 combinations of lines (and directions) and stops are investigated. For each time period, each of these combinations is a potential bottleneck and is checked using the criteria. An AVL dataset of one month has been used (November 2017). For each line, this dataset consists of 80,000 to 200,000 records that contain both planned and recorded departure times $\theta_{l,d,k,r,s}^{sched}$ and $\theta_{l,d,k,r,s}^{real}$ and planned and recorded arrival times $\tau_{l,d,k,r,s}^{sched}$ and $\tau_{l,d,k,r,s}^{real}$. In total, the number of records is approximately 1.9 million.

3.2 Types of bottlenecks

The results are summarized in Table 2: for each time period the number of bottlenecks is shown in relation to the 8 criteria used as bottleneck definitions. It may be the case that one bottleneck is on the list due to more than one criterion: in the last column the number of bottlenecks is listed for which at least one criterion applies. It can be observed that the PM peak contains most bottlenecks: more than one third of the combinations of line and stop is identified as a bottleneck. Furthermore, it can be noted that during the day period more bottlenecks occur than in the AM peak: probably due to the large share of leisure / tourism traffic in Amsterdam.

Table 2 Number of bottleneck occurrences per time period and per criterion

Time period	Large dwell time	Large variation in dwell time	Early departure	Late departure	Large variation in departure time	Punctuality change compared to the previous stop	Low speed	Large travel time compared to free flow	At least one criterion
AM peak	4	0	17	0	27	11	87	7	133
Day period	4	0	11	0	60	10	87	13	164
PM peak	14	0	29	0	102	17	99	21	219
Evening	7	0	20	0	18	7	67	0	109
Saturdays	10	0	12	0	66	11	76	10	158
Sundays	6	0	29	0	0	9	64	10	104

Two observations can be done concerning type of bottlenecks. Firstly, no cases of large variation in dwell time or late departure are found in the tram network of Amsterdam. Secondly, low speeds and large variation in departure time occur most frequently: low speeds can be observed in all time periods, while large variation in departure time (unreliability) is mainly observed in the PM peak, during the day period and on Saturdays. During the AM peak tram operation is more reliable, probably due to limited leisure traffic (including pedestrians) during that period.

3.3 Location of bottlenecks

In Figure 4 the bottlenecks are shown geographically for the PM peak (the time period with the largest number of bottlenecks). The colour of the dot indicates the type of bottleneck. A larger size of the dot indicates that two or more bottlenecks occur at the same stop (on two or more lines).

It can be observed that low speed bottlenecks mainly occur in the old city centre, with a lot of on-street activities like pedestrians and cyclists. Large dwell time bottlenecks are observed in the city centre as well, probably due to large number of passengers. Large variation in punctuality is mainly observed towards the end of long lines between the city centre and the western suburbs and on tangential lines, in some cases in combination with early departures. Finally, the line from the city centre to the eastern suburb IJburg suffers from large changes in punctuality on subsequent stops, indicating that the timetable may be better adjusted to realised travel times.

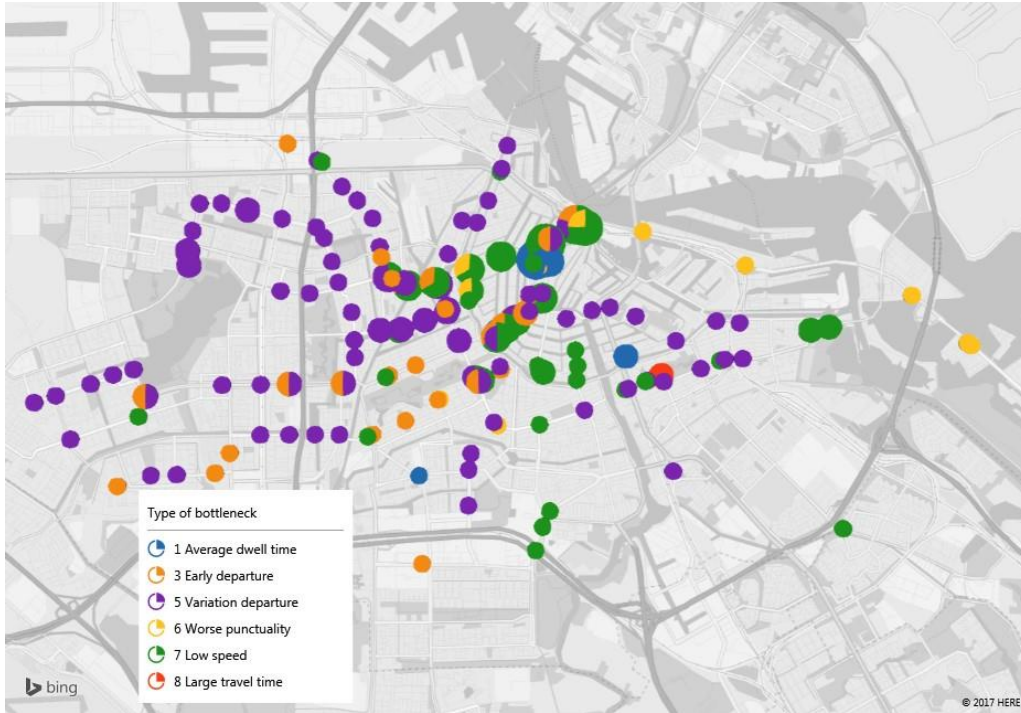


Fig. 4 Geographical representation of bottlenecks during the PM peak

3.4 Sensitivity analysis

To test the influence of the chosen parameter values on bottleneck detection (see section 2.3) a sensitivity analysis is conducted. In this analysis, two additional parameter sets are applied: one with tighter criteria (and therefore less identified bottlenecks) and one with looser criteria (and therefore more identified bottlenecks). The used parameter sets are shown in Table 3.

Table 3 Parameter values for bottleneck detection in the base analysis and in both sensitivity analyses.

Parameter	Base values	Sensitivity values 1	Sensitivity values 2	Unit
α^1 : Large dwell time	60	90	45	Seconds
α^2 : Large variation in dwell time	120	180	90	Seconds
α^3 : Early departure	-60	-90	-45	Seconds
α^4 : Late departure	180	300	120	Seconds
α^5 : Large variation in departure time	300	450	180	Seconds
α^6 : Punctuality change compared to previous stop	60	90	45	Seconds
α^7 : Low speed	15	12	18	Km/h
α^8 : Large travel time compared to free flow	60	90	45	Seconds

The results of the sensitivity analysis, in terms of numbers of identified bottlenecks, are shown in Table 4. The number of identified bottlenecks appears to be very

sensitive to the used parameter values. This stresses that it is very important to think well of the threshold values in relation to the question what is acceptable. This question may be posed from the perspective of society / the traveller, but also from the operator point of view. Another viewpoint may be the resulting numbers. From that perspective, the initial parameter set seems well chosen, since looser parameter values (2) lead to identifying more than half of the possible locations as a bottleneck. The tighter parameter values (1) lead to a relatively small number of bottlenecks and therefore does not seem very ambitious.

When looking at the different types of identified bottlenecks, it can be observed that especially variation in departure time is very sensitive to its parameter value: in case 2 it occurs almost ten times as much, while in case 1 it does not occur at all any more. It is also interesting to note that in case 2 every type of bottleneck occurs in the network of Amsterdam.

Table 4 Total number of bottleneck occurrences (over all time periods) in the sensitivity analysis.

Time period	Large dwell time	Large variation in dwell time	Early departure	Late departure	Large variation in departure time	Punctuality change compared to the previous stop	Low speed	Large travel time compared to free flow	At least one criterion
Base values	45	0	118	0	273	65	480	61	887
Sensitivity 1	0	0	18	0	0	11	154	23	180
Sensitivity 2	207	10	243	25	2310	265	994	145	2677

4 Conclusions

In this paper a method is developed to automatically detect bottlenecks in PT operations. The method first aggregates data (average values and 15, 50 and 85 percentile values) for dwell time, run time and punctuality. Secondly, bottlenecks are identified using 8 criteria that cover multiple aspects of reliability. The parameter values used to apply these criteria strongly influence the number of resulting bottlenecks. Therefore, it is important to set these values such that a reasonable number of bottlenecks are identified.

The method is successfully applied to the current tram network of Amsterdam, before the opening of a new metro line in the summer of 2018. In the PM peak most bottlenecks occur, which are mainly related to low speeds and unreliable departure times. It is expected that the new metro line alleviates these problems, because tram lines will become less busy and less tram lines will have to cross the monumental city centre, which is the busiest area of the city.

As future research we plan to compare the reliability performance of the PT network in Amsterdam before and after the opening of the new metro line. Furthermore, smart card data will be used in combination with AVL data to assess the distribution of passengers over vehicles. That information can be used to weigh bottlenecks depending on the number of passengers that suffer from them. Finally, we plan to compare actual performance of the PT network with quality perception of travellers, based on customer satisfaction surveys. The last recommendation we have for further research is to develop real time bottleneck detection. This could be done by connecting our method to CAD-AVL systems (see for instance Van Oort and Van Nes 2009), including a short term prediction model.

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