Traffic monitoring using handheld GSM phones:

Part B: Simulation Study

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GSM Based Road Traffic Monitoring

Executive summary

The present study contains a general design for a road traffic monitoring system based on vehicle probes, as well as a more detailed description of some of the crucial components of such a system. These components are a travel time estimation algorithm on the one hand and a map-matching algorithm on the other hand.

Travel time estimation
The travel time estimation algorithm has been implemented as a Kalman filter. The behaviour and accuracy of this algorithm has been extensively investigated. This has resulted in a number of design parameters. This investigation has taken place without explicitly considering any end-user applications. Instead the term ‘traffic monitoring’ was explained as ‘estimating section level travel times’. The performance has been evaluated in terms of accuracy and response time.

During the evaluation of the travel time estimation algorithm, two scenarios have been considered:
- A scenario in which the speed drops from 100 km/hr to 40 km/hr
- A scenario in which the speed drops from 100 km/hr to 20 km/hr

For both scenarios, the performance of the travel time estimation algorithm has been evaluated for an ‘average’ set of parameters that specify the average time between calls, the average duration of a call, the percentage of subscribers, the section length, the traffic flow, the polling rate and the accuracy with which the vehicle position is reported. This set of parameters is based on a best guess.

Figure 1 depicts the average relative error of the travel time as a function of time. Note that the speed drop occurs at 8:00. The relative error converges to 12% for scenario 1 and to 8% for scenario 2. A response time of 30 minutes is sufficient to approach the accuracy quite well in both scenarios.

Contrary to what one may expect, the absolute error proportional does not converge to zero. This is because the estimation has to take the possibility of speed changes into account, even if in reality the spread remains constant for a while. Effectively this means that the ‘newest’ (more recent) observations have a higher weight in the estimate than the ‘older’ (previous) ones.

Because both the speed data on which the vehicle trajectories are based and the reported vehicle positions in the probe Measurement Reports (MR’s) contain random errors, the observed individual vehicle speeds also contain random errors. Combined with the fact that the weight factor of the ‘newest’ observation never converges to zero, some of this error will appear in the filtered speed estimate.

Figure 2 illustrates the sensitivity of the relative error of travel time estimation after a response time of 30 minutes for all input parameters considered. It turns out that the error is particularly sensitive to the location accuracy of the MR’s and the average call duration. Also the total number of calls that has been made has a large influence this number of calls depends on the average time between calls and the percentage of subscribers. In the domain that was analysed
the polling rate has only a small impact. Provided the section length is larger than 2 kilometres, the section length has no influence on the relative error.

![AEP absolute error proportional](image)

**Figure 1:** Relative error of travel time estimation as a function of time for scenario 1 and 2

![AEP absolute error proportional: scenario 2 at 08:30](image)

**Figure 2:** Sensitivity of the relative error of travel time estimation after a response time of 30 minutes for the average time between calls, the average duration of a call, the percentage of subscribers, the polling rate, the accuracy with which the vehicle position is reported, the section length and the flow rate. The horizontal axis indicates the relative values in [%]

**Map matching**

A new map matching algorithm has been developed. This algorithm is implemented as a curve-to-curve matching algorithm and has as a distinguishing property that it can deal with large errors in the probe location data, and filter out the route of vehicle, provided that sufficient MR's are available.
The map-matching algorithm has been evaluated using four different scenarios:

- Opposing traffic, balanced demand
- Crossing traffic, balanced demand
- Parallel and crossing traffic, balanced demand
- Parallel traffic, unbalanced demand

Where 'opposing' and 'crossing' relate to the direction of the route and 'balanced' and 'unbalanced' relate to the 'apriori' distribution of traffic over the routes.

For all scenarios the performance of the map matching algorithm has been evaluated for a set of parameters that is identical to the set that has been used for the evaluation of the travel time estimation algorithm. The parameters 'percentage of subscribers' and 'traffic flow' have been ignored since these do not influence the percentage of properly matched vehicles.

In the first two cases the matches are near perfect, suggesting that the matching algorithm is quite suitable for distinguishing traffic that is travelling in opposed or crossing traffic. The third case shows a matching rate of 61%. This rate can only be increased to acceptable values if the accuracy is improved. For the last scenario good results are obtained, but this is only because of the unbalanced nature of the demand.

Again, it turns out that the algorithm is most sensitive to the parameter 'call-duration', while 'accuracy' is the second important parameter.

The current algorithm does not make use of an apriori speed distribution, and values all matching maps equally likely regardless of the speed pattern they imply, as long as minimum and maximum speed are not violated. Taking into account speed distributions will greatly improve the number of successful matches, especially for parallel routes with different average speeds. The only problem is that this will impair the quality of matching during circumstances with extreme slow traffic, while these are the kind of circumstances that one would want to rely on the matching algorithm the most. This topic therefore requires more research.
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1 Introduction

Small, powerful, and affordable cellular phones are a relatively new phenomenon that has now gained widespread acceptance. Since a major part of a cellular telephone network consists of software, this network with relative ease can be made to offer functionality beyond the transmission of conversations.

A promising area for new applications are traffic monitoring and traveller information services. A joint venture has been formed by the telecommunications hardware company Ericsson and GSM service provider Libertel, which will serve as a vehicle for work in this area. The joint-venture is called "Syntrack", the executive authority of which has been vested in the steering committee RRP.

A project proposal titled "Road traffic management" has been drafted by Syntrack which proposes to build a working prototype system that is able to provide on-line traffic information based on locating cellular phones (called probe vehicles or probes). As a first step towards realisation of the prototype, a feasibility study is proposed in which both the applications and the technical set-up of the system are to be investigated.

The TU Delft has been asked by the RRP steering committee to contribute to this feasibility study. The study consists of two parts: Part I concerns the literature scan [1]. Part II concerns the topics architecture, algorithm design, a preliminary feasibility analysis based on simulation and proposals for next steps.

This report concerns part II and addresses the preliminary feasibility analysis and simulation study, specifically the following topics:

- A general design of (GSM) Probe based traffic monitoring system.
- Algorithms for map-matching and travel-time estimation based on probe Measurement Reports (MR's) that may contain large spatial errors.
- A description of simulation study towards the quality of travel time estimation based on GSM probe data.
- A description of simulation study towards the quality of map-matching based on GSM probe data.
- A proposal to set up a feasibility study for a traffic monitoring system based on GSM handhelds.

1.1 Applications of a GSM based traffic monitoring system

This section will highlight the possible role of a GSM-based traffic monitoring system within the context of dynamic traffic management, and will highlight possible applications for the system envisaged, dependent on the characteristics of the system. The main characteristics of the system are: accuracy of measurement, response time.

Typical applications of a GSM based traffic monitoring system are:

- A historic database that contains road section travel times. As many traffic processes are of a highly repetitive nature, a historic database is a powerful component of any traffic forecasting system. Providing data for a historic database may be done with hindsight, as opposed to the requirements for real-time traveller information or traffic control systems.
This means that with the same data a much greater accuracy can be obtained. Even real-time applications rely heavily on accurate and complete data from an historic database.

- *An on-line traveller information system.* The advantage of traveller information systems based on probe data is that potentially a large part of the road network can be covered as opposed to existing systems that cover only freeways.
- *Route guidance.* This requires the highest level of detail and accuracy, as very specific recommendations need to be issued.

As these examples show, different applications imply different requirements to the traffic monitoring system that is used. In Table 1 a correspondence is given between possible applications and monitoring system characteristics.

### Table 1: Match between applications and system characteristics

<table>
<thead>
<tr>
<th></th>
<th>GSM monitoring</th>
<th>Congestion detection</th>
<th>Road monitoring</th>
<th>Historic databases (speed profiles)</th>
<th>Route choice investigation, Dynamic O/D matrix estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importance of</td>
<td>low response time</td>
<td>++</td>
<td>+</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>High accuracy</td>
<td>++</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Many probes</td>
<td>-</td>
<td>-</td>
<td>--</td>
<td>+</td>
</tr>
</tbody>
</table>

In practice the highway authorities aim at integrating a large variety of traveller information and traffic control systems with the traffic monitoring system. The framework that is currently used for that is shown in Figure 3.

The monitoring system that is mentioned in this framework uses road site based techniques (like loop detectors, automated license plate readers, traffic eyes) and vehicle based techniques (like GPS probes and GSM probes) or a mixture (like vehicles that carry a transponder or an electronic tag).

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**Figure 3:** The relationship between the traffic system and traffic monitoring
1.2 Objectives of the present study

As has been said in the introduction the aim of the present study is to determine whether or not a traffic monitoring system based on GSM probes is feasible and if yes, how such a monitoring system should look like.

A first step approach to this problem has been to scan the existing literature for examples that demonstrate the feasibility. The results of this literature scan have been reported in a separate report [1]. A number of interesting examples of probe based traffic monitoring have been reported, of which the US Wireless approach [2] shows the largest similarities with the situation in the Netherlands.

A second approach consists of a quantitative analysis and is described in the present report. To carry out the analysis in the most precise manner it would be necessary to identify the end users indicated in Figure 3 and then draw up a list of requirements with respect to the traffic monitoring system and assess whether these requirements can be met or not. In the present study we will try to answer the question in a somewhat more general manner. We will interpret the term 'traffic monitoring' as 'estimating (road)section level travel times', and evaluate the performance in terms of accuracy and response time.

In order to carry out such a study a quantitative model of a probe based traffic monitoring system should be build. This leads to a number of derived objectives that shall be addressed in this report:

- Provide a general framework for a GSM probe based traffic monitoring system and identify the crucial components of such a system
- Implement prototypes for these components
- Identify a plausible value range for the parameters that define the phone traffic (Like: the number of calls per time unit, the average length of calls, the frequency and accuracy of positioning)
- Identify a plausible range for the parameters that define the road traffic (Like: the amount of vehicles, their speeds and the layout of the road network)
- Evaluate the components based on appropriate criteria

1.3 Structure of this report

In chapter 2 a system design is described for traffic monitoring using hand-held GSM phones. Two crucial components of such a system are described in specific sections of chapter 2. Chapter 3 describes what kind of experiments have been carried out to determine the accuracy and response time of the probe based travel time estimation algorithm proposed in chapter 2 and presents the results of these experiments. Chapter 3 also describes what kind of experiments have been carried out to determine the effectiveness of the map-matching algorithm that has been proposed including the results of these experiments. Chapter 5 summarises the conclusions that may be drawn from the current work. Because the current work is intended as a part of an ongoing stream of research into the area of GSM probe based traffic monitoring, the report concludes with a chapter in subsequent steps in this research stream are proposed.
2 System design

2.1 Introduction

This chapter describes a system for traffic monitoring based on Measurement Reports (MR's) that contain a time stamp, user ID, and location vector. The location vectors in the MR's are determined using the ECGI\(^1\) positioning method. It is assumed that for most monitoring applications it is sufficient to use estimated travel time as the primary input. The specific requirements with respect to the accuracy and response time of these travel time estimates may vary over applications.

First a general framework for estimating road section travel times is presented (section 2.2), then two of its main components are described (section 2.3 and section 2.4). Chapter 3 describes the simulation models that are used to assess the performance of these components and their sensitivity to various road-traffic and phone-traffic related parameters.

2.2 General framework

The framework on which we concentrate our analysis is depicted in Figure 4. The boxes with rounded edges represent actions, while the square boxes represent datasets. The arrows in between represent dataflows. Although this framework is by no means exhaustive, it contains the elements on which the feasibility study in the present study is focused: the route matching component and the map matching component.

Going through the elements of the framework one by one:

- **Measurement Reports (dataset).** This is a list of records each containing the following:
  - **Caller ID:** a unique key for each user.
  - **Location vector.** The X-Y co-ordinates where the MR stems from. Typically this information is not accurate.
  - **Time stamp.** The time instant that the MR was generated.

- **Network data (dataset).** This dataset contains the topology of the road network, consisting of nodes (intersections of 2 or more links), and links (road sections). Also data about the exact location of each road section and maximum speeds for road sections should be available. Some of the network nodes also represent origins or destinations: locations at which trips originate or end.

- **Origin-Destination (OD)-demand (dataset).** This is a matrix that specifies the approximate number of trips that take place between each origin and destination. This information is used to compute the traffic load that is expected a priori (hence not using any probe information) at each route.

- **Select MR's for study area (action).** We assume that we are interested in the travel times at the road-sections in a specific area. The first step in the data processing would then be to filter all MR's and to skip those that do not apply to this area.

- **Route matching (action)** A next step is to find sequences of MR's with identical caller ID's and to match these sequences with specific routes, if possible.

\(^1\) The Enhanced Cell Global Identity (ECGI) method is a cell based method for positioning; its performance was investigated by Ericsson and it resulted more accurate than the other cell based methods.
• **MR's per network section (dataset).** The route matching implicitly assigns each MR to a specific road section.

• **Unused MR's (dataset).** If a sequence of MR's can not be matched to a specific route, the sequence of matches is categorised as 'unused'.

• **Travel time estimation (action).** Once MR's have been matched to a road section, they can be used to estimate the travel time on that road section.

• **Travel times per network section (dataset)**

• **Data processing (action).** The travel time information is processed in order to generate traffic control measures or to inform drivers.

• **Historic information (dataset).** Historic databases are an important additional source of information, also for on-line systems.

• **Traffic information, Route directives, ... (datasets).** Using estimated travel times travellers can be informed about current conditions. If the destination is known, it is even possible to give route directives.

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**Figure 4:** Dataflow diagram of GSM based traffic monitoring and traveller information system based on probe MR's.
2.3 Route matching for individual vehicles

2.3.1 Background

This section addresses the problem of matching probe MR’s to specific road sections. If the position reported in these MR’s would be sufficiently accurate, this would be a trivial task of matching each MR to the road section that is closest, using a point to point or point to curve matching algorithm such as described in the literature study that accompanies this study.

However, large errors have to be taken into account and these errors prevent matching single MR’s to road sections. Therefore we do not consider separate MR’s, but try to match sequences of MR’s to a route through the network. This is an example of curve to curve matching. This enables us to utilise additional information like:

- There are a limited number of ‘logical’ routes: routes then bring a driver from a network entry-point to a network exit in an efficient way.
- The speed with which vehicles move over these routes is constrained by a minimum and maximum.

Applying this knowledge enables the matching sequences of MR’s to specific routes.

Because we impose the constraint that the points to which messages are jointly form a route we use the term route-matching rather than map-matching.

2.3.2 The route matching problem

We will now describe the problem of matching a sequence of GSM messages to a route in mathematical terms.

Notation

\[ \{t_k, x_k, y_k\} \] An ordered series of probe location messages, \( k=1,2, \ldots K \), with \( t_k \) the time instant of the \( k \)th message and \( \{x_k, y_k\} \) the co-ordinates of the \( k \)th message, with \( t_1 < t_2 < \ldots < t_K \).

\[ \{d_{ar}, x_{ar}, y_{ar}\} \] An ordered series of points along route \( r, r=1,2,\ldots R \), \( a=1,2,\ldots A \), with \( d_{ar} \) the distance of the \( a \)th point from the Origin along route \( r \) (see Figure 5), and \( \{x_{ar}, y_{ar}\} \) the co-ordinates of this point. These points can be chosen arbitrarily close to each other. Note that \( d_{ar} < d_{ar} < \ldots < d_{Ar} \).

We are looking for a so-called route-matching map. A route matching map matches every probe-message to a location on the network. In this section we will formulate the constraints that apply to this matching map and define the matching problem as an optimisation problem.

In order to apply this algorithm we will need to assume the following:

- The co-ordinates of the \( k \)th message, \( \{x_k, y_k\} \), are equal to the exact position of the vehicle at instant \( t_k \) increased with and error vector \( \{e_{x_k}, e_{y_k}\} \).
- The distribution of the error vector of the \( k \)th observation \( \{e_{x_k}, e_{y_k}\} \), \( p[e_{x_k}, e_{y_k}] \) is known and independent from observation errors for all other periods.
Figure 5: Example of route matching: Each message is matched to a specific route node.

We will now determine the most likely match $\pi$ between the sequence of messages and the available routes. This match is represented by the matrix $\pi'$ with:

$$
\pi'_{ka} = 1: \text{message } k \text{ originates from point } a \text{ along route } r
$$

$$
\pi'_{ka} = 0: \text{message } k \text{ does not originate from point } a \text{ along route } r
$$

(1)

Obviously message $k$ originates from exactly one point hence:

$$
\sum_{r=1}^{R} \sum_{a=1}^{A} \pi'_{ka} = 1
$$

(2)

Also a vehicle can only travel at one route at a time, hence:

$$
\pi'_{ka} = 1 \Rightarrow \pi'_{pb} = 0, \forall s \neq r, \forall p = k + 1, k + 2, \ldots, K, \forall b = 1, 2, \ldots, B
$$

(3)

In other words: if any message $k$ is matched to route $r$ at any link, no message can be matched to any other route ($s$), regardless of the message ($p$) or link ($b$).

Finally there are a number of speed constraints to be taken into account. Vehicles have a positive speed, hence:

$$
\pi'_{ka} = 1 \Rightarrow \pi'_{k+1,b} = 0, \forall b < a
$$

(4)

In other words: if message $k$ is matched to link $a$ of route $r$, the next message can not be matched to an upstream link ($b$) of $a$.

The speed of vehicles does not exceed a given maximum speed $v_{\text{max}}$, hence:

$$
\pi'_{ka} = 1 \Rightarrow \pi'_{k+1,b} = 0, \forall b \left| (d_{by} - d_{ay}) > v_{\text{max}} \cdot (t_{k+1} - t_{k}) + \Delta \right.
$$

(5)

where $\Delta$ is the distance between two consecutive points along a route.
The objective is to find a map $\pi$ that satisfies these conditions and maximizes the likelihood of observing the messages $\{t_k, x_k, y_k\}$. This likelihood can be written as:

$$L(\pi) = \prod_{r=1}^{R} \prod_{a=1}^{A} \prod_{k=1}^{K} (p^k [x_k - x_{ar}, y_k - y_{ar}])^{\pi_{ka}}$$

The resulting map $\pi$ implies the route for which the most likely curve occurs, as well as the points along this route to which each message will be mapped.

### 2.3.3 A route matching algorithm

It is clear that an effective search strategy is needed to maximize the likelihood specified in (6): for a naïve brute force method the number of matching maps $\pi$ that are feasible in terms of constraints (2), (3), (4), (5) is simply too large. In this section we will define such a strategy.

Suppose that we match message $k$ with point $a$ at route $r$ then the constraint (2) implies that message $k+1$ should be matched to a point along route $r$. Moreover constraints (3) and (4) imply that this point should be somewhere in the interval $[d_{ar}, d_{ar} + v_{max}(t_{k+1} - t_k) + \Delta]$. In other words the vehicle can only travel forward over a route and can not exceed its maximum speed. Graphically this is represented in Figure 6.

![Figure 6: If point $a$ is the point to which message $k$ is matched, the arrows in above figure indicate the feasible matching points for message $k+1$.](image)

We will now construct a so-called hypernetwork consisting of nodes and links to which we will give specific interpretations. These interpretations will enable us to formulate the route matching problem as a shortest path search problem.

We start with defining the nodes. Of each node on each route we make $K$ (=the number of messages) copies, see Figure 7. Each node represents a physical node in a specific time period.
Subsequently we add the links. Links will be added if and only if the following condition is met:

"The existence of a link between node \((a,r,k)\) (node \(a\) on route \(r\) in period \(k\)) and node \((b,r,k+1)\) (node \(b\) on route \(r\) in period \(k+1\)) indicates that the movement of a vehicle between node \(a\) and \(b\) during the period \(t_{k+1}-t_k\) is feasible in terms of constraints (3) and (4)."

Travelling over a link could be given the following interpretation:

"Travelling over the link that connects node \((a,r,k)\) with node \((b,r,k+1)\) represents the action of (matching message \(k\) with node \(a\) on route \(r\)) AND (matching message \(k+1\) with node \(b\) on route \(r\))"
This implies that travelling over a route (a series of links of which each route-link end-point coincides with the start node of the next route link) through the nodes \{(a,r,k), (b,r,k+1), (c,r,k+3)\}... is interpreted with matching message \(k\) with node \(a\), message \(k+1\) with node \(b\), etc.

Hence each route matching map \(\pi\) that is feasible in terms of constraints (2), (3), (4), (5) corresponds to exactly one path that connects the nodes \((1,r,1)\) and \((A,r,K)\) for given nodes \(1,2,...,A\) and route \(r\).

The likelihood of this matching map is given by equation (6). Instead of maximising the likelihood of equation (6), we might as well minimise the negative logarithmic value of this expression:

\[
\log L(\pi) = \sum_{r=1}^{R} \sum_{a=1}^{A} \sum_{k=1}^{K} \pi_{ka} \cdot -\log(p(x_k - x_{ar}, y_k - y_{ar}))
\]

If we associate with each link in the hypernetwork a cost of:

\[
-\log(p(x_k - x_{ar}, y_k - y_{ar}))
\]

where \((a,r,k)\) are the node-number, route number and period number of the end-node, it follows that \(\log L(\pi)\) corresponds to the cost of the path that is defined by \(\pi\).

Finding the route matching map \(\pi\) that maximises the loglikelihood is hence equivalent to finding the shortest path that connects the nodes \((a,r,1)\) and \((b,r,K)\) for any nodes \(a, b\) and route \(r\).

We now extend the earlier defined hypernetwork with an origin-centroid \(A\) and destination centroid \(B\). Subsequently we connect centroid \(A\) to all nodes \((a,r,1)\) (all nodes for period 1) and we connect all nodes \((a,r,K)\) (all nodes for period \(K\)) with centroid \(B\). To the new connector links to \(A\) we attach a cost value analogue to (8) and to the new connector links to \(B\) we attach a cost value of 0 (see Figure 9).

Now finding the route matching map \(\pi\) that maximises the loglikelihood is equivalent to finding the minimum cost path between \(A\) and \(B\) in a network with an additive cost structure.
To find this minimum cost path standard shortest path algorithms can be used, once the network is defined. These algorithms are characterised by a high efficiency. The above can be summarised in the following algorithm:

- **Algorithm**-

  - Define the hypernetwork nodes \{a,r,k\}
  - Define the hypernetwork links between all pairs for \{a,r,k\} and \{b,r,k+1\} that satisfy (4), (5)
  - Define the corresponding costs as (8)
  - Define the origin-centroid A and destination-centroid B
  - Define the cost of the links to A as (8) and zero cost connector links to B
  - Compute the shortest path between A and B

### 2.3.4 A Bayesian route matching algorithm

In the previous section we have derived a method for finding the most likely route matching map. This is the map matching map that maximises the probability of observing the probe messages \(\{t_i, x, y_k\}\). This map not only tells us to which route the messages are matched, but also to which location each message is matched.
Although this information is required in the context of the framework of Figure 4, it does not answer all our questions. Two alternative ways of approaching the map matching problem are the following:

a) Which route maximises the probability of observing messages \( \{ t_k, x_k, y_k \} \)?

b) What is the probability that a vehicle that sends the sequence of messages \( \{ t_k, x_k, y_k \} \) is travelling over route \( r \)?

The answer to question b) will be used in the simulation experiments later in this report. It will be shown that a) and b) are closely related to the theory of the previous section.

Ad a)

The likelihood of a route matching map and the likelihood of a route are not identical because a route matching map does not uniquely imply a route. In other words: it is possible to match a sequence of messages in different sets of nodes that belong to the same route.

The likelihood of a route matching map is defined by:

\[
L(\pi) = p(t_1, J_K, x_1, \ldots, x_K, y_1, \ldots, y_K | \pi) \tag{9}
\]

While the likelihood of a route is defined by:

\[
L(r) = p(t_1, J_K, x_1, \ldots, x_K, y_1, \ldots, y_K | r) \tag{10}
\]

The two are related in the following way:

\[
L(r) = \sum_{\pi \in r} p(t_1, J_K, x_1, \ldots, x_K, y_1, \ldots, y_K | r) \tag{11}
\]

We will assume that given a specific route, all feasible matching maps are equally likely, hence:

\[
p(\pi | r) = 1 / N_r \tag{12}
\]

With \( N_r \), the number of feasible matching maps for route \( r \). More advanced assumptions might be appropriate here if we would have information about the distribution of the travel times between the nodes of the routes.

\[
L(r) = \sum_{\pi \in r} p(t_1, J_K, x_1, \ldots, x_K, y_1, \ldots, y_K | r) \tag{13}
\]

Normally the route that is implied by the most likely matching map will also be the most likely route. Exceptions may occur in specific situations where a lower route matching likelihood is compensated by a higher number of feasible route matching maps (see Figure 10)
Figure 10: The route matching likelihood of the messages (+) is maximised for route A, but the route likelihood is maximised for route B.

Ad b)
Instead of maximising the likelihood of the observations we might also pose the question: "which is the likelihood that the vehicles that generated the messages is travelling over route r?" Mathematically this probability is expressed as:

\[
\Pr[r|t_i..t_K, x_i..x_K, y_i..y_K] = \frac{p[t_i..t_K, x_i..x_K, y_i..y_K | r].Pr[r]}{p[t_i..t_K, x_i..x_K, y_i..y_K | r]} \tag{14}
\]

This can be rewritten as:

\[
\Pr[r|t_i..t_K, x_i..x_K, y_i..y_K] = \frac{p[t_i..t_K, x_i..x_K, y_i..y_K | r].Pr[r]}{\sum_r p[t_i..t_K, x_i..x_K, y_i..y_K | r].Pr[r]} \tag{15}
\]

In this expression we recognise in the numerator the likelihood \(p[t_i..t_K, x_i..x_K, y_i..y_K | r]\). The expression \(Pr[r]\) represents the apriori probability of selecting route r, which should be interpreted as the probability that route r is selected, conditioned on the apriori information. Defining this probability can give some problems, but if an origin-destination demand matrix \(T\) is available, a suitable expression would be:

\[
Pr[r] = \frac{T_r}{\sum_r T_r} \tag{16}
\]

If the likelihood and apriori route selection probabilities are known the denominator follows from the expression:

\[
p[t_i..t_K, x_i..x_K, y_i..y_K] = \sum_r p[t_i..t_K, x_i..x_K, y_i..y_K | r].Pr[r] \tag{17}
\]

The denominator is therefore referred to as the normalisation constant.

Again the derivation of the route likelihood \(Pr[r|t_i..t_K, x_i..x_K, y_i..y_K]\) is a problem. In our present analysis we will assume that:
Where C is a constant that does not depend on r. The approximate Bayesian solution that we will use in our present analysis is hence given by:

\[
Pr[r|t_1, t_K, x_1, x_K, y_1, y_K] = \frac{1}{N} \max_{\pi \in r} \left( p(t_1, t_K, x_1, x_K, y_1, y_K | \pi) \cdot Pr[\pi] \right)
\]  

with:

\[
N = \sum_r \max_{\pi \in r} \left( p(t_1, t_K, x_1, x_K, y_1, y_K | \pi) \cdot Pr[\pi] \right)
\]  

### 2.4 Estimation of the travel speed of individual vehicles

#### 2.4.1 Problem description

In this section we will present a method for the estimation of vehicle speed based on probe messages. This estimator will be formulated as a simultaneous, recursive estimator of probe location and probe speed. We will only consider a one dimensional movement of a probe over a road section. The position and speed of the probe hence refer to the longitudinal position along the section.

The state vector can hence be written as:

\[
s(t_k) = \begin{pmatrix} x(t_k) \\ v(t_k) \end{pmatrix}
\]

with:

- \( s(t_k) \): The state vector at time instant \( k \)
- \( x(t_k) \): Longitudinal position at time instant \( k \)
- \( v(t_k) \): Vehicle speed at time instant \( k \)

Since we assume at the probe is travelling at a constant speed, the following *state transition equation* applies:

\[
\begin{align*}
x(t_{k+1}) &= x(t_k) + v(t_k)(t_{k+1} - t_k) \\
v(t_{k+1}) &= v(t_k)
\end{align*}
\]
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For each time instant $k$ measurements are available. These measurements only apply to the location of the probe vehicle and not to the speed. An observation of a probe consists of a two dimensional or possibly three dimensional vector that indicates the position of the probe in the $x$-, $y$-, $z$- plane. This vector can be mapped to the road-section the probe is travelling on, resulting in a longitudinal position of the probe along the section. This observation process may be described by the following measurement equation:

$$ z(t_k) = x(t_k) + \epsilon(t_k) $$

with:

$$ \epsilon(t_k) : \text{ observation error} $$

Or in matrix notation:

$$ z(t_k) = (1 \ 0) s(t_k) + \epsilon(t_k) = H s(t_k) + \epsilon(t_k) $$

with:

$$ H_k = H = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad E[\epsilon(t_k)] = 0, \quad \text{var}[\epsilon(t_k)] = R_k = R $$

### 2.4.2 Algorithm for estimating state vector

Equations (22) and (24) define a linear system. For this type of systems there exists a recursive estimator, called the Kalman filter, that can be used to estimate the state vector. Under very general assumptions the estimates that are produced by this filter can be shown to be Unbiased Minimum Variance Linear estimates. In other words: of all unbiased estimators that can be written as a linear function of the observations $z(t_k)$ the Kalman filter produces the one that has the smallest error.

For each time instant $k$ the filter produces estimates of the position and speed, based on all observation before and including time instant $k$. This estimated is denoted as: $\hat{s}_{k/k}$. Apart from this point estimate, also a variance-covariance matrix is estimated, which is denoted as $\Sigma_{k/k}$.

The algorithm is formulated in a recursive way, in other words: the estimation at time instant $k+1$ only depends on the observation at time instant $k+1$ and the point estimate $\hat{s}_{k/k}$ and variance-covariance matrix $\Sigma_{k/k}$ at time instant $k$.

At time instant 0 the algorithm should be initialised with a point estimate and variance-covariance matrix that express the 'empty information set'.

The resulting algorithm can be summarised as follows:
-Algorithm-

**Initialisation**
\[ \hat{\theta}_{0/0} = \text{mean value} \]
\[ \Sigma_{0/0} = \begin{pmatrix} \inf & 0 \\ 0 & \inf \end{pmatrix} \]

**Update equations:**

1. \[ \Sigma_{k+1/k} = F_k \Sigma_{k/k} F_k' \]
2. \[ L_{k+1} = \Sigma_{k+1/k} H (H' \Sigma_{k+1/k} H + R)^{-1} \]
3. \[ \hat{\theta}_{k+1/k+1} = F_k \hat{\theta}_{k/k} + L_{k+1} (z_k - H' F_k \hat{\theta}_{k/k}) \]
4. \[ \Sigma_{k+1/k+1} = \Sigma_{k+1/k} - \Sigma_{k+1/k} H_{k+1} (H' \Sigma_{k+1/k} H + R)^{-1} H'_{k+1} \Sigma_{k+1/k} \]

The speed estimate at instant \( k+1 \) is the second element of \( \hat{\theta}_{k+1/k+1} \)
3 Experiments results: quality of travel time estimation

3.1 Introduction

The aim of the following simulation study is to investigate the parameters that determine whether traffic monitoring using Measurement Reports (MR's) is feasible. The quality of traffic monitoring system based on GSM handhelds is focused on the issue of traffic monitoring on motorways, especially estimation of travel times.

In order to assess the performance of travel time estimation using MR's a simulation based approach has been designed. In this approach the sensitivity of a travel time estimation algorithm for the following factors will be tested:

- Properties of traffic:
  - Flow rate: average number of vehicles per hour.

- Properties of road layout:
  - Section length of the road-stretch for which the travel times are estimated and for which the travel speeds are assumed to be constant.

- Properties of callers:
  - Average idle time: average elapsed time between consecutive calls.
  - Call duration: average duration of calls.
  - Percentage of subscribers: percentage of people that potentially can make a call.
  - Polling rate: elapsed time between consecutive generated location MR's.
  - Accuracy of the positioning of GSM handhelds.

Section 3.2 describes the simulation model. Section 3.3 shows the architecture of the simulation approach. The interactive and batch version of the simulation model is given in section 3.4 and 3.5 respectively. The scenarios and the results of the simulation program are reported in section 3.6 and 3.7 respectively.

3.2 Simulation model

Focus of the simulation model is the estimation of travel times by locating vehicles that make GSM calls. The accuracy with which travel times can be estimated determines the traffic monitoring quality. In order to determine the performance of traffic monitoring, travel times estimated through GSM calls are compared with reference travel times. Reference travel times are calculated by considering speed data and passage time data measured at a certain time and point in the section road. Speed data and passage times are used to build up vehicle trajectories within a section road and for a given interval of time. Individual travel times are computed for each vehicle by considering the actual speeds to be constant within the section road.

The location of probe vehicles can be determined through the GSM system only for the period during which probes are making calls. Therefore travel times can be estimated only for vehicles that make calls. In the simulation model calls are generated randomly for a given percentage of probes that are travelling along the road section and are labelled as subscribers. The number of calls per probe vehicle is sampled with an exponential distribution, considering the average elapsed time between consecutive calls. The duration of one call is
also sampled with an exponential distribution, considering the average duration of calls. Location MR’s are generated by the GSM system for each call. Each location MR produces the cell phone location and the time when the reported location is determined. The number of location MR’s generated depends on the polling rate (elapsed time between consecutive generated location MR’s) and of course on the duration of calls. The size of the error that applies to the reported location of the cell phone depends on the accuracy of the positioning of GSM handhelds. Because of the positioning errors, the sequence of location MR’s, generated for a particular call, are filtered in order to estimate the speed of the probe vehicle that makes the call. The estimated speeds are used for determining the travel time of each probe.

The individual travel time computed on the basis of the actual speeds are filtered to obtain the prevailing travel time as a function of time. Likewise, the estimated travel time based on probe MR’s is filtered to obtain the estimated travel time as a function of time. The estimated travel time will be compared with the prevailing time and the mean absolute error proportional and dynamic errors are calculated to assess the traffic monitoring quality.
### 3.3 Description of the simulation model

![Diagram showing the general assessment framework for traffic monitoring using GSM based on travel time estimation algorithms.](image)

Figure 11 shows the general assessment framework for traffic monitoring using GSM based on travel time estimation algorithms.

Input parameters for the simulation model are depicted in the top of diagram:
- **Traffic data:**
  - Analysis period: (start, end).
  - Mean speed: average speed of vehicles during the analysis period.
- **Flow rate:** average number of vehicles per hour.
- **Properties of phone behaviour:**
  - Average idle time ($\lambda_{\text{call}}$): average elapsed times between consecutive calls [hour]. The duration between calls is modelled as an exponential distribution.
Call duration ($\lambda_{\text{duration}}$) average duration of calls [min]. The duration of calls is modelled as an exponential distribution.
- Probe percentage ($P_{\text{probe}}$): percentage of vehicles that potentially are probes, i.e. percentage of vehicles that can make a call ($0 \leq P_{\text{probe}} \leq 1$).
- Trajectory length $L$ [km]: length of the road section in which vehicle speeds are measured ($0 \leq L \leq 5$).
- Polling frequency ($\lambda_{\text{poll}}$): elapsed time between consecutive generated location MR’s [sec].
- Variance of location error ($\sigma_{\text{err}}^2$): accuracy of the positioning of GSM handhelds [km$^2$].

The following modules are distinguished:

1. **Create data set:** generates random traffic data (speed data and passage time data) for each minute of the analysis period. Passage times are sampled with an exponential distribution. Speed data are sampled with a normal distribution.
   - Input:
     - (start, end): time interval between the first and the last passage time.
     - Flow rate (veh/hr): average number of vehicles during the analysis period.
     - Speed (km/hr): average speed of vehicles during the analysis period.
   - Output:
     - $v$ vector of vehicle velocities in [km/h];
     - $p$ vector of passage times corresponding to $v$.
     - $n$ vector of id’s corresponding to $v$.

2. **Compute trajectories:** trajectories within the road section (with length $L$) are calculated for each vehicle.
   - Input: $v$, $p$, $n$, $L$.
   - Output: $v$ and $p$ graphically plotted as trajectories.
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Figure 11: General assessment framework to investigate traffic monitoring accuracy.

3. **Compute travel time**: Speeds (v) within section are considered constant and passage times (p) are measured at the middle of the road section (L). For each vehicle the time \( p_i = p - L/v \) in which the vehicle enters into the road section and the time \( p_2 = p + L/v \) in which the vehicle leaves the road section are computed in order to calculate the individual travel times \( T_{\text{ind}} = p_2 - p_1 \).
   - Input: \( v, p, n, L \)
   - Output: \( T_{\text{ind}} \) vector of individual travel times corresponding to \( v \).

4. **Filter travel time**: the individual travel times are filtered (with a Kalman filter) to obtain the prevailing times as a function of time.
   - Input: \( T_{\text{ind}} \) vector of individual travel times.
   - Output: \( T_{\text{act}} \) actual travel times as a function of time (e.g. for each minute).
5. *Generate calls*: calls are generated randomly for a given percentage of vehicles \( (p_{\text{probe}}) \) that is travelling along the road section \( (L) \) and that is able to make calls during the trip. The number of calls per probe vehicle is sampled with exponential distribution by considering the \( \lambda_{\text{call}} \). The duration of one call is sampled with exponential distribution by considering the \( \lambda_{\text{duration}} \). For each probe a list of calls (with begin and end instant of call) is generated. With a probability of \( \lambda_{\text{duration}} / (\lambda_{\text{duration}} + \lambda_{\text{call}}) \) a vehicle is making a call upon entering the study area. For this vehicle the call initiation instant is 0. A useful property of the exponential distribution is that it is 'memoryless': the expectation of the remaining duration of a call does not depend on the duration of the call that has already expired.

- **Input:** \( v, p, n, \lambda_{\text{call}}, \lambda_{\text{duration}}, p_{\text{probe}}, L \)
- **Output:** \( t^* \) observed trajectory characterised by:
  - caller id (from variable \( n \))
  - speed (from variable \( v \))
  - passage time (from variable \( p \))
  - call list:
    - call initiation instant
    - call end instant

6. *Generate MR's*: location MR's are generated by the GSM system for each call. Each location MR produces the cell phone location and the time when the reported location is determined. The number of location MR's depends on the polling rate \( (\lambda_{\text{poll}}) \) and of course on the duration of calls. The location of cell phone depends on the accuracy of the positioning of GSM handsets \( (\sigma_{\text{err}}) \).

- **Input:** \( t^*, \lambda_{\text{poll}}, \sigma_{\text{err}} \)
- **Output:** MR list generated during the call is added to the observed trajectory \( (t^*) \)
  - MR list:
    - MR instant;
    - reported location.

7. *Estimate travel time*: because of the positioning errors the location MR's generated for each call are filtered (with a Kalman filter) in order to estimate the speed of each probe vehicle. The estimated speeds are used for determining for each probe the travel times observed through the GSM calls. The error estimation is also determined.

- **Input:** \( t^*, L, \sigma_{\text{err}} \)
- **Output:** observed travel times and observed travel time accuracy.
  - \( T_{\text{obs}} \): vector of travel time estimates corresponding to the observed trajectories and estimated through the MR list \( (t^*) \).
  - \( \sigma_{\text{obs}}^2 \): vector with variance of travel time estimates corresponding to the MR list \( (t^*) \).

8. *Filter travel time*: the observed travel times are filtered (with a Kalman filter) by taking into account the estimation errors to obtain the estimated travel times as a function of time.

- **Input:** \( T_{\text{obs}}, \sigma_{\text{obs}}^2 \)
- **Output:** \( T_{\text{est}} \) estimated travel times as a function of time (e.g. for each minute).

9. *Evaluate performance*: the estimated travel times will be compared with the actual travel times and the mean absolute error proportional and dynamic error are calculated to assess the traffic monitoring quality.

- **Input:** \( T_{\text{act}} \) (actual travel time function) and \( T_{\text{est}} \) (estimated travel time function)
- **Output** errors computed at a certain times:
  - absolute error \( (AE) \) \( \varepsilon_{\text{abs}} = |T_{\text{est}} - T_{\text{act}}| \)
absolute error proportional (AEP) $\epsilon_{absrel} = |T_{est} - T_{act}| / T_{act}$
- error (E): $\epsilon = (T_{est} - T_{act})$
- error proportional (EP): $\epsilon_{rel} = (T_{est} - T_{act}) / T_{act}$
- squared error (SE): $\epsilon_{sqr} = (T_{est} - T_{act})^2$
- squared error proportional (SEP): $\epsilon_{sqrrel} = (T_{est} - T_{act})^2 / T_{act}$.

10. **Graphical display** (interactive mode only): the module plots speed data, vehicle trajectories, MR’s generated for each call, actual individual travel times ($T_{ind}$), filtered actual travel times ($T_{act}$), observed travel times ($T_{obs}$), estimated travel times ($T_{est}$) and relative error ($\epsilon_{rel}$). The “graphical display” module is disabled in the batch version.

### 3.4 Interactive version of the simulation model

An important reason for building an interactive version of the simulation model is the need to debug the model. The ‘production’ runs of the models are done in the batch mode (see section 3.5).

Figure 12 depicts the graphical interface of the interactive version of the simulation model that has been implemented as a Matlab program. Traffic data plotted in Figure 13 are the Amsterdam beltway real data collected by loop detectors from 6:00 to 10:00 hours. The speed plot shows congestion between 7:00 and 9:00 hours. The trajectory plot shows the trajectories of probe vehicles that make calls and the generated MR’s for each call (each of the MR represented with a ‘*’ in the time-space diagram). Input values for the parameters are shown on the left of the interface.

The travel time estimation plot (see Figure 14) depicts the actual travel times (blue asterisks) and the filtered ones (blue line), the observed travel times (red circles) and the filtered ones (red line). The dynamic error is also plotted in Figure 14 and the mean absolute error proportional (MAEP) is shown in the top of the (right) plot. The positive dynamic error (black line) indicates that travel times have been over estimated; the negative dynamic error (red line) indicates that travel times have been under estimated.

![Interactive version of the Probe program.](image)
Figure 13: Interactive version of the Probe program: input parameters, speed data and trajectories plots.

Figure 14: Interactive version of the Probe program: travel time estimation and dynamic error estimation plots.
3.5 Batch version of simulation model

In order to determine the influence of each parameter, each parameter is varied over a range of values while all other parameters are kept constant. Table 2 depicts the parameter settings that are used for each run. The range of values for the parameters is 10%, 40%, 100%, 200% and 400%. This analysis is performed for two sets of road traffic data referred to as ‘scenario 1’ and ‘scenario 2’ (see section 3.6).

Figure 15 shows the framework of the batch version of the simulation model. First, input parameter sets for the simulation are generated and stored. Then simulations are carried out for each parameter set. Each run consists of 1000 randomised experiments during which calls and probe MR’s are randomly generated. The results of each simulation are averaged, stored and finally plotted. The batch program has been implemented as a Matlab program.
Table 2: Parameter setting used for each run of the sensitivity analysis.

<table>
<thead>
<tr>
<th>Scenario 1-2</th>
<th>Run 1-5</th>
<th>Run 6-10</th>
<th>Run 11-15</th>
<th>Run 16-20</th>
<th>Run 21-25</th>
<th>Run 26-30</th>
<th>Run 31-35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average idle time</td>
<td>10%</td>
<td>40%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Call duration</td>
<td>100%</td>
<td>10%</td>
<td>40%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage subscribers</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
<td>40%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Section length</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
<td>40%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Polling rate</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow rate</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>
The pivot values for the sensitivity analysis (i.e. the 100% values) are:

- Average idle time [hours]: 3:17
- Call duration [min]: 2:00
- Percentage of subscribers: 31%
- Section length [km]: 5
- Polling rate [sec]: 10
- Accuracy [km²]: 0.4
- Flow rate [veh/hr]: 4000

Table 3 shows all parameter value ranges used during the simulations.

<table>
<thead>
<tr>
<th>Parameter values used for the simulations.</th>
<th>10%</th>
<th>50%</th>
<th>100%</th>
<th>200%</th>
<th>400%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average idle time [hh:mm:ss]</td>
<td>00:19:42</td>
<td>1:38:30</td>
<td>3:17:00</td>
<td>6:34:00</td>
<td>13:08:00</td>
</tr>
<tr>
<td>Call duration [hh:mm:ss]</td>
<td>00:00:12</td>
<td>00:01:00</td>
<td>00:02:00</td>
<td>00:04:00</td>
<td>00:08:00</td>
</tr>
<tr>
<td>Percentage of subscribers [%]</td>
<td>3.1%</td>
<td>15.5%</td>
<td>31%</td>
<td>62%</td>
<td>124%</td>
</tr>
<tr>
<td>Section length [km]</td>
<td>0.5</td>
<td>2.5</td>
<td>5</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Polling rate [hh:mm:ss]</td>
<td>00:00:01</td>
<td>00:00:05</td>
<td>00:00:10</td>
<td>00:00:20</td>
<td>00:00:40</td>
</tr>
<tr>
<td>Accuracy [km²]</td>
<td>0.04</td>
<td>0.2</td>
<td>0.4</td>
<td>0.8</td>
<td>1.6</td>
</tr>
<tr>
<td>Flow rate [veh/hr]</td>
<td>400</td>
<td>2000</td>
<td>4000</td>
<td>8000</td>
<td>16000</td>
</tr>
</tbody>
</table>

The value of the parameter “Average idle time” has been approximated in the following way:

\[ A = L \times h \]
with:

- $A$: the average traffic of one subscriber per hour (traffic/hr),
- $L$: the number of calls per seconds (calls/s),
- $h$: the average call duration (in seconds).

The average idle time is equal to $1/L$ and it is computed by considering the following estimated values for $h$ and $A$:

$$h = 80s$$
$$A = 7/1000 \text{ (with the assumption that people use their cell phone for 0.7% of their time)}.$$ 

Hence:

$$\frac{1}{L} = \frac{h}{A} = 80/(7*10^3) = 3.17 \text{ hours}.$$ 

### 3.6 Scenarios for the sensitivity analysis

The sensitivity analysis is carried out by running the simulation model for different road traffic data sets referred to as 'scenarios' and different values of the parameters defined in 3.3.

The following two scenarios have been considered for the traffic data:

1. **Speed drop to 40 km/hr (see Figure 16):**
   - Analysis period: [6:00, 10:00];
   - Average speed:
     - $v(t)=100 \text{ km/hr for } 6:00 \leq t < 8:00$;
     - $v(t)=40 \text{ km/hr for } 8:00 \leq t < 10:00$;

2. **Speed drop to 20 km/hr (see Figure 17):**
   - Analysis period: [6:00, 10:00];
   - Average speed:
     - $v(t)=100 \text{ km/hr for } 6:00 \leq t < 8:00$;
     - $v(t)=20 \text{ km/hr for } 8:00 \leq t < 10:00$.

For both scenarios the variance of the speed is computed such that 95% of the vehicles has a speed within the range (of 3% of the average speed) $[v-0.03*v, v+0.03*v]$ i.e.

- [97, 103] if $v=100 \text{ km/h}$
- [38.8, 41.2] if $v=40 \text{ km/h}$
- [19.4, 20.6] if $v=20 \text{ km/h}$.

This variance range has intentionally been chosen to be small so that the inaccuracies of the simulated probe based traffic monitoring system will be primarily caused by properties of the applied algorithms and less so by the variations of speeds of the observed vehicles.
Figure 16: Speed data referred to 'scenario 1'.

Figure 17: Speed data referred to 'scenario 2'.

3.7 Performance criteria

The following criteria are evaluated for each minute from the first minute after the speed drop (8:01) until the end of the analysis period (10:00):

- absolute error $\varepsilon_{abs} = |T^{est} - T^{act}|$;
- absolute error proportional $\varepsilon_{abs, rel} = |T^{est} - T^{act}| / T^{act}$

where $T^{act}$ is the actual travel time function and $T^{est}$ is the estimated travel time function.

3.8 Results of the sensitivity analysis

In this section the simulation results are presented. Input data have been generated for each set of parameters and for each scenario. Exactly at 8:00 a drop in the travel speed has been introduced. Depending on the scenario the speed drops from 100 km/h to 40 km/h (scenario 1) or from 100 km/h to 20 km/h (scenario 2). The performance has subsequently been analysed as a function of time.
Figure 18 and Figure 19 effectively summarise the simulation results as they represent the average error as a function of time (Figure 18) and the sensitivity for each separate parameter (Figure 19). Figure 20 - Figure 26 give more detailed results.

If all parameters are set at the 100% value the relative error 30 minutes after the speed drop amounts 10% for scenario 1 and 15% for scenario 2.

Figure 18 shows the absolute performance as a function of time for scenario 1 and 2 with all parameters set at the 100% value. The following remarks can be observed:

- as may be expected, the accuracy increases with time
- for both scenarios, it is needed about half an hour to reach the value of 80% of accuracy
- the absolute error proportional does not converge to zero.

Contrary to what one may expect the absolute error proportional does not converge to zero. This is because the estimation has to take the possibility of speed changes into account, even if in reality the spread remains constant for a while. Effectively this means that the ‘newest’ (more recent) observations have a higher weight in the estimate than the ‘older’ (previous) ones.

Because both the speed data on which the vehicle trajectories are based and the reported vehicle positions in the probe MR’s contain random errors, the observed individual vehicle speeds also contain random errors. Combined with the fact that the weight factor of the ‘newest’ observation never converges to zero, some of this error will appear in the filtered speed estimate.

Figure 19 shows the sensitivity of estimation error 30 minutes after the speed drop. On the x-axis there are the percentages applied to each parameter (10%, 50%, 100%, 200% and 400%). For the first scenarios the worst error (about 100%) is achieved for the 10% of the standard input value of the parameter “section length”. In this case the section length is too short (500 m) and which results in a low number of calls. Moreover the average effective duration of the calls also decreases because probe MR’s that originate outside the current section are not considered. When the section length increases the relative error decreases.

For both scenarios the most influential parameters are the “call duration” and the “positioning accuracy”. Increasing the call duration or decreasing the positioning accuracy reduces the error of estimation considerably.

Sensitivity to the parameter “average idle time”
Figure 20 depicts the absolute and relative error for the parameter “average idle time” and for the scenarios 1 and 2. It is shown that a decrease of the average time between calls improves the estimation accuracy. The smallest absolute and relative error is obtained for the shortest duration between consecutive calls (e.g. 19 min).

Sensitivity to the parameter “call duration”
Figure 21 depicts the absolute and relative error for the scenarios 1 and 2 when the parameter “call duration” is varied. For both scenarios longer call duration’s lead to a better estimation. There is a low system performance when the call duration is too short (e.g. 12 sec).

Sensitivity to the parameter “percentage of subscribers”
Figure 22 depicts the absolute and relative error for the scenarios 1 and 2 with respect to the parameter “percentage of subscribers”. For both scenarios a higher percentage of subscribers improves the estimation accuracy.
Sensitivity to the parameter “polling rate”
Figure 23 depicts the absolute and relative error for scenarios 1 and 2 with respect to the parameter “polling rate” that defines the average time between probe MR’s. For the first scenario a paradoxical affect can be observed (see Figure 23) in the first half-hour after the speed drop (8:00, 8:30): a higher polling rate leads to a slower response curve. This is likely to be due to the extreme speed drop that is specified in the input data. This speed drop is much higher then the one that is specified in the filtering model. If the polling rate is very short the filtering model results in a very small confidence interval for the estimated travel time at 8:00 because of the high number of observations. As a result the filter can not trace the travel time fast enough after the speed drop. If the interval between MR’s increases the reliability interval increases, which makes the system more sensitive to changes. The counter intuitive effect is observed to a lesser extent for scenario 2.

Sensitivity to the parameter “positioning accuracy”
Figure 24 depicts the absolute and relative error for the scenarios 1 and 2 with respect to the parameter “accuracy”. Like expected a smaller location error leads to a better estimation.

Sensitivity to the parameter “section length”
Figure 25 depicts the absolute and relative error for scenarios 1 and 2 with respect to the parameter “section length”. For both scenarios when the road section is too short (e.g. 0.5 km) the system performance is poor. This is because people cannot make enough calls for estimating travel time. When the section length becomes too high, this has an adverse affect on the response time. This is a result of the way the probe observation system has been modelled: probes are only used after the call has been ended or the probe leaves the study area. If the section length increases more time is needed before probe data become available and hence the response time increases. Obviously this problem could be circumvented by a more advanced design of the probe observation system.

Sensitivity to the parameter “flow rate”
Figure 26 depicts the absolute and relative error for scenarios 1 and 2 with respect to the parameter “flow rate”. For both scenarios more number of vehicles reduces the estimate error. This is because a higher total number of vehicles also implies a higher number of phone calls and hence a reduced error.
Figure 18: Absolute error proportional for the scenario 1 and 2. On the left side it is shown the relative error zoomed in.

Figure 19: Absolute error proportional (and zoomed in) at 8:30 for the scenario 1 and 2 respectively.
Figure 20: Absolute and relative error for the scenarios 1 and 2 and parameter "average idle time".
Figure 21: Absolute and relative error for the scenarios 1 and 2 and parameter "call duration".
Figure 22: Absolute and relative error for the scenarios 1 and 2 and parameter "percentage of subscribers".
Traffic monitoring using handheld GSM phones

Figure 23: Absolute and relative error for the scenarios 1 and 2 and parameter "polling rate".
Figure 24: Absolute and relative error for the scenarios 1 and 2 and parameter "accuracy".
Figure 25: Absolute and relative error for the scenarios 1 and 2 and parameter "section length".
3.9 Conclusions

The conclusions of this chapter apply to the travel time estimates on the one hand and map matching algorithm on the other hand.

Travel time estimation

During the evaluation of the travel time estimation algorithm, two scenarios have been considered:
- A scenario in which the speed drops from 100 km/hr to 40 km/hr
- A scenario in which the speed drops from 100 km/hr to 20 km/hr

For both scenarios the performance of the travel time estimation algorithm has been evaluated for an ‘average’ set of parameters that specify the average time between calls, the average duration of a call, the percentage of subscribers, the section length, the traffic flow,
the polling rate and the accuracy with which the vehicle position is reported. This set of parameters is based on a best guess.

Figure 27 depicts the average relative error as a function of time. Note that the speed drop occurs at 8:00. The relative error converges to 12% for scenario 1 and to 8% for scenario 2. A response time of 30 minutes is sufficient to approach the accuracy quite well in both scenarios.

Contrary to what one may expect the absolute error proportional does not converge to zero. This is because the estimation has to take the possibility of speed changes into account, even if in reality the spread remains constant for a while. Effectively this means that the 'newest' (more recent) observations have a higher weight in the estimate then the 'older' (previous) ones.

Because both the speed data on which the vehicle trajectories are based and the reported vehicle positions in the probe MR's contain random errors, the observed individual vehicle speeds also contain random errors. Combined with the fact that the weight factor of the 'newest' observation never converges to zero, some of this error will appear in the filtered speed estimate.

Figure 28 illustrates the sensitivity of the relative error of estimation after a response time of 30 minutes for all input parameters considered. It turns out that the error is particularly sensitive to the location accuracy of the MR's and the average call duration. Also the total number of calls that has been made has a large influence this number of calls depends on the average time between calls and the percentage of subscribers. In the domain that was analysed the polling rate has only a small impact. Provided the section length is larger then 2 kilometres, the section length has no influence on the relative error.

![Figure 27: Relative error as a function of time for scenario 1 and 2](image)
Figure 28: Sensitivity of the relative error after a response time of 30 minutes for the average time between calls, the average duration of a call, the percentage of subscribers, the polling rate, the accuracy with which the vehicle position is reported, the section length and the flow rate. The horizontal axis indicates the relative values in [%].
4 Experimental results: quality of map matching

4.1 Introduction

Before speed-estimates can be produced from a time series Measurement Reports (MR’s), these MR’s have to be matched to a road segment. For this purpose the map matching algorithm proposed in section 2.3.2 has been implemented. This Chapter describes the experimental results that were obtained by applying the method. The analysis concentrates on the sensitivity for various parameters.

In order to assess the performance of the map matching algorithm using MR’s described in section 2.3.2 a sensitivity analysis of the map matching algorithm has been carried out for the following factors:

- Average idle time: average elapsed time between consecutive calls.
- Call duration: average duration of calls.
- Polling rate: elapsed time between consecutive generated location MR’s.
- Accuracy of the positioning of GSM handhelds.

The set-up, the scenarios, the performance criteria and the results of the sensitivity analysis are reported in sections 4.2, 4.3, 4.4 and 4.5 respectively.

4.2 Sensitivity analysis of the map matching algorithm

The sensitivity analysis consists of a method in which each parameter is varied over a range of values while all other parameters are kept constant.

Table 4 shows the parameter settings that are used for each run. The range of values for the parameters is 10%, 40%, 100%, 200% and 400%. This analysis is performed for four sets of network data referred to as ‘scenario 1’, ‘scenario 2’, ‘scenario 3’ and ‘scenario 4’ (see section 4.3). Each run consists of simulating 1000 vehicles travelling through the network and making at least one call.

The total number of vehicles that is simulated hence amounts:

1000 (vehicles per run) * 20 (runs per scenario)* 4 (scenarios) = 80,000 (route matches)
Table 4: *Parameter setting used for each run of the sensitivity analysis.*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Run 1-5</th>
<th>Run 6-10</th>
<th>Run 11-15</th>
<th>Run 16-20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average idle time</td>
<td>10%</td>
<td>40%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>200%</td>
<td>400%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Call duration</td>
<td>100%</td>
<td>10%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>40%</td>
<td>100%</td>
<td>200%</td>
<td>400%</td>
</tr>
<tr>
<td>Polling rate</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>40%</td>
<td>100%</td>
<td>200%</td>
<td>400%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>40%</td>
<td>100%</td>
<td>200%</td>
<td>400%</td>
</tr>
</tbody>
</table>

The standard input values for all parameters of the map matching algorithm set at the 100% value are:

- Average idle time [hours]: **3:17** (it is computed as explained in 3.5)
- Call duration [min]: **2:00**
- Polling rate [sec]: **10**
- Accuracy [km²]: **0.4**

Table 5 shows all parameter values used during the simulations.

Table 5: *Parameter values used for the simulations.*

<table>
<thead>
<tr>
<th></th>
<th>10%</th>
<th>50%</th>
<th>100%</th>
<th>200%</th>
<th>400%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average idle time [hh:mm:ss]</td>
<td><strong>00:19:42</strong></td>
<td><strong>1:38:30</strong></td>
<td><strong>3:17:00</strong></td>
<td><strong>6:34:00</strong></td>
<td><strong>13:08:00</strong></td>
</tr>
<tr>
<td>Call duration [hh:mm:ss]</td>
<td><strong>00:00:12</strong></td>
<td><strong>00:01:00</strong></td>
<td><strong>00:02:00</strong></td>
<td><strong>00:04:00</strong></td>
<td><strong>00:08:00</strong></td>
</tr>
<tr>
<td>Polling rate [hh:mm:ss]</td>
<td><strong>00:00:01</strong></td>
<td><strong>00:00:05</strong></td>
<td><strong>00:00:10</strong></td>
<td><strong>00:00:20</strong></td>
<td><strong>00:00:40</strong></td>
</tr>
<tr>
<td>Accuracy [km²]</td>
<td><strong>0.04</strong></td>
<td><strong>0.2</strong></td>
<td><strong>0.4</strong></td>
<td><strong>0.8</strong></td>
<td><strong>1.6</strong></td>
</tr>
</tbody>
</table>

4.3 Scenarios of map matching algorithm

In this section the scenarios for the map matching algorithm are described. For each scenario the Network data and the OD-demand are defined.

Scenario 1: Opposing traffic
The road network for the first scenario consists of 4 nodes and 2 links that represent 2 routes. The length of each route is 5000 m and the maximum speed allowed for each road section is 120 km/hr. The distance between the two parallel roads is 5 m. Nodes 1 and 3 are origins and nodes 2 and 4 are destinations for the 2 routes and for the OD-demand.
Figure 29 depicts the road network topology there are 2 one-way parallel routes with no intersections. Nodes (with the X-Y co-ordinates), links and OD-demand matrix are given in Table 6.

![Figure 29: Road network for scenario 1.](image)

**Table 6: Nodes, links and OD-demand matrix for scenario 1**

<table>
<thead>
<tr>
<th>Nodes</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5000</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>5000</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Links</th>
<th>Begin node</th>
<th>End node</th>
<th>Length (m)</th>
<th>Max speed (km/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>5000</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5000</td>
<td>120</td>
</tr>
</tbody>
</table>

**Scenario 2: crossing traffic**

The road network for the second scenario consists of 4 nodes and 2 links that represent 2 routes. The length of each route is 5000 m and the maximum speed allowed for each road section is 120 km/hr. Nodes 1 and 3 are origins and nodes 2 and 4 are destinations of the 2 routes and for the OD-demand. Figure 30 depicts the road network topology there are 2 one-way routes with no intersections. Nodes (with the X-Y co-ordinates), links and OD-demand matrix are given in Table 7.

![Figure 30: Road network for scenario 2.](image)
Table 7: Nodes, links and OD-demand matrix for scenario 2

<table>
<thead>
<tr>
<th>Nodes</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5000</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>2500</td>
<td>2500</td>
</tr>
<tr>
<td>4</td>
<td>2500</td>
<td>-2500</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Links</th>
<th>Begin node</th>
<th>End node</th>
<th>Length (m)</th>
<th>Max speed (km/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>5000</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5000</td>
<td>120</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Orig./Dest.</th>
<th>2</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1000</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>1000</td>
</tr>
</tbody>
</table>

Scenario 3: Parallel and crossing traffic

The road network for the third scenario consists of 4 nodes and 2 links that represent 2 routes. The length of each route is 5000 m and the maximum speed allowed for each road section is 120 km/hr. Nodes 1 and 3 are origins and nodes 2 and 6 are destinations of the 2 routes and for the OD-demand. Figure 31 depicts the road network topology there are 2 one-way routes with no intersections. The distance between the two parallel routes is 100 m. Nodes (with the X-Y co-ordinates), links and OD-demand matrix are given in Table 8.

![Diagram](https://via.placeholder.com/150)

Figure 31: Road network for scenario 3

Table 8: Nodes, links and OD-demand matrix for scenario 3.

<table>
<thead>
<tr>
<th>Nodes</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5000</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>2500</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>2500</td>
<td>-100</td>
</tr>
<tr>
<td>6</td>
<td>5000</td>
<td>-100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Links</th>
<th>Begin node</th>
<th>End node</th>
<th>Length (m)</th>
<th>Max speed (km/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>5000</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4</td>
<td>2500</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>5</td>
<td>200</td>
<td>120</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>6</td>
<td>2500</td>
<td>120</td>
</tr>
</tbody>
</table>
Scenario 4: Parallel traffic
The road network for the fourth scenario consists of 4 nodes and 2 links that represent 2 routes. The length of each route is 5000 m and the maximum speed allowed for each road section is 120 km/hr. Nodes 1 and 3 are origins and nodes 2 and 4 are destinations of the 2 routes and for the OD-demand. Figure 32 depicts the road network topology there are 2 one-way routes with no intersections. The distance between the two parallel routes is 30 m. Nodes (with X-Y the co-ordinates), links and OD-demand matrix are given in Table 9.

Table 9: Nodes, links and OD-demand matrix for scenario 4

<table>
<thead>
<tr>
<th>Nodes</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>5000</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>-30</td>
</tr>
<tr>
<td>4</td>
<td>5000</td>
<td>-30</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Links</th>
<th>Begin node</th>
<th>End node</th>
<th>Length (m)</th>
<th>Max speed (km/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>5000</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5000</td>
<td>120</td>
</tr>
</tbody>
</table>

4.4 Performance indicators for map matching algorithm
In the experiments we try to assess the influence of the following parameters on the reliability of the map matching algorithm:
- Network layout and apriori travel demand over the various routes
- Average duration between calls
- Average duration of calls
- Polling rate
- Average error of the reported position
To assess the performance of the map matching algorithm a high number \( (N) \) of vehicle-trips over a test network are simulated. For each vehicle-trip the following properties are determined randomly:

- The route of the vehicle
- The call initiation instant
- The call duration
- The probe MR’s

After that the route matching algorithm is applied, the map matching algorithm determines the probability \( \hat{p}_{ik} \) that vehicle \( k \), \( (k=1,2,..,N) \), is travelling over route \( i \), \( (i=1,2,..,R) \). Without doing any map matching the probability of travelling at route \( i \) can be estimated at the *apriori probability* \( p_{ik} \) that is derived from the travel demand over the various routes.

We now seek performance criteria that express the reliability of the map matching process. We will use the following notation:

**Notation**

\[
\begin{align*}
    p_{ik} & \quad \text{Apriori probability that vehicle } k \text{ is travelling on route } i. \\
    \hat{p}_{ik} & \quad \text{Estimated probability that vehicle } k \text{ is travelling on route } i. \\
    x_{ik} & \quad \text{Route-vehicle assignment map.} \\
    x_{ik} = 1 & \text{ if vehicle } k \text{ is travelling on route } i. \\
    x_{ik} = 0 & \text{ if vehicle } k \text{ is not travelling on route } i. \\
    \hat{x}_{ik} & \quad \text{Matched route - vehicle assignment map.} \\
    \hat{x}_{ik} = 1 & \text{ if } \hat{p}_{ik} = \max_i \{ \hat{p}_{ik} \} \\
    \hat{x}_{ik} = 0 & \text{ if } \hat{p}_{ik} < \max_i \{ \hat{p}_{ik} \}
\end{align*}
\]
Performance indicators

To assess the route-matching performance, the following performance criteria have been defined. These criteria are selected for their ease of interpretation and their informative content.

Percentage of vehicles matched correctly

\[ p_{\text{succes}} = \left( \frac{1}{N} \sum_{r=1}^{R} \sum_{k=1}^{N} \hat{x}_{rk} x_{rk} \right) \cdot 100\% \]

Bias before matching

\[ \bar{b}_{i}^{B} = \frac{1}{R} \sum_{i=1}^{R} b_{i}^{B} \quad \text{with:} \quad b_{i}^{B} = \left| \frac{1}{N} \sum_{k=1}^{N} \hat{p}_{ik} - x_{ik} \right| \cdot 100\% \]

Bias after matching

\[ \bar{b}_{i}^{A} = \frac{1}{R} \sum_{i=1}^{R} b_{i}^{A} \quad \text{with:} \quad b_{i}^{A} = \left| \frac{1}{N} \sum_{k=1}^{N} \hat{x}_{ik} - x_{ik} \right| \cdot 100\% \]

Mean Likelihood

\[ \bar{L} = \frac{1}{N} \sum_{k=1}^{N} \prod_{i=1}^{R} \hat{p}_{ik} x_{ik} \]

Mean Likelihood-improvement

\[ \Delta \bar{L} = \frac{1}{N} \sum_{k=1}^{N} \left( \prod_{i=1}^{R} \hat{p}_{ik} x_{ik} - \prod_{i=1}^{R} p_{ik} x_{ik} \right) \]

The following table summarises the indicators and their ranges.

<table>
<thead>
<tr>
<th>Table 10: Indicators and their ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indicator</td>
</tr>
<tr>
<td>Percentage of vehicles matched correctly</td>
</tr>
<tr>
<td>Bias before matching</td>
</tr>
<tr>
<td>Bias after matching</td>
</tr>
<tr>
<td>Mean Likelihood</td>
</tr>
<tr>
<td>Mean Likelihood-improvement</td>
</tr>
</tbody>
</table>
4.5 Results of map matching algorithm

In this section the results of the sensitivity analysis are presented.

An example of how the map matching algorithm is functioning is shown in Figure 34, Figure 35, Figure 36 and Figure 37. Figure 34 shows the hypernetwork that is constructed for matching the first vehicle of the run for scenario 1 with all parameters at the 100% value. The fact that the shortest path seems to vertically traverse the network, reflects the constraint that vehicles can not travel backwards over a route. Therefore the best match is obtained if all MR’s are matched to a single point (see Figure 35), suggesting that if the vehicle is travelling over route 1, it has not been moving during the time that it has been observed. In fact the vehicle has been travelling over route 2, the reverse direction. For this route a much better match is obtained as can be seen from Figure 36 and Figure 37. According to the algorithm the probability that this particular vehicle has been travelling on route 1 may be neglected. Figures, similar to the ones discussed above, applying to scenarios 2, 3 and 4 may be found in appendix B.

Figure 35 summarises the map matching algorithm results. Table 12 – Table 15 give more detailed results of the sensitivity analysis for each performance indicator, separate parameter and scenario.

Figure 33 shows the sensitivity of percentage of vehicles matched correctly for each scenario. On the x-axis there are the percentages applied to each parameter (10%, 50%, 100%, 200% and 400%). For the first scenarios the worst p\text{success} (about 60%) is achieved for the 10% of the standard input value of the parameter “call duration”. In this case the call duration is too short (12 sec.) and it is not possible to have enough MR’s for matching the vehicles effectively. As the call duration increases the relative error decreases.

For the second scenario the p\text{success} is within the interval [90%, 100%]. For the third scenario the p\text{success} is about 100% if the parameter “accuracy” is very high. If the accuracy is very low the p\text{success} drops to 55%. For the scenarios 1, 2 and 3 the most sensitive parameters are the “call duration” and the “accuracy”. By increasing the x-value of the parameters “call duration” and “accuracy” the p\text{success} increases and decreases respectively.

The percentage of vehicles matched correctly is nearly 100% for all parameters of the scenario 4.

One should note that without any map matching the percentage of vehicles matched correctly on the basis of the apriori knowledge for scenarios 1, 2 and 3 would be on average 50%. For scenario 4 this figure would be (1000^2+10^2)/1010^2=0.9804. This puts the number of successes for scenario 4 into perspective.
Table 12 – Table 15 show all performance indicators for each parameter varied and for each scenario. The following remarks can be observed from the Table 11 that shows the performance indicators by considering the parameter value of each scenario set at the 100% value:

- the *Percentage of vehicles matched correctly* is greater than 90% for the scenarios with opposing or crossing traffic (scenario 1 and 2) and for the scenario with a high apriori probability of travelling route 1. For the scenario with two parallel routes that have equal apriori probability the success-rate drops to 61%;
- the *Bias before matching* indicator is nearly zero for almost all scenarios, the indicator value is smallest for scenario 3;
- the *Bias after matching* indicators are nearly zero for almost all scenarios, but is higher then the bias before matching indicator; For scenario 4 the bias after matching (8/1000) is high in relation to the success-rate (992/1000) and represents the entire error;
- The *Mean Likelihood* is almost perfect for almost all scenarios, except for scenario 3;
- the *Mean Likelihood-improvement* is nearly zero for almost all scenarios, the greatest value is obtained with scenario 2 (see Table 13);
- the best results by taking the $p_{\text{success}}$ and the *Mean Likelihood* into account are obtained with the scenario 4;
- the worst results by taking the $p_{\text{success}}$ and the *Mean Likelihood* into account are obtained with the scenario 3.

The current algorithm does not make use of an apriori speed distribution, and values all matching maps equally likely regardless of the speed pattern they imply, as long as minimum and maximum speed are not violated. Taking into account speed distributions will greatly improve the number of successful matches, especially for parallel routes with different average speeds. The only problem is that this will impair the quality of matching during circumstances with extreme slow traffic, while these are the kind of circumstances that one would want to rely on the matching algorithm the most. This topic therefore requires more research.

<table>
<thead>
<tr>
<th>Performance indicators for all scenarios with the parameter values set at 100% of the standard value.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario</strong></td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Scenario 1</td>
</tr>
<tr>
<td>Scenario 2</td>
</tr>
<tr>
<td>Scenario 3</td>
</tr>
<tr>
<td>Scenario 4</td>
</tr>
</tbody>
</table>
Figure 33: Percentage of vehicles matched correctly for scenario 1, 2, 3 and 4.
Figure 34: Hypernetwork used for matching MR's of run 1 (of 1000) to route 1 of scenario 1. The optimal path is indicated and corresponds with the optimal match.

Figure 35: Result of matching MR's of run 1 (of 1000) to route 1 of scenario 1. The MR's are indicated with '*' symbols. The best feasible match is obtained if all MR's are matched to a single point because the road direction is opposite to the probe vehicle direction.
Figure 36: Hypernetwork used for matching MR's of run 1 (of 1000) to route 2 of scenario 1. The optimal path is indicated and corresponds with the optimal match.

Figure 37: Result of matching MR's of run 1 (of 1000) to route 2 of scenario 1. This sequence of MR's fits better to route 2 than to route 1.
### Table 12: Results of the sensitivity analysis for the scenario 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Relative size of parameters [%]</th>
<th>10%</th>
<th>50%</th>
<th>100%</th>
<th>200%</th>
<th>400%</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Percentage of vehicles matched correctly (0%, 100%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Average idle time</td>
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<td>90.40</td>
<td>90.70</td>
<td>92.70</td>
<td>90.70</td>
<td>90.40</td>
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<tr>
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<td>96.90</td>
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<td>92.70</td>
<td>88.30</td>
<td>80.70</td>
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<td>94.30</td>
<td>92.70</td>
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<td>82.30</td>
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<td></td>
</tr>
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Table 13: Results of the sensitivity analysis for the scenario 2

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<th>Relative size of parameters [%]</th>
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<th>100%</th>
<th>200%</th>
<th>400%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percentage of vehicles matched correctly (0%, 100%)</td>
<td></td>
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</tr>
<tr>
<td>Average idle time</td>
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<td>95.60</td>
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<td>0.60</td>
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<td>Mean Likelihood (0, 1)</td>
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</table>
Table 14: Results of the sensitivity analysis for the scenario 3

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<th>Parameter</th>
<th>Relative size of parameters [%]</th>
<th>10%</th>
<th>50%</th>
<th>100%</th>
<th>200%</th>
<th>400%</th>
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<tbody>
<tr>
<td>Average idle time</td>
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<td>61.20</td>
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</tr>
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<td>61.00</td>
<td>64.90</td>
<td>66.60</td>
</tr>
<tr>
<td>Polling rate</td>
<td></td>
<td>82.30</td>
<td>66.30</td>
<td>61.00</td>
<td>60.40</td>
<td>54.70</td>
</tr>
<tr>
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<td>61.00</td>
<td>56.00</td>
<td>53.50</td>
</tr>
</tbody>
</table>

Percentage of vehicles matched correctly (0%, 100%)

<table>
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<th>Parameter</th>
<th>0% , 100%</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
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<td>Average idle time</td>
<td>62.10 61.00 64.70 62.50</td>
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</tr>
<tr>
<td>Call duration</td>
<td>57.20 61.00 64.90 66.60</td>
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<tr>
<td>Polling rate</td>
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</tr>
<tr>
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Bias before matching (0%, 100%)

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<th></th>
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Bias after matching (0%, 100%)

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</tr>
<tr>
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</tr>
<tr>
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</tr>
<tr>
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Mean Likelihood (0, 1)

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Mean Likelihood-improvement (-1, 1)

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<tr>
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</tr>
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### Table 15: Results of the sensitivity analysis for the scenario 4

<table>
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<th>100%</th>
<th>200%</th>
<th>400%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percentage of vehicles matched correctly (0%, 100%)</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Average idle time</td>
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<td>99.20</td>
<td>99.20</td>
<td>99.20</td>
<td>99.20</td>
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<td>99.20</td>
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### 4.6 Conclusions

The route-matching algorithm described in section 2.3.3 has been evaluated using four different scenarios:
- Opposing traffic, balanced demand
- Crossing traffic, balanced demand
- Parallel and crossing traffic, balanced demand
- Parallel traffic, unbalanced demand

Where ‘opposing’ and ‘crossing’ relate to the direction of the route and ‘balanced’ and ‘unbalanced’ relate to the ‘apriori’ distribution of traffic over the routes.

For all scenarios the performance of the map matching algorithm has been evaluated for a set of parameters that is identical to the set that has been used for the evaluation of the travel time estimation algorithm. The parameters ‘percentage of subscribers’ and ‘traffic flow’ have been ignored is these do not influence the percentage of properly matched vehicles.
In the first two cases the matches are near perfect, suggesting that the matching algorithm is quite suitable for distinguishing traffic that is travelling in opposed or crossing traffic. The third case shows a matching rate of 61%. This rate can only be increased to acceptable values if the accuracy is improved. For the last scenario, good results are obtained, but this is only because of the unbalanced nature of the demand.

Again, it turns out that the algorithm is most sensitive to the parameter 'call-duration', while 'accuracy' is the second important parameter.

The current algorithm does not make use of an apriori speed distribution, and values all matching maps equally likely regardless of the speed pattern they imply, as long as minimum and maximum speed are not violated. Taking into account speed distributions will greatly improve the number of successful matches, especially for parallel routes with different average speeds. The only problem is that this will impair the quality of matching during circumstances with extreme slow traffic, while these are the kind of circumstances that one would want to rely on the matching algorithm the most. This topic therefore requires more research.
5 Conclusions

The present study contains a general design for a road traffic monitoring system based on vehicle probes, as well as a more detailed description of some of the crucial components of such a system. These components are a travel time estimation algorithm on the one hand and a map-matching algorithm on the other hand.

Travel time estimation
The travel time estimation algorithm has been implemented as a Kalman filter. The behaviour and accuracy of this algorithm has been extensively investigated. This has resulted in a number of design parameters. This investigation has taken place without explicitly considering any end-user applications. Instead the term 'traffic monitoring' was explained as 'estimating section level travel times'. The performance has been evaluated in terms of accuracy and response time.

One of the conclusions has been that in case of a drastic speed drop on a typical motorway stretch of 5 kilometres with a moderate traffic load (4000veh/hr) the asymptotic relative error of estimation is reached in approximately 30 minutes and amounts about 8%. For less sudden speed drops the response time would be less. The asymptotic relative error of estimation of 8% is caused by variations in travel speeds among vehicles and inaccuracies that occur when individual vehicle speeds are estimated.

A complete sensitivity analysis has been carried out. The estimation error turns out to be highly sensitive to the average call duration and to a lesser extent to the accuracy of determining a vehicle's position.

Map matching
A new map matching algorithm has been proposed. This algorithm is implemented as a curve-to-curve matching algorithm and has as a distinguishing property that it can deal with large errors in the probe location data, and filter out the route of vehicle, provided that sufficient MR's are available.

Also this component has been tested using a typical range of input parameters and network layouts. The test results indicate that the matching algorithm is quite suitable for distinguishing traffic that is travelling in opposed or crossing directions. To distinguish traffic that is travelling in parallel directions close to each other the location error of the MR's should be reduced before useful results can be obtained with the current algorithm. There are a number of untested possibilities to improve the algorithm though.
6 References


Appendix A: Examples of matched MR sequences

Figure 38: Result of matching MR’s of run 1 (of 1000) to route 1 of scenario 2.

Figure 39: Result of matching MR’s of run 1 (of 1000) to route 2 of scenario 2. This sequence of MR’s fits better to route 2 than to route 1.
Figure 40: Result of matching MR's of run 1 (of 1000) to route 1 of scenario 3.

Figure 41: Result of matching MR's of run 1 (of 1000) to route 2 of scenario 3. According to the matching algorithm this sequence of MR's fits route 2 with probability 0.6898.
Figure 42: Result of matching MR's of run 1 (of 1000) to route 1 of scenario 4.

Figure 43: Result of matching MR's of run 1 (of 1000) to route 2 of scenario 4. According to the matching algorithm this sequence of MR's fits route 2 with probability 0.0076. The apriori probability that the vehicle has travelled route 2 is 0.0100.
De sectie Verkeerskunde houdt zich bezig met Onderwijs en onderzoek op het gebied van Planning, alsmede het functioneel ontwerp van verkeersinfrastructuur.

De sectie Verkeerskunde maakt deel uit van de Faculteit Civiele Techniek en Geowetenschappen van de Technische Universiteit Delft en participeert in de onderzoeksschool TRAIL.

The Transportation Planning and Traffic Engineering Section provides university education and performs fundamental-scientific research on the wide area of traffic, transport, logistics and infrastructure; in addition to that, the section makes develops new fundamental design for traffic infrastructures.

The section is part of the Faculty of Civil Engineering and Geosciences of Delft University of Technology in the Netherlands and is a partner in the post-graduate Research School TRAIL.