

# Trade-offs between inductive loops and GPS probe vehicles for travel time estimation: A Mobile Century case study

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## ABSTRACT

This article addresses the trade-offs between (i) velocity data collected from GPS smartphones in probe vehicles, and (ii), velocity data obtained from inductive loop detectors, for the purpose of computing travel times on a stretch of roadway. It is a case study which uses experimental data collected on one day in the San Francisco Bay Area, obtained as part of a 2008 field experiment known as *Mobile Century*. Estimates of the traffic velocity field are constructed using a velocity model equivalent to the *Cell Transmission Model*, and a traffic state estimation algorithm known as *ensemble Kalman filtering*. More than 900 combinations of inductive loop detector data and GPS data of various data volumes are considered. Instantaneous and a posteriori dynamic travel times are computed by integrating the estimated velocity field, and are compared to travel times recorded using license plate re-identification. Key findings include (i) dynamic travel time estimates can be computed with less than 10% error using only probe data, only inductive loop data, or a mixture of inductive loop and probe data (ii) by combining loop detector data with probe vehicle data, better estimates for travel times are obtained especially when loop data or probe data is sparse.

## 1. INTRODUCTION

### 1.1. Objective

Probe data will likely become ubiquitous in the not too distant future, due to the rapid expansion of consumer generated probe data from cellphones, personal navigation devices, and intelligent vehicles. As the use of probe data for traffic monitoring increases, so does the need to understand the benefits and trade-offs between GPS data and conventional data sources. Yet, a complete analysis of the trade-offs between probe data and fixed sensors is difficult, because the value of the data from any sensor (probe, loops, etc.), is dependent on the specifics of the sensing technology, the method used to process the data, and the specific traffic monitoring objective in question.

The goal of this article is to make a first step towards answering a larger question, which is the following. *to what degree can GPS probe data act as a substitute for conventional traffic monitoring technologies such as inductive loop detectors?* Specifically, we focus our attention on estimating travel times by integrating various data volumes from inductive loop detectors and GPS equipped probe vehicles into a velocity flow model equivalent to the *Cell Transmission Model* [1, 2], using an estimation technique known as *ensemble Kalman filtering* (EnKF). This article presents an empirical study using data collected during a one day field experiment known as *Mobile Century* [3].

### 1.2. Related work

Several field experiments have been conducted to assess the applicability of cell phone-based measurements for traffic monitoring [4, 5, 6, 7, 8, 9, 10, 11], including data generated from cell phone towers, which produces less accurate vehicle position and speed measurements compared to GPS. Bar-Gera [6] compared several months of network data from cellphones to inductive loop detector data on a 14 km freeway segment in Israel, and found them to be in good agreement. Liu et al. [8] evaluated a different network-based cell phone system in Minnesota, and compared travel times to license plate re-identification, and found the system generated results with varying accuracies. A summary of the major network-based cell phone experiments to date can be found in Liu et al. [8].

Several studies have also been conducted to assess the trade-offs between inductive loop detector data and data collected from GPS equipped probe vehicles. In Kwon et al. [12], it is shown that annual estimates of total delay, average duration of congestion, and average spatial extent of congestion can be made with less than 10% error by using either inductive loop detectors placed with half-mile spacing, or by using probe vehicle runs at a rate of about three vehicles an hour. Approximately four to six days of data is needed for reliable estimates from either data source.

The work of Herrera et al. [13] compares a nudging algorithm and a mixture Kalman filtering algorithm to examine how the addition of probe vehicle measurements sampled at a fixed time interval can decrease errors in estimating traffic velocity. On a 0.4 mile stretch of roadway, sampling 5% the traffic at 150 second intervals with inductive loops at both ends of the domain leads to a 16% improvement over the inductive loop detector data alone. The article also uses the *Mobile Century* experiment data to compare three scenarios of time-based sampling of probe vehicles, finding that probe data outperforms inductive loop detector data for estimating traffic velocity if a sufficient number of measurements can be obtained from probe vehicles. This work uses the same data set from *Mobile Century*, but we now consider nearly one thousand scenarios to compare probe data to inductive loop detector data.

### 1.3. Methodology overview

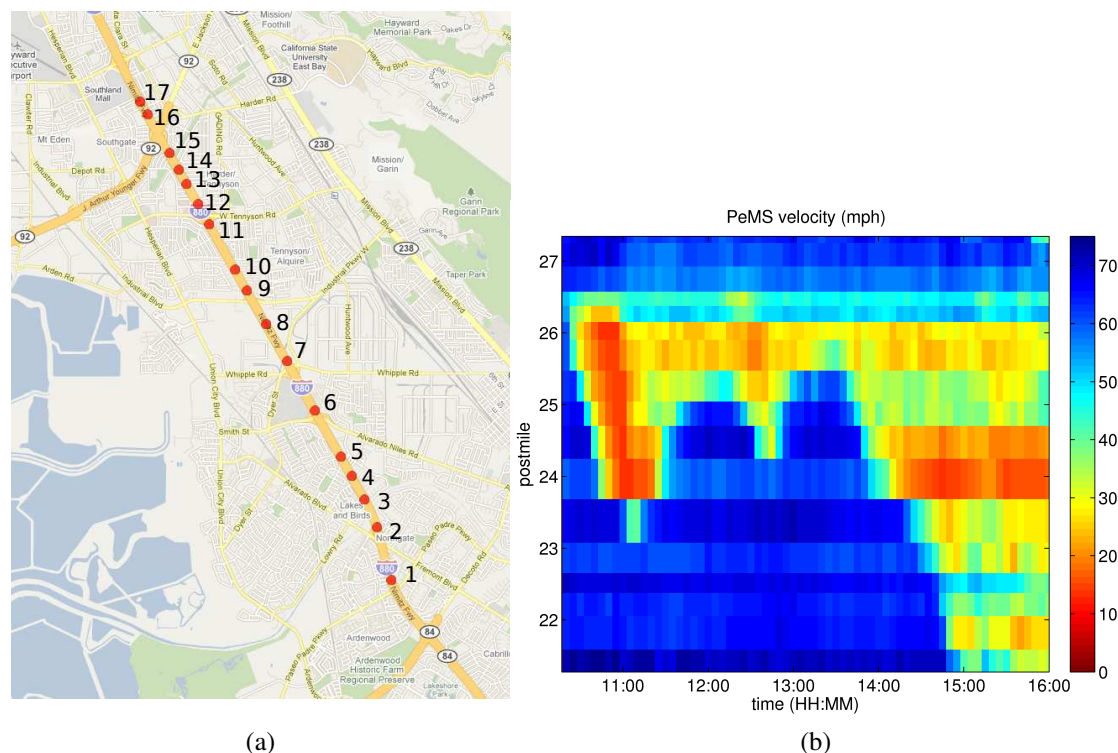
In order to assess the trade-offs between velocity data collected from GPS smartphones and velocity data obtained from inductive loop detectors, it is necessary to define the process by which the data is transformed into an estimate of travel time. In this article, we rely on a velocity estimation algorithm developed at Berkeley as part of the *Mobile Millennium* project [14]. The algorithm combines velocity measurements from GPS smartphones or inductive loop detectors with a model of traffic evolution, using a technique known as *ensemble Kalman filtering* (EnKF) to produce an improved estimate of the velocity field, from which the travel time is computed. The resulting travel time computed from this process is then compared to the travel times recorded from the license plate re-identification video data.

With the data processing algorithm determined, we create a number of scenarios in which the volume of probe data and number of inductive loop detectors made available to the processing algorithm are adjusted. For example, this allows us to compare the accuracy of computing travel times when all of the probe data is made available, to travel times which are computed when only some of the probe data is available, to travel times when some probe data is available and some inductive loop detector data is available. In this way, we can quantify the trade-offs of various amounts of data from probes and inductive loop detector data in terms of increased or decreased accuracy of the computed travel times.

In order to describe and quantify what probe data is made available to the travel time processing algorithm, we introduce two metrics of importance to probe data, namely the *penetration rate* and the *sampling rate*. The penetration rate is defined as the percentage of cars on the roadway reporting probe data compared to the overall traffic flow, including the vehicles which do not send data. In addition to increasing the number of measurements, as the penetration rate increases, the sample of vehicles which generate measurements are more likely to be representative of the total traffic flow. The sampling rate refers to the frequency at which data is collected from the probe vehicles, and can be used to increase or decrease the number of measurements made available for estimating travel times from the same vehicles. The probe data collection technique used in this work collects data from probe vehicles at fixed points in space using a technique known as *Virtual Trip Lines* (VTLs) [15] invented by Nokia. By decreasing spacing between the VTLs, the probe vehicles will send more measurements, with smaller spacing between measurements.

In order to modify the amount of data obtained from inductive loop detectors, the number of inductive loop detectors which are made available to the processing algorithm is adjusted. Because this article is a case study of a real highway, it is not possible to modify the location of the inductive loop detectors. Instead, given a fixed number of inductive loop detectors to include for a given scenario, we select the specific loop detectors such that they achieve as uniform of a spacing along the highway as is possible.

The remainder of this article describes in detail the specific components of this case study. In Section 2, the data collected from the *Mobile Century* experiment is described. The key features of the processing algorithm used for velocity estimation is given in Section 3, and the methods for computing travel times from the velocity field are described. In Section 4, the techniques for generating scenarios with various amounts of input data from probe vehicles and inductive loops are presented. In Section 5, the results of nearly one thousand scenarios using various amounts of inductive loop detector data and probe data for travel time estimation is presented and summarized. Finally, the discussion in Section 6 summarizes the results of the case study.



**FIGURE 1** : I-880N experiment inductive loops. (a) Location of the northbound inductive loop detector stations on the area where travel times are estimated. (b) Velocity contour plot from the PeMS system. Color denotes speed in mph.  $x$ -axis: time of day.  $y$ -axis: postmile (northbound from station one (a)).

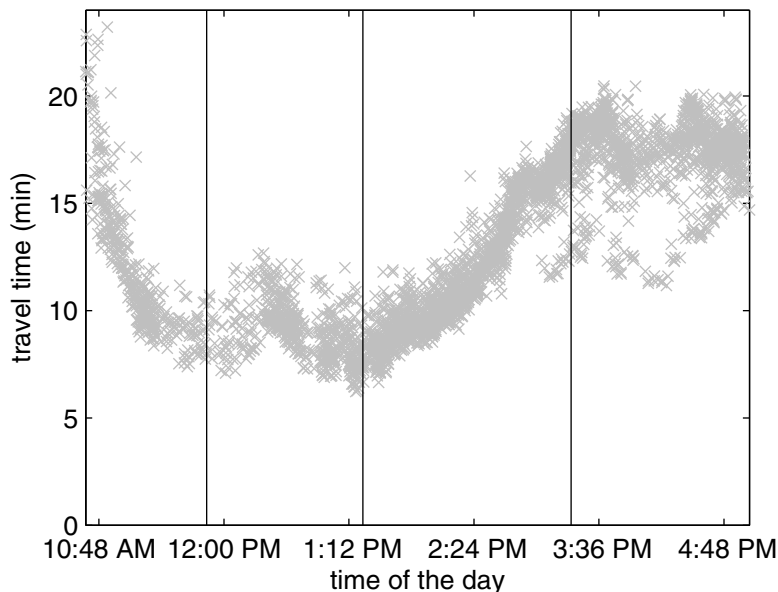
## 2. MOBILE CENTURY EXPERIMENT

In this section, the key features of the data collected during the *Mobile Century* experiment are presented. For a complete description of the experiment, the interested reader is referred to [3].

The *Mobile Century* field experiment was a one-day test in the San Francisco Bay Area which collected GPS data from cell phones in probe vehicles, inductive loop detector data, and travel time data from license plate re-identification video data. The experiment took place on February 8th, 2008, and involved 100 probe vehicles equipped with Nokia N95 cell phones which repeatedly drove a stretch of the I-880 freeway near Union City, CA, generating 2,200 vehicle trajectories.

The experiment site is also covered with 17 working inductive loop detector stations which feed measurements into the PeMS system [16]. The inductive loop detectors record the sensor occupancy and vehicle counts every 30 seconds, which is processed by a *Mobile Millennium* filtering algorithm in order to obtain the 30 second average velocity at the sensor. At 5 minute intervals, the PeMS system produces an estimate of the 5 minute average velocity at the sensor, which is shown in Figure 1b for the northbound traffic. The locations of the inductive loop detector stations are shown in Figure 1a.

Finally, as part of the experiment, high definition video cameras were temporarily installed to record license plates of northbound traffic. The travel times recorded from the re-identified



**FIGURE 2 :** *Mobile Century* northbound travel times divided into four time bins from left to right: morning accident (10:00am-11:50am), free flow (11:50am-1:20pm), congestion building (1:20pm-3:20pm), and full congestion (3:20pm-). The travel times obtained from the license plate reidentification video recordings are marked with crosses.

vehicles traveling northbound is shown in Figure 2. During the morning, a 5 car accident caused significant delay, and some drivers experienced travel times in excess of 20 minutes around 10:48 AM. Between 11:50 AM and 1:20 PM, vehicles experience travel times between 8 and 10 minutes on the same stretch of roadway, which steadily increased from 1:20 PM to 3:20 PM. By 3:20 PM, most re-identified drivers experienced heavy evening congestion with travel times increasing to 15–20 minutes.

### 3. ALGORITHM FOR ESTIMATING TRAVEL TIMES

Given the velocity data obtained from inductive loop detectors and GPS equipped probe vehicles, a processing algorithm is needed to convert the velocity data into an estimate of travel time. The processing algorithm used in this report is based on a velocity estimation algorithm developed in the *Mobile Millennium* system. The algorithm takes velocity data from inductive loop detectors and probe vehicles as input, combines the data with a physical model of traffic evolution, and produces an improved estimate of the velocity along the corresponding stretch of roadway. Using this improved estimate of velocity, an estimated travel time is computed using an instantaneous method and a dynamic method, to compare against the travel times recorded from video data. A brief overview of this process is described in this section.

#### 3.1. Mobile Millennium velocity estimation algorithm

The velocity estimation algorithm developed in the *Mobile Millennium* system is based on a discretization of a traffic flow model known as the *Lighthill-Whitham-Richards* (LWR) partial differential equation [17, 18] which describes the evolution of traffic density on the highway. In its

discrete form, this model is also known as the *Cell Transmission Model* [1, 2]. In order to simplify the velocity estimation problem, this model is transformed into an equivalent velocity evolution equation [19] operating on a 30 second time step. The complete mathematical details of the employed traffic velocity evolution equation, and the fusion of velocity measurement data with the evolution equation using *ensemble Kalman filtering* (EnKF) are presented in the article of Work et. al. [19].

A few remarks on the performance of the velocity estimation algorithm described above are in order. First, it is noted that the algorithm was designed as part of the *Mobile Millennium* system, where it is not possible to track probe vehicles for privacy reasons, and thus no continuous GPS records from probes are available for the estimation algorithm. In practice, it is expected that the performance of the estimation algorithm could be improved when tracking of individual probe vehicles is allowed.

Second, the *Mobile Millennium* algorithm does not directly estimate travel times. Instead, travel times are computed from the estimated velocity field, assuming that a vehicle travels at the mean speed reported in each cell. Again, it is expected that the performance of the estimation algorithm could be further improved by directly estimating the travel times in addition to estimating the velocity field. Regardless of the potential for further improvement, preliminary studies suggest the approach used in this report works well in practice.

Third, it should be noted that the flow model requires some historical flow information to calibrate the model. In this study, historical inductive loop detector data from PeMS was used to estimate constant mainline inflow and outflows, and thus all results presented use inductive loop data in this way.

Next, the methods for computing the instantaneous and dynamic travel times from an estimated velocity field are described.

### **3.2. Methods for computing travel times**

The instantaneous method of computing an estimate of the travel time along a stretch of roadway is as follows. At the time when the instantaneous travel time estimate is produced, the current estimate of the velocity field is recorded. The travel time of a vehicle is simulated, assuming the vehicle travels at the estimated velocity in each cell (approximately 300 m long). The velocity field is assumed to remain constant in time, as the simulated vehicle travels through the velocity field. The main advantage of the instantaneous travel time is that it does not require a prediction of the evolution of the velocity field, and it should produce accurate travel times when the velocity does not change significantly during the computation.

The dynamic method of computing an estimate of the travel time is obtained similarly, with one important modification. Unlike the instantaneous method which assumes the velocity field does not evolve during the computation, in the dynamic method, the velocity field is updated during the computation. In practice, the computation of a dynamic travel time must be done a posteriori, or using a prediction algorithm, since the method requires knowledge of the speed evolution from the future time steps. It is worth noting that for the present study, the dynamic travel time for individual vehicles is measurable via license plate re-identification.

## 4. DATA SELECTION

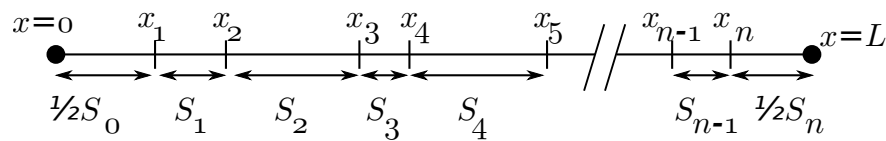
To assess the trade-offs between different amounts of probe data and inductive loop detector data for the purpose of estimating travel times, we algorithmically select different subsets of loop and GPS probe data from the *Mobile Century* experiment, and use these subsets as inputs to the estimation process described in the previous section. This section describes the scenarios which modify the type and amount of the data which is made available for estimation, and the selection criteria which are used to generate the scenarios.

### 4.1. Algorithms for data selection

#### *Selection of inductive loop detector data*

In order to modify the number of inductive loop detector stations which are made available for computing travel times, a simple selection criterion is developed. Specifically, given a fixed number of stations to include, the loops are selected in order to minimize the variance of the distance between consecutive sensors, resulting in approximately uniformly spaced sensors.

We consider a stretch of highway of length  $L$ , starting at  $x = 0$  and ending at  $x = L$ , with  $n$  inductive loop detector stations located at  $x_1, x_2, \dots, x_n$ , as shown in Figure 3.



**FIGURE 3** : Highway segment of length  $L$ , with  $n$  inductive loop detector stations located at  $x_i$ .

Let  $S_i$  denote the spacing between sensor  $i$  and  $i + 1$ . In order to treat the boundaries without explicit knowledge of sensors outside the domain  $x \in [0, L]$ , it is assumed only half of the first inter-station spacing  $S_0$  and the last inter-station spacing  $S_n$  is in the domain of interest. The weighted average spacing between the sensors is given by:

$$\bar{S} = \frac{\frac{1}{2}S_0 + S_1 + S_2 + \dots + S_{n-1} + \frac{1}{2}S_n}{n} = \frac{L}{n} \quad (1)$$

where the first and last spacings have a weight  $\frac{1}{2}$ , since only half of these spacings actually lie within the  $[0, L]$  domain. Note that the average spacing is independent of the specific locations of the sensors  $x_i$ , and consequently cannot be used as a selection criterion.

Instead, we use a selection criterion which explicitly takes the uniformity of the inter-station distances  $S_i$  into account. This is achieved by minimizing the variance  $\sigma^2$  of the inter-station spacings  $S_k, 0 \leq k \leq n$ , given by:

$$\sigma^2 = \frac{1}{2n}(S_0 - \bar{S})^2 + \frac{1}{n} \sum_{1 \leq i \leq n} (S_i - \bar{S})^2 + \frac{1}{2n}(S_n - \bar{S})^2 \quad (2)$$

Again, the first and last spacings have a weight  $\frac{1}{2}$ , since only half of these spacings actually lie within the  $[0, L]$  domain.



In practice, rather than minimizing the variance  $\sigma^2$ , it is convenient to minimize an equivalent loop detector placement criterion denoted  $\tilde{S}$ :

$$\tilde{S}(x_1, x_2, \dots, x_n) = 2 \sqrt{\frac{x_1^2}{2n} + \frac{(L - x_n)^2}{2n} + \sum_{1 \leq k < n} \frac{(x_{k+1} - x_k)^2}{n}} \quad (3)$$

which shares the same minimum as  $\sigma^2$ . The best set of  $k$  inductive loop detector stations is then given by:

$$U^*(k) = \operatorname{argmin}\{\tilde{S}(U) \mid U \subset \{x_1, x_2, \dots, x_n\} \text{ and } |U| = k\} \quad (4)$$

where  $|U|$  represents the number of elements in the set  $U$ . The resulting selections for the inductive loop detector stations are shown in Table 1.

In the case when the chosen inductive loop detector stations are uniformly spaced within the section of interest, the criterion  $\tilde{S}$  is equal to the average spacing  $\bar{S}$ . Because  $\bar{S}$  serves as a lower bound for  $\tilde{S}$ , the difference between  $\tilde{S}$  and  $\bar{S}$  indicates the degree of non uniformity of the sensor spacings caused by the fixed set from which the sensors are selected. Table 1 shows the difference between the inductive loop detector placement criterion  $\tilde{S}(U^*(k))$  and its lower bound, the average inductive loop detector spacing  $\bar{S}(k)$ , is small, indicating that the sensor spacing is relatively uniform.

#### *Penetration rate for probe data*

A few remarks about probe penetration rates are in order, before criteria to modify the penetration rate are discussed. In general, the penetration rate is difficult to determine for probe vehicles specifically because it depends on the number of equipped probe vehicles, the total traffic flow, and the evolution of the traffic flow in space and time. Typically, only the total number of equipped probe vehicles is known to probe data providers. Similarly, the total traffic flow can only be estimated from counts recorded by inductive loop detectors at predefined locations. Finally, because the evolution of the traffic flow is not under the control of the probe vehicles, it is nearly impossible to a priori specify a penetration rate which is both uniform in space, and uniform in time.

Because of the inherent difficulty in specifying the penetration rate a priori, we instead elect to directly modify the number of equipped probe vehicles as a proxy for modifying the penetration rate. The number of equipped probe vehicles in this study varies from 0% to 100% of the 2,200 *Mobile Century* vehicle trajectories, increasing by increments of 10%. Over the eight hour experiment, this corresponds to an average rate of probe vehicles between 27.5 veh/hr and 275 veh/hr. At a probe rate of 275 veh/hr, the 20 minute average penetration rate at the center of the experiment site ranges between 1.5% and 3%. When a subset of the vehicle trajectories is required, the subset is determined by selecting the trajectories at random before the simulation.

#### *Space-based sampling*

In order to modify the number of measurements used from each probe vehicle trajectory under spatial sampling, the number of locations where measurements are collected are modified. The locations where measurements are obtained are encoded through the placement of virtual trip lines (VTLs), which can be viewed as virtual geographic markers which trigger vehicles to send measurements when the vehicle trajectory intersects the VTL. A complete description of the VTL sampling strategy is described in detail in Hoh et al. [15].

**TABLE 1** : Inductive loop detector selection results. Given a number  $k$ , the selection algorithm returns the set  $U^*(k)$  of  $k$  inductive loop detector stations which minimizes the inductive loop detector placement index  $\tilde{S}(U^*(k))$ . The labels in  $U^*(k)$  correspond to the labels of the inductive loop detectors in Figure 1a.

$k$	$\bar{S}(k)$ (mi)	$\tilde{S}(U^*(k))$ (mi)	$U^*(k)$
0	$\infty$	$\infty$	$\emptyset$
1	6.50	6.51	{ 8 }
2	3.25	3.25	{ 4, 11 }
3	2.17	2.17	{ 3, 8, 14 }
4	1.62	1.63	{ 2, 6, 9, 15 }
5	1.30	1.33	{ 2, 6, 8, 11, 16 }
6	1.08	1.11	{ 1, 3, 6, 8, 11, 16 }
7	0.93	0.95	{ 1, 3, 6, 8, 10, 13, 16 }
8	0.81	0.83	{ 1, 3, 6, 7, 9, 11, 14, 16 }
9	0.72	0.73	{ 1, 2, 4, 6, 7, 9, 11, 14, 16 }
10	0.65	0.66	{ 1, 2, 4, 6, 7, 8, 10, 11, 14, 16 }
11	0.59	0.60	{ 1, 2, 3, 5, 6, 7, 8, 10, 11, 14, 16 }
12	0.54	0.55	{ 1, 2, 3, 5, 6, 7, 8, 10, 11, 13, 15, 16 }
13	0.50	0.51	{ 1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 13, 15, 16 }
14	0.46	0.48	{ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15, 16 }
15	0.43	0.46	{ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15, 16, 17 }
16	0.41	0.43	{ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16, 17 }
17	0.38	0.41	{ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17 }

Because the VTLs are virtual, it is possible to place them anywhere on the experiment site. The determination of optimal VTL placement is complex, so instead we elect to place the VTLs uniformly across the experiment site. The number of VTLs  $n_{\text{VTL}}$  tested in our scenarios varies from nine VTLs to 99 VTLs, increasing by increments of 10 VTLs. This corresponds to an average spacing between 0.72 to 7.1 VTL/mi. Note the number of VTLs used on the experiment site is significantly higher than the number of inductive loop detector stations. This is possible because unlike inductive loop detector stations, the marginal cost of virtual trip lines is small.

#### 4.2. Summary of scenarios considered

A summary of the various combinations of input data used for computing travel times considered in this article are as follows.

- **Number of inductive loop detectors.** Nine sets of inductive loop detector data, ranging from scenarios with zero to 16 stations, increasing by increments of two.
- **Number of probe data measurements.** The amount of probe data is modified in two ways.
  - **Penetration rate.** Eleven penetration rates are considered, ranging from scenarios with no probe data, to scenarios when 100% of the 2,200 probe vehicle trajectories are used, increasing by increments of 10%. This corresponds to an average rate of probe vehicles between 27.5 veh/hr and 275 veh/hr.
  - **Number of measurements per vehicle.** Ten sets of VTL locations are considered, ranging from scenarios with 9 (8.68 VTL/mi) to 99 VTLs (0.79 VTL/mi), increasing by increments of 10 VTLs.

In total, 917 scenarios are created by instantiating scenarios with all combinations of the 9 sets of inductive loop detector data sets, 11 probe penetration rates, and the 10 VTL sets.

## 5. RESULTS AND DISCUSSION

In this section, we present the results of 917 runs with varying amounts of probe and inductive loop detector data. We also vary the type of travel time computed (instantaneous or dynamic). First, the quantification of error is described, then the computational results are presented.

### 5.1. Error quantification

Because validation data is available for dynamic travel times via license plate re-identification, an error metric is used to compare the velocity estimation algorithm output that has been converted to travel times with the travel time measured from video recordings. By using the travel time error as a performance metric, estimation algorithm results can be compared with the results obtained when using different types and quantities of the input data.

Since the license plate reidentification data provides a distribution of individual vehicle travel times (see Figure 2), we define the true travel time as a one minute moving average of the recorded travel times. Figure 2 also shows the division of the experiment into four time periods that represent the different phases of the traffic during the experiment. These periods are (i) the *morning accident*, where travel times are decreasing as an incident clears, (ii) a *free flow* period

during the middle of the day when travel times are low, (iii) a *congestion building* period before the evening rush hours, and (iv) *full congestion* during the evening rush hours. Because of the different traffic conditions present in these time intervals, in addition to computing the error across the full day, the error is also computed for each time interval.

The travel time error is computed as follows. Let  $n$  be the number of estimates given in a period for which the error is to be computed, with each estimate indexed by  $i$ . Let  $T_v(i)$  be the mean travel time from the video data at time  $i$ ,  $T_{\text{inst}}(i)$  ( $T_{\text{dyn}}(i)$ ) be the estimated mean travel time computed with the instantaneous (dynamic) method at time  $i$ , respectively. The *mean absolute percent error* (MAPE) for the travel time computed with the instantaneous method is:

$$\varepsilon_{\text{inst,MAPE}} = \frac{1}{n} \sum_{i=1}^n \left| \frac{T_v(i) - T_{\text{inst}}(i)}{T_v(i)} \right| \quad (5)$$

while the MAPE for the travel time computed with the dynamic method is computed similarly.

## 5.2. Computational results

### *Implementation*

The estimates were computed using the existing *Mobile Millennium* highway model. The model was run 917 times with various data inputs. Each run consisted in the computation of the mean speed field evolution and computation of both instantaneous and dynamic travel time every 30 seconds, from 10 am to 6 pm. The runs took 320 CPU-hours, and were distributed on 8 servers equipped with 2.2 GHz dual core AMD Opteron CPUs and 8 GB RAM, which reduced the computation time to 39 hours.

### *Using only inductive loop detector data in the model*

The first analysis of the traffic estimates is based on the results obtained when using inductive loop detector data as the only input to the model. These results give us a baseline for the comparison between probe and loop detector data. A total number of 17 runs were conducted based only on the inductive loop detector data, by varying the number of sensors according to the selection algorithm in Section 4.1. Both instantaneous and dynamic travel times were computed. The labels of the inductive loop detector stations used in the estimation are presented in Table 1 as a function of the number of stations selected (see also Figure 1a).

The results of these runs are shown Figure 4. The subfigures show the estimation error broken down by time of the day, as defined in Figure 2. During the morning accident (Figure 4a), the dynamic travel times converge to estimates with 7% error, while the instantaneous estimates remain above 20% error. The instantaneous and dynamic estimates have between 6% and 7% error during the free flow and congestion building periods (Figure 4b and 4c), and 13% error during the full congestion period (Figure 4d), with the instantaneous and dynamic estimates performing similarly.

The number of inductive loop detector stations used tends to have a positive impact on the quality of the estimate when less than eight inductive loop detector stations are used. Note that the curve is not monotonic decreasing. This is because when only a few sensors are deployed, the error becomes highly dependent on the placement of the sensors. It is expected that an optimal sensor placement algorithm would reduce the error. The threshold of eight inductive loop detector stations corresponds to the inductive loop detector placement index  $\tilde{S}(U^*(8)) = 0.83$  mi (Table 1).

However, using data from more than eight inductive loop detector stations does not improve the quality of the estimates. If fewer than three inductive loop detectors are used, the estimation error is unacceptably high, at some points reaching as high as 100% error.

#### *Using only VTL data in the model*

The second part of the analysis consists of the travel time estimates obtained when using VTL data only. The changing parameters of the input data are the number of VTLs deployed on the experiment site and the rate of the probe vehicles used to produce speed measurements at the locations of VTLs. The estimation errors of the travel times obtained with the dynamic method are shown in Figure 5.

In each of the time periods, estimates of the travel time can be achieved with less than 6% MAPE, with sufficient probe vehicles and virtual trip lines. However, when more than 137.5 veh/hr are used with more than 2.54 VTL/mi, only small improvements in the accuracy of the estimates can be achieved. When compared with inductive loop detectors, using 137.5 veh/hr and 2.54 VTL/mi performs as well as the estimates using more than eight inductive loop detector stations during the morning accident, free flow, and congestion building periods, but has less than half the error of inductive loops during the full congestion period.

#### *Fusing VTL and loop detector data*

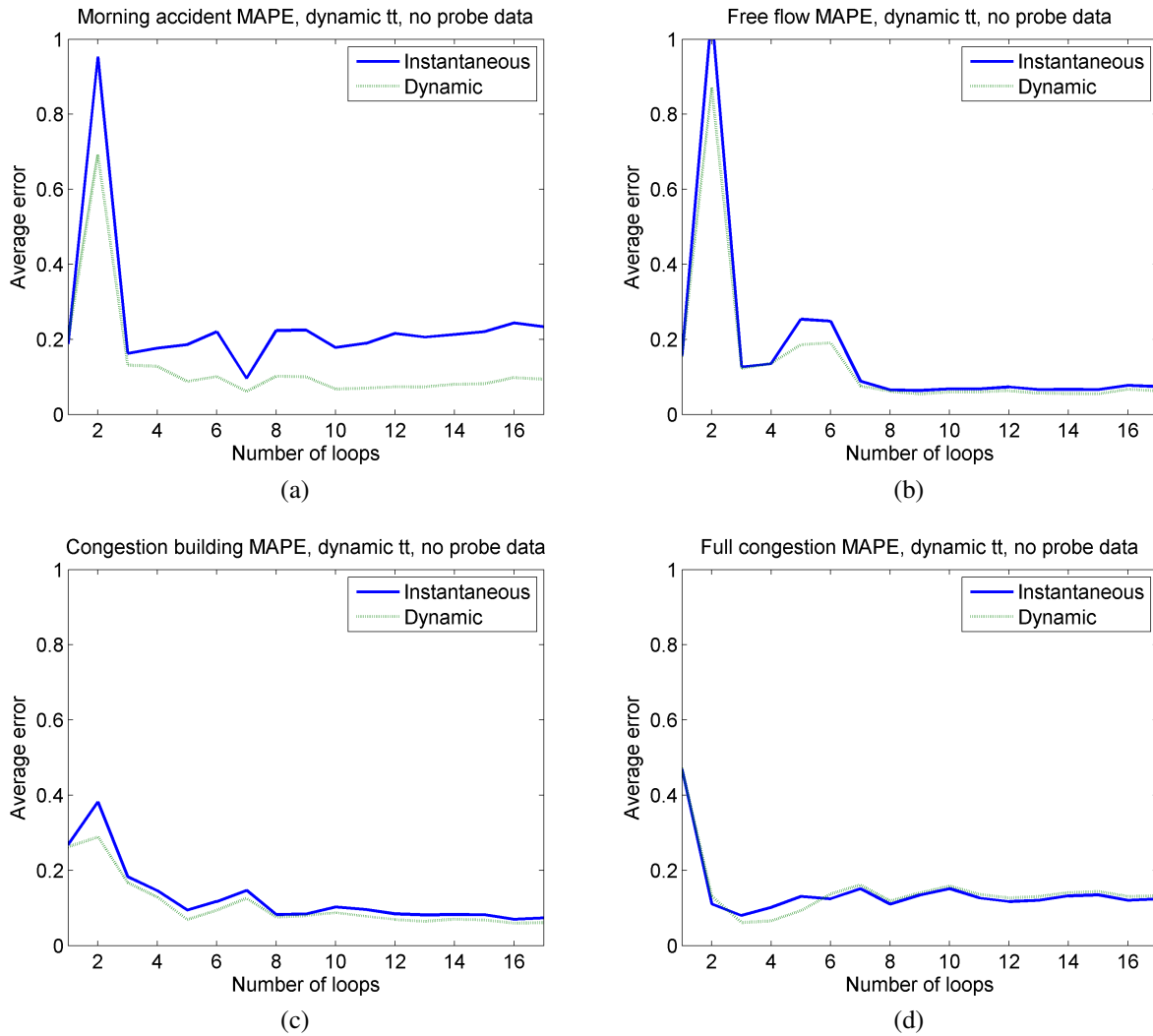
The dynamic travel time estimation errors using both VTL and loop detector data simultaneously is assessed in Figure 6, where the change in the dynamic travel time MAPE due to the addition of data from six inductive loop detectors is computed. The results shown are a representative subset of all the runs performed when mixing the two data types.

At low probe data rates during the morning accident, free flow, and congestion building periods, adding inductive loop detector data increases the accuracy of the dynamic travel time estimates. For example, during the morning accident (Figure 6a), with a probe rate of 27.5 veh/hr and a VTL spacing of 0.79 VTL/mi, adding inductive loop detector data reduced the error from 29% to 8%. During the full congestion period, the dynamic travel time estimate accuracy decreased when inductive loop detector data was added at low probe rates (27.5 veh/hr). This is likely due to the fact that the estimates based on virtual trip line data only were unusually accurate, even performing better than simulations with more probe vehicles.

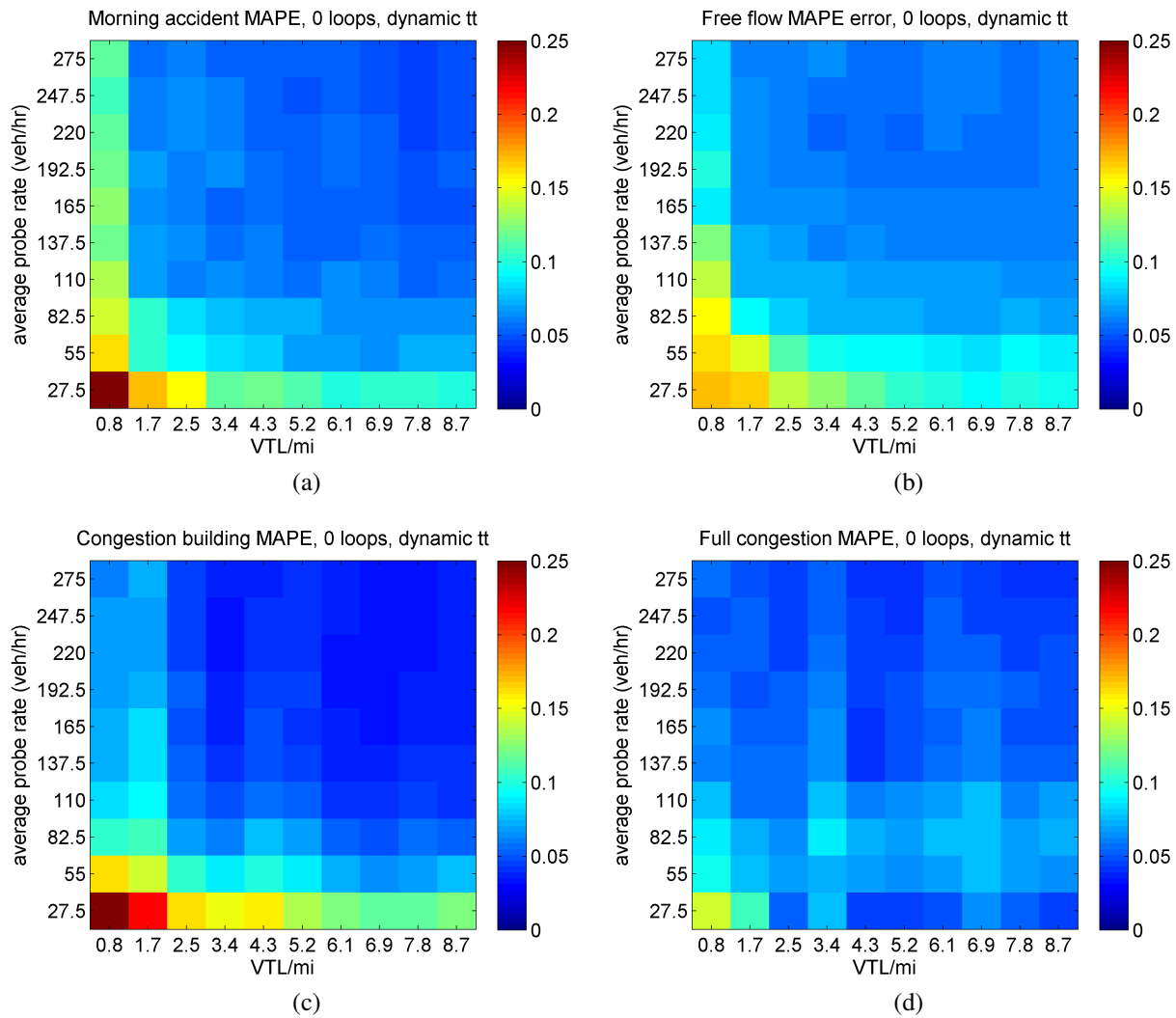
At higher penetration rates (above 137.5 veh/hr) adding data from the six inductive loops has negligible effect, increasing or decreasing the accuracy only slightly. The exception is during the free flow period, when the MAPE increased (between 0.05 and 0.08) even at high probe rates, when 0.79 VTL/mi were used. The errors in the free flow period are magnified due to the small base travel time, which is under 10 minutes, and it is in fact not constant during the period (see Figure 2). Moreover, it is clear from Figure 1 that there is an area of heavy congestion around postmile 26 even during the free flow period, which is difficult to capture correctly with sparse sampling.

#### *Using instantaneous travel time as an estimate for dynamic travel time*

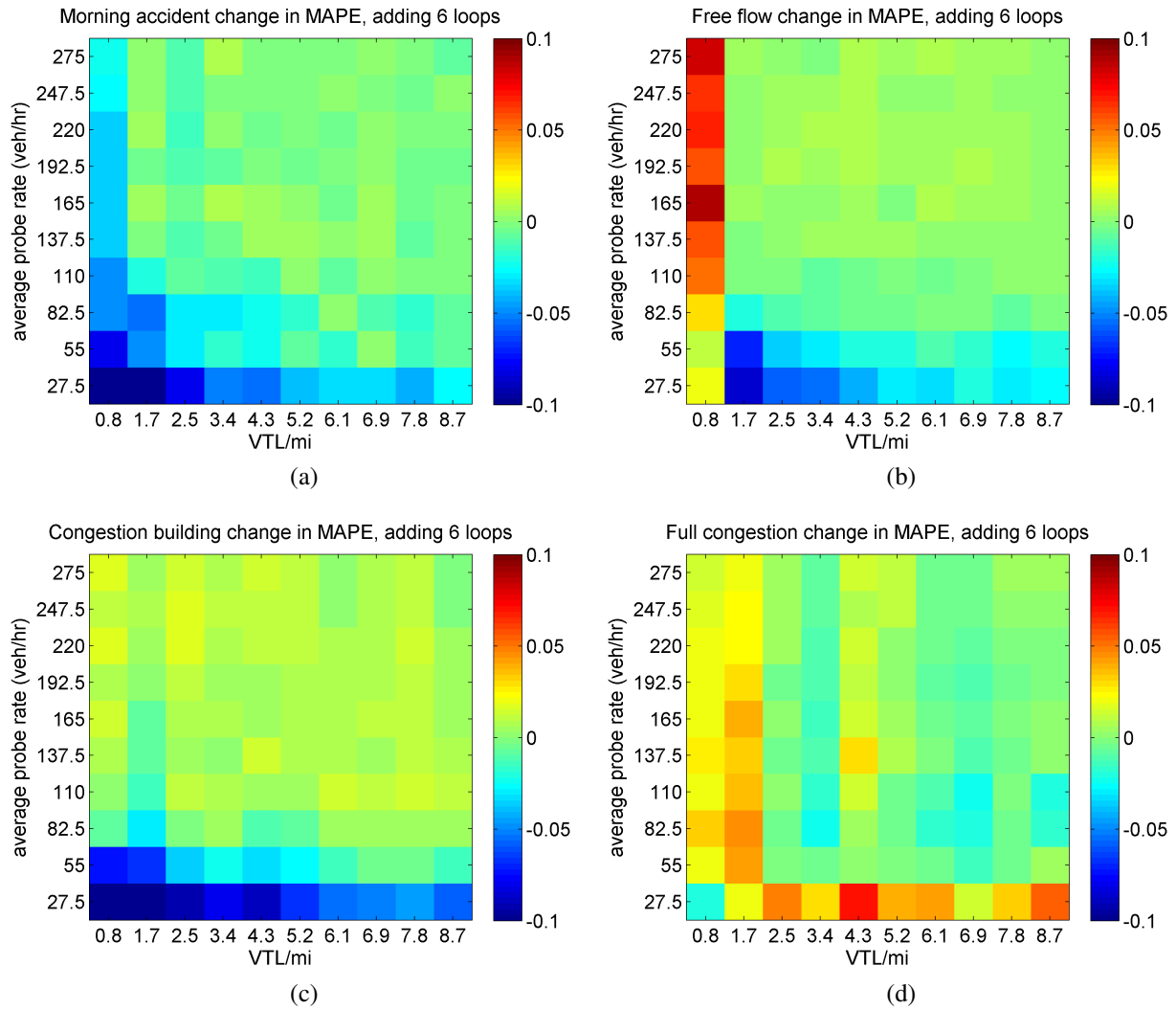
Figure 7 shows a comparison of the estimation errors when using instantaneous and dynamic travel times for the morning accident period. Instantaneous travel times can be determined at any time on any route using the speed estimates, and used as a proxy for dynamic travel times. As was shown for the inductive loop detector data in Figure 4b and 4d, instantaneous and dynamic travel



**FIGURE 4** : MAPE computed using inductive loop detector data only, no probe data. Travel time is computed using the dynamic method (green dash) and instantaneous method (solid blue). *x*-axis: number of inductive loop detector sensors, *y*-axis: MAPE (a) morning incident; (b) free flow; (c) afternoon as congestion increases; (d) evening congestion.

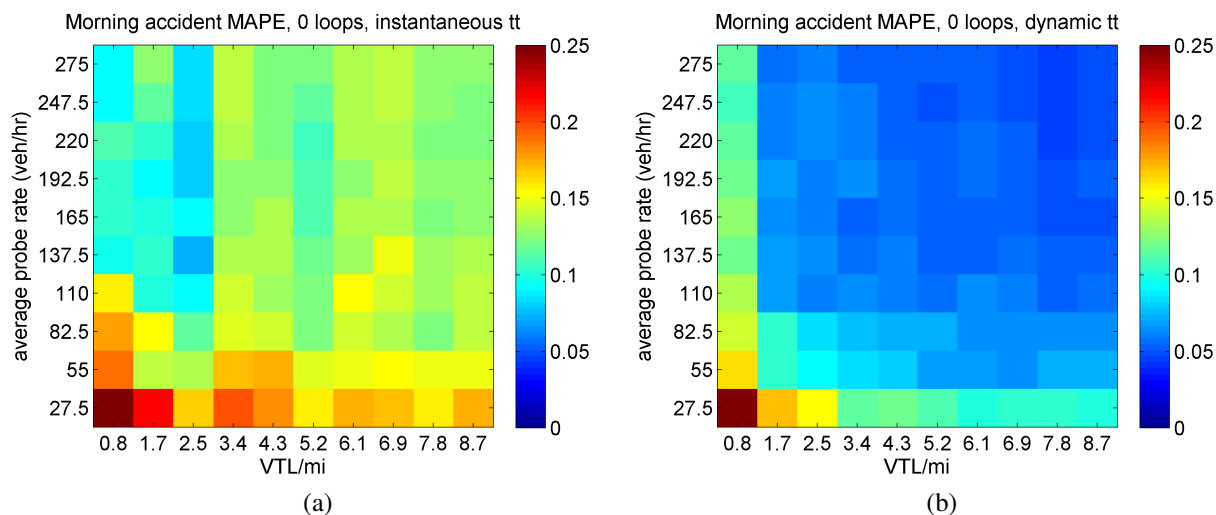


**FIGURE 5** : MAPE contours computed using VTL data only, no inductive loop detector sensors. Travel time is computed using the dynamic method.  $x$ -axis: number of VTLs,  $y$ -axis: average probe data rate (a) morning accident; (b) free flow; (c) congestion building; (d) full congestion. Color scale limited to 0.25.



**FIGURE 6** : Change in MAPE contours when adding six inductive loop detectors to VTL data. *x*-axis: number of VTLs, *y*-axis: average probe data rate (a) morning accident; (b) free flow; (c) congestion building; (d) full congestion. Color scale limited to  $\pm 0.1$ .





**FIGURE 7** : MAPE contours computed for the morning accident using VTL data and inductive loop detector sensors.  $x$ -axis: number of VTLs,  $y$ -axis: average probe data rate (a) 0 inductive loop detector sensors, instantaneous travel time; (b) 0 inductive loop detector sensors, dynamic travel time. Color scale limited to 0.25.

time estimates are very similar when traffic conditions change sufficiently slowly. The same holds when estimating travel times from probe data.

By looking at the instantaneous travel time errors in Figure 7a, an interesting result can be seen. The results suggest that adding more probe data results in an increased travel time estimation error. However, this result is expected, and can be explained by focusing on the scenarios (in Figure 7a) in which the penetration rate of the probe vehicles is low and no loop detectors are used. Here, the instantaneous travel time estimate performs well, and may seem like a valid estimate of the true travel time during the incident. However, this gives a misleading indication of the quality of these travel time estimates. The good performance of the instantaneous estimate is caused by the fact that the current state of the traffic (speed field) is very poorly captured in the underlying scenario and the speed of the traffic is heavily overestimated. This causes the instantaneous travel time estimate to perform as a good predictor of the future traffic conditions, namely, as a predictor of the clearing incident. When the number of probe measurements increases, the speed field estimate is captured more accurately, and the increased error in the travel time estimate is caused by the instantaneous approximation.

## 6. SUMMARY

In this study, trade-offs between velocity data collected from GPS smartphones in probe vehicles, and velocity data obtained from inductive loop detectors, for the purpose of computing travel times on a stretch of highway were studied.

This work was a case study that used experimental probe data obtained from the Mobile Century field experiment. The loop detector data was obtained from PeMS. The measurements were combined with a mathematical traffic model in a highway traffic estimation algorithm using a data assimilation technique called ensemble Kalman filtering, developed as a part of the *Mobile*

*Millennium* project. The results of the algorithm were compared against the true travel times experienced by the drivers, obtained through license plate re-identification. A number of scenarios were created in which the volume of the probe data and number of inductive loop detector stations available for the estimation algorithm could be adjusted.

The following is a summary of the key results found in this study:

1. **Achieving 10% error for dynamic travel times.** In this study, it was found that the dynamic travel time estimates can be achieved with less than 10% error when using a flow model with data assimilation, by using either inductive loop detector data, probe data, or a mixture of both inductive loop detector data in probe data. Moreover, the estimates from virtual trip line-based probe data can achieve a higher degree of accuracy when all available probe data is used compared to estimates from inductive loop detectors when all inductive loops on the experiment site are used, although in general the performance is similar.
2. **Minimum loop detector spacing for travel time estimation.** In this study, using data from more than eight inductive loop detector stations (average spacing 0.83 miles) did not give additional benefit in the travel time estimation. The error remains constant between 6–13% depending on the time of day, regardless of the added loop detector stations.
3. **Diminishing travel time accuracy improvement.** When sampling probe vehicles at a rate of 137.5 veh/hr with more than 2.54 VTL/mi, increasing the number of probe measurements by adding more probe vehicles or additional trip lines causes only small improvement on the travel time accuracy.
4. **A mixture of probe and loop detector data in travel time estimation.** It was found that when complementing loop detector data with probe vehicle data, better estimates for travel times are obtained, especially at low penetration rates. For example, if using loop detectors spaced more than 2.11 miles apart, probe data can give over 50% increase in the travel time accuracy.

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