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Vehicles as Probes [*]

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Abstract

In this paper we discuss the use of vehicles moving in traffic as probes that provide data for estimation and prediction of traffic behavior. The probe vehicles can report data on their speeds, locations, or travel times which can be used by an algorithm that updates estimates of traffic state and makes predictions for the future. We address some of the key issues involved in the design of such a traffic monitoring system.

1   Need for Alternate Sensors

In many situations the primary motivation for obtaining traffic information is to provide the vehicles on the highway with information relevant for them. This relevant information may be the expected travel times from a specific starting location to a specific destination, information on congestions, or routing advice. For such applications, one possible approach to obtain traffic estimates is to use some of the vehicles on the highway as a source of data. Also, the trajectory followed by a vehicle is an integral part of the highway travel experience

and hence important for a traffic management system. A system with vehicles acting as probes has the distinctive capability of providing this information in an inexpensive way.

Using vehicles as sensors instead of the conventional stationary sensors (such as the inductive loops used in many places) may provide benefits such as lowered costs for maintaining the information system and an easier implementation. It also offers a higher flexibility in operation since with the present technology, changes in the information that the probes vehicles provide or the algorithms that use this information are relatively inexpensive. It is important to note that travel times measured on the highways will be needed to evaluate the performance of delay prediction techniques, including those that are based on other sensors.

In several places where highways are not equipped with inductive loops, the amount of construction work that would be required to install them is significant, and requires closing those highways to the traffic. Several other kinds of sensors, for instance those based on machine vision are being developed. However, with the increase in the market penetration of Advanced Traveler Information systems, using equipped vehicles as sensors is likely to be among the most cost effective schemes. In this paper we discuss the organization, requirements, objectives, and performance of a scheme that uses probe vehicles as sensors.

2   Concept of Probes

The key idea towards using vehicles as probes is that a vehicle traveling in traffic is a reasonable representative of the behavior of the traffic that it is a part of, with some deviation that is statistical in nature. Hence, if the trajectories of a sufficiently large number of vehicles are monitored, good estimates for the collective flow variables may be obtained. However, monitoring the movement of a large number of vehicles that report over a wireless data-link requires a large share of the radio spectrum. In addition, a large set of reporting vehicles implies that the computational resources required can be significant. **A** more pragmatic approach is to have the vehicles transmit their reports at regular intervals and limit the number of vehicles allowed to serve as probes. Clearly, this will affect the performance of the traffic monitoring system in terms of the accuracy in estimation and prediction and the tradeoffs between accuracy and costs of implementing such a scheme have to be examined.

The vehicles on the highway that act as probes need to be equipped with the required IVHS technologies and report information on different variables (like location, speeds etc)

using a packet radio based communication system. Some estimation/filtering techniques can be applied to this data and information of interest for the highway traveler, such as the speeds, expected travel times etc can be obtained. This information can then be disseminated to the travelers who may then change their routes, reschedule travel or just get a better picture of the highway, based on the information. The specialized hardware installed in each of the probe vehicles that enables it to serve as a probe can also manage the services provided to the vehicles on the road such as route guidance and information on the state of traffic. Also, in order to optimize the use of bandwidth, algorithms that control the number of probes in use need to be be designed.

The main issues that need to be addressed in order to design such a system and implement it economically are

- *o* How to organize such a data collection system for the highways.

- *o* What are the formal objectives and priorities.

- *o* How many vehicles need to serve as probes in such a system.

- *o* How often should the probes send their reports.

- *o* What are the measurements/data that the probes should report.

3   Organization of a Probe System

We shall consider a highway that is divided into n links. The fraction of vehicles on this highway that serve as probes is denoted by p_f. Each link is assumed to have a corresponding base station and the the probe vehicles on the link communicate with the base station using packet radio. The communication bandwidth assigned to each link is fixed and its use is left to the corresponding base station. The probe vehicles are equipped with measurement and communication devices and an on-board computer. Using data from Global Positioning System(GPS), the odometer and a some inertial direction systems, these vehicles can recursively update estimates of their position on the highway. Each base station is required to be linked to the Traffic Management Center (TMC) by a robust data communication network.

The data packets transmitted by the probes to the base station contain an identification for the probe, the location of the probe and may contain the probe speed or the time taken to traverse the previous link. This information can be used to compute estimates of the macroscopic traffic flow variables and link travel times. The TMC uses these link level estimates to generate the reports of speeds, predicted travel times, and recommended control measures such as routing advice that can be provided to travelers. This estimation/prediction scenario can be described by Figure 1.

The estimation and the state information can be organized at two levels, the link level and the TMC level. The information that needs to be maintained for each link includes the link speed, link travel time, number of probes on the link, and locations of these probes. On the other hand, the information that the TMC needs to maintain includes the highway configuration and the possible origin-destination routes, the travel time predictions and the speeds on different routes, based on the link level information. In a practical situation the TMC also needs to be able to use other forms of information such as incidents on the highway and their expected durations.

4   Position Estimation

One of the significant issues that needs to be addressed for a scheme using vehicles as sources of traffic data is that of measurement. The measurement of vehicle speed can be obtained using the odometer on the vehicle. The rate at which odometer ticks are observed can be used to measure the speed, along with some odometer calibration factors. Similarly, the measurement of travel times between certain marked locations can also be obtained trivially, provided that the vehicle knows its location accurately when it passes by these locations. Hence, the significant problem that needs to be addressed here is that of obtaining position information for the vehicles. In this section we discuss some possible approaches [8] for obtaining position information.

For open areas on the highways, where signals from transmitting stations (such as satellites or fixed beacons) are not obstructed, the simple options include
[a] Global Positioning System(GPS) [b] Loran [c] TACAN.
The accuracy specifications offered by b and c are in the range of < 1 mile, which are not very useful for obtaining vehicle positions. The GPS (or the equivalent Russian GLONASS)

systems offer the best estimates of these systems.

In the GPS system, a set of satellites is used, each of which transmits signals containing 1ms (**300** meters) pulses and their ranges (pseudoranges). From this information, the position of the (vehicle mounted) receiver can be computed. Further, each satellite uses 2 carrier frequencies and the doppler shift can be used for estimation of speed. Although such a system is capable of giving a very accurate estimate for a stationary receiver over time, the accuracy for a moving receiver is rather limited. An improvement offered by most GPS providers is the use of Differential GPS[7]. This approach uses a land based stationary receiver that receives the GPS signals and uses the knowledge of its precise location to obtain the corrections for the errors/biases due to the effect of Ionosphere, the propagation in the Troposphere, the atmospheric disturbances, and the correction information for the uncertainty due to the lack of the SA-code'. These corrections are transmitted to the vehicles, which use them to obtain a highly accurate estimate of their positions. The accuracy that may be obtained by a static vehicle is about 5 cm for a measurement rate of **2** Hz. For a moving vehicle, the position may be measured with an accuracy of about the distance traveled in 0.5 seconds. This accuracy would be adequate for using vehicles as probes in open spaces. However, in the presence of obstructions (such as tall buildings, bridges etc.), the accuracy suffers due to loss of the GPS signals.

An alternative approach which requires more infrastructure investment is the use of a beacon based system. This requires that a number of beacons (radio transmitters) be placed at several locations in such a manner that all points on the routes of interest have a set of beacons directly in line of sight. Knowing the positions of these transmitters, the vehicle can obtain position information with high degree of precision. Such systems offer moderately cost effective solutions in certain urban settings. They are more expensive than GPS due to the hardware installation and positioning/planning costs, but provide reliable position information. Such systems are being used for bus routes and Taxis in some countries and have a position measurement accuracy of about 5 meters.

For many applications, where the spaces are not open and obstruction may result, or in situations where a higher degree of accuracy may be required, it may be necessary to use an approach that uses integration of inertial sensors and GPS. The sensors that can be used

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[1]The Selective Availability-code **based** uncertainty is introduced by the military to control the use of GPS in strategic applications

include accelerometers, gyroscopes, and inclinometers. The problems encountered in the use of inertial sensors include

1. Sensor Biases

2. Scale Factors

3. Misalignment

4. Cross-axis Sensitivity

5. Schuller Cycle

The GPS measurement obtained can be treated as the actual position of the vehicle with an additive measurement noise. This measurement can be used along with estimates of the biases, scale factors, and other corrections as state variables to design adaptive filters such as a Kalman filter **[6]** that will recursively update the position and state estimates. The filters designed to achieve this may be (in increasing order of complexity)

1. Complimentary Kalman Filters

2. Extended Kalman Filters

3. Non-Linear Filters

Systems that use such filtering techniques are being developed that will provide the final position information in an integral package. It should be noted that the computational costs of these methods are not to be drawn from the main on-board computer, but should be incorporated in the design of the position information module (The current trend in the design of such systems is to implement the data processing algorithms on dedicated DSP processors). Among other places, work is being pursued towards the design of such systems [8] at the PATH Lab, EECS, U.C. Berkeley, and has involved testing systems based on various accelerometers, including some integrated micromachined sensors that were designed and fabricated at Berkeley Sensor and Actuator Center (BSAC). It is expected that generic integrated navigational systems[2] will be available in the near future that will be suited to vehicle positioning applications.

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[2]Design and testing of such systems is one of the objectives being pursued at the **PATH** Lab.

5   Speed Estimation

Consider the following problem of estimating the link speeds from the probe data. In the highway system with probes as described in section **3**, suppose the actual speeds for the traffic in link j as a function of the time t be $v(j,t)$, where $j = 1, 2, ..n$ and the interval of interest is $[0, T_f]$. Also, let the speeds and positions of the ith probe vehicle on this highway as a function of time be $(v_p^i(t), x_p^i(t))$. The probe speeds can be related to the average speeds by

$$v_p^i(t) = v(l(x_p^i(t)), t) + Z_i(t)$$

where the function $l : R \rightarrow \{1, 2, ..n\}$ maps the position of the probe vehicle to the link, and $Z_i(t)$ is a random process that represents the deviation of the speed of vehicle i at time t from the collective flow at time t.

The objective of the estimation is to obtain an estimate $\hat{v}(j,t)$ for $v(j,t)$ for $j = 1, 2, ..n$, from the instantaneous measurements of some of $(v_p^i(t), x_p^i(t))$ at times $t \in \{t_1, t_2, t_3, ...\}$. This problem is difficult to solve even in a discretized form. We will address the discretized version of this problem with some additional assumptions and constraints.

We consider a discrete time frame where for the kth interval, the speed in section j is $v_j[k]$. Also, we have $n_d[k]$ measurements $v_p^1, v_p^2, ...v_p^{n_d}$ available as the reported speeds from the probes in section j. These speeds v_p^i can now be written as the speed $v_j[k]$ with an additive noise $Z_i[k]$. The problem we now address is that of finding $\hat{v}_j[k]$, the estimate for $v_j[k]$.

We impose the constraint that the variation of the section speed from one interval to the next is bounded and in the absence of any other information is given by

$$v_j[k] = v_j[k-1] + \eta[k]$$

where $\eta[k]$ is a sequence of independent, identically distributed random variables. We also assume that the estimate from the previous interval $\hat{v}_j[k-1]$ is known and that the noise $Z_i[k]$ is zero mean white noise, that is, it is uncorrelated over time, and is independent for the reports from different probe vehicles. Then we may write the estimation equation for $\hat{v}_j[k]$ as

$$\hat{v}_j[k] = (1 - \alpha[k])\hat{v}_j[k-1] + \alpha[k]\frac{1}{n_d[k]}\sum_{i=1}^{n_d} v_p^i \tag{1}$$

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We will choose $\alpha[k]$ in order to minimize the mean squared estimation error $E[(\hat{v}_j[k] - v_j[k])^2]$. Denoting the kth prediction error by $\epsilon_j[k]$, we can write

$$\epsilon_j[k] = \hat{v}_j[k] - v_j[k]$$

We may therefore write

$$\hat{v}_j[k-1] = v_j[k] - \eta[k] + \epsilon_j[k-1]$$
$$v_p^i = v_j[k] + Z_i$$

this implies that

$$\epsilon_j[k] = (1 - \alpha[k])(\epsilon_j[k-1] - \eta[k]) + \alpha[k]\frac{1}{n_d}\sum_{i=1}^{n_d} Z_i$$

Denoting the variances of $\epsilon_j[k]$, $\eta[k]$, and Z_i by $\sigma^2_{\epsilon_j}[k]$, σ^2_η, and σ^2_Z respectively, we now obtain

$$\sigma^2_{\epsilon_j}[k] = (1 - \alpha[k])^2(\sigma^2_\eta + \sigma^2_{\epsilon_j}[k-1]) + \alpha^2[k]\frac{\sigma^2_Z}{n_d}$$

And in order to minimize this, the value of a to be chosen is

$$\alpha[k] = \frac{\sigma^2_\eta + \sigma^2_{\epsilon_j}[k-1]}{\sigma^2_\eta + \sigma^2_{\epsilon_j}[k-1] + \sigma^2_Z/n_d} \qquad (2)$$

This filter defined by equations *1* and *2* computes the estimates of link speed that are optimal for the mean square error criterion. The estimates thus obtained are the Bayesian estimates. Some small increments in improvement may be obtained by modeling dependence of $\eta[k]$ on $v_j[k]$, but for a computational price.

6   Performance Evaluation

In order to evaluate the performance of probes, we need to compare the trajectories of probes with the collective speed based trajectories. Since the evolution of speeds with time is given by complicated dynamical system (as in [2]), an analytical comparison is ruled out. Hence we develop a simulation model to obtain some numerical conclusions on the performance of probe based system. The accuracy of the estimates obtained from probe data depends on the number of probes operating in the system, the frequency of reports f_R, the contents of

the report, and the algorithm used to obtain the estimates. We simulate a highway with probe vehicles traveling on it and use the reports to predict future travel times. By varying the parameters we obtain the variation in prediction accuracy with the parameters. In the following sections we describe the model, the criteria and obtained performance, and the communication needs for the system.

6.1   Simulation Model

For simulating the movement of probe vehicles in traffic, our model uses velocity profiles over the highway as an input. Such profiles may be obtained either from field measurements [1] or from macroscopic traffic flow models [2]. Based on characteristics like origin destination flow rates, probe vehicles are introduced in the system with preassigned destinations. The speeds for the probe vehicles are obtained by a systematic perturbation from the mean speed for the location of the vehicle. The fractional deviation in speed for the vehicle is obtained using a zero mean triangular probability distribution which is taken as a simplification of the distributions observed by Herman [9]. As these probe vehicles travel on the highway, the desired data (*e.g.* speeds, locations and travel times) are reported to a module that represents a network monitoring station and does the estimation of the state of traffic flow and prediction of future travel times. This module can also be responsible for the detection of incidents and the computation of desirable routing decisions for multipath origin-destination pairs.

The algorithm for simulating probe vehicles is outlined in Figure 2. The algorithm reads in the highway configuration, the simulation parameters, and the flow and speed data from user provided files. The algorithm then creates probe vehicles and keeps track of their movement and obtains the data that the probes would report via packet radio.

The monitoring algorithm starts with an initial set of traffic flow estimates and, using the probe data received, it updates its estimates and makes predictions for the future travel times. Also by monitoring the past travel times, it can adapt its parameters to correct for biases in prediction. Figure **3** outlines this algorithm.

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6.2 Evaluation Criteria

To evaluate the performance of a probe based scheme with respect to the parameters like the data reported, the fraction of probes p_f, and the frequency of reports, we consider the following cases:

1. Probes report their position and speed periodically and using the reported speeds from the probes in each section of the highway, the algorithm adjusts the estimate for the speed in that section.

2. Probes report link travel times and using these travel times, the TMC/base station update the estimates of travel time for those links for which probe reports are available.

These two cases need to be considered separately since the estimation from the probe reports has to be done differently in them. In case 1, the estimation is synchronous since the probes report at periodic intervals, and the estimate updates can be done at the reporting frequency. In this case the approach outlined in section 5 is applicable. In case 2, the reports are made asynchronously, when the probes complete travel over the links. Since the times at which these reports are obtained also contain some information, a periodic approach to update of estimates will be suboptimal. However, if the rate at which the reports are received is high, the gains made by the optimal approach (see Appendix **A**) are small.

The highway chosen for our simulations is the 1-880 in California between the Marina and Whipple exits in Oakland, since field data is available for this from the Freeway Service Patrols evaluation study [3]. This stretch of 1-880 is divided into 21 sections. The flow and speed data is obtained from the field measurements and is used by the model to simulate the movement of probes. The prediction based on probe reports is repeated for the various values of the parameters (p_f, f_R and ER) and the mean square prediction errors as the fraction of the travel times obtained from the measured speeds is computed. It should be noted that the travel times predicted from the simulated probes are compared with travel times calculated from the known speeds, and that they are not compared with actual vehicles travel time data.

Figure **4** shows the prediction errors for case 1, where the probes report their speeds. The different curves are for the various values of f_R in reports per minute per probe.

For case 2, when probes report travel times for each link, the error performance is indicated in Figure 5.

Next, we consider the case when the vehicles in a particular link report their speeds only if the speeds are off by more than a certain fraction from the speeds estimated for that link. This fraction and the estimated speeds are computed and broadcast by the TMC and the base station for that link. We will refer to this fraction expressed as percent as the exception range (ER). The idea behind this approach is that if the speeds on the highway are very close to the estimated speeds, then the probe reports do not contain much useful information. Further, since the fraction of probe vehicles in a real highway traffic is likely to be variable, and the bandwidth allocated is fixed, such a scheme would allow the base station to adjust the rate at which vehicles generate reports (by computing and broadcasting the desired exception range) to make better use of the available spectrum. The prediction errors for this case for various values of the exception range (ER) are shown in Figure **6** for $f_R = 1$ per minute.

6.3   Communication **Needs**

Implementation of a probe based traveler information system requires the use of a wireless channel for the probes to send their reports to the base stations. This method requires reserving a part of the radio spectrum and using it efficiently. Since we are addressing the collection of probe data and derivation of inferences from it, we examine the probe to base station communication[3].

In order to use the spectrum efficiently, a dedicated packet radio based scheme would be desirable. Some communications system designs for IVHS are addressed in [5] and [4]. We propose using a service described in [5] as $PROB$. The penetration grade (fraction of vehicles transmitting data) in our case is p_f, and the reporting frequency for the case of speed based prediction can be 1 report/min or lower, and for link travel time based prediction it is of the order of the typical link travel times. Although a frequency reuse pattern of $C = 2$ is recommended for linear highways, $C = 3$ would allow us to better handle data from traffic

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[3]The requirements for base station to vehicles communication may vary significantly depending on the services provided. For simple broadcast of information, use of **FM** subcarrier modulation techniques is possible to reduce allocation **of** additional bandwidth

in the vicinity of highway junctions. The spectrum required can thus be estimated using the approach of [5] as listed in Table 1. It should be noted that with good coordination and acceptance of a small probability for the needs to retransmit, the overhead factor can be reduced significantly.

size of a cell	1 Km
vehicles per cell	800
typical packet size	**200** bits/packet
penetration grade	p_f
frequency	$f_R/60$ packets/sec
Reuse pattern C	**3**
modulation efficiency	**2** Hz per bit/s
overhead factor	**1.4**
TOTAL	**22.4** $\times p_f \times f_R$ KHz

Table **1:** Spectrum usage recommendation

For the case of **4%** probe vehicles on the highway $(p_f = 0.04)$ each reporting once a minute $(f_R = 1.0)$ the bandwidth that we need to reserve is 896 Hz. Whether this bandwidth is fully used depends on the actual density of probe vehicles on the highway and that can vary with time. The above calculation assumes that the highway has a high vehicle density. It should be noted that improvements in spectrum usage are possible by changing the cell size or by adaptively changing the reporting pattern. Allocating 896 Hz implies that the number of messages per cell can be up to **32** per minute. If we allocate only **448** Hz, then we can handle up to 16 messages per minute per cell and the base station needs to ensure that.

Heuristically, a larger number of probe reports imply a better accuracy in estimation of flow parameters and prediction of travel times. However, beyond a certain point, the incremental accuracy ceases to be worth the extra communication costs. Depending on the fraction of vehicles that are equipped to function as probes and the cost of spectrum usage, a suitable bandwidth should be reserved. To optimize the use of bandwidth, we assume that the control unit can send messages to probe vehicles through a broadcast link. The goal of the controller is to keep the rate of messages per cell close to but below the maximum

number of messages per minute per cell (which is determined by the allocated bandwidth). Figure 7 shows the total rate of reports for our highway as a function of the fraction of probes and the exception range.

It is clear that the rate of reports can be suitably chosen by choosing the exception range and the fraction of active probes. The control unit can adaptively improve the use of the allocated spectrum by issuing the following commands over the broadcast channel

- *o* increase/reduce the number of active probes to p'_f

- *o* increase/decrease ER, the exception range

- *o* increase/decrease f_R, the reporting frequency

- *o* change contents of reports(*e.g.* report probe travel time over two sections at a time).

7   Comparison with Fixed Sensors

The speeds on the highway are usually measured by inductive loops embedded in the road surface. However, the installation of these in existing highways is quite expensive and the existing loop detectors require periodic maintenance (tuning) in order to obtain reliable measurements of traffic variables. In this section we will compare the performance of probes in predicting the speeds that would conventionally be obtained from the loop detectors.

The speeds reported by probes is used to update the current estimates of the speeds for each section. These estimates of speed as a function of time and space can be compared to the mean speeds on the respective sections **as** measured by the fixed loop detectors. To judge the extent to which the estimates match the actual speeds, the mean square variation between the speeds ontained by using probes and the corresponding highway speeds is used as the degree of imperfection in estimation. If measured speeds are denoted by v_m and the probe based speed estimates by v, then the fitness criterion[4] denoted by R^v_{fit} is given by

$$R^v_{fit} = 1 - \frac{E[(v - v_m)^2]}{E[v_m^2]}$$

this measure of fitness is introduced in [2] and approaches unity as the quality of the estimate improves.

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[4]We use E to denote the average over the sections and the time intervals

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The simulation results for this goodness of fit criterion are shown in Table **2** for a few different values of f_R, the frequency of reports (per minute). **As** can be expected, the fit improves with the increase in the fraction of probe vehicles and with the reporting frequency.

8   Improvements in Prediction

For a slight increase in computational complexity, the probe reports can be used to improve the accuracy and content of the information extracted. We describe here a heuristics based algorithm that attempts to detect incidents/congestions. The key idea here is that when an incident occurs or a congestion builds up, the speed of the probe vehicles in the affected links goes down. Hence, if at each update the location/time of the next update is estimated, then the mismatch can be used to find if the vehicle is affected by road congestion. However before making a conclusion, a chosen number (say M_I) of confirmations from other probe reports are allowed.

In order to achieve that, the following variables can be added for each link with i denoting the link number.

$n_p(i)$: number of probes in link i

$C_I(i)$: congestion indicator for link i

$I_I(i)$: incident indicator for link i

$n_I(i)$: number of confirmations on link i

Also, for each probe known to be active in the system, a data structure containing the location, speed, and time of last report for the two most recent reports is allocated. Further, a suitable threshold Δ_I is chosen such that a drop in speed of Δ_I indicates the start of a congestion. Similarly a speed V_{sm} is chosen above which the traffic flow is considered smooth.
Probe updates

```
for each probe report received, check link probe is in
for each probe report received, update
        link state
```

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link travel time estimate

whether probe may exit

expected speed at next report

expected location/time at next report

for each probe report, test

if probe not is database

include probe in database

increment $n_p(link)$

else

if expected speed - speed $>$ **A₁,**

increment $n_I(link)$

if expected location - location $>$ A,,

increment $n_I(link)$

if speed $> V_{sm}$

decrement $n_I(link)$

for each probe **j** in database

if time since last report $\geq T_{max}$

if exit possible for probe **j**

remove probe **j**

for each **link,**

if $0 < n_I(link) < M_I$

$C_I(link) = 0$

if $n_I(link) \geq M_I$

$C_I(link) = 1$

$n_I(link) = M_I$

if $n_I(link) \leq 0$

$C_I(link) = -1$

$n_I(link) = 0$

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From the algorithm outlines above the state of traffic flow (speeds, travel times, flow) can be obtained from the state estimates. In addition this algorithm can provide conclusions as to which links are developing congestion and this can be used to judge the presence of incidents. Testing and training of such an algorithm to obtain the acceptable compromise solutions between the detection rate and times and the false alarm rates may be obtained by a pilot study, where probe data from sufficient number of probes is obtained.

9 Conclusions

In this paper, a system level framework for the operation of a scheme using moving vehicles as traffic probes is presented and evaluated. The results of the evaluations indicate that it is feasible to use vehicles in traffic as a source of traffic data. In order to obtain accurate results, the fractions of vehicles that need to serve as probes is obtained as a function of the desired performance. The speeds measured by probes are found to correlate well with those obtainable by loops.

It is found that the number of probes required for a good estimate of travel times is about 4% of the vehicles on the highway, based on the simulation results. The communications bandwidth requirement in this case is fairly modest and can be satisfied economically. However, it should be pointed out that this result is obtained from simulations performed with with specific link configurations that were chosen due to availability of the corresponding loop data. A key parameter that determines the performance of the scheme is the rate at which the probe reports in a link of the highway are received. The link lengths also play a role in determining the variability of speeds over the link and extremely large link lengths may result in deviations from the assumption of homogeneous flow over the links. The scheme is recommended for implementation provided that the penetration of probe vehicles in traffic meets the desired accuracy in estimation and prediction as obtained in section 6.2.

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A   Asynchronous Estimation

Consider the problem of providing estimates of quantities like travel times which are of interest in ATIS. A problem that has to addressed is that the sensor information may not be available in a periodic manner. In the absence of any sensors, there usually is a prior distribution for the quantity of interest, and any sensor data that is obtained thereafter can be used to improve the estimates. This new estimate relaxes to the prior distribution with time unless new updates are obtained.

   In this Appendix we discuss a statistical approach to the solutions of the prediction problem for travel times over a chosen length of a highway. This approach is justified by the fact that we have uncertainty in the state of traffic and that the travel times may vary from an estimate as time progresses due to the local variations in traffic. With respect to travel times it can be noted that

1. A vehicle is drawn from a population of vehicles with distributed characteristics. Hence a travel time measured by a vehicle is an observation for a random variable from the corresponding distribution.

2. Due to variations in traffic, the farther in past the most recent observation is, the higher the degree of variability from an estimate is. But at worst, the degree of variability is limited to the prior distribution of the travel time.

3. In the context of vehicles serving as probes, any vehicle that completes traversing this highway may be a probe vehicle with a fixed probability. Therefore the arrival process for vehicles that will report their travel time is a Poisson process.

In the following we assume that the travel time is given by the sum of a constant (which is the average) and a random component which has a normal distribution.

$$T_t = T^B + X_t \tag{3}$$

The dynamics of X_t are assumed to be given by

$$\dot{X}_t = -\gamma X_t + \eta_t \tag{4}$$

where γ is a constant and η_t is white gaussian noise. At times $t_i, i = 1, 2, 3..$ that correspond to a Poisson arrival process with rate λ the measurements $T_{t_i}^M = T^B + Y_{t_i}$ are made, where Y_{t_i} are estimates of X_{t_i} with an additive gaussian noise w_{t_i} that has a variance σ_w^2.

$$Y_{t_i} = X_{t_i} + w_{t_i} \tag{5}$$

In this formulation, if at any time the mean and variance of X_t are known, then from that time onwards X_t relaxes to an Ornstein-Uhlenbeck process. Given that the distribution of X_t at time t_i is Gaussian with mean μ_i and variance σ_i^2, the mean and variance of X_t for times $t; < t < t_{i+1}$ are given by:

$$\mu_t = \mu_i e^{-\gamma(t-t_i)} \tag{6}$$
$$\sigma_t^2 = \sigma_\eta^2 + (\sigma_i^2 - \sigma_\eta^2)e^{-2\gamma(t-t_i)} \tag{7}$$

However, at times t_i, $i = 1, 2, 3...$, an observation Y_{t_i} is obtained and using this, we can update the estimate at t_i for the distribution of X_t using:

$$E[X_{t_i}/Y_{t_i}] = \frac{\sigma_w^2}{\sigma_w^2 + \sigma_t^2}\mu_{t_i} + \frac{\sigma_t^2}{\sigma_w^2 + \sigma_t^2}Y_{t_i} \tag{8}$$
$$Var[X_{t_i}/Y_{t_i}] = \frac{\sigma_w^2\sigma_t^2}{\sigma_w^2 + \sigma_t^2}[1 + \frac{2Y_t(Y_t - \mu_t)}{\sigma_w^2 + \sigma_t^2}] \tag{9}$$

To find the expected error variance for the travel time prediction if a predictor based on the current conditional mean travel time, we can perform a simulation for this predictor. From the ergodicity of the observation process and the filtering process, we know that the mean square error for this prediction scheme can be obtained by

$$E[\sigma_t^2] = \lim_{T \to \infty} \frac{1}{T} \int_0^T \sigma_t^2 dt \tag{10}$$

Hence, for a numerical simulation of the estimation procedure, if the average variance of X_t is computed then this average converges to the expectation as the averaging time becomes large.

Remarks

- For a system in which the measurements are sparse, and the quantity to be estimated can change suffixed ficiently between measurements, this method can offer a good

estimate, especially in situations where one is interested in not only the estimate, but also in the variability of that estimate. There are estimation problems where this variability is a part of the utility of the information, since it can be used to characterize risks in decision making.

- Although the problem is formulated in terms of a system that relaxes to an Ornstein-Uhlenbeck process, other systems may be mapped into this framework via a nonlinear transformation of the variables of interest.
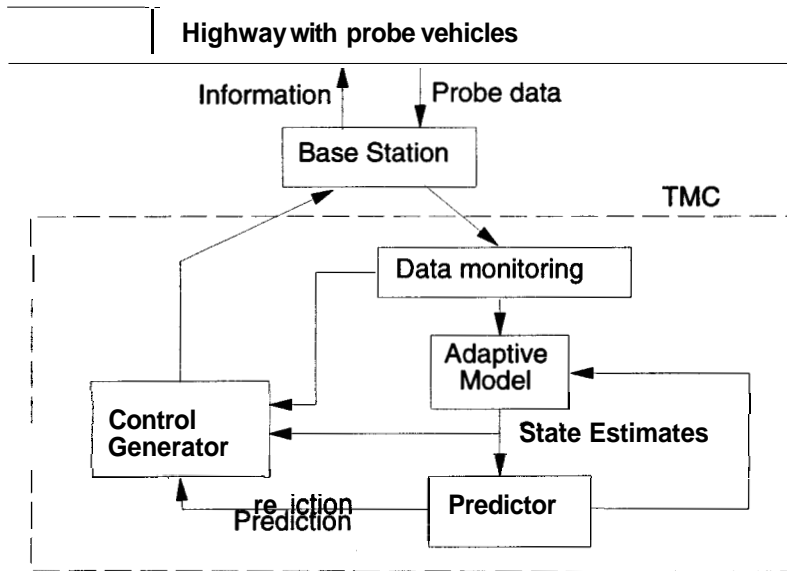
Figure 1: Probe based Estimation: System Model

percent probes	0.8	1.6	2.4	3.2	4.0	4.8	5.6	6.4	7.2	8.0
with $f_R = 1$	.972	.976	.977	.979	.980	.981	.982	.983	.984	.984
with $f_R = 0.5$	.967	.972	.974	.976	.978	.978	.980	.980	.981	.982
with $f_R = 0.25$	.963	.971	.971	.974	.977	.977	.978	.977	.979	.979
with $f_R = 0.125$	.951	.966	.964	.970	.972	.974	.974	.975	.977	.975

Table 2: Goodness of fit with fixed sensors
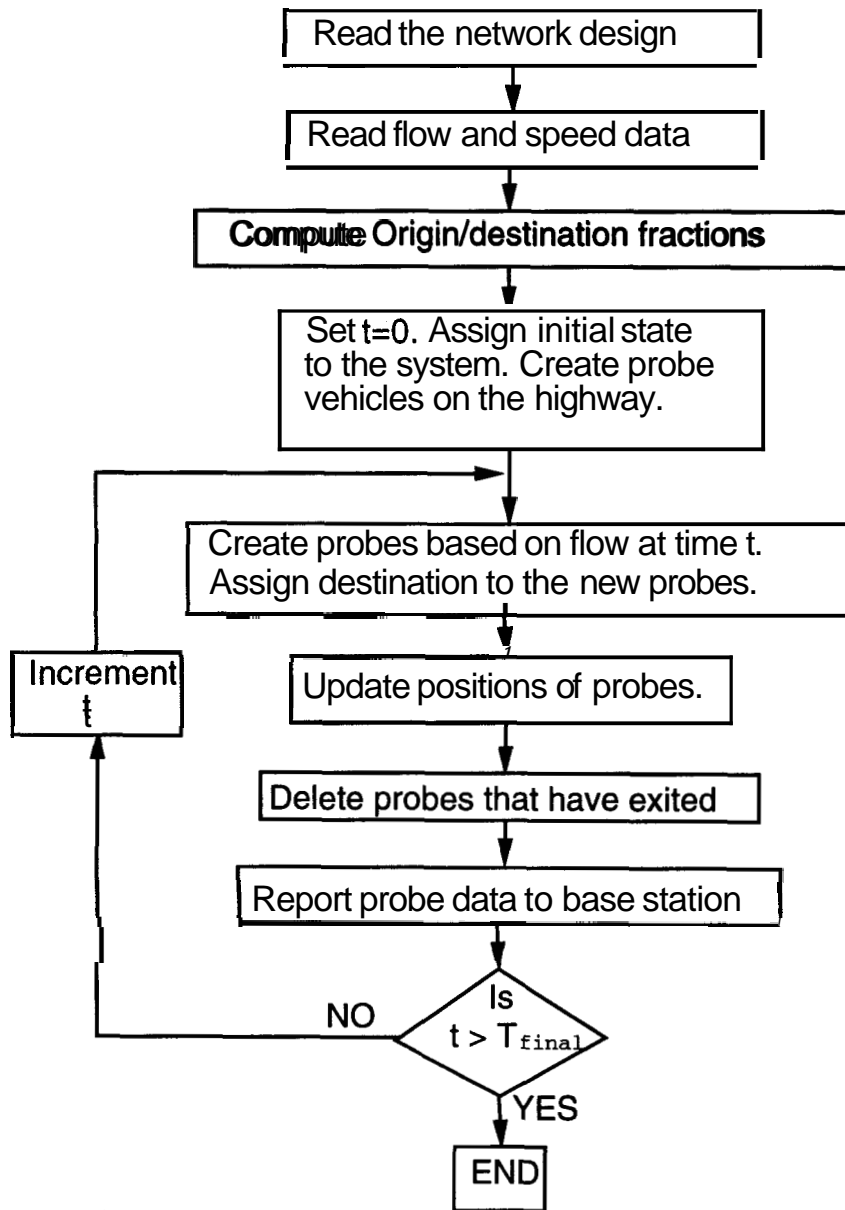
Figure 2: Probe Simulation
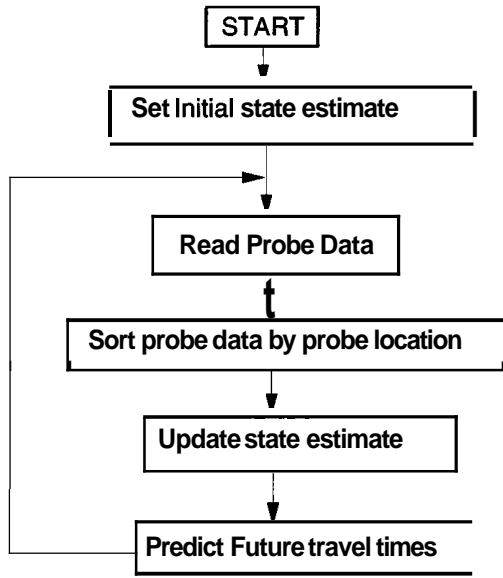
Figure **3:** Traffic Monitoring
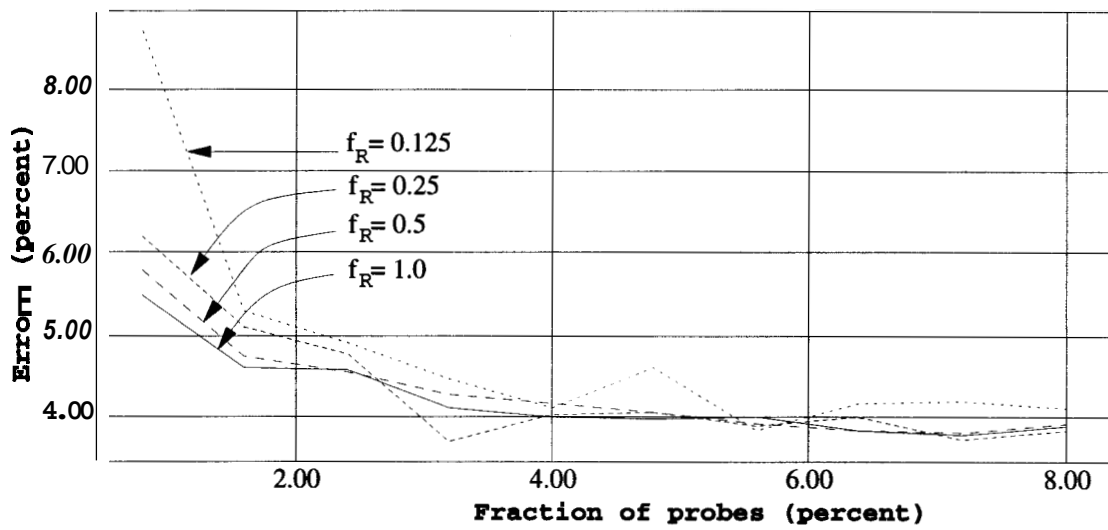
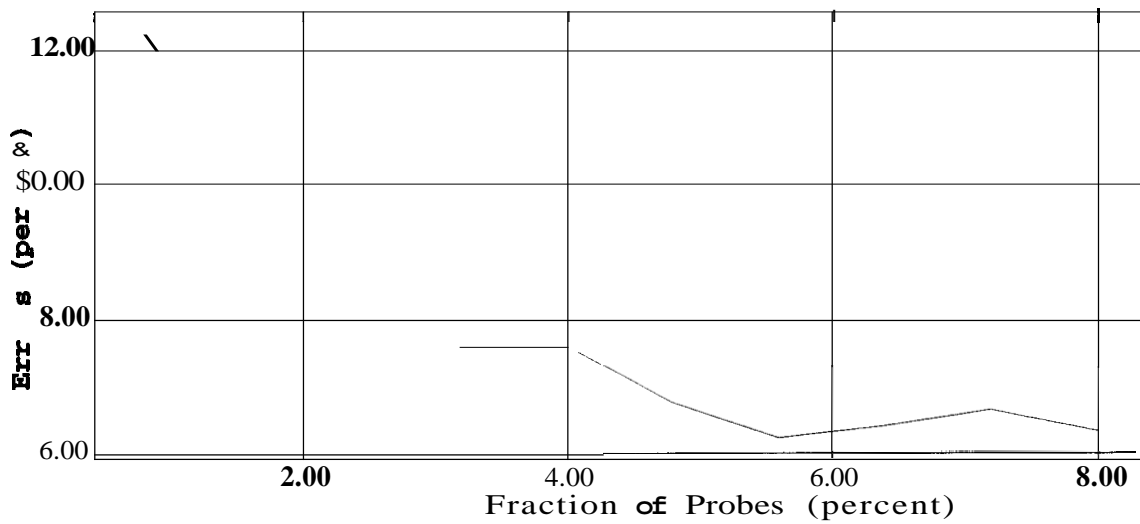Figure **4:** Speed based prediction
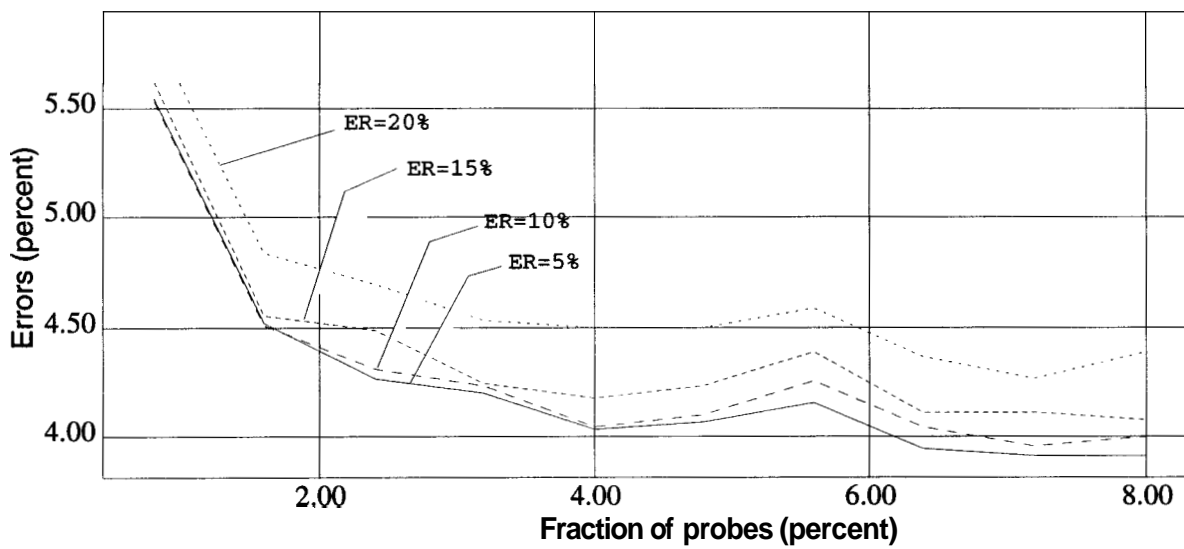
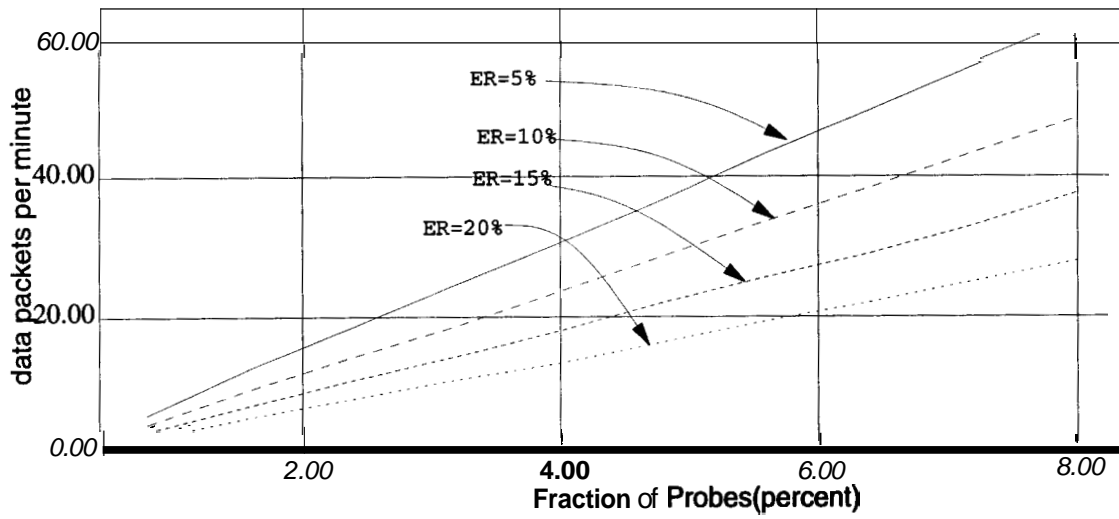Figure *5:* Travel time based prediction

Figure 6: Speed based prediction with Exception Ranges

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Figure 7: Variations in the Reporting Rate