

ESTIMATING LINK TRAVEL TIMES FROM DIFFERENT DATA SOURCES FOR USE IN ATMS AND ATIS

Bruce Hellinga and Rajesh Gudapati

ABSTRACT: Many of the benefits that Intelligent Transportation Systems are anticipated to provide are dependent on the accurate knowledge of link travel times. Unfortunately, in the near term, when the number of probe vehicles is expected to be small, agencies providing ATMS and ATIS services will likely need to estimate link travel times on the basis of traffic data obtained from a variety of data sources and surveillance methods, such as loop detectors, probe vehicles, driver reports, video camera monitoring, etc. This paper examines several models for estimating link travel times on the basis of individual data sources (i.e. detectors, probe vehicles, and driver reports) and proposes a framework for combining traffic data from various sources into a single link travel time data base

1 INTRODUCTION

In most large urban centres in North America, Ministries and Departments of Transportation operate several different traffic monitoring systems. Typical systems include dual-loop detectors installed on freeways, single-loop detectors at actuated and semi-actuated signals, video surveillance cameras, driver based reports (e.g. cellular phone calls), emergency personnel, automatic vehicle location systems on fleet vehicles such as public transit buses, and automatic vehicle identification tags such as those used for electronic tolling. Each of these systems provides a unique stream of traffic surveillance data that is incomplete in time (does not provide data continuously) and/or space (does not provide data for the entire network). It is anticipated that the development of travel time information for use in ATIS and ATMS could benefit in terms of accuracy and spatial and temporal coverage if data from different sources were combined in some systematic fashion. The challenge is how to conduct this data fusion in a statistically sound manner, while also meeting the constraints and limitations likely to be encountered with actual field implementation.

1.1 Background

Previous research has been conducted to examine the accuracy and reliability of various traffic data sources (for example, Hellinga, 1998; Hellinga and Van Aerde, 1994; Hellinga and Fu, 1999). These studies have generally examined the reliability of population measures (e.g. O-D demands, link travel times) estimated from samples from a single traffic data source (e.g. probe vehicles). While these studies provide insights into the reliability of the examined data sources, they have not addressed the problem of combining different data in an effort to make better population estimates.

A review of the literature indicates that only a limited number of studies have been conducted in which the issue of data fusion has been explicitly addressed. Two of

these studies (Tarko and Rouphail, 1993; Nelson and Palacharla, 1993) relate to work conducted as part of the ADVANCE project in Chicago. In this work, estimates of average link travel time are made on the basis of Bayesian updating. Data from probe vehicles and from detectors were combined with historical data to estimate the current average link travel time. Tarko and Rouphail propose a regression-based approach for estimating 15-minute average link travel times on the basis of measured detector occupancy. A limitation of their proposed approach is that a separate regression model must be calibrated for each arterial link in the network. Calibration can only be done for links for which actual link travel times can be obtained. Furthermore, the evaluation of the accuracy of their regression models was conducted only for undersaturated traffic conditions.

1.2 Research Approach

This paper describes a prototype data fusion system that can integrate information from loop detectors, probe vehicles, and driver-based linguistic reports (e.g. cellular phone reports) to provide a time-varying estimate of link travel times for the entire traffic network. A sub-model has been developed for each individual data source to transform the incoming data into an estimate of link travel time. These link travel time estimates are then combined to provide a composite estimate.

This paper describes the system and the development of each sub model. Evaluation results for each sub model are presented and examined. These preliminary results are used to make recommendations for changes to the sub models and the evaluation process.

2. PROPOSED DATA FUSION SYSTEM

The proposed data fusion system consists of four main elements, as illustrated in Figure 1. Each unique data source is used as input to a sub-model, which then makes an estimate of average link travel time on the basis of the input data. The output streams from each sub-model are used as input to the data fusion sub-model, which estimates a composite average link travel time for each link in the network. It is this composite travel time estimate that could be used to support traffic management decisions and/or as the basis for traveller information reports.

The following sections describe each of the sub-models.

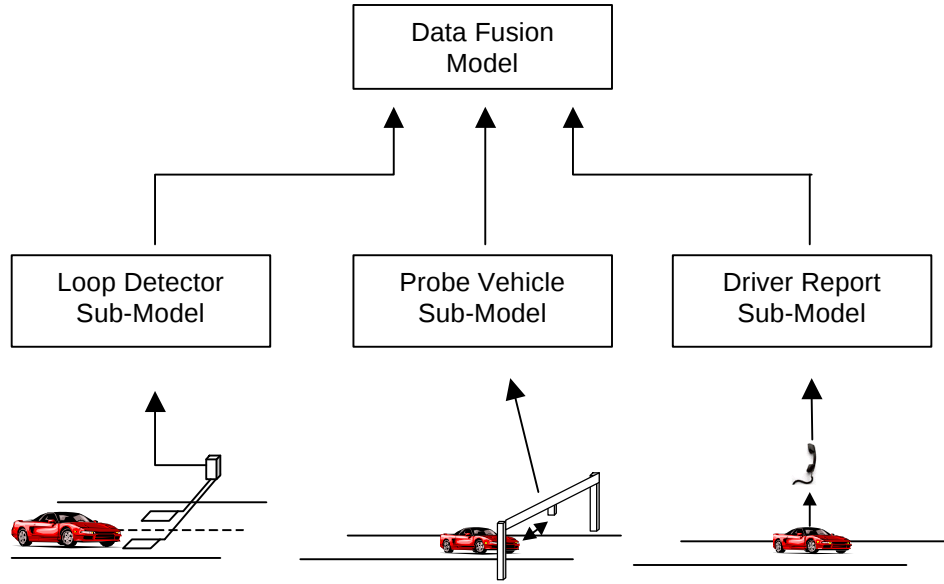


Figure 1: Data fusion framework

2.1 Loop Detector Sub-Model

The loop detector sub-model makes an estimate of the link travel time on the basis of point measurements of speed, volume, and occupancy. Separate models have been developed for arterial links (arterial sub-model) and for freeway links (freeway sub-model).

Freeway Loop Detector Sub-Model

Loop detectors provide measurements of volume and occupancy, and in the case of dual-loop detectors, speed. For freeway traffic monitoring, loop detectors are typically installed with a spacing of approximately 600m. The availability of detector stations at regular intervals permits the roadway to be segmented, with the boundary of each segment being located midway between adjacent loop detector stations. Thus, if a freeway has detector stations spaced every 600m, roadway segments would also be 600m in length, with the segment boundaries located 300m to either side of each detector.

The proposed freeway detector sub-model estimates roadway segment travel time on the basis of measured point speed and the length of each roadway segment (Equation 1).

$$t_t = \sum_{i=1}^n \frac{L_i}{S_i} \quad (1)$$

Where:

- t_t = estimated travel time on freeway link (sec)
- L_i = length of roadway segment associated with detector i (km)
- S_i = speed measured at detector i (km/h)
- n = number of detectors on freeway link

The validity of this model was tested using data generated by the INTEGRATION traffic simulation model (Van Aerde, 1999). A simple freeway section (Figure 2) with an on ramp was simulated for 21 different traffic demand levels ($D_{\text{mainline}} = 200, 4000, 5000$; and $D_{\text{on ramp}} = 0, 250, 500, 750, 1000, 1250, \text{ and } 1500 \text{ vph}$). A capacity of 2000 vphpl was assumed. Each demand level was simulated for 5000 seconds. When the combined on-ramp and mainline traffic demand exceeded the capacity of the freeway downstream of the on ramp, a queue formed upstream of the merge area. The time required to traverse each of the three links was recorded for each vehicle. These travel times were aggregated for three separate durations, namely 100s, 300s, and 900s. Figure 3 illustrates the correlation between the travel times estimated using Equation 1, and those observed from the simulation model for an aggregation period duration of 100 seconds. The comparison is shown for three different freeway sections, namely link 1 (using data from two detectors), link 3, and the overall 2.4 km freeway section. A correlation of 0.97, 0.79, and 0.97 was achieved for link 1, link 3 and the entire freeway section respectively. These results are encouraging as they indicate that it is possible to accurately estimate the average travel time of vehicles traversing a freeway section on the basis of spot speeds measured by loop detectors.

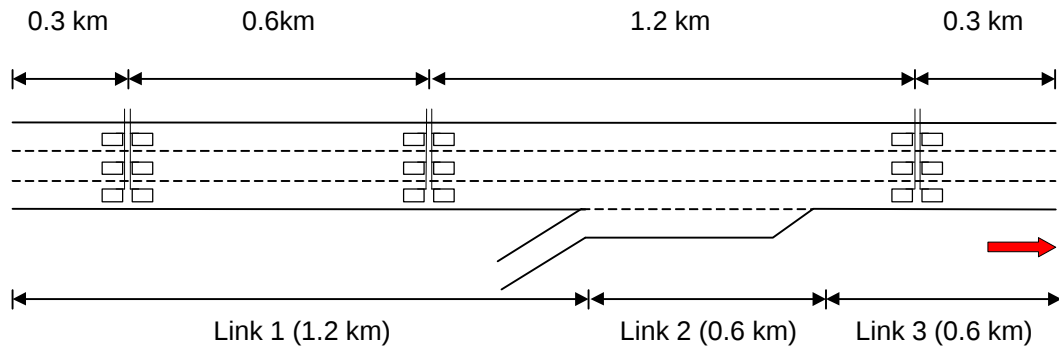


Figure 2: Freeway simulation network

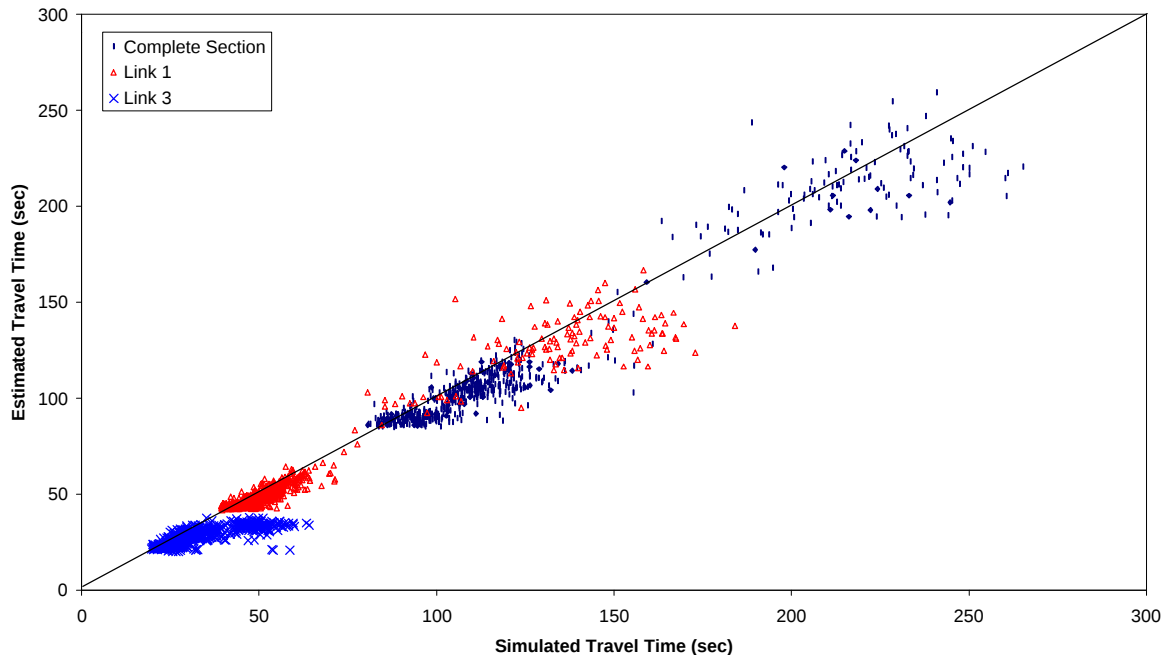


Figure 3: Estimated versus observed travel times for a freeway application (aggregation period =100 seconds)

Arterial Loop Detector Sub-Model

Unlike a freeway link, a link that is controlled by a traffic signal is subject to periodic changes in capacity as the traffic signal cycles through the red and green intervals. These changes in capacity result in the formation and subsequent dissipation of queues. The information provided by a loop detector located on a signal approach link is dependent on the detector's location relative to the stop line and the behaviour of the queue. If the queue does not spill back over the detector, then the measured volume represents the traffic demand and the measured speed represents the speed at which vehicles travel when not in queue. However, if the queue spills back over the detector, then the measured volume reflects capacity of the signal rather than demand and the measured speed represents the speed of travel for vehicles in the queue. Therefore, whatever detector measurement is used (i.e. speed, volume, or occupancy), the interpretation of the data is dependent on the detector location relative to the intersection stop line.

A number of other researchers have also examined the problem of estimating arterial link travel time from detector data. In one of the earliest research efforts, Gipps (1977) used detector occupancy and arrival time at the detector to develop regression estimates of link travel time based on simulated data. Gault (Gault and Taylor, 1981; Gault, 1981) improved Gipps' initial model and observed a linear relationship between travel time and detector occupancy up to occupancies of approximately 70 percent. She chose to ignore higher occupancies and formulated a model which reflected the effects of occupancy levels, cruise time, degree of saturation, and signal settings on link travel time.

We adopted a similar approach in our work in that we used a calibrated regression model to estimate link travel time on the basis of detector location and measured detector occupancy. It is likely that under field conditions, signal control parameters would not be known and therefore we did not include these as independent variables within our regression model, even though these would likely have significant explanatory power. Data for calibration was generated using the INTEGRATION traffic simulation model. A signalised approach roadway was simulated for a variety of traffic demands ($D = 200, 500, 700, 950, 1050, 1100$). Demands entered the roadway with exponentially distributed headways. The network consisted of a single lane roadway controlled by a 2-phase traffic signal with a cycle length of 100 seconds and a g/c ratio of 0.6. The link was assumed to have a saturation flow rate of 1800 vph and a free speed of 60 km/h. A loop detector was modelled at 4 different locations ($x = 5, 30, 100, 250$ m from the stop line). Three different data aggregation intervals were considered ($d = 100, 300, 900$ seconds).

Figure 5 depicts delay (t_d) as a function of detector occupancy and detector position for a 300-second aggregation period. These data illustrate the highly non-linear relationship between link delay, detector occupancy, and detector position.

For each level of aggregation, a regression model of the form provided in Equation 2 was calibrated to the simulation data. The best model was found to be the one obtained for the 900-second level of aggregation with an adjusted R^2 of 0.84. We chose to estimate link delay (t_d) rather than link travel time because delay is primarily a function of signal control impact and is independent of link length. Therefore, we can use the same calibration regression equation for all signalised arterials, regardless of the length of the link. The estimated link travel time can be computed using Equation 3.

$$t_d = e^{a_1 + a_5 K^2} K^{a_2 + a_4 x + a_6 x^2} x^{a_3} \quad (2)$$

Where:

t_d = link delay time (sec) defined as the different between travel time on link and the free speed travel time on link

K = detector occupancy (%)

x = detector location measured from the stop line (m)

a_i = regression coefficient

$$t_t = t_f + t_d \quad (3)$$

Where:

t_t = estimated link travel (sec)

t_f = free speed link travel time (sec)

The correlation between the link delay (t_d) estimates provided by Equation 2 and those produced by the simulation model is illustrated in Figure 6. These results are also encouraging as they also seem to indicate that a reasonable degree of accuracy in estimating signal induced delay can be achieved on the basis of detector occupancy,

and detector location. However, two significant limitations must be noted. First, the test scenarios on which this relation was developed did not consider variation in cycle length or variation in g/c ratio. The relationship between delay and detector occupancy and location should be evaluated for a range of cycle lengths and g/c ratio to determine whether this degree of correlation can be achieved over a range of signal timing parameter values.

Second, the regression model structure, as presented in Equation 2 is difficult to justify in any other way than on the basis that it resulted in a regression model that explained the largest proportion of the variance of all the models examined. There is no physical justification for this model structure. The structure identified in Equation 2 may have resulted more directly from the characteristics of the scenario parameters combinations examined, than any causal relationship between detector location, detector occupancy, and vehicle delay.

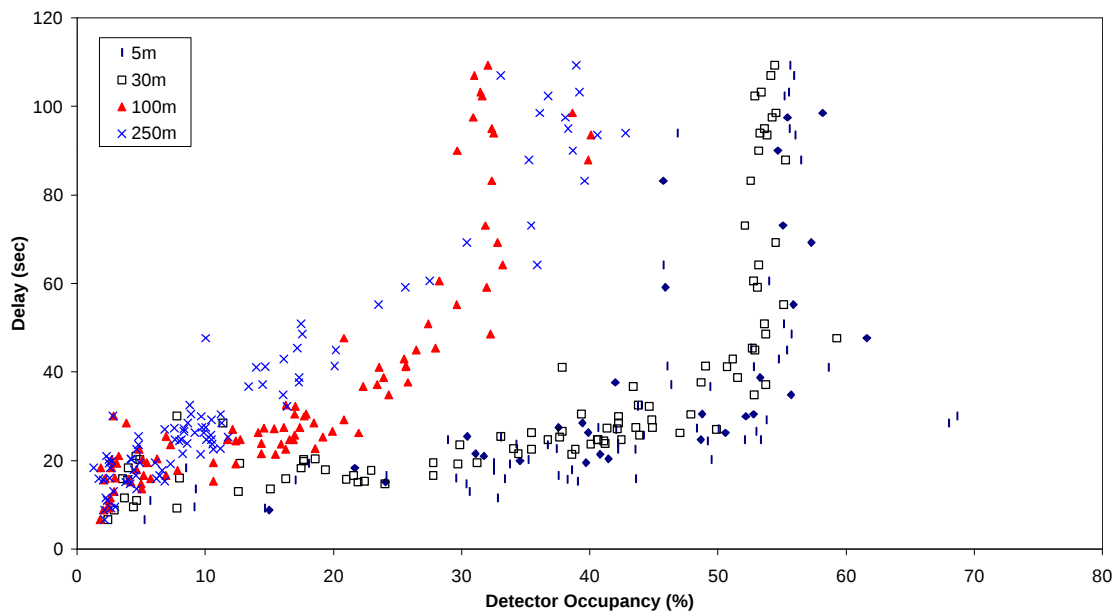


Figure 5: Arterial delay as a function of detector occupancy and location (300-second aggregation)

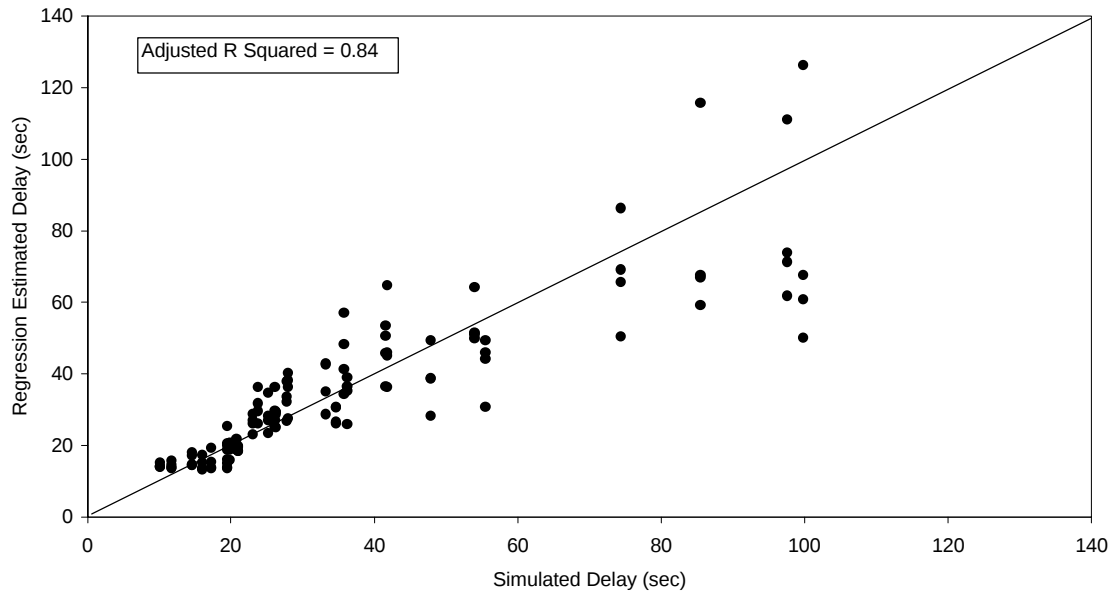


Figure 6: Estimated versus observed arterial link travel times (900-second aggregation)

2.2 Probe Vehicle Sub-Model

Probe vehicles are vehicles that can be uniquely identified by roadside equipment, such that vehicle identification at two different locations along a roadway enables the travel time of that particular vehicle to be measured. Generally, vehicle identification is made through the use of short-range communication hardware such as the toll tag technology used for electronic tolling on Highway 407 in Toronto. Other means of uniquely identifying vehicles are also possible, including automatic license plate recognition systems. For the purposes of this research, probe vehicle are those vehicle for which link travel time data can be obtained. Furthermore, it is assumed that this link travel time information is obtained only when the vehicle exits a link.

A significant amount of research has been conducted to evaluate the accuracy of population estimates made on the basis of a sample of observation as obtained from probe vehicle reports. The literature describes efforts to quantify the level of market penetration required to achieve desired level of reliability in population origin-destination traffic demands and link travel times (Hellinga and Van Aerde, 1994; Van Aerde et al., 1993; Hellinga and Fu, 1999). Some of this research (Hellinga and Fu, 1999) has demonstrated that under certain conditions, probe travel times provide a biased estimate of the population travel times. More recently Hellinga and Fu (2000) have proposed a method of determining when this bias is present and of reducing the magnitude of this bias.

The probe report sub-model in this research makes use of these previously developed techniques.

2.3 Driver Report Sub-Model

Driver reports are linguistic reports that are provided by a driver and are initiated by the driver. Note that in this research we do not distinguish between a report provided by a driver and one provided by a passenger in the vehicle. We refer to all linguistic reports made by an occupant of a vehicle as a driver report. Using driver-based reports to obtain traffic network information is quite different from using loop detectors or probe vehicles. Driver reports are unique in two specific ways, namely the driver initiates driver reports, and driver reports are linguistic. These two characteristics are discussed in more detail below.

Initiation of Driver Reports

Driver reports are initiated by the driver, and therefore data can only be obtained when drivers decide to provide them. Furthermore, only drivers with some means of wireless communication (e.g. cellular phone) are able to provide a report. Thus, the availability of driver reports depends on many factors, including the number of vehicles passing a given location, the proportion of drivers with wireless communication access, and the likelihood that a driver with wireless communication access will initiate a report. Very little research has been conducted to determine the probability that a driver, with access to wireless communication, will initiate a report. It is likely that this probability is not constant, but is also a function of the traffic conditions that the driver is experiencing, and their knowledge of whether or not the authorities (or current traffic information providers such as radio stations) are already aware of unexpected traffic conditions. In this current research, we do not attempt to directly address this question, rather we attempt to quantify the value of driver reports under several assumptions about driver reporting behaviour.

We have assumed that the probability that drivers with cell phones will make a report is dependent on the degree of congestion they are currently experiencing (Equation 4). The probability that a driver has access to wireless communication is assumed to be constant.

$$P(\text{report}) = 1 - e^{a(R-1-b)^g} \quad (4)$$

Where:

$P(\text{report})$ = Probability, that a driver with a cell phone make a report

a, b, g = Calibration parameters

R = Ratio of current link travel time to free speed link travel time

Each time a vehicle exits a link, a check is made to determine if it is equipped with wireless communication equipment. If it is, then Equation 4 is used to determine the likelihood that the driver will initiate a report. The form of Equation 4 enables a wide range of probability distributions to be created depending on the choice of values for parameters a , b , and g . Figure 7 illustrates four example distributions. We make no attempt at this point to recommend values for a , b , and g since we do not have any field data on which to base such a recommendation. For purposes of demonstrating the data fusion process, we examine a limited range of parameter values.

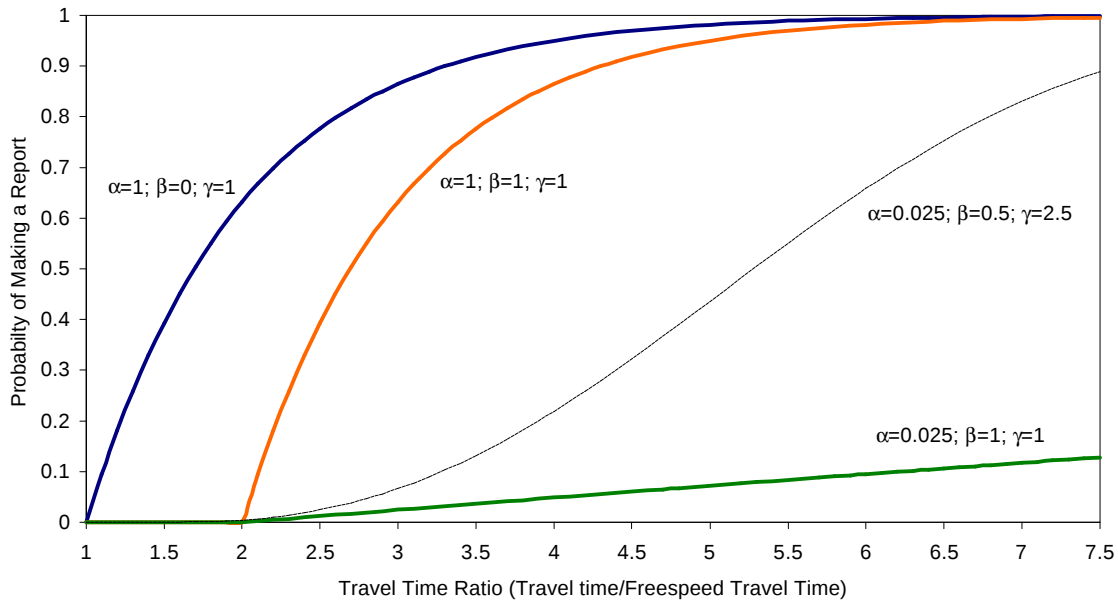


Figure 7: Family of probability functions for drivers with wireless communication abilities making a report

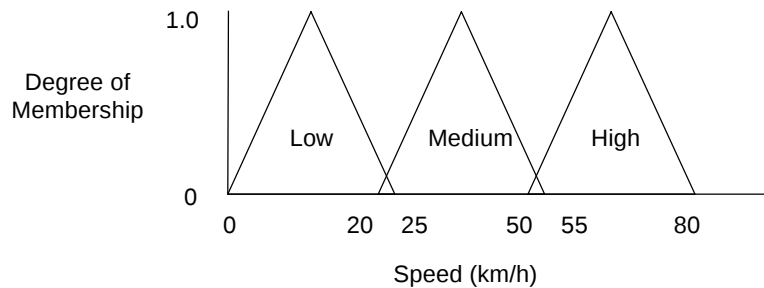


Figure 8: Membership function definition for speed on arterial roadways

Modelling Imprecision in Driver Reports

Driver reports are linguistic and often qualitative, rather than numerical and quantitative. For example, a driver may report that the road on which she is travelling is severely congested. While this description contains useful information pertaining to the state of the traffic network at the specified location and time, there is some uncertainty associated with the precise meaning of the term "severely congestion". Does this mean a speed of 10 km/h or a speed of 30 km/h? Driver reports require that the linguistic report be interpreted and translated into some quantitative descriptor.

The Driver Report sub-model is built on the assumption that driver linguistic reports are inherently imprecise in their description of traffic condition. Following this assumption, we formulated a fuzzy logic rule-based model for estimating delay as a function of driver reports. We assume that in addition to providing location, drivers are able to provide an estimate of one or more of the following; speed on the link (km/h), length of

a queue (km), severity of an incident (in terms of the number of effective lanes blocked), time remaining before an incident is cleared, and current traffic demand. Drivers only report those traffic conditions that are relevant to their particular situation. For example, if a driver is in a queue and has initiated a call, she could report her average speed and some estimate of the queue length, but would not report on the severity of an incident or the expected time remaining for an incident to clear unless an incident was currently active on her current link.

Fuzzy membership functions were defined for each of the five driver report information items (i.e. volume, speed, queue length, incident severity, incident time remaining). Triangular membership functions were used for all categories. Figure 8 illustrates the membership functions defined for speed for arterial roadways.

The fuzzy logic system developed for this research is based on the Mamdani inference system, in which a set of if-then rules is defined. Each rule is evaluated using the inputs provided by the driver. The results of each rule are aggregated and an estimate of delay is obtained by computing the centroid of the aggregated membership shape. Figure 9 illustrates this process when only two rules are applied.

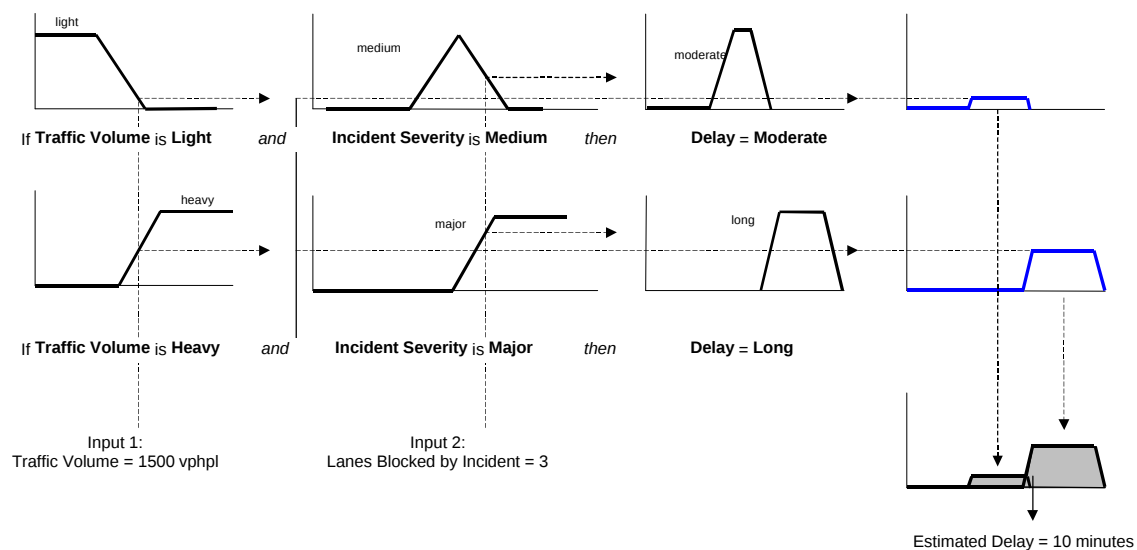


Figure 9: Illustration of Mamdani's fuzzy logic inference system

3. EVALUATION OF SUB-MODELS

3.1 Evaluation Network

An arterial corridor with three signalised intersections and one stop controlled intersection was simulated using INTEGRATION. Loop detectors were placed at random locations on all links. A level of market penetration of 10% was assumed for probe vehicles. It was assumed that 70% of drivers had cell phones and these drivers could make reports when necessary. The network was simulated for 25 minutes. Average link delay (i.e. travel time – free speed travel time) was estimated from each

data source (i.e. detectors, probes, and driver reports) for 5-minute periods. Thirteen links were randomly selected from the network for analysis.

3.2 Results

Figure 10 indicates the root-mean-squared error (RMSE) associated with each of the link delay estimation sub-models. In each case, the RMSE is computed across the thirteen links and the five 5-minute estimation periods. As a reference, it can be noted that the true average delay computed for all links is 73 seconds. From these results, it is apparent that the delay estimates provided by the probe vehicles are the most accurate, but that even these estimates have a RMSE of 19 seconds or 26% of the mean link delay. Figure 11 illustrates the correlation between the individual link delay estimates and the actual link delay. It is evident from this figure that under some conditions, the driver report sub-model estimates a very large delay, when the true delay is quite small and under other conditions, estimates a very small delay when the true delay is very large. These results seem to indicate that the current fuzzy logic sub-model is inadequate for use in estimating link delays.

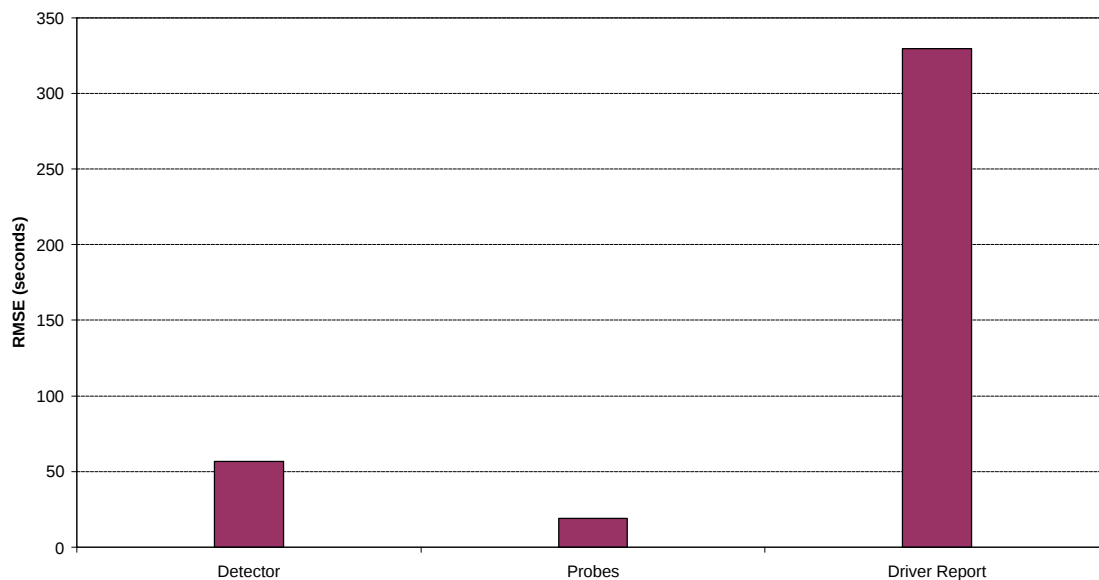


Figure 10: Delay estimation error by data source

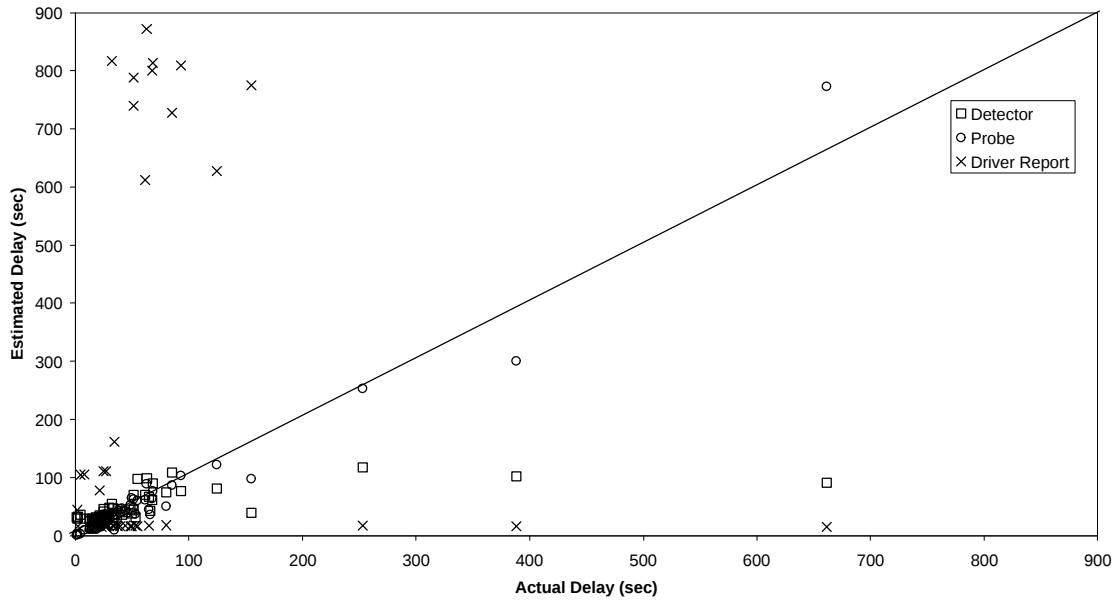


Figure 11: Estimated versus actual average arterial link delay

4. CONCLUSIONS AND RECOMMENDATIONS

ATMS and ATIS require the availability of accurate and reliable network traffic data. In most urban centres, multiple sources of traffic data exist, offering different spatial and temporal coverage.

It is expected that the simultaneous consideration of all available data sources would provide a more accurate description of network traffic conditions than the reliance on only a single data source.

One means of combining disparate data sources is to estimate a common traffic condition metric from each individual data source and then to compute a composite metric on the basis of some systematic combination of the individual data source metrics.

Preliminary tests indicate that non-linear regression appears to be an adequate method of estimating arterial link delay on the basis of detector data. However, these evaluations have been carried out for a limited range of signal control conditions. Utilising speed data from detectors on freeways enables travel times to be estimated for short roadway segments (i.e. in the range of 600m).

A fuzzy logic model was proposed for estimating of link delay from linguistic driver reports. Preliminary results from testing this rule-based model on simulated arterial link data indicate that the model can lead to highly inaccurate estimates of link delay. It is recommended that further testing of the fuzzy model be undertaken to determine the cause for these large estimation errors. It may be necessary to modify or add rules or to modify the current fuzzy membership functions.

It is also recommended that testing of the proposed sub-models be carried out over a much wider range of traffic and signal control conditions.

5. ACKNOWLEDEMENTS

The authors gratefully acknowledge the financial support provided by the Natural Science and Engineering Research Council of Canada.

6. AUTHORS

Bruce Hellinga PEng, PhD, Associate Member of ITE

Assistant Professor, Department of Civil Engineering, University of Waterloo
200 University Ave. West, Waterloo ON N2L 2G1.

Phone: (519) 885-1211; Fax: (519) 888-6197; Email: bhellinga@uwaterloo.ca

Rajesh Gudapati

MASc Candidate, Department of Civil Engineering, University of Waterloo.

7. REFERENCES

Gault, H.E and I.G. Taylor (1981) *The use of the output from vehicle detectors to assess delay in computer - controlled area traffic control systems*, Transport Operations Research Group, Research Report no 31, University of Newcastle upon Tyne, U.K

Gault, H.E. (1981) *An on-line measure of delay in road traffic computer controlled systems*, Traffic Engineering and control, 22(7) 384-389, London

Gipps, P.G. (1977) *The estimation of a measure of vehicle delay from detector output*, Transport Operations Research Group, Research Report no.25, University of Newcastle upon Tyne, U.K

Hellinga, B. (1998) *Incident Detection via Commuter Cellular Phone Calls*. Presented at the 1998 Institute of Transportation Engineers 68th Annual Meeting held August 9-12, 1998 in Toronto, Ontario.

Hellinga, B. and M. Van Aerde (1994) *A statistical analysis of the reliability of using vehicle probes as estimators of dynamic O-D departure rates*. IVHS Journal Vol.2 (1), pp 21-44

Hellinga, B. and L. Fu (2000) *Reducing Bias in Probe-Based Arterial Link Travel Time Estimates for ITS Applications* Submitted to Transportation Research - Part C.

Hellinga, B. and L. Fu (1999) *Assessing the Expected accuracy of probe vehicle travel time reports*. Journal of Transportation Engineering, published by the American Society of Civil Engineers, Vol. 125, No. 6., pp 524-530, 1999.

Nelson, P. and P. Palacharla (1993) *A neural network model for data fusion in ADANCE*, Proceedings of Pacific Rim Conference, Seattle, 1993, pp. 237-243

Tarko, A. and N.M. Roupail (1993) *Travel time data fusion in ADVANCE*, the third ASCE international conference on applications of Advanced technologies in Transportation engineering, Washington D.C. July 1993, pp. 36-42

Van Aerde, M. B. Hellinga, L. Yu, and H. Rakha (1993) *Vehicle Probes as Real-Time ATMS Sources of Dynamic O-D and Travel Time Data*. Large Urban Systems - Proceedings of the ATMS Conference held in St. Petersburg, Florida. pp. 207- 230

Van Aerde, M., "INTEGRATION User's Guide Vol. II," May 1999