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BAYESIAN APPROACH TO INTEGRATION OF TECHNOLOGY AND METHODOLOGY FOR TRAVELLER INFORMATION SYSTEM

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ABSTRACT

Over the years, researchers have defined the travel time and other advantages of traveller information systems. Since these systems based on past and present technology were found to be worthwhile, the next generation traveller information systems can potentially offer enhanced benefits provided that methodological innovations can be integrated with the rapidly developing technology. For example, in the case of predictive travel time, the technologies of data capture and delivery are projected to further evolve in the short-to-medium term. These will require processing and fusing data for developing special purpose models. This paper reports research in the Bayesian approach to integration of technology and methods in predictive travel time modelling. In addition to projecting technological advances, methodological requirements and architecture of the new generation traveller information system are defined and applications are illustrated.

Keywords: Advanced traveller information system; new generation traveller information system; data fusion; Bayesian; predictive space mean speed; predictive travel time.

NEXT GENERATION TRAVELLER INFORMATION SYSTEM

The need for traveller information correlates with unpredictable travel environment. Even commuters who are very familiar with their usual travel route as well as alternative routes in terms of re-current traffic congestion cannot be sure about prevailing traffic flow conditions that reflect a multitude of influences. Some of these are incidents, road works, and road weather conditions. It is logical that road users frequently seek information on traffic conditions (i.e., travel time and delay) prior to and during their travel to work or other destinations.

The technology for capturing traffic flow condition, compiling corridor and route level travel flow information and delivering the information to road users and other stake holders has been improving over many decades. However, in recent years, owing to advances in intelligent transportation systems (ITS), such information became readily available. In the past decade, research aimed at the development of advanced traveller information system (ATIS) has advanced the state of knowledge and has also been instrumental in the implementation of basic forms of traveller information systems. Figure 1 illustrates a basic form of an ATIS system that can be found in most jurisdictions of technologically advanced countries.

The present state of technology development enables ITS-based installations to provide real-time data on traffic conditions and this information can be conveyed to road users through variable message signs (VMS) and in-vehicle devices of equipped vehicles. Although much progress has been made in ATIS technology, transportation experts as well as the driving public have been aware for about a decade that the information sourced primarily from technology by itself becomes obsolete quickly. Therefore it has been suggested by researchers that to be of use to travellers, such information should be used as a steppingstone to providing predictive travel time that the road users require (Khan et al 2004, PBS&J 2004, Al-Deek 2003).

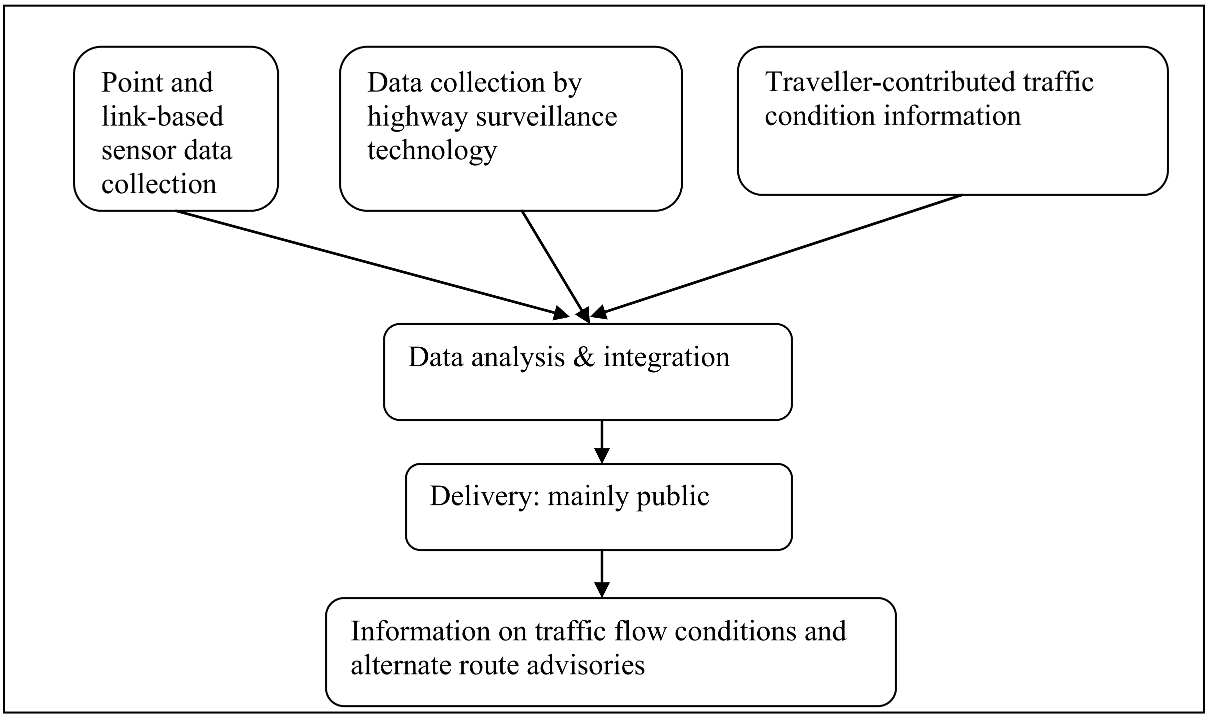


Figure 1- Basic form of a traveller information system

The need for predictive travel time is obvious. So, it is not surprising that it continues to be of research interest in ITS circles. For example, a special interest group of the ITS America in association with the Canadian arm of the ATLANTIC project and Carleton University held a workshop on this subject as early as July 2003 at Carleton University campus. This workshop contributed ideas to the development of the Orange Book on Predictive Travel Time, which described the then current state of knowledge and highlighted the need for research and development in this subject (PBS&J 2004).

A number of other research papers/reports have also stressed the importance of advancing the state of knowledge in this subject. For example see Nikovski et al (2005) and Mahmassani (2006). On the commercial business side of predictive travel time, estimates of point-to-point driving time became available from some notable sources (Traffic Cast International 2003, Lexdon Business Library 2006, INRIX 2012). However, details of their methodological basis are not reported.

Looking ahead, we are about to enter the era of inexpensive telematics, in-vehicle ITS units, connected vehicles, and vehicular ad hoc networks (VANETS). Likewise, our knowledge on data fusion and predictive methodologies has improved considerably (Khan 2010a). Another area of knowledge enhancement is dynamic assignment and route guidance. These advances enable the development of a new generation of a traveller information system. As a contribution to knowledge, this paper reports research in the Bayesian approach to integration of technology and methods in predictive travel time modelling.

NEXT GENERATION TRAVELLER INFORMATION SYSTEM ARCHITECTURE

Logically, the new generation advanced traveller information system (ATIS) should aim to provide all items of information required by travellers before commencing intra-city or intercity travel as well as while the journey is in progress. Among these, space mean speed, travel time, and travel condition in applicable alternate routes are of much importance.

Another consideration in building and operating an ATIS is that factors broader than technology and methodology have to be studied (e.g., business model). Although these are important considerations, due to space limitation, this paper focuses on the following key components: (1) real time data collection networks, (2) data processing and adding value to real time data by enhancing the reliability of processed/fused data and to make predictions (e.g. of travel time) prior to dissemination of information, and (3) distribution of information to travellers and other users.

On the technical side, the major components of a new generation ATIS and the high level architecture can be conceptualized as shown in Figure 2. Figure 3 presents details of data collection and delivery means are shown in Figure 4.

The traveller information system context is defined as freeway and major arterial corridors. That is, in this paper, no attempt is made to define and serve urban networks with high density of route alternatives. As for concept level illustration of the new generation ATIS, two examples are presented. The first example is a freeway corridor in Toronto (Canada) and the second example features a major highway with a major arterial alternate route in Ottawa (Canada).

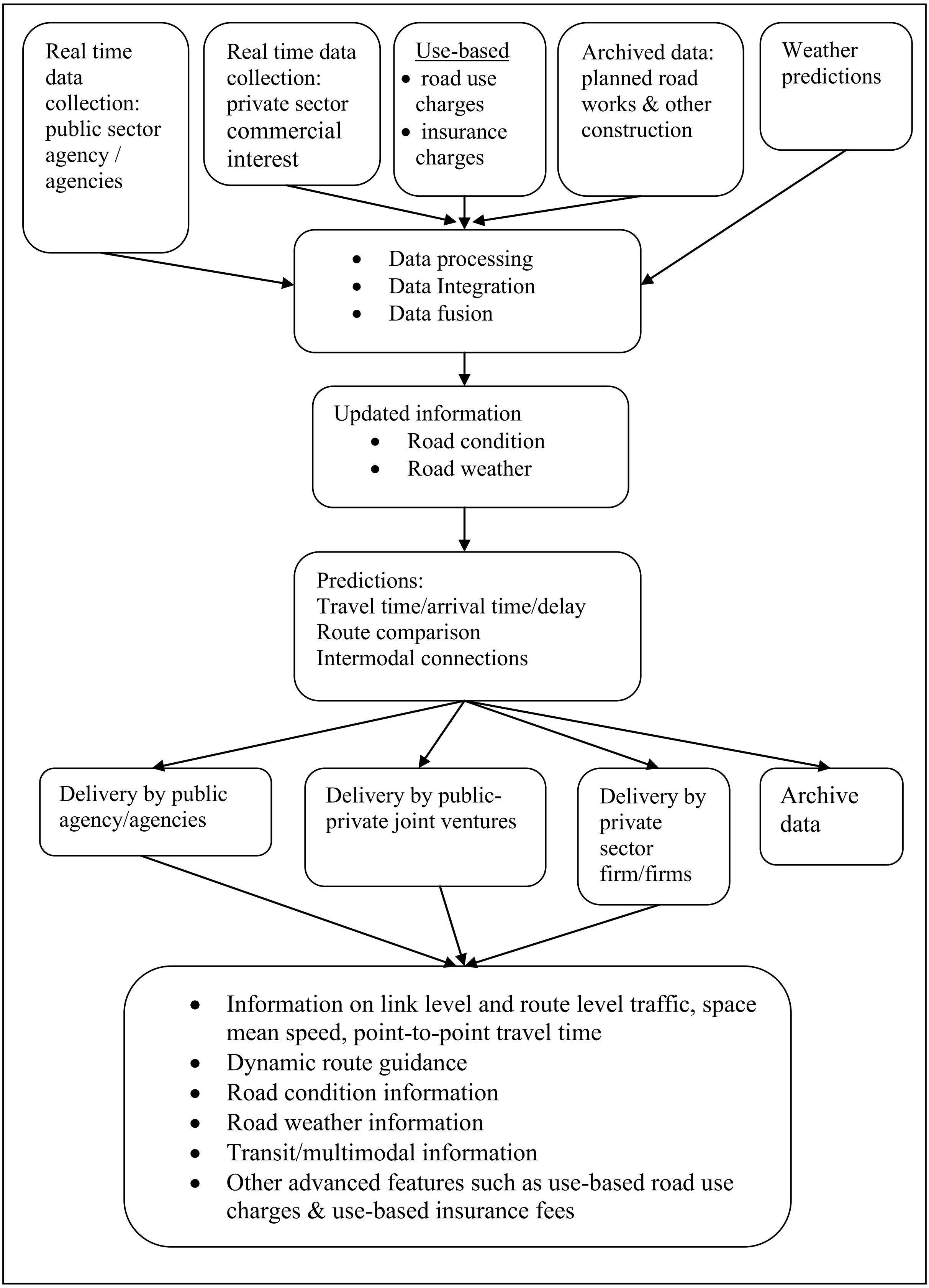
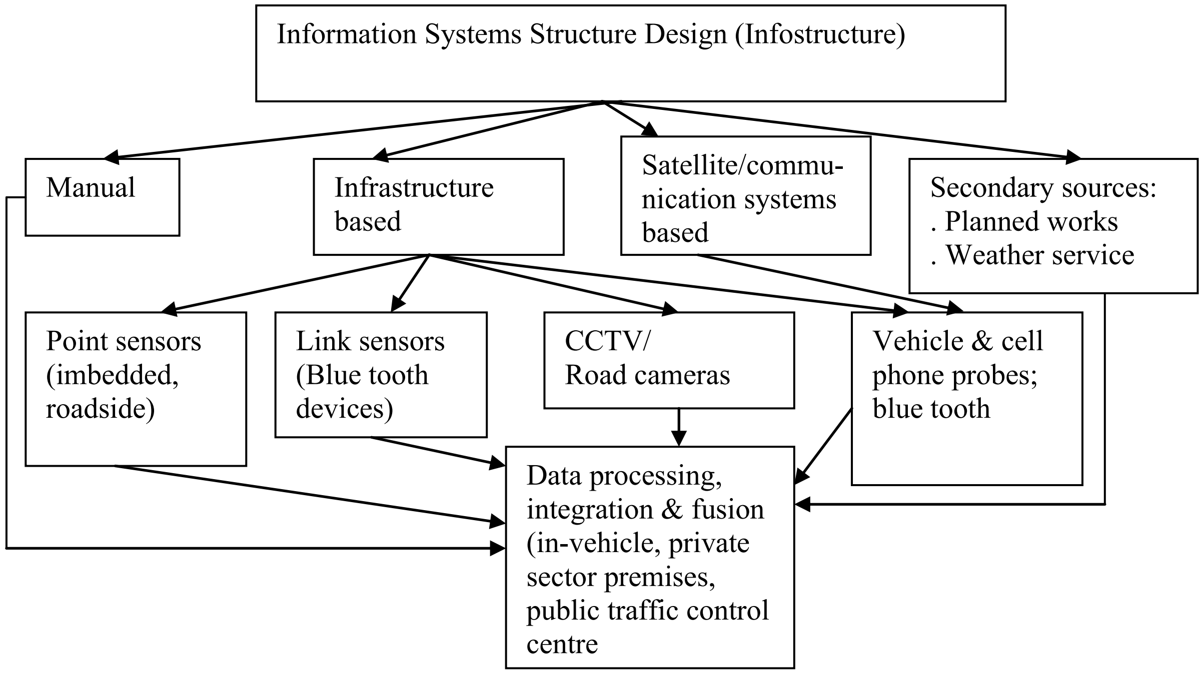
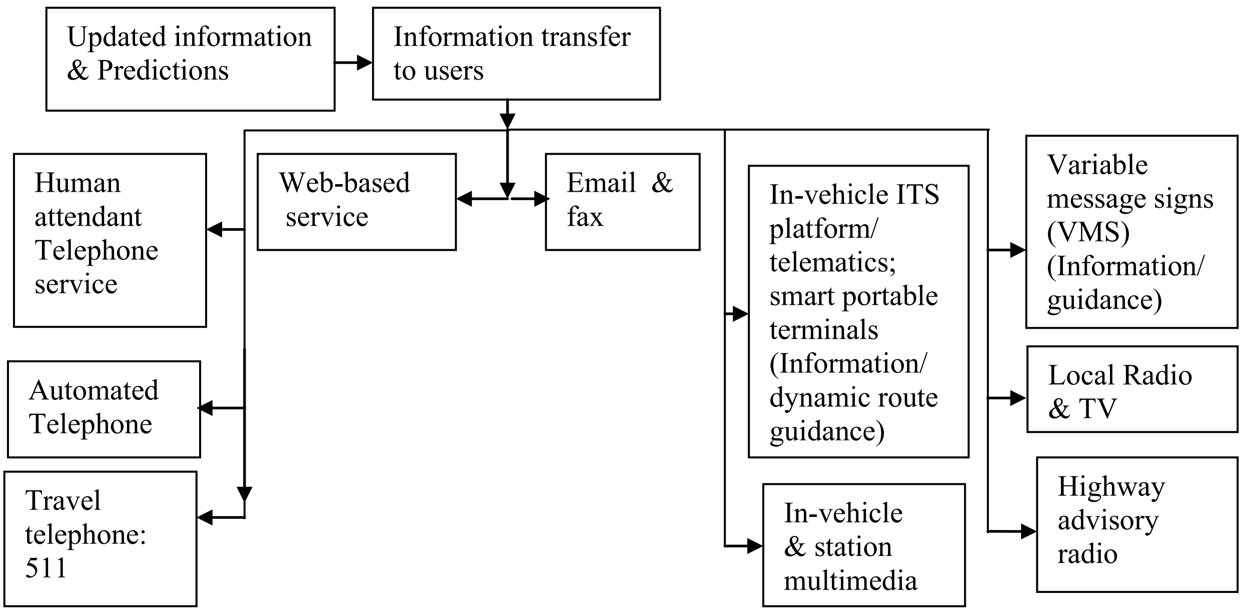


Figure 2 - Components of new generation ATIS and high level architecture



Note: data communication means are cables, telephone line, fibre optics, cellular systems, 4G communication system, common phone, radio

Figure 3 - Data collection



Note: Note: data communication means are cables, telephone line, fibre optics, cellular systems, 4G communication system, common phone, radio

Figure 4 - Delivery methods

PREDICTIVE SPACE MEAN SPEED AND TRAVEL TIME METHODOLOGY

Requirements

Archived travel speed and time data are useful for obtaining a general indication of traffic conditions on a route. Next in importance is real time data captured by ITS technology. But, even this type of data becomes obsolete quickly since it cannot provide an indication of what will be the prevailing traffic condition in the following minutes as the journey progresses. Therefore, the need for predictive space mean speed and travel time becomes obvious since these give an indication of travel condition ahead of time or upstream of a destination of interest.

Predictive travel speed and time can be estimated from the knowledge of the performance of the route/network, as obtainable from a model in association with real time information obtained from sensors/detectors and other devices used for traffic management. Such methods overcome the deficiency of out-dated real time information which may not be very reliable from the perspective of going beyond that point in time. Therefore, if possible, predictions from a model (e.g., a neural network model trained and validated with performance data) in association with real time data should be used for finding expected travel time. Further, there is a need to fuse the real time data with the model outputs in order to obtain expected travel time.

Methodological framework

The concept design of the predictive travel speed and travel time system encompasses modules for the acquisition of real-time information, prediction of travel time by the route/network performance model, fusion of real time information with model-produced information, and dissemination of result to road users (Figure 5). This concept design is based on the technical aspects of new generation ATIS shown in Figures 2 to 4.

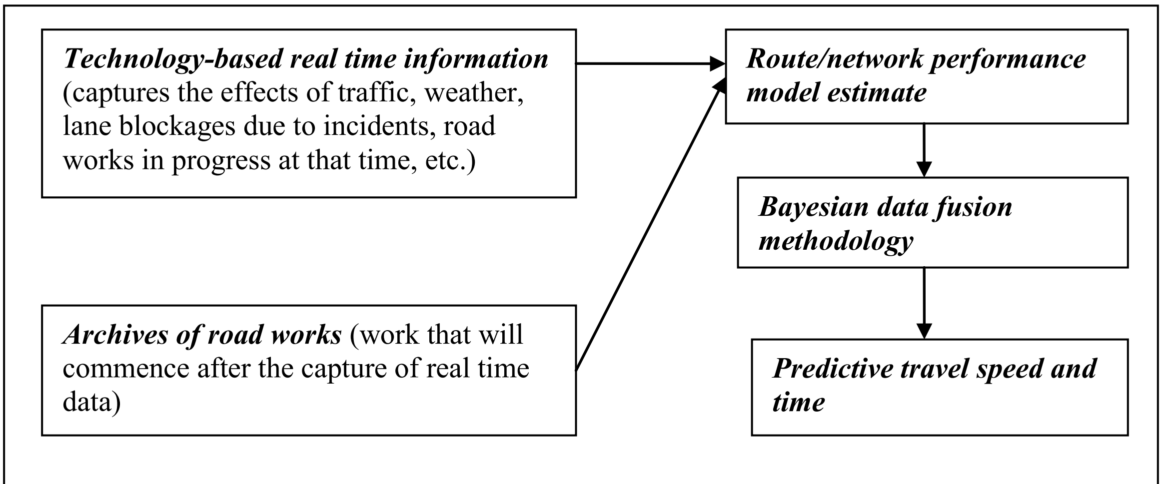


Figure 5 - Methodological framework

As shown in Figure 5, the process of obtaining predictive travel speed and associated point-to-point travel time starts with the real time data that reflect the effects of traffic, weather, lane blockages due to incidents, road works, etc. Since these data indicate driving conditions prior to the immediate future time of interest, these serve as the starting point.

Functions or models are available for estimating route or network performance or a microsimulator of traffic can be used for this purpose. Also, these tools can be used to generate data for performance models (Van Lint et al 2002). Given that stochastic microsimulators of traffic are capable of treating random variables of traffic flow and modelling the interaction between vehicles on a second by second or even fraction of a second basis, researchers and practitioners regard these tools as acceptable for traffic flow studies. As for performance models, the Artificial Neural Network (ANN) methodology is frequently employed for their development. The ANN models can be verified by using available field data and/or microsimulation-generated data that are not used for training these models (Khan 2010a).

The next step in the predictive performance is to obtain estimates that take into account the real time traffic input, archives of road works whose effects will be felt shortly, and any other known events that will affect route performance (Figure 5). Although the use of the performance model is desirable, the information obtainable from the model alone is not sufficient since it does not include the real travel speed information that was captured and associated travel time for the immediate past period.

Data fusion is a key methodological step and for this purpose methodology is required with the capability to work with these two sources of information identified above. The real time data of the previous period obtained from sensors/detectors/probes/other devices have to be fused with the predicted highway performance indicators. As noted previously, data fusion is necessary, given that the real time data by themselves become obsolete from the perspective of going beyond that point in time. For this purpose, the Bayesian statistical method is used for data fusion in this research.

Data fusion methodology

A data fusion methodology reported by Khan (2010b), based on Bayesian statistical analysis technique, has the capability to blend real time data and the ANN model predictions. For an introduction to Bayesian method, please refer to Korb and Nicholson (2004).

Since space mean speed and travel time predictions cannot be made with “certainty”, a probabilistic approach based on continuous or discrete probabilities is required. Since prior information has to be updated by using new information, Bayesian statistical method can play a role. The methodology can be imbedded in an algorithm designed to run over time. That is, answers produced at say 8:00 a.m. for display on variable message sign (VMS) boards (or other ATIS devices such as in-vehicle units) can be used as inputs for the following period.

The results produced should be reliable so that travellers can accept these as true representation of travel experience and if applicable, they can make route choice and other travel decisions.

The theoretical basis as well as the operational aspects of the predictive travel time methodology is described by Khan (2010b). In this paper, the methodology is further advanced as a part of the new generation ATIS. The relationships between variables and the sequence of steps for computing expected travel speed and time are presented in Figure 6.

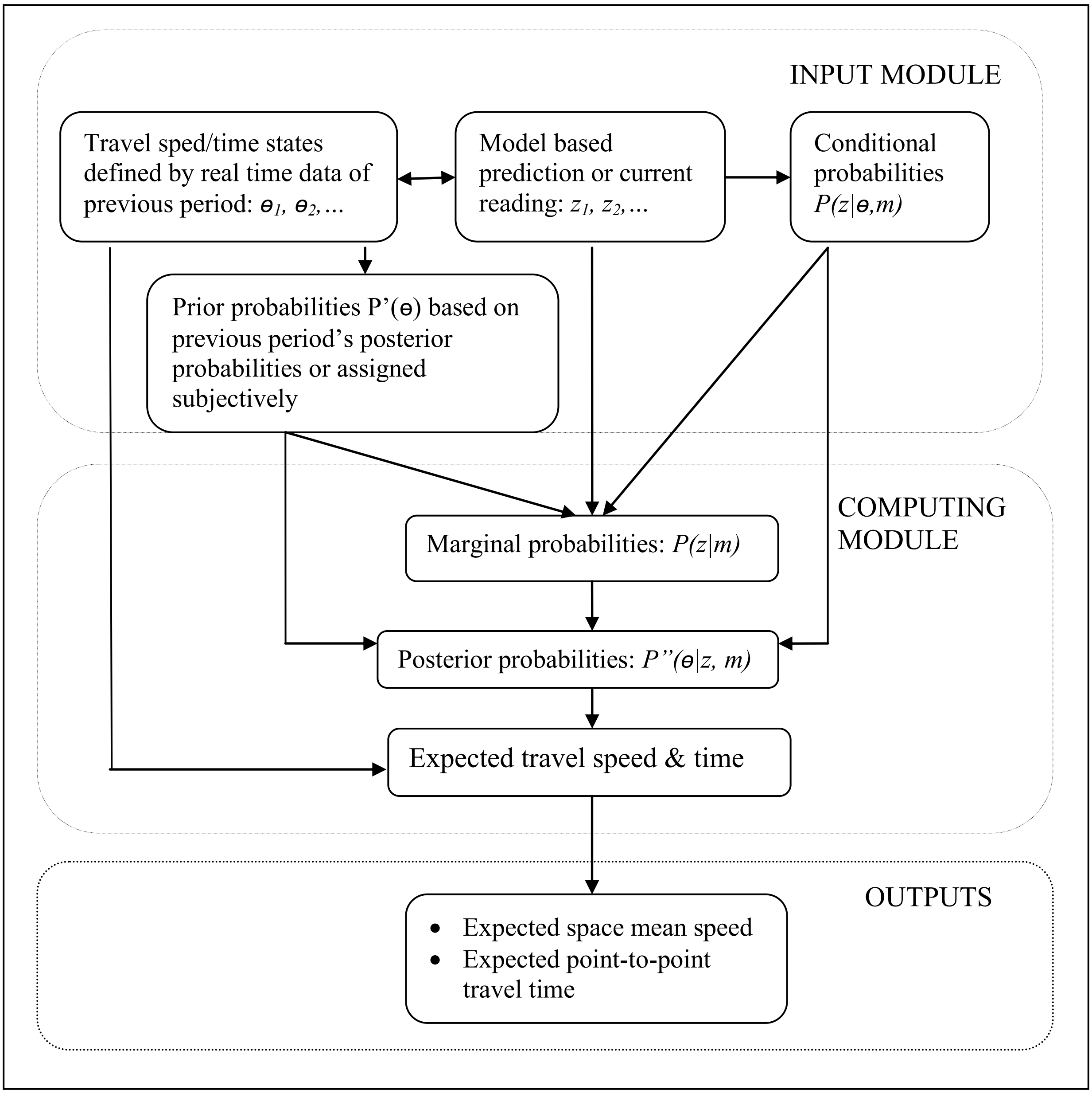


Figure 6 – Computation of expected travel speed and time

EXAMPLE APPLICATION 1

Taking the Highway 401 (Toronto, Canada) example shown in Figure 7, the objective is to predict speed and travel time. This example uses archived data for travel speed on a segment of the freeway that was the scene of an incident which adversely affected traffic flow on a segment of Highway 401 (Toronto, Canada). A part of the affected area is shown in Figure 7. The approximate start and end times of the incident were 7:20 AM and 8:00 AM, respectively. The shock wave that travelled upstream was responsible for a drop in speed and increased travel times. Following the end of the incident, the travel time gradually returned to the normal pattern.

For the section of the highway that contained the location of the incident, data captured by upstream and downstream sensors were used as a basis for the estimation of travel time. During the period of 7:00 AM to 8:30 AM, no road construction work was in progress. The developed Bayesian methodology was used to obtain the predictive travel time estimates and these were compared with the actual (estimated) travel time.

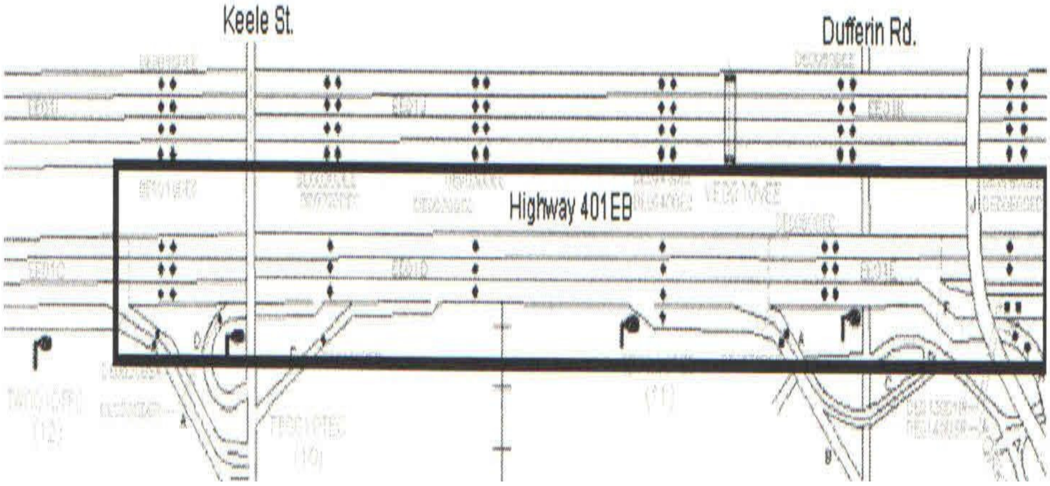


Figure 7 - Travel time prediction on Highway 401 (Toronto)

According to the methodology shown in Figure 6, the uncertain travel time states are designated by θ. On the basis of real time data that were captured and processed shortly before 7:00 a.m., the travel time by the freeway route was established as the starting point. Let us call this a middle estimate or Θ_2. From this, we can define low and high estimates. For example, 0.75 and 1.25 multipliers are used here for this purpose. Following field experience gained, the forecaster can set another range.

The Θ_1, Θ_2 and Θ_3 are the travel time states for the period that begins at 7:00 a.m. These time values should be read as the average values of travel time bands.

Prior probabilities $P'(\theta)$ can be assigned on the basis of posterior probabilities of travel time states $P''(\theta|z,m)$ for the previous time period, say from the period that started at 6:55 a.m. Alternatively, default values can be assigned by the analyst on the basis of traffic flow patterns that are normally encountered. In the above mathematical term, z is an estimate of travel time provided by the route performance model that corresponds to θ and m represents the model. The posterior probability is the updated probability of a state of travel time, given outcome z of model m.

At 7:00 a.m. for the freeway segment under study, the following prior probabilities are used: $P'(\Theta_1) = 0.3$, $P'(\Theta_2) = 0.4$, $P'(\Theta_3) = 0.3$ and the $\sum P = 1.0$.

Conditional probabilities can be defined as $P(z|\Theta,m)$, where
Θ = travel time state (which is uncertain)
z = an outcome of the performance model
z_1 corresponds to Θ_1
z_2 corresponds to Θ_2
z_3 corresponds to Θ_3
m is the performance model (that produces the route performance information by using available real time traffic data as well as archived road work information).

The conditional probability $P(z|\Theta,m)$ is read as follows: "Given that Θ is the true travel time state that will be experienced by the traveller on the freeway, the probability that m will produce an answer z".

It is a measure of the reliability of the performance model as well as the input data on traffic, captured by sensors as well as archived road works information. The better the quality of the performance model and the higher the coverage of sensors in the transportation network (i.e., the better the quality of the overall infostructure), the higher will be the $P(z|\Theta,m)$. Please note that traffic flow information can also be obtained by using probe vehicles, cell phone probes, and other means of data acquisition (Figure 3). EIS Inc. (2010) provides an introduction to a new generation of traffic sensors that are capable of capturing many traffic flow characteristics.

The posterior probability distribution can be calculated as follows.

$$P''(\Theta | z, m) = \frac{P'(\Theta)\, P(z | \Theta, m)}{\sum \text{for all states}[P'(\Theta)\, P(z | \Theta, m)]}$$

For the Highway 401 segment that was studied, the $P(z|\Theta,m)$ are assigned as shown in Figure 8. Next posterior probabilities $P''(\Theta \mid z, m)$ are computed. These are also presented in Figure 8.

Expected travel times were computed by weighting the travel time states with the corresponding posterior probabilities for various *z*. These estimates belong to the various *z*. Next, these are weighted by the marginal probabilities $P(z|m)$. The result is the expected travel time for Highway 401 segment for the period commencing at 7:00 a.m.

For most periods, traffic changes were experienced on the freeway and the performance model indicated the corresponding *z* to characterize traffic flow. For example, *z3* was observed for increasing travel time. Therefore, prior probabilities were set equal to posterior probabilities that correspond to z_3 in the previous period. Also, the middle estimate of the new travel time state Θ_2 was set equal to Θ_3 of the previous period.

The process was repeated for all time periods by following the methodological steps shown in Figure 6.

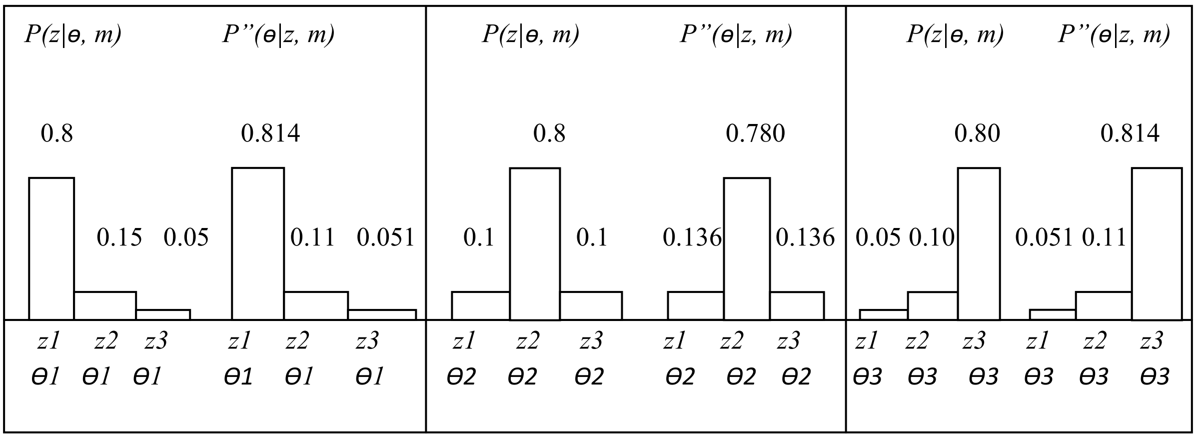


Figure 8 - Conditional probabilities $P(z|\theta,m)$ and posterior probabilities $P''(\Theta|z,m)$

Results illustrated in Figure 9 show that the predictive travel time compares fairly well with the experienced time. The difference between the actual and predictive travel time ranges from 1.4% to 21.6%. Given the abrupt and severe changes in traffic speed due to the incident-induced shock wave of unique characteristics, this degree of closeness of two travel time estimates is remarkable. Therefore, in the application of the methodology to real world traffic networks, the difference between actual and predictive travel time for some brief time periods may reach or even exceed 25%.

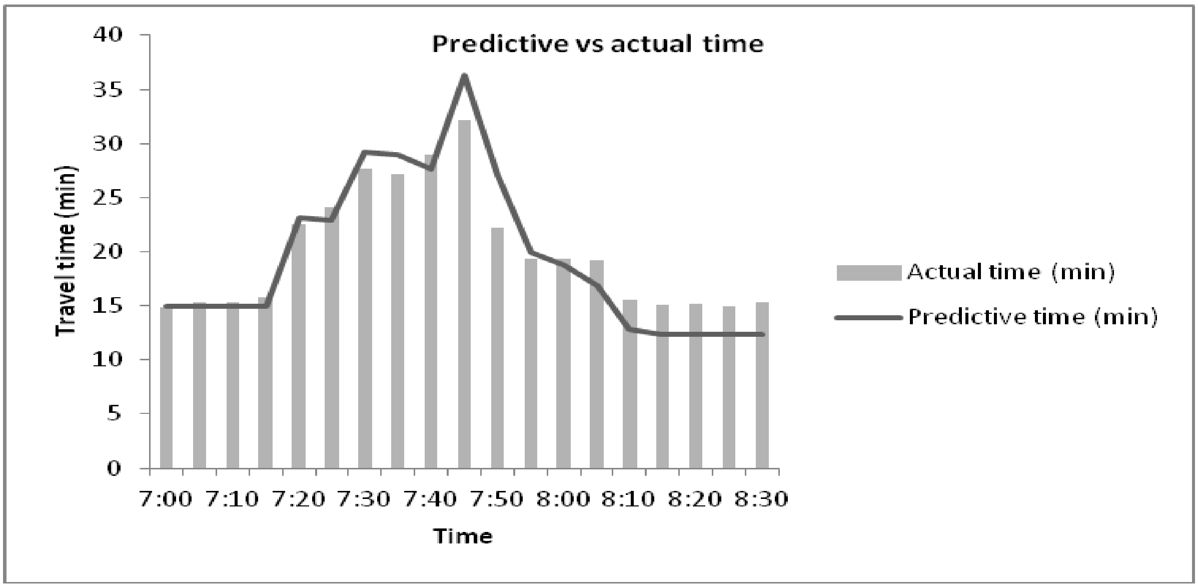


Figure 9 - Comparison of predicted and actual travel time (Highway 401)

Example Application 2

This example application is on traveller information useful for route choice decision. The location of the application is Ottawa (Canada) (Figure 10). In this example, we are interested in predicting travel time from Fellowfield Road interchange to CBD of Ottawa by two applicable routes. These are the freeway route, and the alternate route based on Fellowfield Road and other arterials. In travel environments characterized by high traffic surges or incidents, the freeway route may no longer be the quickest route and therefore drivers should be given this information in order to avoid overloading the already congested freeway route and therefore to encourage diversion of some traffic to the alternate route.

The methodology to be used in this case is in essence the same as for Example 1. That is, for the freeway and alternate routes, real time information available from the immediate past period can form the basis of estimating operating speeds and from these, travel times can be found. Likewise, the route performance function/model can be used in conjunction with real time traffic volumes and archived road works data in order to develop travel time estimates.

Travel speed data can be captured on a real time basis which inturn can be used to compute travel time to a location of interest downstream. For example, travellers may wish to know travel time from the interchange of Fellowfield Road to the central business district of Ottawa (Figure 10).

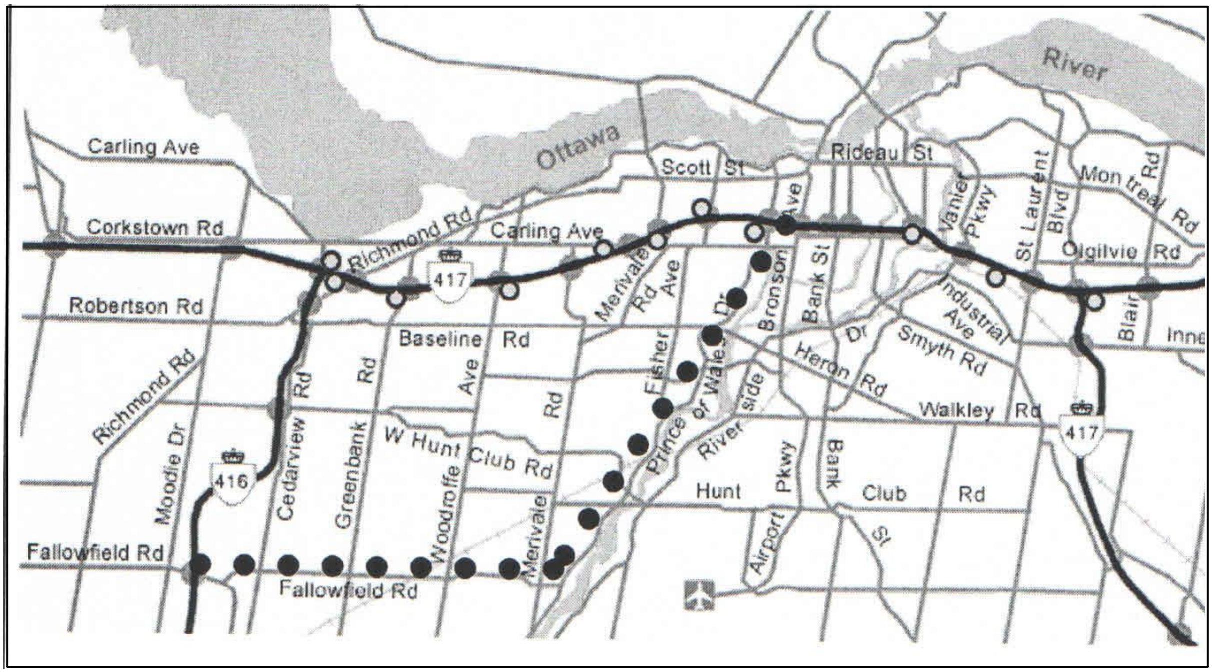


Figure 10 - Example route alternatives (Ottawa, Canada)
(Source of map: courtesy Ministry of Transportation, Ontario, website)

In the absence of severe congestion or incidents, the all-freeway route is likely to be the optimal route and predictive travel time could be displayed on a variable message sign (VMS) board and via an in-vehicle ITS platform. On the other hand, in the case of an incident on the freeway route or an unusual surge in traffic, an alternate route shown Figure 10 (with large dots) may be the choice and therefore the message on the VMS board should advise travellers to take the alternate route. As soon as the freeway route becomes the optimal route, the advice regarding alternate route should not be shown.

In the context of the present example, the new generation ATIS must have the capability to predict the travel time to reach Ottawa CBD via the freeway route and also via the alternate route. If the freeway route is the optimal route, travellers on Highway 416 should be informed about the expected travel time to Ottawa CBD on the VMS board installed upstream of the Fellowfield Road interchange.

The real time data on speed along the two routes captured shortly before 8:00 a.m. reflect travel conditions at that time but may not represent travel experience following 8:00 a.m. Since traffic flow is highly dynamic, this information by itself is not appropriate for dissemination to the public at that moment. Therefore, there is a need to fuse real time data with a model estimate that can take into account among other factors, the downstream effects of traffic detected at or shortly before 8:00 a.m.

Repeated applications of the predictive space mean speed and travel time methodology explained in Example 1 resulted in expected travel time information via two routes (Figure 11). On the basis of results, dynamic route guidance information can be developed as shown in Table 1.

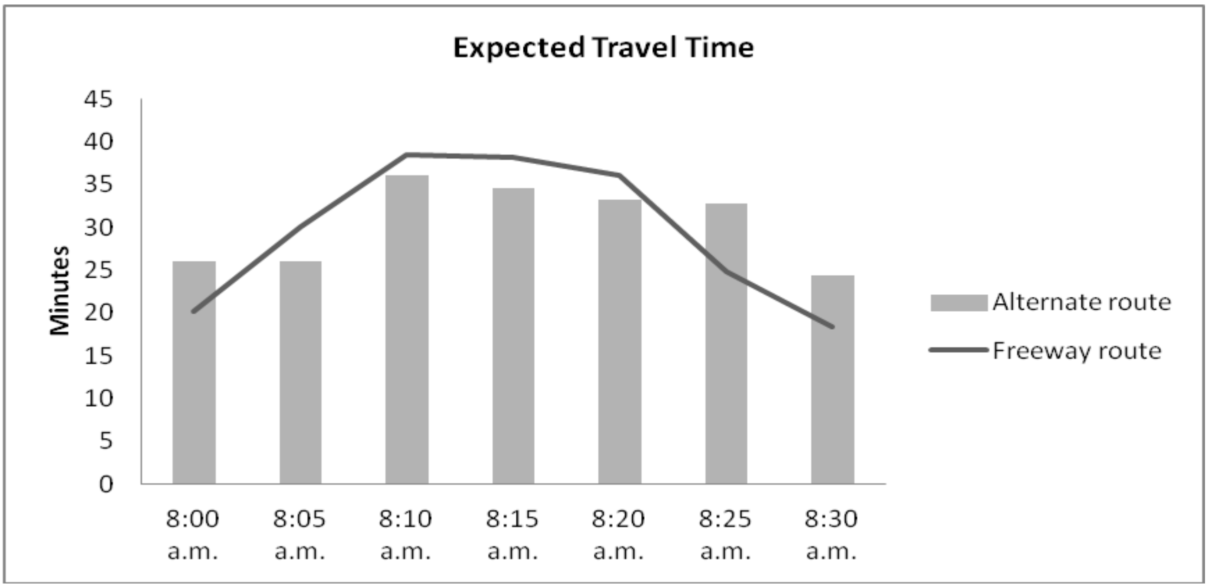


Figure 11 - Comparison of predictive travel time by route alternatives

Table 1 - Route guidance information

Time period starting	Expected travel time via Freeway route (min)	Expected travel time via Alternate route (min)	Comment
8:00 a.m.	20.2 (best)	26.00	There is no need to show alternate route information
8:05 a.m.	30.0	26.00 (best)	Alternate route advice can be given to divert some traffic from the freeway route
8:10 a.m.	38.5	36.00 (best)	Alternate route advice can be given
8:15 a.m.	38.23	34.50 (best)	Alternate route advice can be given
8:20 a.m.	36.13	33.23 (best)	Alternate route advice can be given
8:25 a.m.	24.86 (best)	32.74	There is no need to show alternate route information
8:30 a.m.	18.34 (best)	24.40	There is no need to show alternate route information

CONCLUSIONS

Conclusions drawn from findings of this research are multi-faceted.
(1) The high level architecture of the next generation traveller information system must integrate technology and methodology for effectiveness. Therefore, the developed predictive travel time information system combines these. The ITS technologies are a pre-requisite for the design and implementation of the predictive travel time information system and the methodological advances enable these to achieve the mission of ITS.

(2) The Bayesian modelling approach is best suited for dynamically fusing data and updating predictive elements of the traveller information system (i.e., travel speed/time in this paper). In order to avoid the past practice of mainly technology-driven closed architecture and fragmented traveller information products, this research provides a framework for the design of the next generation traveller information system that offers improvements, particularly the use of the Bayesian method for overcoming the methodological deficiency.

(3) Results of example cases are logical.

(4) The scope of the advanced traveller information system with the predictive travel time capability can be broadened to include additional traveller information needs such as weather, use-based road pricing and insurance.

ACKNOWLEDGMENTS

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