Real-time, Adaptive Prediction of Incident Delay for Advanced Traffic Management and Information Systems

Liping Fu and Bruce Hellinga
Department of Civil Engineering, University of Waterloo, Waterloo, Canada
Phone: 519 885-1211 Ext. 3984; Fax: 519 888-6197; email: lfu@uwaterloo.ca

ABSTRACT

This paper presents a fuzzy queuing model that can be used to predict the possible delay that a vehicle will experience at an incident location based on real-time information on current queuing conditions, future traffic arrivals, lane closings and the vehicle's arrival time. Compared to most existing methods, the proposed model is unique in three aspects. First, it explicitly accounts for uncertainties involved in all influencing factors and thus allows easy incorporation of imprecise and vague information typically available in this type of prediction environment. Second, the model is adaptive in the way that it allows continuous update of estimates as new information is made available in real time. Third, delays obtained from the model are fuzzy numbers that can be conveniently mapped to linguistic terms for use in systems such as changeable message signs (CMS). A case study is presented to demonstrate the application of the proposed model in facilitating the composition of location-dependent delay messages for CMS.

INTRODUCTION

Provision of timely and reliable information on traffic incidents and subsequently induced congestion is a critical ability to the successful deployment of many envisioned Advanced Traffic Management and Information Systems (ATMIS). Ideally, anticipated and *quantitative* information such as time-dependent delay caused by an incident should be estimated and provided to drivers to maximize the effect of information provision (1). Procurement of such information is however not a trivial task because of the complex interactions among various factors such as incident location and severity, incident response capacity, demand fluctuation and diverse driver responses to information. Moreover, most of these factors are subject to high uncertainty and information available to quantify them is often incomplete and subjective in nature. Consequently, provision of crisp values of expected delays to drivers through systems such as changeable message signs (CMS) would inevitably lower drivers' trust in the accuracy of the provided information because the actual delays they would experience will be either larger or smaller than what were suggested. This underlying dilemma has become a major reason for many traffic management authorities to opt for less effective, but more credible alternatives such as providing qualitative information only (2). The goal of this paper is to demonstrate that, with an appropriate delay prediction model, it is possible to resolve this dilemma.

Incident delay that a vehicle may experience at an incident location can be obtained using a deterministic model such as a deterministic queuing model or shock wave theory if the future values of the associated parameters such as traffic arrival rate, capacity reduction, and incident duration can be identified exactly (3, 4, 5). In real-time application environments, however, these parameters are often subject to large variations and can not be predicted exactly. As a result, a deterministic model is not appropriate for use to model incident conditions (6).

Estimation and prediction of link travel time, which would include incident delay if an incident has occurred on the associated link, have been one of the major research interests in the area of ATMIS. Various methods have been proposed for demonstration ATMIS projects and simulation studies (7, 8, 9). The fundamental idea behind most of the proposed methods is a data fusion process that combines real-time travel time estimates from loop detectors and probe vehicles with historical travel times. Although the impact of incident occurrences on travel times is considered by allocating a higher weight to real-time estimates, these methods do not fully make use of available information such as lane closures, estimates of incident duration and expectations of future traffic volume.

This paper proposes a framework based on fuzzy set theory to model the evolution of incident congestion or queue development. The rationale behind this approach is that information typically available under incident conditions is often in the form of linguistic descriptions characterized by imprecision and vagueness. The paper first describes various uncertainties involved during incident conditions and how they can be systematically modeled on the basis of fuzzy set theory. A fuzzy queuing model is subsequently presented for predicting the possible delay that a vehicle will experience at an incident location based on real-time information on current queuing conditions, future traffic arrivals, capacity reductions and the vehicle's arrival time. Lastly, a case study is presented to demonstrate the application of the proposed model in composing location-dependent delay messages for CMS.

A FUZZY INCIDENT DELAY MODEL

Delay that a vehicle will experience as a result of an incident depends on many factors including incident severity (capacity reduction), incident duration, traffic volume and the time when the vehicle arrives at the incident location. In a practical situation, each of these factors is subject to uncertainty. It would be a matter of a simple application of deterministic queuing theory or shock wave theory if we could predict the exact value of these factors. However, in a practical situation, each of these factors may be subject to a certain level of uncertainty and the information that may be available for estimating these factors is commonly imprecise or vague, as discussed below (10).

Traffic Arrival Rate (V): Under normal traffic condition, the traffic arrival rate is usually stable and can be fairly accurately estimated based on historical traffic counts. However, during incident conditions, the prediction of traffic arrivals is no longer a trivial task because some drivers may have been informed of the incident occurrence and decide to divert to other routes. How much traffic will divert and at what rate will depend on many factors such as traffic information coverage, drivers' acceptance of the provided information and local network conditions. Currently, there is no dependable model available that can be used to capture these complexities and provide an accurate prediction of the dynamic traffic conditions. However, it can be reasonably expected that an approximate estimation of the traffic diversion may be available. For example, an experienced traffic manager may be able to give such estimation as "About 20%~30% of the traffic will divert to avoid the incident congestion", or "Majority of the drivers will still use the route even though one lane is closed due to the incident". These linguistic terms can be properly modeled by a fuzzy set or a fuzzy number.

Incident Duration (L): The time taken to remove an incident and recover the road capacity, or incident duration, is another key piece of information needed for predicting the incident delay. It has been observed that incident duration usually has a large variation depending on incident severity and location, traffic conditions and the availability of incident management (11). For example, Giuliano (11) showed that the mean incident duration is about 37 minutes with a standard deviation of 30 minutes. Therefore, it is nearly impossible to give a precise prediction of the incident duration even when there is a large amount of historical data available. However, it is not unusual for an experienced incident response team or highway police to give an estimation of the duration after they know the incident situation and location. For example, they may provide statements such as "it would take about 30 to 40 minutes to remove the debris", "it will take at least one hour" or "It shouldn't take longer than two hours". Such information presented in linguistic terms is commonly imprecise or vague and can be adequately represented using fuzzy numbers.

Current Queue (Q): There is usually a time lag between the current time (the time to make a prediction) and the incident occurrence. Therefore, it is likely that a queue has formed at the incident location. The current queue can be estimated based on information such as the elapsed time from incident occurrence, traffic arrivals and reduced capacity. However, it is more likely that it can be directly obtained from various information sources such as observers, police or a special incident response team. This information is usually a linguistic description on the queuing status (e.g. "the queue is about to backup to the 12th street"). It should be noted that in most cases, these descriptions often describe the current queue reach instead of the queue length. However, these two variables can be considered as the same before the incident is removed. For the same reason as for the previous parameters, it can be nicely represented using a fuzzy set.

Incident Capacity (C): The capacity under normal traffic condition can be considered as constant for a given road section and estimated based on HCM (12). During incident conditions, it has been observed that the departure rate from the queue (or capacity during the incident) varies significantly because of the stop-and-go process and "gawkers block". The actual value can be as low as 1500 to as high as 2000 pcu/hour/lane, depending on the local conditions and driver behavior (12). It has also been observed that the lane-blocking incidents have more than a proportional impact on capacity. For example, Urbanek and Rogers (13) indicated that the blockage of a single lane on a three-lane facility reduced freeway capacity by 40~50% (instead of 33% based on space reduction). Accordingly, it is desirable to use a fuzzy number to model the reduced capacity during incident.

Vehicle Arrival Time (T): The incident delay that a vehicle may experience also depends on when the vehicle will arrive at the incident location. For example, if a Traffic Information Center (TIC) is to provide information to a vehicle currently at a known location, the prediction of incident delay also requires the estimation of travel time from the current location to the incident location. There is no doubt that this travel time involves uncertainty caused by many factors such as variation of traffic demands, traffic control and driving conditions. Although this travel time can be modeled as a random variable, the underlying distribution may not follow a popular mathematical distribution such as normal, log-normal or Beta distribution. Therefore, it is also appropriate to use a fuzzy number to represent the travel time or arrival time at the incident location.

A methodology that applies a traditional deterministic queuing model with fuzzy input parameters has recently been proposed (10). Given the input parameters described above, the functional relationship between the fuzzy incident delay and the input variables was established based on arithmetic operations of fuzzy numbers using the α-cut concept (14). Figure 1 shows the α-cut representation of a fuzzy queuing model where the current queue (Q) is represented by its α-cut interval $[q_1^{(\alpha)}, q_2^{(\alpha)}]$, the possible cumulative traffic arrival at the incident location is represented by two straight lines with rates of $v_1^{(\alpha)}$ and $v_2^{(\alpha)}$ - the α-cut interval of the fuzzy traffic arrival rate V. The cumulative departure at the incident location is represented by two straight lines with rates of $c_1^{(\alpha)}$ and $c_2^{(\alpha)}$, which intersect with lines representing the recovered full capacity (s) at the incident removal time, L, represented by $l_1^{(\alpha)}$ and $l_2^{(\alpha)}$. The α-cut interval of the incident delay, D_α, for a vehicle arriving at the incident location at a given time (T) - represented by $t_1^{(\alpha)}$ and $t_2^{(\alpha)}$, can then be obtained by Equation 1:

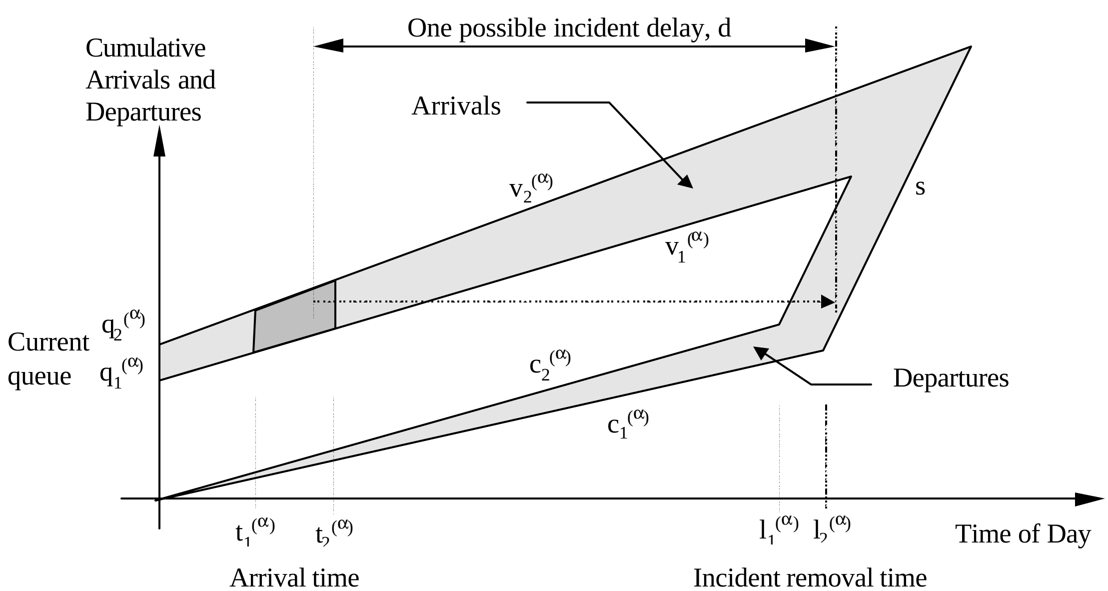


Figure 1. An α-cut representation of a fuzzy incident delay queuing model

$$D_\alpha = [d_1^{(\alpha)}, d_2^{(\alpha)}] \tag{1}$$

where $d_1^{(\alpha)}$ and $d_2^{(\alpha)}$ are known functions of $v_1^{(\alpha)}, v_2^{(\alpha)}, q_1^{(\alpha)}, q_2^{(\alpha)}, c_1^{(\alpha)}, c_2^{(\alpha)}, s, l_1^{(\alpha)}, l_2^{(\alpha)}$, $t_1^{(\alpha)}$ and $t_2^{(\alpha)}$ (refer to (10) for the complete equations).

The developed fuzzy incident delay model allows prediction of uncertainty associated with incident delay and can be readily used by ATMIS applications that need to consider uncertainty in information provision. Real-time information, such as queue length reported by traffic patrol and/or eyewitnesses, updated short-term prediction of traffic volume and estimate of incident duration provided by on-site incident response team can be translated into fuzzy numbers and fused as input to corresponding parameters. Prediction of delay can therefore be updated and improved adaptively in real time.

CASE STUDY

This section presents a hypothetical case to demonstrate the use of the proposed model. Consider the case that an accident was detected on a three-lane freeway section at 3:20pm, as shown in Figure 2. Two CMS are available for the traffic management center (TMC) to post incident delay information. The messages are intended for drivers who are just in the view of one of the CMS. In order to determine what message should be displayed, the TMC needs to predict the possible delays that would be experienced by vehicles if they were to continue to travel on the freeway section instead of diverting to other routes. It is assumed that some incomplete pieces of information are available which permit the representation of the traffic arrival rate, incident duration, capacity during incident, and current queuing status as fuzzy trapezoidal numbers (TrFN) represented by {a, m, n, b}. The data used for analysis are summarized in Figure 3. Two prediction scenarios are considered. Scenario 1 represents the estimation task at the time 3:20pm, that is, right at the time the incident is detected while Scenario 2 models the prediction task at 3:40pm, at which time the incident is expected to be removed soon. Note from the data that a larger value of current queue was used in Scenario 2 as compared to Scenario 1 to reflect the likely congestion development.

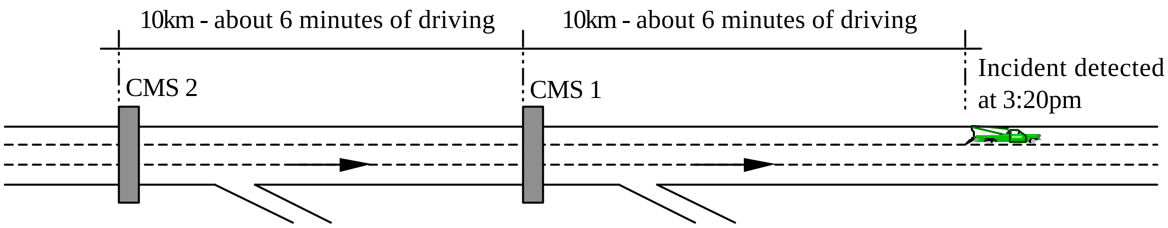


Figure 2. Freeway section with an incident

Based on the given data, the fuzzy incident delay, as approximated using five levels of presumption with a ={0; 0.2; 0.4; 0.6; 0.8; 1.0}, can be calculated for further analysis. Figure 3 shows the predicted fuzzy incident delays under the two given scenarios for vehicles at each CMS. The arrival times of the vehicles at a given CMS were generated based on the distance from the CMS to the incident location and a speed of 100km/h. The following findings are observed from the predicted delay values shown in Figure 3:

- There exists a significant amount of uncertainty in incident delay. This indicates the need to recognize it explicitly in information provision. For example, instead of displaying a single estimate of delay on a CMS, an interval of possible delay, such as "incident delay between 15-20 minutes", should be used.

- CMS at different locations (distances from an incident spot) should display different delay information to account for differences in vehicles' expected arrival time. Generally, during the time period that incident congestion starts to build up (Scenario 1), CMS farther away from the incident spot (CMS 2) should display delay values higher than those on CMS nearer to the incident spot (CMS 1). Conversely, when the incident is soon to be removed (Scenario 2), CMS near the incident spot (CMS 1) should display delay values higher than those on CMS farther away from the incident spot (CMS 2).

CONCLUDING REMARKS

This paper has presented a fuzzy queuing model that can be used to predict the delay that a vehicle would experience if traveling through an incident location. In contrast to the traditional deterministic models, the new model explicitly considers the uncertainties involved in future traffic arrivals, incident duration, departure rate during incident, current queue status and vehicle arrival time, allowing easy incorporation of imprecise and vague information on these variables. The proposed model does not require significant additional data or computational requirements over traditional methods and therefore may readily be adopted for ATMIS applications or simulation studies. The numerical example has demonstrated the necessity for providing drivers with incident delay information that is location-varied and explicit in informing uncertainties.

It should be pointed out that the methodology presented in this paper assumes that the input variables can be modeled as fuzzy numbers and the related membership functions are known *a priori*. As a result, the implementation of the proposed model requires an interface to generate membership functions of the input variables based on various sources of information in real-time. The next step of this research will focus on the development of this type of interface and the calibration and refinement of the proposed model for application in ATMIS.

ACKNOWLEDGEMENT

This research is funded by the Natural Science and Engineering Research Council of Canada.

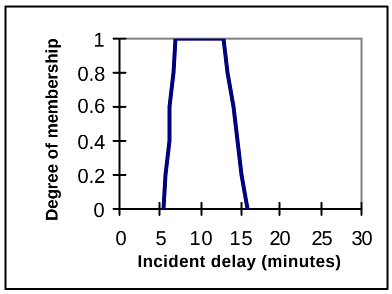
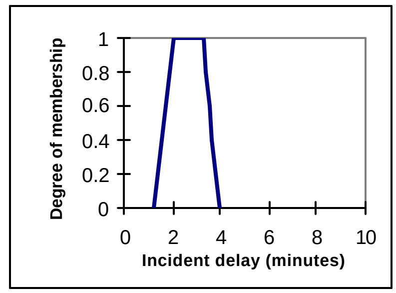
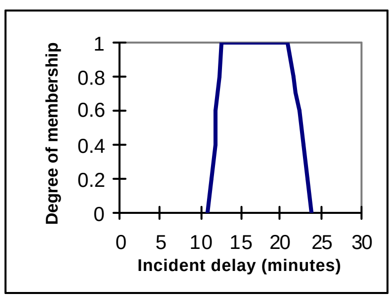
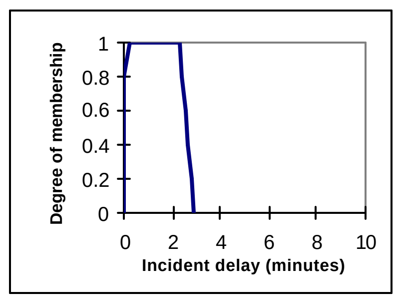
		Scenario 1	Scenario 2
	Prediction time:	3:20pm	3:40pm
	Current Queue, Q (pcu):	{14,18,22,26}	{52,56,64,68}
	Incident duration, L (min):	{25,29,31,35}	{4.5,5,5,5.5}
	Traffic volume, V (pcu/h):	{3590,3610,4390,4410}	{3590,3610,4390,4410}
	Capacity with incident, C (pcu/h):	{1430,1450,1750,1770}	{1430,1450,1750,1770}
	Full capacity (pcu/h):	5400	5400
CMS 1	Arrival time, T (min)	{4.9,7.1,5.9,6.1}	{4.9,7.1,5.9,6.1}
	Predicted Delay, D (min)		
	Suggested Message	"Incident Delay 5-15 min."	"Incident Delay 1-4 min."
CMS 2	Arrival time, T (min)	{10.3,11.3,12.7,13.7}	{10.3,11.3,12.7,13.7}
	Predicted Delay, D (min)		
	Suggested Message	"Incident Delay 10-25 min."	"Incident Delay under 3 min."

Figure 3. Estimation of fuzzy incident delay for CMS

REFERENCES

[1] Wardman, M , P. W. Bonsall and J. D. Shires (1998) "Driver Response to Variable Message Signs: A Stated Preference Investigation", *Transportation Research – C*, Vol. 5, No. 6, pp. 389-405.

[2] Masters, P., G. Paesani and A. Coady (1995) "Congestion Management by Dynamic Guidance on Toronto's Dual Roadway Freeway", Proceedings of the Advanced Traffic Management Conference, St. Peterburg, Florida, October 3-8, 1993, pp. 271-299.

[3] Messer, J. C., C. L. Dudek and J. D. Friebele, (1973) "Method for Predicting Travel Time and Other Operational Measures in Real-time During Freeway Incident Conditions" *Highway Research Record* 461, TRB, National Research Council, Washington, D. C., pp. 1~16, 1973.

[4] Wirrasinghe, C. S. (1978) "Determination of Traffic Delays from Shock Wave Analysis", *Transportation Research*, Vol. 12, pp. 343~348, 1978.

[5] Morales, M. J. (1986) "Analytical Procedures for Estimating Freeway Traffic Congestion" *Public Road*, Vol. 50, No. 2, September, pp. 55~61, 1986.

[6] Fu, L. and L. R. Rilett (1997) "Real-time Estimation of Delay due to Incidents in Dynamic and Stochastic Networks", *Transportation Research Record* 1603, Transportation Research Board, National Research Council, Washington DC, 1998.

[7] Hoffman, C. and J. Janko (1990) "Travel Time as a Basis of the LISB Guidance Strategy" Paper presented at the IEEE Road Traffic Control Conference, London, 1990.

[8] Koutsopoulos, H. N. and A. Yablonski (1991) "Design Parameters of Advanced Information System: the Case of Incident Congestion and Small Market Penetration", *Proceedings of the Second Vehicle Navigation and Information System Conference*, Dearborn, MI, 1991.

[9] Boyce, D., Rouphail, N., and A. Kirson (1993) "Estimation and Measurement of Link Travel Times in the ADVANCE Project", *IEEE-IEE Vehicle Navigation & Information Systems Conference*, Ottawa, Ontario, 1993.

[10] Fu, L (2001) "A Fuzzy Queuing Model for Prediction of Incident Delay under Imperfect Information", working paper, Department of Civil Engineering, University of Waterloo.

[11] Giuliano, G. (1989) "Incident Characteristics, Frequency, and Duration on a High Volume Urban Freeway", *Transportation Research -A*, 23A, No. 5, pp. 387~396, 1989.

[12] TRB, *Highway Capacity Manual*, 1994 Update, Special Report 209, Transportation Research Board, National Research Council, Washington, D.C., 1994.

[13] Urbanek, G. L. and R. W. Rogers (1977) "Alternative Surveillance Concepts and Methods for Freeway Incident Management, Volume 1: Executive Summary, Federal Highway Administration. Report # FHWA-RD-77-58, Washington, D.C.

[14] Kaufmann, A. and M. M. Gupta, *Introduction to Fuzzy Arithmetic: Theory and Applications*, Van Nostrand Reinhold Company, New York, 1985.