

ASSESSING THE POTENTIAL FOR THE AUTOMATIC DETECTION OF INCIDENTS ON THE BASIS OF INFORMATION OBTAINED FROM ELECTRONIC TOLL TAGS

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ABSTRACT

The recent introduction of electronic toll collection technology on several toll highways in Canada and the United States provides an opportunity to devise automatic incident detection schemes that rely on measured individual vehicle travel times over a section of roadway.

This paper provides an initial examination of the potential performance characteristics of AID algorithms that are based on travel times obtained from electronic toll tags (ETT). These characteristics are quantified on the basis of travel time data obtained by simulating a 12-km section of Highway 401 in Toronto, Canada. For this study, it is assumed that, similar to the configuration used on Highway 407, an all electronic toll facility in Toronto, tag readers are located only at on and off-ramps. Using two rudimentary travel time based AID algorithms, preliminary AID performance results indicate that travel time data collected via ETT may provide significant opportunity for improving AID. It is observed that the location of ETT readers has a significant impact on the ability to directly identify roadway segments on which the incident has occurred.

It is recommended that the potential of AID on the basis of travel times obtained from ETT, be further explored by expanding the study described in this paper to examine the performance impacts of mainline tag readers and level of market penetration. It is also recommended that the performance of travel time based AID algorithms be quantified on the basis of field data.

1. INTRODUCTION

Timely and accurate incident detection is recognised as an integral component of advanced traffic

management. Currently, most jurisdictions perform incident detection in one or more of the following three methods: Rely on commuters, emergency services, and/or media, to inform the traffic management centre (TMC) of an incident; obtain complete visual coverage of the roadway, typically via closed circuit television, and rely on operators in the TMC to scan the camera views and identify incidents; or rely on an automatic incident detection algorithm to process induction loop detector data and alert the operator when an incident is detected.

Most AID algorithms currently in use, such as the McMaster algorithm [1], the California Algorithms [2], and the Minnesota algorithm [3], rely solely on spot traffic data, such as spot speed, volume, and/or occupancy, that can be obtained from in-road induction loop detectors. However, the recent introduction of electronic toll collection systems that use dedicated short range communication between a transponder, or electronic toll tag (ETT) in the vehicle, and a reader over the roadway, permit the acquisition of individual vehicle travel times. This paper provides an initial examination of the potential for performing AID on the basis of travel times obtained from vehicles equipped with an ETT.

Nomenclature

t_t	vehicle trip time reported at time t (minutes)
$\bar{t}_p$	mean trip travel time for period p (minutes)
$\bar{t}_{t^*}$	mean trip travel time (minutes)
p	discretized period within 24 hour day
n_p	number of probe reports received in period p
s_{t^*}	standard deviation of travel time (minutes)
s_p	standard deviation of travel time in period p (minutes)
d	duration of averaging period (minutes)
UL_p	upper confidence limit of travel time in period p (minutes)
UL_{t^*}	upper confidence limit of travel time

- (minutes)
- t current time of day (in minutes from start of analysis window)
- t^* time of previous probe report (in minutes from start of analysis window)

Structure of paper

Section 2 of this paper describes the characteristics of the problem. Section 3 describes two potential travel-time based AID approaches. Section 4 describes the generation of travel time data for incident and non-incident conditions. Section 5 provides the results of the application of the two candidate AID algorithms to these travel time data. Finally, conclusions and recommendations are made in Section 6.

2. PROBLEM DESCRIPTION

In the event that the road network of interest is a toll route, and existing toll rates are sufficiently high to prevent periodic demands fluctuations that exceed system capacity (i.e. recurring congestion), then congestion detection alone may serve as a suitable incident detection approach. A simple approach to congestion detection relies on the comparison of observed travel times with a fixed travel time threshold. If a travel time is found to exceed this threshold, then congestion is declared, and appropriate response measures can be taken.

While this approach is simple, there exist several practical limitations:

First, the definition of congestion, as defined by the travel time threshold, is fixed, resulting in a system that cannot respond to situations in which the speed-flow characteristics of the roadway are altered by influences such as weather.

Second, for systems in which toll rates do not change dynamically in response to conditions on the toll road relative to the alternate routes, congestion can occur as a result of demands exceeding system capacity. When this occurs, it is not useful to have only a congestion detection process, since it cannot discriminate between recurring and non-recurring congestion.

Discriminating between recurring and non-recurring congestion

While the application of a simple travel time threshold may be of some limited benefit, more robust approaches are likely to provide additional

capabilities. One such approach is the application of statistical inference to determine if an observed travel time is likely to have resulted from an incident rather than a non-incident situation. The application of statistical inference requires that the characteristics of the process be known and quantified, such that the likelihood that an observation has been drawn from a population other than the population associated with the process, can be determined.

3. POTENTIAL AID APPROACHES

Despite the realisation that vehicle travel time is a result of a non-stationary process, two approaches can be identified which permit an analysis assuming stationary conditions. These approaches, termed *Historical* and *Real-time Adaptive*, are described in the following sections.

Historical data approach

The first approach, termed *Historical*, assumes that periods of the day can be defined, during which travel times can be reasonably assumed to result from a stationary process. Thus, if a database of historical travel times, incident occurrences, weather conditions, and road repairs, were available, travel times could be obtained from different days of the week, and weeks of the year, representing travel conditions without incidents, adverse weather, and road maintenance. From these data, Equations 1 and 2 could be used to compute the mean and variance of the observed travel times for a set of defined periods during the day.

$$\bar{t}_p = \frac{1}{n_p} \sum_{i=1}^{n_p} t_i, (p-1)d < t \leq pd \quad (1)$$

$$s_p = \sqrt{\frac{1}{n_p-1} \sum_{i=1}^{n_p} t_i^2, (p-1)d < t \leq pd} \quad (2)$$

$$UL_p = \bar{t}_p + 3s_p \quad (3)$$

$$\text{if } (t_t > UL_p) \text{ alarm} = \text{true} \quad (4)$$

$$p = \text{int}(t/d) + 1 \quad (5)$$

Assuming that the travel times are normally distributed, confidence intervals can be established for each period of the day (Equation 3). When performing AID in real-time, as each new travel-time is received, it can be compared to the established confidence limits. If the observed travel time falls outside of these limits, it can be stated with the specified level of confidence, that the observed travel

time has resulted from a process other than that associated with ideal traffic conditions (i.e. no incidents, no adverse weather, and no road maintenance).

While this approach provides a statistical basis for examining the travel time data, it is unable to distinguish between the range of events that may effect travel time (e.g. adverse weather, incidents, and road repairs). Furthermore, it is quite likely that the range of confidence limits about the mean travel time for each period of the day, will be quite large, as different days will all experience slightly different traffic patterns. The larger the range in the confidence limits, the more severely impacted travel times must be before they will be considered as resulting from a different population.

Real-time adaptive approach

Another approach, termed *Real-time Adaptive*, relies only on travel time data from the past d minutes to describe the current population of travel times. This would permit the statistical description of the population to be dynamically responsive to gradual changes experienced in travel times.

$$\bar{t}_{t^*} = \frac{1}{n_p} \sum_{i=1}^{n_p} t_{t'}, (t^* - d) \leq t' \leq t^* \quad (6)$$

$$s_{t^*} = \sqrt{\frac{1}{n_p-1} \sum_{i=1}^{n_p} t_{t'}, (t^* - d) \leq t' \leq t^*} \quad (7)$$

$$UL_{t^*} = \bar{t}_{t^*} + 3s_{t^*} \quad (8)$$

$$\text{if } (t_t > UL_{t^*}) \quad \text{alarm} = \text{true} \quad (9)$$

It must be assumed that the past d minutes of data can be reasonably assumed to represent a stationary process. The validity of this assumption increases as d decreases. However, the reliability of estimates of the mean and variance of the population decreases as d decreases. The issue is whether a sufficient number of observations (n_p) can be obtained within a period of duration d minutes, without grossly violating the assumption of a stationary process.

The significant advantage of this approach over the historical data approach, is that this approach is responsive to changes in weather and demands. Unfortunately, this characteristic can also be problematic, as a series of increasingly extreme values may not be seen as resulting from a different process, since each new value is considered as part of the population in the next time interval.

The next section describes the generation of the travel time data used to illustrate the application of the *Historical* and *Real-time Adaptive* AID approaches.

4. GENERATION OF DATA

Field travel time data from vehicles equipped with ETT were not available at the time of this study. However, in order to perform an initial examination of the potential of AID via travel time data, travel time data were generated through the use of the INTEGRATION traffic simulation model.

Description of the simulation model

The INTEGRATION model [4] is a microscopic routing-oriented simulation model of integrated freeway and surface street networks. Individual vehicle movements are traced through the network as they interact with traffic control devices, such as traffic signals, and with other vehicles.

The model permits the modelling of probe vehicles, which report key characteristics of their current travel experience, including trip start time, origin, destination, unique vehicle identification number, current location, time to traverse the previous link, and time of probe report.

Description of study network

The study area is composed of eight interchanges along a 12-km freeway section on Highway 401 in Toronto, Canada. This facility experiences an average daily traffic flow of approximately 340,000 vehicles, making it one of the most heavily travelled freeways in North America. The section utilised in this study extends from Bathurst Street in the east to Dixon Road in the west, as illustrated in Figure 1. This 12-km freeway section includes an express facility and a parallel collector facility, each of which typically consists of three or more lanes in each direction. The express and collector facilities are connected at some locations by transfer lanes.

This roadway section was selected for this study for several reasons. First, the section experiences severe recurring congestion at several locations during both the AM and PM peaks, permitting the testing of AID during both uncongested and congested conditions. Second, the network had already been used in a previous study in which the model had been calibrated against field data [5].

The coded network is composed of 478 nodes, 30 origin-destination zones, and 597 links. The O-D

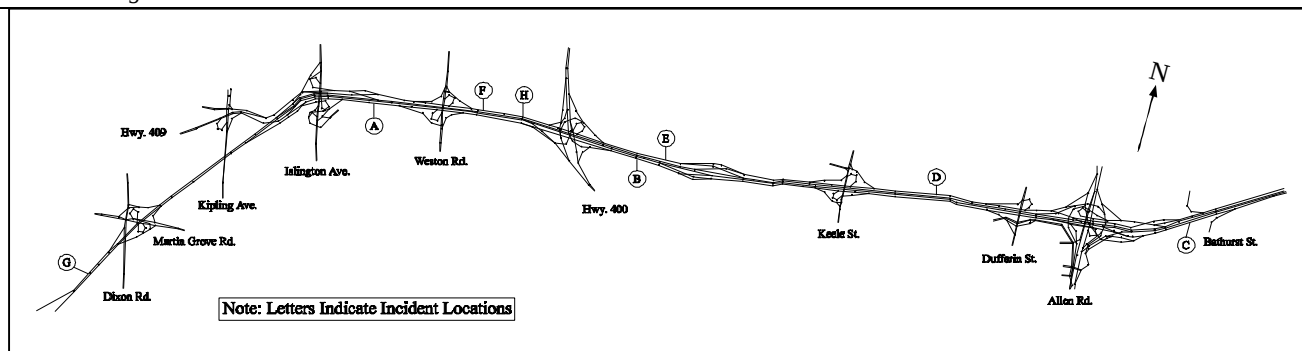


Figure 1: Study Network

demand had been constructed to replicate the build up of the AM peak from 5:00 AM to 11:00 AM. A total of 200,139 vehicle trips were simulated during this 6 hour time period.

It was assumed that ETT readers were located at all on and off-ramps, (i.e. at the location of the origin and destination zones), such that travel time data from all trips could be considered. It was assumed that no mainline readers existed. This configuration of readers was deliberately chosen, as it most closely represents the configuration typically used for electronic toll roadways, such as Highway 407, where the tag readers are placed at all access and egress points, in order to facilitate billing. As will become evident from the results, AID would be expected to benefit from the inclusion of mainline readers.

Two separate scenarios were simulated. The first represented the base case, in which no incidents were modelled. This scenario was used to represent historical conditions. The second scenario used the same network and O-D demand characteristics, but included the modelling of 8 incidents. As illustrated in Table 1, these incidents occurred at different locations on the network, at different times, and had different durations and severities. The location of

these incidents is also illustrated in Figure 1.

5. RESULTS

The results obtained from the simulated network are examined first from a disaggregate perspective, with the goal of determining the characteristics of the observed travel times, confidence limits, and the number, location, and timing of incident alarms. The second examination consists of an aggregate analysis of the performance characteristics of the incident detection methods described in Section 3.

For all of the analyses performed within this paper, the length of the aggregation period, d , is assumed to be equal to 15 minutes. The impact of different period durations is not examined within this study.

Disaggregate Analysis: Historical data approach

The process of performing AID on the basis of travel times obtained from ETT is made more complex when tag readers are located only at access and egress location (i.e. on and off-ramps). Such a configuration results in a data stream of vehicle travel times that are origin and destination zone specific. For example, the stream of vehicle travel time data obtained from the tag reader located at Weston Road South includes data for trips originating from several different origins (e.g. eastbound mainline, Martin Grove, Hwy. 409, and Islington Ave.). Travel times for different origin - destination pairs cannot be directly compared. Thus, the data obtained at each destination must first be stratified by origin zone before the equations developed in Section 3 can be applied.

Figure 2 illustrates the non-incident travel times obtained from the simulation and the computed 99.9% confidence limits for vehicles entering the network at the Eastbound mainline and exiting at Weston Road South. During the 6 hour period from 5 AM to 11 AM, a total of 1,823 vehicle trip travel

Table 1: Incident Descriptions

Incident	Time (AM hr)		Lanes Blocked	Total Lanes	Location ¹
A	5:30	5:50	2	4	EBC
B	7:30	7:50	1	5	EBC
C	5:45	5:46	2	3	EBE
D	5:45	6:05	1	3	WBE
E	6:00	6:01	1	4	WBC
F	8:15	8:16	1	3	WBE
G	8:30	8:50	2	5	WBS
H	8:00	8:01	2	4	WBC

¹ EBC = Eastbound Collector; EBE = Eastbound Express
WBC = Westbound Collector; WBE = Westbound Express
WBS = Westbound Single

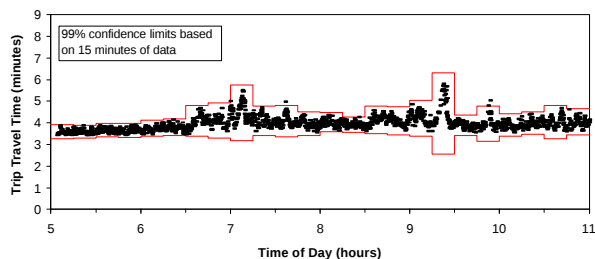


Figure 2: Historical (non-incident) travel times and 99.9% limits for vehicles travelling between EB mainline and Weston Rd.

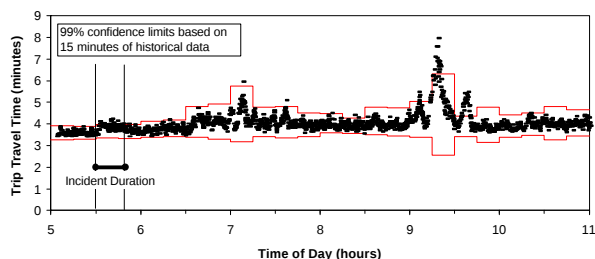


Figure 3: Incident travel times and historical 99.9% limits for vehicles travelling between EB mainline and Weston Rd.

times are obtained. Trip travel times vary from a minimum of approximately 3.4 minutes at 5 AM to a maximum of 5.8 minutes at 9:24 AM. The confidence limits are observed to also vary with time of day. This variation is a function of changes in the mean trip time, and also variation in the number of observed travel times within the 15 minute period.

The data illustrated in Figure 2 are considered to represent historical non-incident travel time experience. Confidence limits are developed from these data using Equations 1 - 3. AID is performed by comparing observed real-time travel time data with these historical estimates of the confidence limits (Equation 4). Figure 3 illustrates the time series of travel times obtained from the simulation model for trips entering the network at the Eastbound mainline and exiting at Weston Road South when incidents are modelled. The illustrated confidence limits are those developed on the basis of the historical non-incident data (as illustrated in Figure 2). The travel time observations falling outside of the confidence limits are considered as incident alarms. As indicated in Figure 1 and Table 1, the only incident occurring on the network in the eastbound traffic lanes between the eastbound mainline entrance and Weston Road, occurs between 5:30 AM and 5:50 AM.

To more clearly illustrate those travel time data resulting in an incident alarm, Figure 4 illustrates

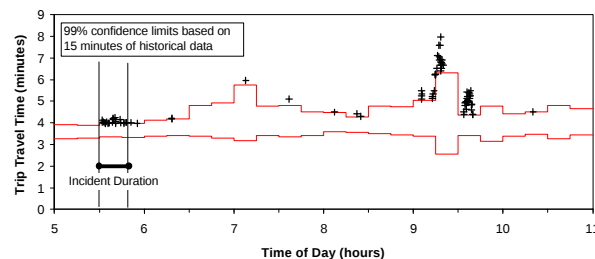


Figure 4: Incident travel times exceeding historical 99.9% upper limit for vehicles travelling between EB mainline and Weston Rd.

only those travel time data that exceed the upper 99.9% confidence limit. It is evident that a number of alarms are declared during the time when an incident has actually occurred (i.e. 5:30 to 5:50 AM). However, a substantial number of alarm declarations are also made between 9 AM and 9:45 AM, when no incident occurs on this section of roadway. Clearly, the travel times of vehicles traversing this section of the network have been impacted by incidents occurring elsewhere in the network, but it is not obvious where or when this incident occurred.

These results reveal a limitation of using historical data to identify incidents. Once an incident has occurred, the traffic patterns are disrupted, and disturbances may be observed in the network in the immediate vicinity of the incident and at the time of the incident. However, these disturbances may also appear after the incident has been cleared and at locations removed from the immediate incident location. Using this method of comparing observed travel times to historical data, does not provide a mechanism for identifying the location and time of the incident that is responsible for an observed traffic disruption.

In addition to the problem of correctly identifying the incident time and location responsible for observed travel time disturbances, the location of tag readers at only the entrance and exit locations, prevents the direct identification of the roadway segment on which a traffic disturbance has occurred. For example, consider the incident alarms declared between 5:30 and 5:50 AM, as illustrated in Figure 4. It is not possible, on the basis of the data presented in Figure 4, to more specifically identify the incident location, than to declare the incident to have occurred somewhere between the trip origin (in this case the eastbound mainline entrance) and the trip destination (in this case Weston Road). However, the occurrence of an incident typically impacts trips that have begun

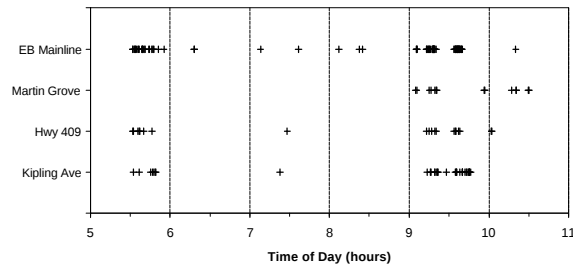


Figure 5: Distribution of incident alarms at Weston Road by time of day and origin zone

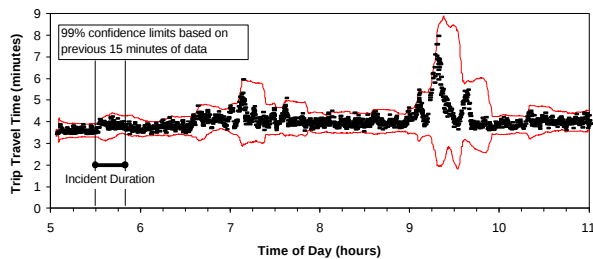


Figure 6: Incident travel times and adaptive 99.9% limits for vehicles travelling between EB mainline and Weston Rd.

at different origins and are enroute to different destination. Thus, it may be possible to examine all of the trips impacted by an incident, and then more precisely identify the location of the incident.

To illustrate, consider, Figure 5, in which the incident alarm declaration are depicted by origin and time of day. It can be noted that alarms are declared between 5:30 AM and 5:50 AM for trips originating at eastbound mainline entrance, Hwy. 409 and Islington Ave. No alarms are declared during this time for trips originating at Martin Grove. It would be expected that all trips passing through the incident site, would be impacted by the incident, while those trips originating downstream of the site, would not be impacted. In this case it appears that trips originating at Martin Grove and Islington Ave., are not impacted, however, no trips are actually observed to travel from these origins to Weston Road during this period. Thus, it can be stated that the incident is likely to have occurred between Kipling Ave. and Weston Road.

Note that it is not possible to identify whether the incident occurred in the express lanes or the collector lanes, since in the field, it is not possible to distinguish between those travel times experienced by vehicles that used the express lanes from those using the collector lanes.

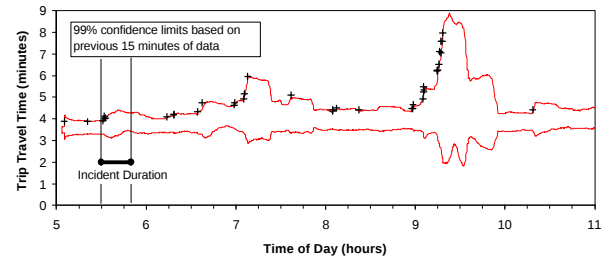


Figure 7: Alarm declarations and adaptive 99.9% limits for vehicles travelling between EB mainline and Weston Rd.

This method of identifying an incident location does not appear to be either robust or sufficiently accurate for the dispatching of emergency vehicles or for the purposes of implementing congestion management schemes.

Disaggregate Analysis: Real-time adaptive approach

The second AID method identified in Section 3 does not rely on travel time confident limits derived from historical data, but on the travel time data experienced during the past d minutes. This approach ensures that the confidence limits are adaptive to current conditions.

Figure 6 illustrates the time series of travel times obtained from the simulation model for trips entering the network at the Eastbound mainline and exiting at Weston Road South when incidents are modelled. The illustrated confidence limits are those developed on the basis of Equations 6 - 8. Comparing these confidence limits to those illustrated in Figure 2 indicates that the adaptive method provides confidence limits that respond to changes in observed travel times. In particular, note the difference in the limits between 9:15 AM and 9:45 AM.

Figure 7 illustrates the incident alarm declarations associated with the real-time adaptive AID method. It can be observed that most of the declaration are made prior to a sharp increase in the confidence limits. This characteristic results from the choice to determine the confidence limits on the basis of the observations obtained within the past d minutes. When travel times increase or decrease, the confidence limits increase. If these changes are abrupt, then the observed travel times fall outside of the confidence limits, and an incident is declared.

Aggregate Analysis

While the previous sections have illustrated the disaggregate characteristics of both the historical and adaptive AID approaches, the overall performance characteristics of these approaches has not yet been evaluated. This section presents these aggregate results, and contrasts them with the performance characteristics of a traditional loop detector based AID algorithm.

While the definition of an incident alarm declaration has been given earlier by Equations 4 and 9, the evaluation of the performance of the AID requires that a distinction be made between correct incident alarms and false alarms. Correct alarms are those that are declared at the time that an incident is actually in effect, and for a road segment on which the incident is actually located. Screening for the correct time is accomplished by comparing the time of the declaration with the log of simulated incidents. If an incident is active during the time of the declaration, then the incident is correct with respect to the temporal criteria. Testing the spatial validity of a declaration is accomplished by determining whether the vehicle providing the report traversed the longitudinal roadway segment on which the incident was located. It is not possible to distinguish between the express and collector facilities. Alarm declarations that pass both the temporal and spatial tests are declared to be correct alarms. All other alarms are declared to be false alarms.

Table 2 provides the aggregate performance characteristics of the historical and adaptive AID methods. There are three primary measures used to characterise the performance of AID algorithms, namely detection rate (DR), false alarm rate (FAR), and mean time to detect. In this study, only the DR and FAR are used to compare performance

characteristics. Mean time to detect is not used, as it is not clear what meaning this value has when applied to the AID algorithms presented in this paper. Unlike many conventional algorithms, the historical and adaptive algorithms presented herein may initiate multiple alarms for the same incident, reflecting the continued impact of the incident. However, it would not be appropriate to compute the mean time to detect on the basis of these multiple alarms for the same incident, and no mechanism has been incorporated within these simple AID algorithms, to only declare an alarm when an incident is first detected. Furthermore, the intention of this paper is to provide an initial assessment of the potential of using travel times from ETT to perform AID, not to recommend the most appropriate travel time based AID algorithm.

Table 2 also provides performance measures for the McMaster AID algorithm, a leading conventional AID algorithm that is based on spot loop detector measures. These results were obtained by coding the McMaster algorithm on the basis of descriptions of the algorithm provided in the literature, and applying this algorithm to the detector data obtained from the simulation model. It must be noted that this coded version of the McMaster algorithm may differ from the commercial version of the algorithm. A detailed description of the application of this algorithm to this network is available elsewhere [5].

The results in Table 2 indicate that the detection rates for the travel time based algorithms are significantly higher than the detection rate of the McMaster algorithm. However, the off-line FARs for the travel time based AID algorithms are more than two orders of magnitude higher than the off-line FAR for the McMaster algorithm. The on-line FARs are similar for all three AID algorithms.

Table 2: Aggregate comparison of AID algorithm performance characteristics

Parameter		Travel Time Based		Loop Detector Based
		Historical	Adaptive	McMaster ¹
Number of incidents	A	8	8	75
Incidents detected	B	6	5	28
Detection rate ($B/A \times 100\%$)	C	75%	62.5%	37.3%
Correct alarms	D	1,174	484	28
False alarms	E	25,686	4,068	473
Number of tests	F	197,040	197,055	2,235,600 ²
Off-line FAR ($E/F \times 100\%$)	G	13.0%	2.1%	0.0212%
On-line FAR ($E/(D+E) \times 100\%$)	H	95.6%	89.4%	94.4%

¹ Data obtained from reference [5]

² $10 \text{ runs} \times 6 \text{ hours/run} \times 60 \text{ minutes/hour} \times 3 \text{ tests/minute} \times 207 \text{ detectors} = 2,235,600$

Table 3: Detection status for each incident

Incident	Duration (min)	Detected by Algorithm?		
		Historical	Adaptive	McMaster
A	20	Yes	Yes	Yes
B	20	Yes	Yes	
C	1	Yes	Yes	
D	20	Yes	Yes	
E	1	Yes	Yes	
F	1			
G	20	Yes		
H	1			

The results for the travel time based algorithms are based on a small data set containing only 8 incidents. As such, the results provided in Table 2 are intended to give only a preliminary assessment of the potential of travel time based AID, rather than to provide absolute performance statistics.

Despite the limited data on which this analysis is based, it is instructive to examine the characteristics of the incidents that were and were not detected. Table 3 provides such a listing for each of the three AID algorithms. These data, in conjunction with the incident characteristic data provided in Table 1, indicate that the incidents, that the travel time based algorithms tend not to correctly detect, are those incidents of very short duration (i.e. 1 minute). It is also interesting to note that although the McMaster algorithm had an overall detection rate of 37.3%, its detection rate on just the 8 incident sample that the travel time based algorithms were tested on, was only 12.5%.

6. CONCLUSIONS AND RECOMMENDATIONS

The opportunity for obtaining individual vehicle travel time data from ETT enables a whole new generation of AID algorithms to be developed. This paper has examined the potential that these travel time AID algorithms may achieve. The examination described in this paper has been preliminary, rather than comprehensive, however, it has been illustrated that even very simple algorithms, based on estimating statistical confidence limits, can provide results that, when compared with existing loop detector based algorithms, indicate potential for improving existing AID.

It has been demonstrated that the location of tag reader can have a significant impact on AID algorithm performance. In particular, without

mainline readers, data streams must be segregated by origin and destination and analysed separately, reducing the number of observations available. Furthermore, without mainline readers, it is very difficult to identify the location of an incident.

It is recommended that a similar analysis be conducted assuming the presence of mainline tag readers instead of readers at ramp. This is likely to be the configuration for non-toll road facilities. Furthermore, this analysis should be extended to include more incidents.

It is also recommended that field data be obtained from a freeway facility and be characterised to determine similarities and differences between field travel time data and those obtained from the simulation model.

ACKNOWLEDGEMENTS

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