AVI Based Freeway Incident Detection

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Bruce Hellinga, Assistant Professor
Department of Civil Engineering, University of Waterloo
200 University Ave. West
Waterloo, ON N2L 3G1
Phone: 519-888-4567 Ext. 2630
Fax: 519-888-6197
Email: bhellinga@uwaterloo.ca

and

Geoff Knapp
IBI Group
230 Richmond Street West, 5th Floor
Toronto, ON M5V 1V6

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Bruce Hellinga, Assistant Professor
Department of Civil Engineering, University of Waterloo
200 University Ave. West, Waterloo, ON N2L 3G1
Phone: 519-888-4567 Ext. 2630 Fax: 519-888-6197 Email: bhellinga@uwaterloo.ca
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230 Richmond Street West, 5th Floor
Toronto, ON M5V 1V6

ABSTRACT

The recent emergence of automatic vehicle identification (AVI) technology for use in electronic toll collection has provided an opportunity to develop automatic incident detection (AID) methods that rely on individual vehicle travel time data rather than loop detector data.

This paper examines the performance of three AVI based AID algorithms. Travel time data for testing the algorithms was obtained by simulating a 12-km section of the collector facility of Highway 401 in Toronto, Canada. The results from the three AVI based AID algorithms are compared to the performance of a leading loop detector based algorithm, which was independently tested on similar simulated data. The AID performance results indicate that AVI based AID can provide similar incident detection performance as existing loop detector based AID methods.

INTRODUCTION

Most urban freeways throughout North America are heavily utilised and experience ever increasing congestion during the peak commuting periods. Recurrent congestion results from high traffic demands and limited roadway capacity. Non-recurring congestion results from the occurrence of unexpected events (incidents) such as collisions, stalled vehicles, or material spills. The U.S. Federal Highway Administration estimates that approximately 60% of travel time lost to congestion is a result of incidents and the percentage is believed to be increasing (Lindley, 1987).

The early detection of incident events minimises the delay experienced by drivers, wasted fuel, emissions, and lost productivity, and also reduces the likelihood of secondary collisions. The goal of automatic incident detection (AID) is to minimise the human requirements in the efficient and effective detection of incident events.

The emergence of automatic vehicle identification (AVI) technology has provided a new and previously unavailable form of real-time traffic data, namely individual vehicle travel times. This paper examines three freeway AID algorithms that rely on vehicle travel time data obtained from AVI equipped vehicles. The performance of these algorithms is compared to a leading conventional AID algorithm that relies on data obtained from in-road inductive loop detectors.

<u>Nomenclature</u>

i	20-second interval
j	Road segment reference (section of roadway between 2 AVI antennae)
t	time of day
t_{ti}	segment travel time reported by an AVI equipped vehicle at time t during interval i
n_i	number of AVI equipped vehicle reports received during interval i
d	duration of the comparison window
n_d	number of intervals within comparison window of duration d
$\bar{t}_i$	mean interval travel time for all AVI equipped vehicles in interval i
$\bar{t}_d$	mean of all mean interval travel times $\bar{t}_i$ in comparison window
var_d	variance of all mean interval travel times $\bar{t}_i$ in comparison window
s_d	log-normal variance of $\bar{t}_i$ in comparison window
m_d	log-normal mean of $\bar{t}_i$ in comparison window
z	z value associated with the level of confidence
UL_i	upper confidence limit for the mean travel time for interval i

Structure of the Paper

The following section describes the network and the data that were used for testing the proposed AVI algorithms. This is followed by a description of the three proposed algorithms. Algorithm performance results are presented and compared to a conventional loop detector based AID algorithm. In the last section, conclusions are made and recommendations are provided.

DATA FOR EVALUATING THE PROPOSED AVI BASED AID ALGORITHMS

This section describes the simulated data and the different parameter values used to test and calibrate the three proposed AVI based AID algorithms. The data for testing the algorithms was generated using a simulation model because no AVI field data were available. The use of a simulation model also provides the following benefits:

1. Complete knowledge of true incident start and end times.
2. Control over the number, location, severity, and duration of incidents within the evaluation data set.
3. Ability to test algorithm performance for a range of level of market penetration (LMP) of AVI equipped vehicles.

Network Description

The network used in this study is modeled after eight interchanges along a 12-km freeway section of 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 traveled freeways in North America. This freeway section includes an express facility and parallel collector facility. Initial simulation results on this network exhibited unrealistic congestion patterns, which were attributed to limitations in the model's route selection capabilities. Consequently, the network was modified to provide only a single route from any origin to any destination with the result that only the collector facility was modeled for this study. As illustrated in Figure 1, the eastbound and westbound freeway directions are both divided into 10 segments approximately 1.2 km in length with AVI roadside antennas at both ends of each segment.

The network was simulated using the Integration traffic simulation model (Van Aerde, 1998). The origin-destination traffic demand was constructed to replicate the build up of the AM peak from 5:30 AM to 10:30 AM. A total of 101,142 vehicle trips were simulated during this 5 hour time period. The network experiences severe recurring congestion at several locations during the simulation. This permits the testing of AID during both uncongested and congested traffic conditions.

As an AVI equipped vehicle passes a roadside antenna the vehicle is uniquely identified through wireless communication between the vehicle's transponder and the antenna. Since an AVI equipped vehicle can be uniquely identified, its travel time between antennas can be calculated. If a vehicle is not equipped with a transponder, the roadside antenna can not communicate, and no data can be collected for the vehicle.

The simulation model permits tracking of the link travel times of individual vehicles. The model was run assuming travel times could be obtained for all vehicles. A post processor was developed to combine the individual link travel times for each vehicle to produce a travel time associated with each roadway segment between AVI antennas. Travel time reports were not created for vehicles that failed to pass the upstream antenna on a segment (i.e. vehicle entered the segment via an onramp downstream of the antenna) or failed to pass the downstream antenna on a segment (i.e. exited the freeway via an off-ramp upstream of the antenna). The resulting data sets provided individual segment travel times by time of day assuming all vehicles were equipped with AVI transponders. When the AVI AID algorithms were tested, samples of vehicles were selected from this data set according to the LMP assumed. This time-series of data was considered representative of the time-series of data that would be received by a traffic management centre in real-time. Figure 2 illustrates typical individual vehicle segment travel time data obtained from the simulation for vehicles traversing the westbound direction of Highway 401 between Highway 400 and

Weston Road. These data also illustrate the impact on vehicle travel times of an incident that occurs on this segment from 7:30 AM to 7:40 AM. The second peak in travel times (between 8 and 9 AM) is a result of recurrent congestion.

Incident Data

In addition to the base non-incident case, twenty-four separate incident scenarios were simulated, resulting in a total of 125 hours of simulated traffic conditions. All the scenarios used the same network and O-D demand characteristics. However, each incident scenario included the modelling of 5 unique incidents, for a total of 120 simulated incidents. The key characteristics of these 120 incidents were varied, included incident location (20 locations), duration (5, 10, 20, and 30 minutes), time of day (60 during peak and 60 during off-peak), severity (100 single lane closures and 20 two-lane closures on roadways have three lanes), and traffic conditions.

PROPOSED AVI BASED ALGORITHMS

Three algorithms have been developed for examination in this paper, the *Confidence Limit Algorithm*, the *Speed and Confidence Limit Algorithm*, and the *Dual Confidence Limit Algorithm*. All algorithms are based on travel time data from AVI equipped vehicles. The algorithms can be considered to be statistical time-series models. The premise for all three models is that the travel time experienced by vehicles over a section of roadway increases more rapidly as a result of a change in capacity (i.e. such as the reduction in capacity that results from the occurrence of an incident) than it does as a result of a change in demand. Therefore, each of these algorithms attempts to characterise the mean and variance of the travel times associated with the traffic conditions prior to an incident. When an incident occurs, the traffic situation from which the travel times result, is changed and the statistical characteristics also change. Thus, the travel times resulting from traffic conditions prior to an incident can be thought of as belonging to one population, and those from traffic conditions after an incident has occurred, belonging to another population. The proposed algorithms attempt to determine if reported travel times are outside of the confidence limits associated with the current population, and if so, it is assumed that an incident has occurred.

For all three algorithms, the individual AVI travel time reports were aggregated over 20-second time intervals. Aggregation was carried out to reflect practical implementation requirements. If aggregation were not carried out, the AID algorithm would need to be applied each time an AVI report was received. For the data illustrated in Figure 2, a total of 13,307 AVI reports would be received for this section during the 5 hours of simulation if all vehicles were AVI equipped. This would mean the algorithm would need to be applied, on average, every 0.5 seconds. Furthermore, for multiple lane roadways, if two AVI equipped vehicles passed the AVI antenna at the same time, the algorithm would need to be applied twice during the same time instance. Clearly this is not desirable. An aggregation time interval duration of 20-seconds was chosen as it corresponds to the polling frequency of most loop detector systems. Thus a mean AVI interval travel time (MITT) was computed for each interval on the basis of all of the AVI travel time reports received during the interval (Equation 1). All algorithms were then applied to each roadway segment every 20-second interval. Figure 3 illustrates the resulting mean interval travel time data corresponding to the individual vehicle travel time data illustrated in Figure 2 assuming LMP = 10%.

$$\bar{t}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} t_{ti} \tag{1}$$

<u>Confidence Limit Algorithm</u>

The *Confidence Limit Algorithm* characterises the time-dependent stochastic process on the basis of recently acquired travel time data by computing the mean and variance of mean interval travel times from the previous *N* intervals. The mean interval travel times contained within the previous *N* intervals is referred to as the *comparison window*. It is assumed that the individual mean interval travel times are log normally distributed. The log-normal mean (Equation 4) and variance (Equation 5) of the mean interval travel times contained within the comparison window are used to establish an upper confidence limit for the mean segment travel time of the interval following the comparison window (Equation 6). The validity of this approach relies on the assumption that the underlying mean of the mean interval travel time distribution does not change during the comparison window and the interval for which the confidence limit is being estimated. The likelihood of this assumption being violated increases as the duration of the comparison window increases.

$$\bar{t}_d = \frac{1}{n_d}\sum_{j=1}^{n_d}\bar{t}_i \tag{2}$$

$$\mathrm{var}_d = \sqrt{\frac{1}{n_d - 1}\sum_{j=1}^{n_d}\left(\bar{t}_i - \bar{t}_d\right)^2} \tag{3}$$

$$m = \ln\left(\bar{t}_d\right) - 0.5 s_d^{\,2} \tag{4}$$

$$s_d^{\,2} = \ln\left(1 + \frac{var_d}{\bar{t}_d^{\,2}}\right) \tag{5}$$

$$UL_i = e^{\left(m_d + z s_d\right)} \tag{6}$$

When performing AID in real-time, the mean interval travel time is calculated for the current interval and is compared to the upper confidence limit calculated for the corresponding comparison window. If the mean interval travel time (MITT) is greater than its corresponding upper limit, it can be stated with a specified level of confidence (z) that the current MITT has resulted from a process other than that associated with the conditions experienced during the comparison window. Consequently, it is assumed that an incident has occurred.

A persistence check can be used so that an alarm is not called until a predefined number of consecutive intervals have a mean interval travel time greater than the corresponding upper confidence limit. Figure 4 illustrates the application of the *Confidence Limit Algorithm* to the mean interval travel time data depicted in Figure 3.

Speed and Confidence Limit Algorithm

The *Speed and Confidence Limit Algorithm* is similar to the *Confidence Limit Algorithm*, but requires the additional capability to capture vehicle speeds as they pass roadside antennas. The speed data does not have to be limited to the AVI equipped vehicles and can be collected by a variety of different sources. These sources include radar, wide area video detection, or even inductive loop detectors. In this research it has been assumed that speed data are obtained from only AVI equipped vehicles. The mean speed of AVI equipped vehicles is calculated for each interval, as well as for the comparison window.

When an incident occurs, the capacity at that location decreases. The decreased capacity at an incident is likely to create congestion upstream of the incident and reduce the flow downstream of the incident. The decrease in flow downstream is in turn likely to allow an increase in speed downstream. Therefore, if an incident occurs on a segment it is likely that the speed of the vehicles exiting the segment will increase.

Using the same process as the *Confidence Limit Algorithm*, the *Speed and Confidence Limit Algorithm* determines whether a mean interval travel time is greater than the corresponding confidence limit. If the mean interval travel time exceeds the confidence limit, then an alarm is called only if the mean speed of vehicles exiting the segment during the interval is greater than the mean vehicle speed for the comparison window.

Dual Confidence Limit Algorithm

The *Dual Confidence Limit Algorithm* differs from the *Confidence Limit Algorithm* in its use of the comparison window. In the *Confidence Limit Algorithm* the comparison window always includes the previous *N* intervals regardless of the outcome of the decision of whether or not the mean interval travel time for the current interval is statistically part of the comparison window population. The *Dual Confidence Limit Algorithm* attempts to exclude mean interval travel times from the comparison window when these data exceed a confidence limit threshold. Figure 5 illustrates this process.

Figure 5 illustrates the mean interval travel time data previously illustrated in Figure 3 between 7:15 AM and 7:40 AM. For this particular application of the algorithm, a comparison window duration of 760 seconds (38 intervals) is used. Two confidence limits, the *Window Limit* and *Alarm Limit*, are computed on the basis of the data contained within the comparison window.

When a mean interval travel time is greater than the *Window Limit*, then it is hypothesised that this mean interval travel time belongs to a different population and consequently the comparison window is not moved forward one interval when testing the next interval. To illustrate, consider mean interval travel time point *A* in Figure 5. The mean interval travel times contained within Comparison Window 1 are used to compute a *Window Limit* and *Alarm Limit*. Point *A* is greater than the *Window Limit*, but not the *Alarm Limit*, so no alarm is declared, but the comparison window does not advance when assessing the next interval (Point *B*). Points *B*, *C*, *D*, *E*, and *F* are all greater than the *Window Limit*, so Comparison Window 1 is used for all of these intervals. A maximum stationary time of 8 interval was chosen. Thus, for interval G the maximum stationary time has been exceeded and the window is advanced (Comparison Window 2).

Using the described logic, the *Dual Confidence Limit Algorithm* declares 5 alarms during the 10-minute duration of the incident, compared to 8 alarms from the *Confidence Limit Algorithm* (Figure 4).

Parameters Varied in Testing the Algorithms

For each level of market penetration the duration of the comparison window, the confidence level and the number of persistence checks were varied. As illustrated in Table 1, the initial testing of the algorithms was performed for a total of 27 different parameter combinations for each level of market penetration. Based on the results from these initial tests, a second set of 27 parameter combinations (Table 1) was also tested for each level of market penetration.

RESULTS

The level of market penetration of AVI equipped vehicles on a facility can vary significantly. Therefore, the three proposed algorithms were each tested at 6 different levels of market penetration (1%, 5%, 10%, 25%, 50% and 100%). A total of 54 combinations of the three control parameters (comparison window duration, confidence limit, and persistence checks) were evaluated for each algorithm at each of the 6 levels of market penetration.

Three primary measures of performance, namely detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD) are used to evaluate AID algorithms. The detection rate is defined as the number of incidents correctly detected by the AID algorithm divided by the total number of incidents known to have occurred during the observation period. The off-line false alarm rate is calculated by dividing the number of false alarms by the total number of alarm tests during the observation period. The mean time to detect is computed as the average length of time between the start of the incident and the time the alarm is initiated. When multiple alarms are declared for a single incident, only the first correct alarm is used for computing the detection rate and the mean time to detect.

AVI Algorithm Results

Detection rate, false alarm rate, and mean time to detect were computed for 54 parameter combinations for each level of market penetration for each algorithm. Figure 6a illustrates the detection rate versus false alarm rate for the *Speed and Confidence Algorithm* for a level of market penetration of 10%. It is clear from these results that a wide range of detection rates can be obtained depending on the false alarm rate deemed acceptable. For this research, a maximum false alarm rate of 0.2% was considered acceptable. Therefore, the performance of all algorithms was evaluated on the basis of maximising the detection rate while ensuring the false alarm rate ≤ 0.2%. Figure 6b illustrates the same performance results as Figure 6a but for only those parameter combinations that provide a false alarm rate of ≤ 0.2%.

Table 2 provides a summary of the algorithm performance results for the parameter combinations that provided the highest detection rate, while providing an off-line false alarm rate of less than 0.2%, for each level of market penetration, for all three algorithms. Figures 7a and 7b depict the associated detection rate and false alarm rate (expressed as the number of false alarms per km per hour) respectively.

<u>Comparison to Loop Detector Based AID Algorithms</u>

The performance results provided in Table 2 can be compared to the performance provided by leading loop detector based algorithms. A number of loop detector based algorithms have been developed, including comparative algorithms such as the California Algorithms (Payne and Tignor, 1978), and the McMaster Algorithm (Gall and Hall, 1989); neural network algorithms (Ritchie and Cheu, 1993; Stephanedes and Liu, 1995); fuzzy logic algorithms (Chang and Wong, 1994); and data smoothing algorithms (Chassiakos and Stephanedes, 1993).

The McMaster Algorithm was chosen as the basis of comparison for this research for the following reasons:

- The algorithm is currently being used by the Ministry of Transportation of Ontario as part of the COMPASS freeway traffic management system along this section of Highway 401 in Toronto.
- Previous research (Rakha and Van Aerde, 1996) compared the performance of the McMaster Algorithm on Highway 401 using field data and simulation data using a similar network.

The McMaster algorithm, developed by Dr. Fred Hall at McMaster University maps current detector data on predefined regimes on the detector volume vs. occupancy domain. Two separate templates, defining the six flow-occupancy regimes, are used depending on the location of the station with respect to recurring congestion.

The McMaster algorithm has undergone comprehensive testing on two occasions on the Queen Elizabeth Way (QEW) in Mississauga, Canada (Hall *et al.*, 1993). The first test was conducted off-line using 39 days of field data and the second test was conducted on-line over 64 days in 1992. The off-line testing resulted in a detection rate of 60% at an off-line false alarm rate of 0.001%, with a mean time to detect of approximately 2 minutes. On-line testing resulted in a detection rate of 68%, an off-line false alarm rate of 0.00078%, and a mean time to detect of 2.1 minutes. It should be noted however that a large number of incidents that were not detected by the algorithm, were omitted from the analysis for a variety of reasons. Had these incidents been included in the analysis, the detection rate would likely have been much lower. It is not clear what impact including these incidents would have had on the false alarm rate.

Independent testing of the McMaster algorithm was conducted on the same section of Highway 401 in Toronto that was used in this paper (Rakha and Van Aerde, 1996). This section is also part of the Highway 401 COMPASS freeway traffic management system, which uses the McMaster algorithm for AID. It should be noted however that both the collector and express facilities are included in the COMPASS system and were considered for the independent testing, but only the collector facility is used in this research. Rakha and Van Aerde coded the McMaster algorithm based on information provided in the literature (Gall and Hall, 1989; Hall *et al.*, 1993) and therefore their algorithm may not necessarily coincide directly with the proprietary McMaster logic used by the COMPASS system at the time of their study.

The coded McMaster algorithm was calibrated and tested on one week (168 hours) of field data obtained from the COMPASS system in order to verify that the performance of the coded algorithm was consistent with the performance of the algorithm in the field for the same data. A comparison of the two algorithms can be found in Table 3. A total of 26 incidents were included in the field data, and of these 26 incidents the coded McMaster algorithm detected 10 incidents compared to 11 incidents detected by the McMaster algorithm used by the COMPASS system in the field. This is a difference of less than 4%

in the detection rate. The false alarm rates are also comparable. The difference in performance of the McMaster algorithm on Highway 401 compared to the QEW is believed to be due to the more complex nature of Highway 401.

The coded McMaster algorithm was then tested using 60 hours of simulated data from a network based on the collector and freeway facilities of the same section of Highway 401. The results of this test are also illustrated in Table 3 and were compared to the results from the field data in order to verify that simulated data produced similar results. The simulation included 75 incidents during 60 hours, a shorter period than was used for testing with field data, and therefore there were correspondingly fewer alarm checks. It was concluded that the performance of the coded McMaster algorithm was similar for both field data and simulated data on the basis that the detection rates were within 2% of each other. However, the false alarm rate was much higher for the simulated data. Two potential causes of this discrepancy were identified. First, the smaller amount of data (60 hours versus 168 hours) resulted in a smaller denominator in computing the off-line false alarm rate for the simulated versus field data. Second, the larger number of incidents (75 versus 26 incidents) resulted in more false alarms as a result of shockwaves that are generated by the incidents.

The simulated data used for testing the AVI based AID algorithms presented in this paper (120 incident in 120 hours of data) was obtained from Integration, the same simulation model used in the study by Rakha and Van Aerde. It is speculated that the characteristics of the simulated data that resulted in a much higher off-line false alarm rate in the work by Rakha and Van Aerde, are also likely to increase the off-line false alarm rate results obtained in this research. Therefore, the performance of the coded McMaster algorithm on simulated data, as reported by Rakha and Van Aerde, instead of field data is used as a comparison for the results of the AVI based AID algorithms.

As illustrated in Table 2, the off-line false alarm rate for the McMaster algorithm is almost an order of magnitude smaller than the results obtained in this study. However, the McMaster off-line false alarm rate is based on a greater number of alarm checks since the inductive loop detectors are spaced closer together than are the AVI roadside antennae modelled for testing the AVI based algorithms. In order to reasonably compare the results, this off-line false alarm rate is converted to a value of false alarms (FA) per km, per hour (FA/km/hr). The network modelled for the coded McMaster algorithm was composed of approximately 12 km of express facilities and 8 km of collector facilities, for a total network length of 20 km in each direction (Rakha and Van Aerde, 1996). The testing of the coded McMaster algorithm on this network resulted in 473 FA during the 60 hours of simulation. This results in a false alarm rate of approximately 0.20 FA/km/h at a detection rate of 37.3%.

The false alarm rate results of the AVI based algorithms presented in Table 2 have been similarly converted, based on a total network length of 12 km in each direction and 120 hours of simulated data.

<u>Discussion</u>

Table 2 and Figure 7a indicate that the detection rates of the *Speed and Confidence Limit Algorithm* are substantially higher than the other AVI algorithms and the McMaster Algorithm for all levels of market penetration. Figure 7b illustrates the corresponding false alarm rates, indicating that for the parameter values chosen, approximately 75% of the results produced higher false alarm rates than the McMaster algorithm. However, it should be noted that while the false alarm rate is higher for many of the cases, the maximum false alarm rate is only 0.3 FA/km/hr compared to the McMaster false alarm rate of 0.2 FA/km/hr. In addition, the false alarm rates for the AVI algorithms are primarily dictated by the cut-off value of 0.2% selected. If a lower cut-off value had been selected, a lower false alarm rate would have been obtained for all levels of market penetration, albeit at the expense of a lower corresponding detection rate.

These results indicate that the addition of a vehicle speed check to the base *Confidence Limit Algorithm* provides substantially better AID performance (almost twice the detection rate) without an significant increase in the false alarm rate.

Variability of Performance

The AVI algorithm results presented thus far reflect a single application of each algorithm to the 120 hours of simulated traffic conditions for each parameter and level of market penetration combination. Since the algorithms rely on stochastic sampling, an investigation was conducted into the sensitivity of algorithm performance as a function of this random sampling. The *Speed and Confidence Limit Algorithm* was applied 15 times to the 120 hours of data for each of the 6 levels of market penetration (comparison window duration = 900 seconds; confidence limit (z) = 2.5; persistence = 0). For each application, a different random sample of vehicles was assumed to be AVI equipped. Figure 8 illustrates the resulting variation in detection rate, false alarm rate, and mean time to detect.

Four observations can be made on the basis of Figure 8:

1. There is a significant improvement in detection rate as level of market penetration increases from 1% to 5%. There is an addition small improvement as the level of market penetration increases to 10%. Detection rate remains almost constant for levels of market penetration greater than 10%.
2. As level of market penetration increases, the false alarm rate also increases. This is likely because at low levels of market penetration, the sample mean interval travel time is a relatively inaccurate estimate of the true population interval travel time, thus increasing the computed confidence limit and reducing the false alarm rate.
3. The mean time to detect decreases continuously with increasing level of market penetration, with mean time to detect decreasing by approximately 35% with an increase in level of market penetration from 1% to 25%.
4. The degree of variability of the results associated with random sampling does not appear to be large, with an average coefficient of variation of approximately 0.09 for detection rate, false alarm rate, and mean time to detect for all levels of market penetration.

A primary operational advantage of the AVI based AID algorithms is that the surveillance infrastructure can be maintained without lane closures and is not affected by pavement resurfacing, unlike loop detectors which generally require replacement after pavement rehabilitation.

Furthermore, the collection of travel time data for AVI based AID can also be used as primary inputs to ATIS.

CONCLUSIONS AND RECOMMENDATIONS

The research described in this paper provides the basis for the following conclusions:

1. Simulation models provide the opportunity to create engineered data sets for testing that contain a defined number and type of incidents and traffic conditions. Furthermore, simulation models enable testing of algorithms under conditions (e.g. levels of market penetration) that do not yet exist in the field.

2. Simulated data may contain unique characteristics that result in improved or deteriorated AID algorithm performance, as compared to field performance. However, it is reasonable to expect that the performance of one algorithm relative to another algorithm would remain consistent under simulated conditions and field conditions.

3. The *Speed and Confidence Limit Algorithm* provided the highest detection rate for all levels of market penetration when compared with the other AVI algorithms. Furthermore the detection rate and false alarm rate of the *Speed and Confidence Limit Algorithm* are comparable to those of the loop-detector based McMaster Algorithm.

4. For the conditions examined within this paper, maximum detection rate was obtained for a level of market penetration of 10%, while the mean time to detect continued to decrease as the level of market penetration increased.

It is recommended that once available, field data be used to test and further develop AVI based AID and that the impact of factors such as antennae placement be quantified. It is also recommended that a comparative AVI algorithm be developed in which the conditions of downstream segments are examined prior to declaring an alarm in order to determine if the increase in travel time on the current segment is a result of queue spill-back from an incident on a downstream segment.

ACKNOWLEDGEMENT

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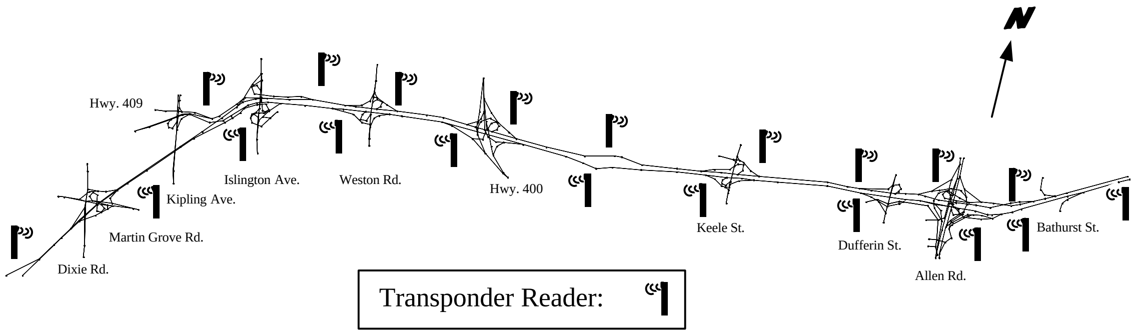


Figure 1 – Simulation Network

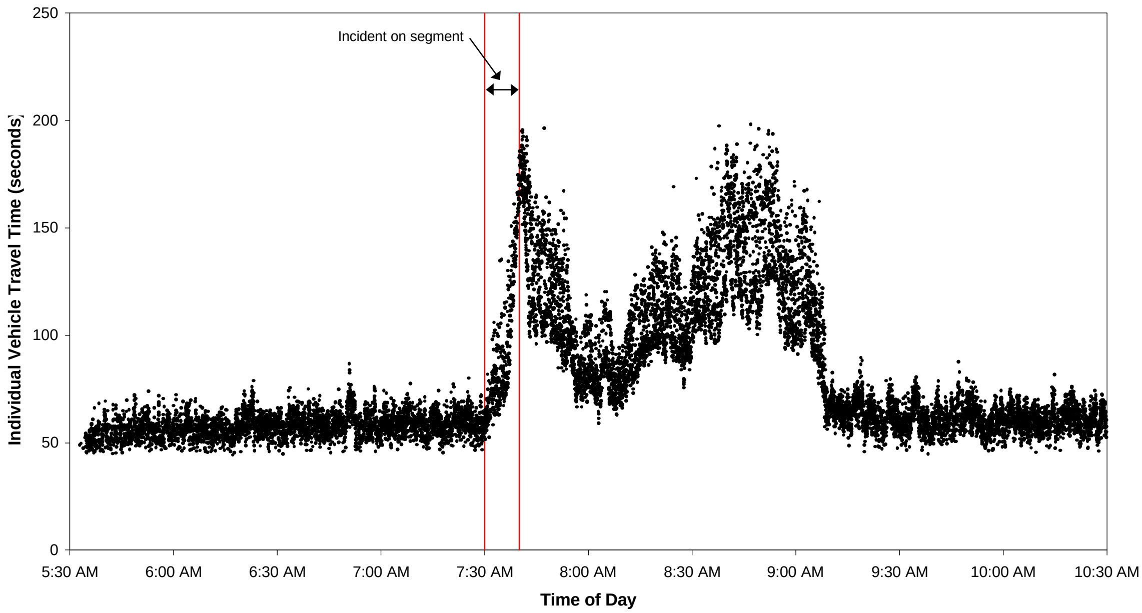


Figure 2: Sample simulated AVI vehicle travel time data

(WB between Hwy 400 and Weston Rd.)

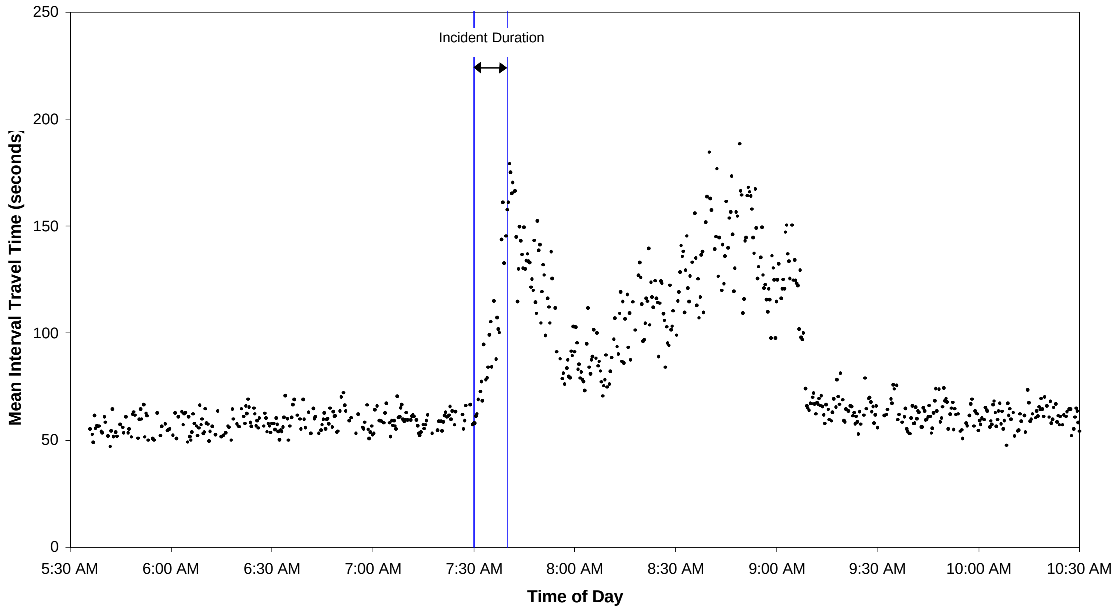


Figure 3: Sample mean interval travel time data for LMP = 10%
(WB between Hwy 400 and Weston Rd.)

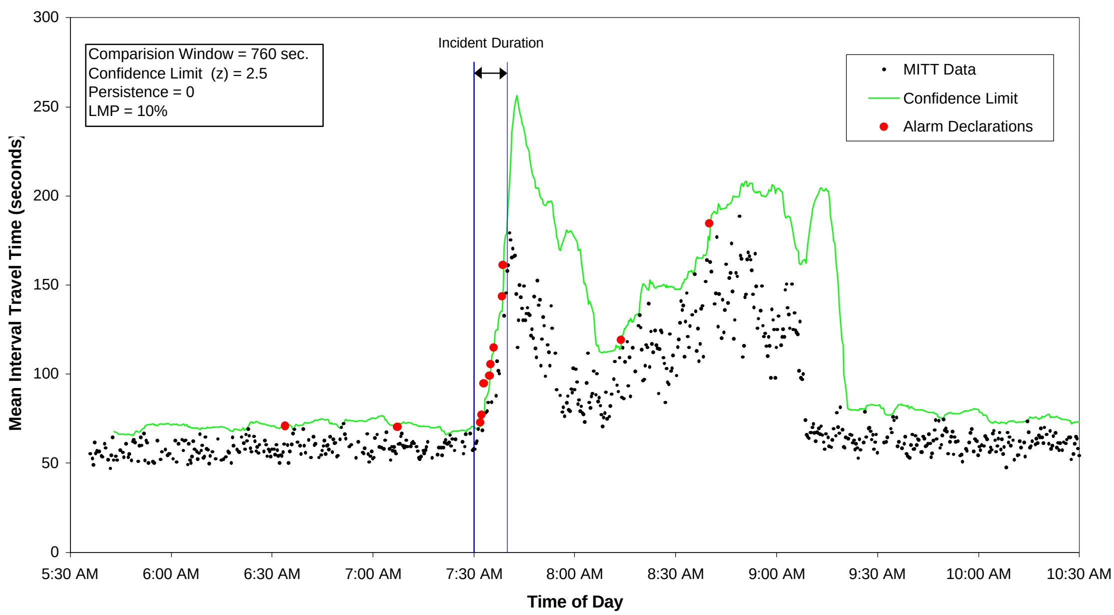


Figure 4: Application of the *Confidence Limit Algorithm* to a Specific Incident
(WB between Hwy 400 and Weston Rd.)

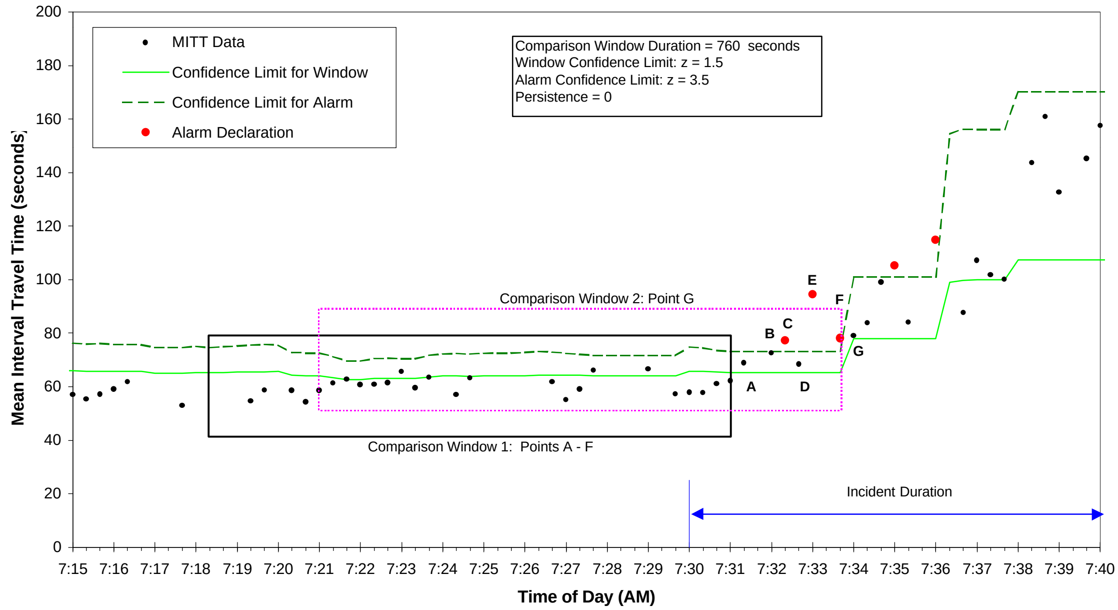
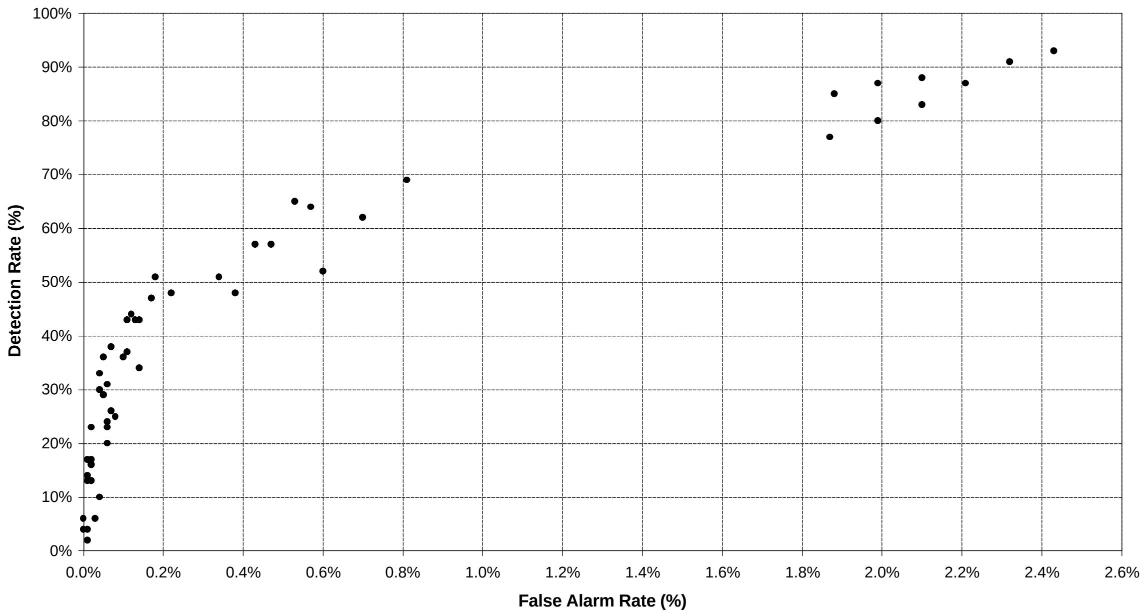
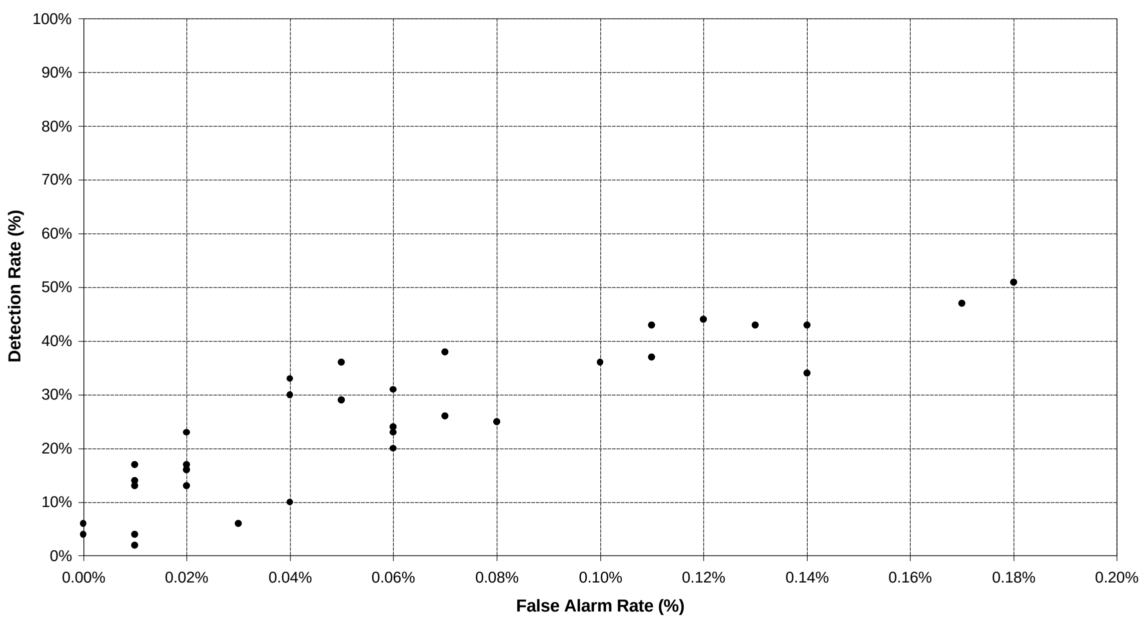


Figure 5: Illustration of Dual Confidence Limit Algorithm Logic

(LMP = 10%; WB between Hwy 400 and Weston Rd.)



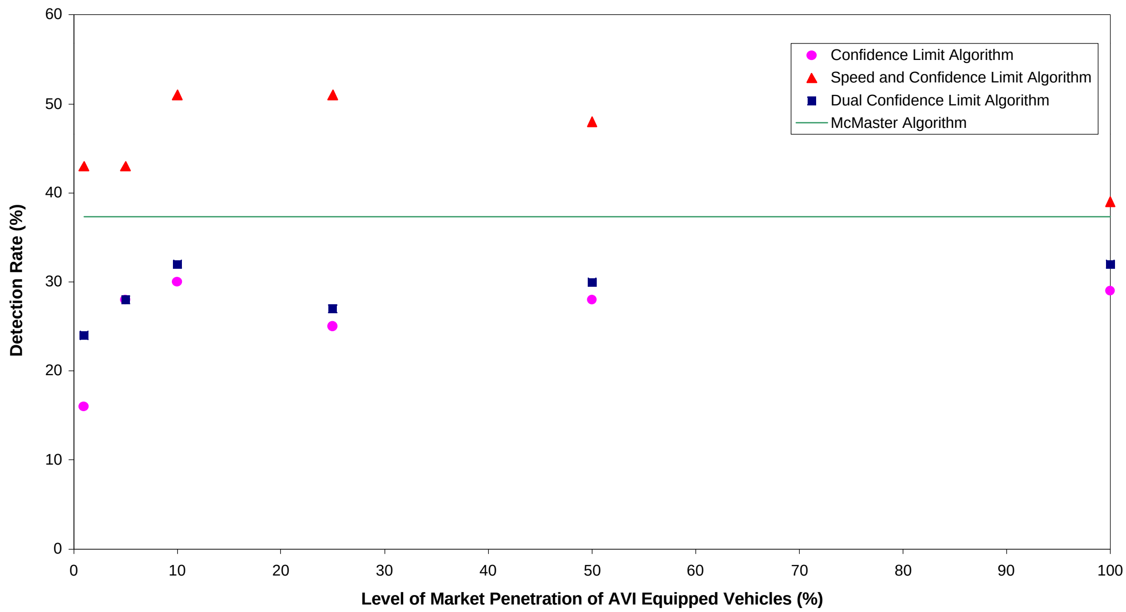
(a) Results for all 54 parameter combinations



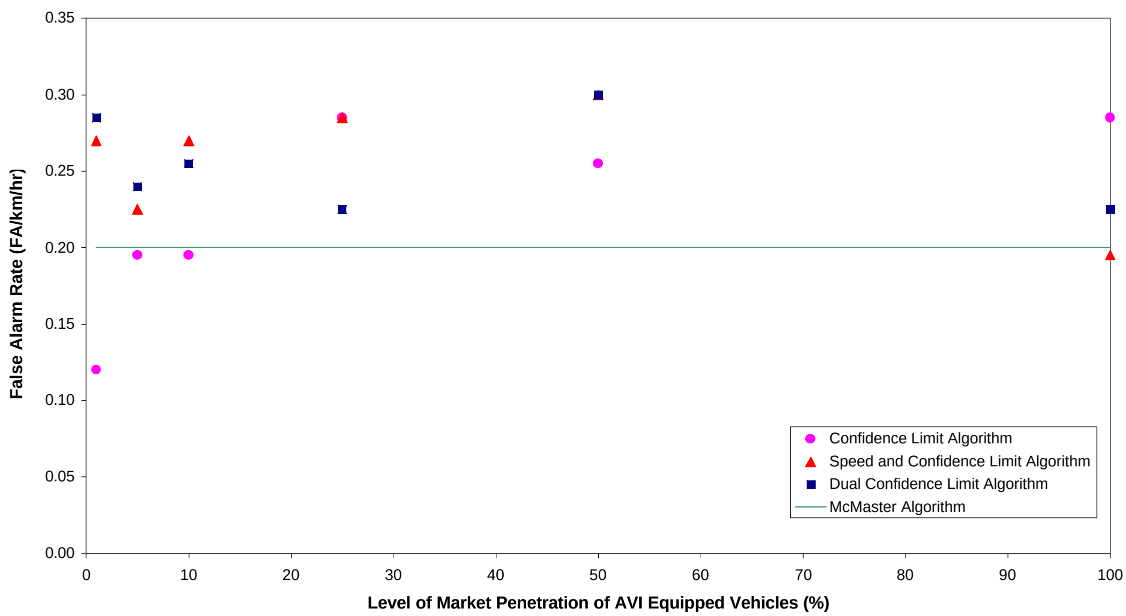
(b) Results for only those combinations with a false alarm rate ≤ 0.2%

Figure 6: Detection Rate versus False Alarm Rate

(Speed and Confidence Limit Algorithm; LMP = 10%)

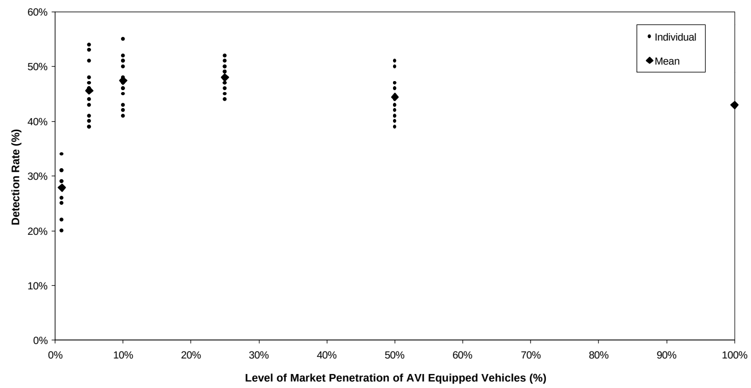


(a) Detection rate as a function of level of market penetration

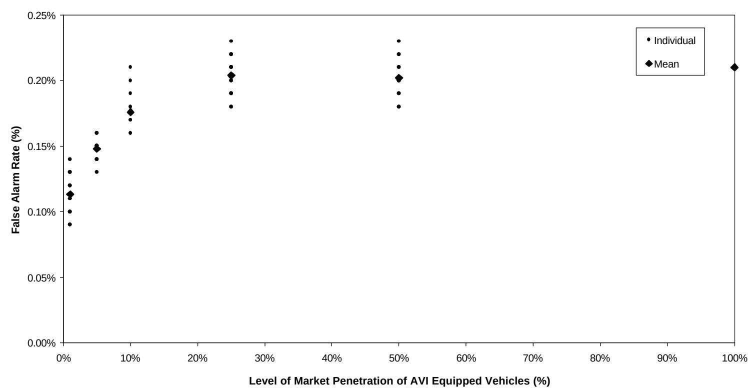


(b) False alarm rate as a function of level of market penetration

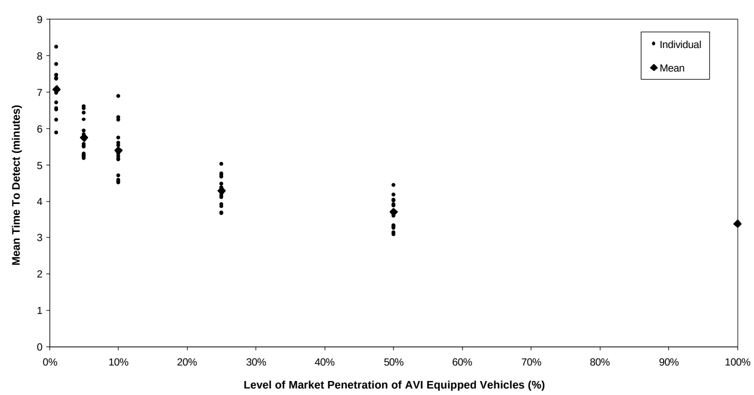
Figure 7: Comparison of AVI algorithm detection rate and false alarm rate with the McMaster loop detector based algorithm



(a) Variability in detection rate



(b) Variability in false alarm rate



(c) Variability in mean time to detect

Figure 8: Variability in performance as a function of random sampling

(*Speed and Confidence Limit Algorithm***)**

Table 1: Algorithm Parameter Combinations Tested

Initial Set of Parameter Combinations				
	Confidence Limit	*Speed & Confidence Limit*	*Dual Confidence Limit*	
			Low	High
Confidence Level (z)	1.28, 1.96, 3.08		1.28 1.28 1.96	1.96 3.08 3.08
Comparison Window Duration (sec)	300, 600, 1800			
Persistence Checks	0, 1, 2			
Second set of Parameter Combinations				
	Confidence Limit	*Speed & Confidence Limit*	*Dual Confidence Limit*	
			Low	High
Confidence Level (z)	2.5, 2.75, 3.25	2.5, 2.75, 3.25	1.5 2.0 2.5	3.5 3.5 3.5
Comparison Window Duration (sec)	460, 760, 900	460, 760, 900	760, 900, 1200	
Persistence Checks	0, 1, 2	0, 1, 2	1, 2, 3	

Table 2 – AID Results as a Function of the Level of Market Penetration

	LMP	DR	MTTD	Off-line FAR	
	(%)	(%)	(minutes)	(%)	(FA/km/h) [a]
Confidence Limit Algorithm	1	16	9.30	0.08	0.12
	5	28	4.94	0.13	0.20
	10	30	3.37	0.13	0.20
	25	25	2.99	0.19	0.29
	50	28	2.27	0.17	0.26
	100	29	2.44	0.19	0.29
Speed and Confidence Limit Algorithm	1	43	7.12	0.18	0.27
	5	43	5.89	0.15	0.23
	10	51	4.82	0.18	0.27
	25	51	4.01	0.19	0.29
	50	48	4.07	0.20	0.30
	100	39	2.94	0.13	0.20
Dual Confidence Limit Algorithm	1	24	8.70	0.19	0.29
	5	28	4.48	0.16	0.24
	10	32	4.14	0.17	0.26
	25	27	3.08	0.15	0.23
	50	30	2.93	0.20	0.30
	100	32	3.25	0.15	0.23
McMaster Algorithm	N/A	37.3 [b]	--- [d]	0.02 [b]	0.20 [c]

[a] FAR presented as false alarms per km of highway per hour.
[b] as reported by Rakha and Van Aerde,1996
[c] calculated based on data from Rakha and Van Aerde, 1996
[d] Rakha and Van Aerde, 1996 do not report MTTD.

Table 3 – Comparison of Performance of the McMaster AID Algorithm on Field Data and Simulated Data (Source: Rakha and Van Aerde, 1996)

Parameter	COMPASS McMaster Algorithm Field Data	Coded McMaster Algorithm	
		Field Data	Simulated Data
Number of Incidents	26	26	75
Number of Incidents Detected	11	10	28
Number of False Alarms	225	287	473
Number of Tests	6,259,680	6,259,680	2,235,600
Detection Rate (DR)	42.3%	38.5%	37.3%
False Alarm Rate (FAR)	0.00407%	0.00458%	0.0212%