Neural network incident detection on arterials using fusion of simulated probe vehicle and loop detector data

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ABSTRACT

This paper describes the development of neural network models for Automatic Incident Detection (AID) on arterials, using simulated data derived from Inductive Loop Detectors (ILDs) and probe vehicles. This study extends previous research by comparing the performance of various neural network architectures for data fusion and by providing a comparison of model performance for various probe vehicle penetration rates and detector configurations. Data from 108 incidents was collected from ILDs and probe vehicles at two locations on a previously validated network for two detector configurations. Configuration 1 was similar to a freeway link, while Configuration 2 conformed to the standard configuration on road networks. The best performance obtained for Configuration 1 was a Detection Rate (DR) of 59% for a False Alarm Rate (FAR) of 0.5%, for a probe vehicle penetration rate of 20%. The best performance obtained for Configuration 2 was a DR of 86% for a FAR of 0.36% for a probe vehicle penetration rate of 20%. Satisfactory performance can also be obtained using ILD data alone (DR = 86% for FAR = 0.41%). Inclusion of speed data further improves performance (DR = 90% for FAR = 0.5%) and its use when available is highly recommended. This research demonstrates the feasibility of developing a neural network model for detection of incidents on arterials using loop and probe vehicle data. Options for further study are also presented.

KEYWORDS
Automatic Incident Detection, AID, Arterials, Probe Vehicles, Loop Detectors, Neural Networks, Data Fusion, Traffic Microsimulation.

INTRODUCTION

In 1998, the cost of urban congestion to the Australian community was estimated at $5 billion annually (**1**). The number of vehicles making use of metropolitan road networks has continued to increase. The social and economic costs resulting from congestion, poor air quality, noise, delays, decreased productivity and accidents have risen accordingly. For every minute that an incident remains uncleared, it takes around four minutes for the traffic to recover (**2**). Early incident detection and prompt response, including provision of real-time traveller information and rapid dispatch of emergency services can significantly reduce the duration of an incident. This in turn reduces delays and associated air and noise pollution. Road safety is also improved, as there is less chance of secondary incidents. To facilitate early incident detection, Automatic Incident Detection (AID) systems have been developed for the freeway environment. More recently, AID systems have been under development for the more complex arterial environment.

Artificial neural networks (ANNs) are very simple models of the human brain, combining the storage of knowledge with the ability to perform calculations. They consist of assemblies of interconnected units called neurons or processing elements (PE's). Neurons are connected to each other by weighted connections. Data flows along these connections and is scaled by the weightings. Each neuron calculates the weighted sum of the data flowing to it as an input and uses an internal transfer function to compute an output, which is forwarded to downstream neurons. By optimising the connection weightings and features of the neurons through a training process, ANNs can be trained to perform various tasks, such as classification. AID models classify traffic data as incident or non-incident.

Two neural network architectures were used: Multi-Layer Feedforward (MLF) networks, which are commonly used for AID (**3, 4**); and Modular Networks, as used by Khan and Ritchie (**5**). MLF networks consist of an input layer, linked by weighted connections to one or more hidden layers, which are in turn linked by weighted connections to the output layer. The hidden layers allow the network to learn nonlinear relationships. The number of hidden layers and the number of neurons is determined by trial and error. Modular networks consist of two or more modules or experts (**6, 5**), typically MLF networks, which operate independently but receive the same input data. Depending on the architecture used, an additional network called the gating network may control the degree to which each module's output affects the final network output, giving greater priority to the best performing module.

Automatic incident detection models have been under development for the past two decades, but limited work has been done on arterial models, with the research focus on development and implementation of freeway AID models (e.g. **4**). Arterial Automatic Incident Detection is more problematic:

- Freeways have limited access points whereas arterials have multiple access points;
- Left and right turn movements at intersections make traffic movements more unpredictable;
- Intersection control results in variable and periodic interruptions of flow, queuing of vehicles at intersections, and dispersion of vehicle platoons downstream;
- Arterials usually operate at lower speeds which make lane changes easier, hiding the effects of an incident; and
- Arterials typically have more limited surveillance infrastructure than freeways.

EVALUATION CRITERIA AND DEFINITIONS

There are a variety of definitions for incidents in the literature. For this research, incidents are defined as events that cause a capacity reduction, and are associated with non-recurrent congestion. Performance of incident detection models is evaluated based on the following evaluation criteria:

- **Detection Rate (DR):** This is defined as the number of detected incidents divided by the total number of incidents that occurred during the recorded time. Detection rates greater than 90% are desirable. An additional requirement is that the incident must be detected within a short time (5 minutes) of the start of the incident, which can reduce the DR.

- **False Alarm Rate (FAR):** This is defined (**4**) as the number of detection intervals that gave false alarms divided by the number of incident free time intervals. There are a wide range of definitions for this criterion, and it is important to check which one was used. False alarm rates well below 1% are desirable. For this research, results were compared for a false alarm rate of 0.5%.
- **Mean Time to Detect (MTTD):** This is the average difference between the time of occurrence and the time at which an alarm was raised by the algorithm. The mean time to detect should be well below 5 minutes.
- **Performance Envelope Curve Area (PECA):** This is calculated from a plot of Detection Rate as a function of False Alarm Rate. The higher the PECA, the better the model has performed. A PECA of 10,000 is a perfect score, corresponding to a detection rate of 100% for false alarm rates from 0% to 100%.

The DR and FAR measure the effectiveness of the algorithm while the MTTD reflects its efficiency. The DR and FAR are positively correlated: to detect more incidents, the algorithm thresholds are relaxed which causes some incident-free intervals to be interpreted as alarms. A persistence test can be implemented. This involves testing for detections in a few consecutive time intervals before producing an alarm. This increases the time to detect an incident, but can reduce the FAR, without too much effect on the DR.

AUTOMATIC INCIDENT DETECTION MODELS

Recent improvements in communications have allowed researchers to collect traffic data from other sources. Probe vehicles can be used to collect time stamped locations and speeds. Buses, taxis and other commercial vehicles are commonly used, in the absence of other more representative vehicles. Vehicles equipped with tags for electronic toll collection can also be used, provided the necessary infrastructure is available. The proportion of probe vehicles on the road network is called the penetration rate. The reliability of the probe vehicle data is strongly dependent on the penetration rate. AID models based on probe vehicle data have performed satisfactorily (**7, 8**), although some had uncommonly high probe vehicle penetration rates (38%).

Generally, traffic measurements are derived from ILDs embedded in the road surface, which report flow (vehicles per hour, vph), occupancy (%) and speed (km/h). Measuring speed reliably requires two loops, meaning that this data is generally not available on arterials. Probe vehicle data can be used to augment data collected from ILDs. Various simulations have been run (**9-13**) to collect both probe and ILD data. Attempts were made to fuse probe vehicle travel time and speed data with ILD flow and occupancy data. It was found that models based on ILD data performed better than those based on probe vehicle data, but that combining the data produced the best results.

Ivan *et al* (**9-11**) tested whether pre-processing loop and probe vehicle data improved the performance of models. The results indicated that pre-processing the data produced better results. Other research (**12**) contradicted the above results, reporting that raw data produced better results, postulating that networks trained on raw data performed better as they had the advantage of being able to learn interrelationships between the raw data. It was also found (**11**) that including data and outputs from previous time intervals improved performance.

An innovative approach (**5**) made use of a modular neural network based on ILD data. Despite their apparent complexity, modular networks can learn faster, by breaking a task down into smaller sub-tasks. Further, the performance of a single module does not affect the performance of the others. This is a particular advantage in real-world situations, where data may sometimes be unavailable.

The review of arterial incident detection literature highlighted the challenges in developing automated incident detection systems for arterials and illustrated how the problem is more complex than freeway AID. The difficulty of collecting field incident data was a common theme reported in most papers, with most previous studies relying on data generated from traffic micro-simulation. Neural network analysis was found to be particularly promising for arterial AID.

This study extends previous research by developing and testing various neural network data fusion architectures based on simulated ILD and probe vehicle data for varying penetration rates. This study also considers the impacts of using data from previous time steps and for two detector configurations.

METHODOLOGY

Although traffic microsimulation has its own problems (high level of detail and input data requirements in addition to the need for proper calibration and validation), it offers a viable alternative to field data collection. A major advantage is that once a model has been developed and validated, it is possible to generate data for a wide range of situations. For development of models of sufficient generality, a variety of incident conditions were required, with varying probe vehicle penetration rates. Data was collected using the Paramics traffic microsimulation package. A network including two major arterials in Brisbane, Coronation Drive and Milton Road, was developed and validated (**14, 15**). Plugins were developed to collect the travel time and ILD data, and to simulate incidents (**16**). Two detector configurations were simulated (Figure 1), with ILD and probe data collected for each configuration.

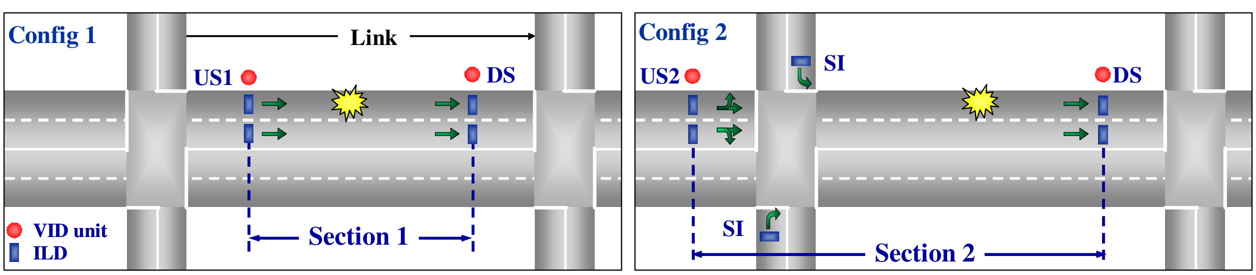

Figure 1 Modelled Detector Configurations

Configuration 1 attempts to treat arterials like freeways, and makes use of detectors installed downstream of intersections, which are currently not available on most Queensland arterials. Configuration 2 is the standard configuration on Queensland roads where ILDs are located upstream of intersections. Vehicle Identification units (VIDs), used to detect the probe vehicles, were modelled in the same locations as the ILDs. To develop a standard input vector for Configuration 2, detector site measurements were apportioned to the left turn, through and right turn movements at the upstream intersection.

Data was generated for a wide range of situations. Simulation model variables included: link length; incident location on link (upstream, midstream or downstream); incident duration (15, 30 or 60 minutes); incident severity (degree of blockage); and flow (> 600 vph/lane or < 600 vph/lane). Varying these features resulted in a set of 108 incidents for each configuration. Data was collected for each time step, irrespective of the traffic signal phase.

The output files from each simulation were then merged into a single file, containing ILD measurements and probe vehicle travel times. Data was aggregated to 20 s time intervals, in keeping with more recent freeway incident detection algorithms (**4**). While speed measurements were collected from the simulated ILDs, they were not used as input, as most Queensland ILDs would not have speed data available. Instead Flow divided by Occupancy was used as a proxy for speed. With the exception of calculation of the flow/occupancy ratios, no input data was pre-processed. The 108 data sets were then randomly allocated to the Training (50%), Cross Validation (10%) and Validation (40%) sets (**16**). The Cross Validation set is used to prevent overtraining of the network (**17**, **6**). Identical allocations were made for Configuration 1 and 2, to facilitate comparison of results.

The NeuroSolutions software package was then used to develop and train a series of MLF and Modular networks. Two types of MLF architectures were trained: generalized feedforward (GFF) networks have connections that jump over layers for speedier learning; and Jordan/Elman (JE) networks which have additional processing elements (PEs), called context units, that remember past activity using a configurable exponentially decaying recency gradient. In addition, two types of modular networks architectures were also trained: MOD1 networks were provided in NeuroSolutions and contained two expert modules; and MOD2 networks, which were built using the NeuroSolutions breadboard and contained four experts and a context unit.

A large number of neural networks were trained, for various numbers of PEs in the hidden layers. Once trained, the performance of each network on the validation data set was determined. It was found that the best performance was obtained using upstream and downstream occupancy, flow and flow/occupancy ratio, supplemented with travel times for varying probe vehicle penetration rates. In general, performances improved with increased probe vehicle penetration rate.

RESULTS

The best performances are presented below, with analysis of the performance for different simulation model variables and probe vehicle penetration rates. For this research, all results are quoted for a standard false alarm rate of 0.5% to facilitate comparison. For a measurement interval of 20 seconds, this false alarm rate could result in about 20 false alarms per link per (24 hour) day. This is a large number of false alarms, and ongoing improvement of these models is necessary to reduce FARs while maintaining acceptable DRs.

Detector Configuration 1

A series of MLF and Modular neural networks were developed for various probe vehicle penetration rates and hidden layer structures. The best performances for each neural network architecture are tabulated below. All mean times to detect were well below 3 minutes.

Table 1 Best Detector Configuration 1 Results

Neural Network Architecture	Persistence Test Steps	Time Constant	Best DR	PECA	Penetration Rate
GFF	0	-	40%	9476	20%
JE	0	0.5	59%	9667	20%
MOD1	0	-	49%	9715	20%
MOD2	0	0.5	49%	9508	20%

Best results were obtained in all cases for a probe vehicle penetration rate of 20%. The best detection rate of 59% for a false alarm rate of 0.5% was obtained using a Jordan/Elman MLF network, which allows input of data from previous time steps. PECAs were all fairly high. Performance envelope curves for the JE network are plotted in Figure 2 for various probe vehicle penetration rates.

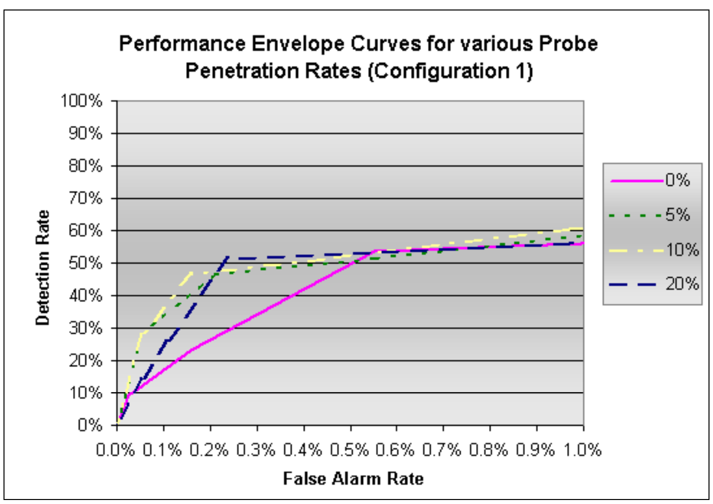

Figure 2 Configuration 1: JE Performance for various Penetration Rates

The best performance for the Modular neural networks was obtained with the more complex MOD2 network, with a detection rate of 49%. While performance did improve with increased probe vehicle penetration rate, the performance improvements were not substantial. Overall, the results for Detector Configuration 1 were not very promising.

Detector Configuration 2

As for Detector Configuration 1, a series of MLF and Modular neural networks were developed for various probe vehicle penetration rates and hidden layer sizes. The best performances for each neural network architecture are tabulated below. All mean times to detect were well below 3 minutes.

Table 2 Best Detector Configuration 2 Results

Neural Network Architecture	Persistence Test Steps	Time Constant	Best DR	PECA	Penetration Rate
GFF	0	-	54%	9298	0%
JE	1	0.8	86%	9697	20%
MOD1	0	-	35%	9041	0%
MOD2	0	0.8	77%	9732	5%

The best results were obtained using a Jordan/Elman MLF neural network, as for Detector Configuration 1 (DR 86% and FAR 0.36%). These results were obtained with a probe vehicle penetration rate of 20%; however, performances were good for 0%, 5% and 10% probe vehicle penetration rates (DR 86% and FARs from 0.41% to 0.36%). PECAs were again reasonably high. The figure below shows the JE network performance envelope curves for various probe vehicle penetration rates.

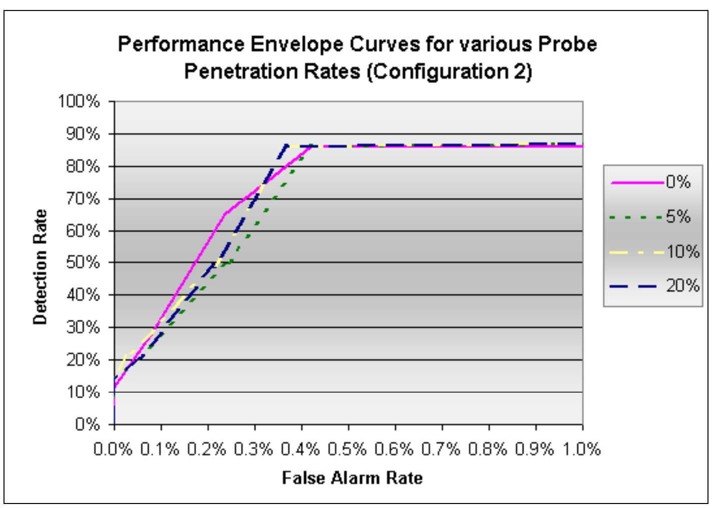

Figure 3 Configuration 2: JE Performance for various Penetration Rates

The best performance for the Modular neural networks was obtained with a probe vehicle penetration rate of 5%, with a detection rate of 77%. This result was again achieved with the more complex MOD2 network. The model performed substantially better with the inclusion of probe vehicle data.

For the best performing JE network, there was only a marginal improvement in performance with increased probe vehicle penetration rate, demonstrating that, while desirable, probe vehicle data is not essential. The results for Detector Configuration 2 are promising, and demonstrate the feasibility of developing an arterial AID model using ILD data, with some value obtained by augmenting the detector data with probe vehicle data.

Comparison of Detector Configuration 1 and 2 Results

Overall, the model performance for Detector Configuration 2 was better, with all simulation model variable detection rates substantially better than for Detector Configuration 1. The performances of the best performing networks for each Detector Configuration are presented in Table 3 for each simulation model variable.

Table 3 Detector Configuration 1 and 2 Performances for Simulation Model Variables

Variable	Subtype	Configuration 1		Configuration 2	
		DR	PECA	DR	PECA
Link Length	Coronation Dv (Long)	82.0%	9961	96%	9969
	Milton Rd (Short)	38.0%	9527	76%	9531
Incident Location on Link	Upstream	53.5%	9522	87%	9555
	Midstream	65.5%	9692	86%	9849
	Downstream	48.0%	9810	78%	9586
Incident Duration	15 minutes	77.0%	9905	83%	9790
	30 minutes	44.5%	9529	88%	9704
	60 minutes	53.0%	9592	85%	9622
Incident Severity (Lanes blocked)	Slow lane	77.0%	9745	100%	9998
	Fast lane	69.0%	9732	72%	9192
	Both Lanes	8.5%	9632	52%	9936
Traffic Flow	High (> 600 vph/lane)	55.0%	9347	77%	9199
	Low (< 600 vph/lane)	44.0%	9920	95%	9963
Overall Performance		59.0%	9667	86%	9697

The performance for Detector Configuration 2 was far better than that for Detector Configuration 1, with substantially better detection rates achieved for all simulation model variables. Results for the simulation model variables are compared in Table 4.

Table 4 Performances for Simulation Model Variables

Variable	Comments
Link Length	The detection rate for the longer link was better for both detector configurations. This result is fairly surprising, as the measurements upstream of an incident on a long link take some time to be affected, which was expected to cause a decreased detection rate.
Incident Location on Link	For Configuration 1, performance is best for incidents occurring midstream, and worst for downstream incidents. For Detector Configuration 2, performance dropped off for incidents further away from the upstream detector, as expected. This is fairly intuitive, for the reasons given above.
Incident Duration	For Configuration 1, the best performance was obtained for incidents of 15 minute duration. The worst performance was for 30 minute incidents. For Detector Configuration 2, the performance was directly opposite, although the detection rates were all fairly close. It was thought that the longer duration incidents would cause longer clearance times. The traffic measurements during the clearance would look like traffic measurements during an incident, and would therefore produce more false alarms. However, trends during traffic clearance did not affect the performance of the Configuration 2 model.
Incident Severity	For both Configurations, performance decreased with increasing incident severity. This trend has been seen in all of the network results, and appears to be related to the input data rather than variability in the patterns learned by the neural networks. During major blockages, a lot of the input data is zero, and neural networks do not learn well with zero inputs. Further research is needed to find ways to better present the data to the neural network.
Traffic Flow	Detector Configuration 1 had better detection under high flow conditions, opposite to the trend for Detector Configuration 2, where the detection rate was very high for low flow incidents. This behaviour was also reported by Dia and Rose (**4**).

Overall, it can be seen that model performance for Detector Configuration 2 was better, with all model variable detection rates substantially better for the Detector Configuration 2 input data. It was expected that the traffic measures derived from Detector Configuration 1 would more clearly highlight traffic behaviour in incident and non-incident conditions, and would hence be more suited to arterial incident detection.

The better performance obtained for the Detector Configuration 2 data is unexpected but very welcome, as AID models can be developed for existing infrastructure. Another favourable result for the Detector Configuration 2 data is that while probe vehicle data does improve model performance, gains are relatively small and good performance can still be achieved without probe vehicle data.

Inclusion of Speed Data

When speed data was included in the Detector Configuration 2 data set for a probe vehicle penetration rate of 20%, neural network performance improved further, resulting in a DR of 90% for a FAR of 0.5% (Figure 4).

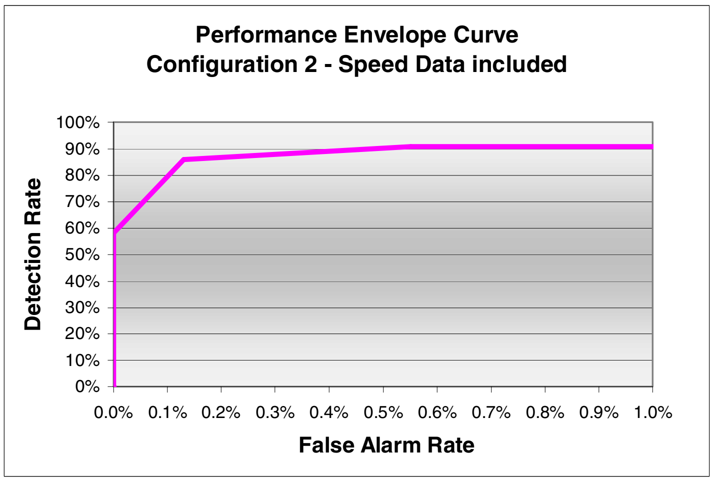

Figure 4 JE Performance with Speed Data

Similar improvements in results have been obtained for freeway AID models when speed has been an input (**4**). This detection rate is comparable to detection rates for freeway AID models.

CONCLUSIONS

This research has demonstrated the feasibility of developing a neural network model for detection of incidents on arterials using loop and probe vehicle data. Simulated data was used to train and test a series of neural network architectures. The performance of the architectures was compared for the detector configurations and other simulation model variables to determine which features were associated with better performance. Probe vehicle penetration rates were also varied to determine the effects of increasing penetration rates.

In keeping with much prior research (**9-13**), it was found that an MLF neural network structure, the Jordan-Elman network, performed best. This network allows inclusion of data from previous time steps, which was found to greatly enhance model performance. Of the two modelled detector configurations (Figure 1), neural network architectures trained using Detector Configuration 2 data produced consistently better results. This was unexpected, as it was anticipated that Detector Configuration 1, which mimicked the simpler detector configuration on freeways, would be simpler to analyse, and would therefore produce better results. This is, however, an excellent outcome as most Queensland arterial road networks are already capable of providing data from detectors set up in this configuration.

Overall, the best performance was obtained for Detector Configuration 2 when Occupancy, Flow, Flow/Occupancy and Vehicle Probe data for a penetration rate of 20% were used as inputs to the neural networks. However, the performance improvement for increased probe vehicle penetration rate was small, with a DR of 86% achieved for all penetration rates (FAR 0.5%). This means that adequate performance can be obtained without the use of probe vehicles, which is a good outcome for networks where probe vehicles are not available. The inclusion of speed data further improved the neural network's performance (DR 90% for a FAR<0.5%). Unfortunately, it is unlikely that speed data will be made available on arterial road networks in the short term. However, road authorities are to be encouraged to improve instrumentation on roads whenever possible.

The findings for Detector Configuration 2 were similar for the different neural network architectures. The model performed better on longer links, and for incidents located closer to the upstream detector, as expected. The model also performed better for incidents occurring in low flow conditions. Incident detection performance was not strongly affected by the incident duration, but was greatly affected by the incident severity. Further research is needed to improve model performance for severe incidents.

Very few studies reported in the literature have attempted to test the performance of arterial AID models on a statistically reliable number of field incidents. Unfortunately, it was not possible to collect field incident data in this study either and this remains a high priority for future research in this field. While the following options were not considered in this research, it is worth noting that this data may be useful in future research:

- Queue length is a good indicator of an incident in high flow conditions; while
- Lane changes are a good indicator of an incident in low flow conditions.

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