【土木計画学研究・論文集 Vol.27 no.5 2010年9月】

OPTIMUM DETECTOR SPACING FOR REAL-TIME MONITORING OF HAZARDOUS LOCATIONS ON URBAN EXPRESSWAYS*

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1. Introduction

Predicting crash risk in real-time is an emerging concept in proactive road safety management system which estimates the probability of crash in real-time using data from traffic flow sensing devices. This derives an additional use of the existing underground loop detectors or other traffic flow data sensing devices which are now-a-days commonly used for surveillance, traffic forecasting and/or continuous data collection. Oh *et al.*[1)] were among the pioneers to separate traffic dynamics into two categories – disruptive and normal, and assess the likelihood of crash data belonging to each category. Standard deviations of speed[2)] as well as average occupancy[3)] were found to be the most significant predictors. Some contemporary studies can be found with similar but different objectives, such as, to improve the prediction capability of the conventional non-real time models[1)], identify crash patterns[4), 5)] and to develop proactive road safety management systems [6)-8)]. Bayesian statistics[2), 8)], matched case-control logistic regression[9)], probabilistic neural network [3), 7), 10)] and a combination of multiple models [11)] were the most common methods used so far. The modeling approach followed were relatively similar – i) separate traffic flow data into two categories, i.e., hazardous and normal, ii) collect data from a single detector or a set of detectors for each crash point, iii) select different descriptive statistics of the traffic flow parameters as variables and finally, iv) treat the problem as a classification problem and use a suitable method to predict the crash. Previous studies [1)-3), 7), 10)] in most cases considered a 5 minute time period some times prior to the crash to represent the traffic condition leading to crash. Some studies [7), 10)] argued that 5 minutes may not be sufficient enough to take any counter measure even if crash potential is accurately calculated and recommended for a time period which ends 10 minutes prior to crash. Regarding the non-crash traffic condition, Oh *et al.* [1)-3)] defined it as a 5 minute time period ending 30 minutes prior to the crash, whereas, some studies[7),10)] defined it as a 5-minute time period corresponding to the traffic condition leading to crash, but taken from the same weekdays throughout the year except for the crash day. Thus, although the overall modeling approach was similar, the studies varied in their definition about crash and non-crash situations and the modeling methods.

Most of the previous studies were conducted on North American freeways where the number of lanes (4-5 in each direction) as well as the inter detector spacings (around 0.8 kilometer on an average) are high and access points are widely spaced. However, urban expressways in different parts of the world normally have fewer numbers of lanes and denser access points and detector spacings, raising issues related to transferability of the existing conceptual models. Another concern is, for new roads or roads without detectors, placing detectors throughout the road may become extremely expensive and road authorities may want to place detectors only on black spots or areas with high time varying crash potential. Thus, it is of high interest to know the appropriate place and optimum spacing for setting up detectors on urban expressways. Some of these queries were answered partially by Abdul-Aty *et al.*[10)] where they assessed the prediction capability of their North American real-time crash prediction models on Dutch freeways, which have higher detector density (always less than 0.8 kilometer). They tested three detector spacings between the upstream and downstream of each crash location. The inter-detector spacings used were minimum 0.5 kilometer, 1.0 kilometer and 1.5 kilometers with 142, 162 and 143 crash cases respectively. Three major drawbacks of the study were a) they built the model around each crash point, where in reality, we still lack in the knowledge to predict crash locations precisely; b) only three different detector spacings were tested and c) there was no mention in the study whether preclusions were taken to avoid detectors which were placed too near the access points as traffic condition in those areas are supposed to vary substantially from those located in the basic freeway segments [12)]. Most probably, a different experimental design is required to predict crash probability in those regions than the one used for the basic freeway segments.

This paper developed a real-time crash prediction model for the basic freeway segments of the Shinjuku 4 Tokyo Metropolitan Expressway – which is one of the busiest in Japan. The expressway has mainly two lanes in each direction and accommodates several access points, making it very different from the North American expressways used as study areas so far. The average detector spacing is 0.26 kilometer (standard deviation of 0.09); making it highly suitable for investigating various detector settings. Unlike the previous studies, the entire road was subdivided into small segments of 250 meters length and the model was built to predict the probability of crash occurrence in every 250 meter section. The results of this

* Keywords: real-time crash prediction, Bayesian Network, hazardous location, urban expressway
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paper can be used by practitioners in two ways: i) on an expressway without existing detectors, if one would like to predict crash potential in real-time for hazardous locations then they can identify the risk for every 250 meter road section using conventional frequency based method and select the most risk prone areas to layout the detectors, or, ii) if the road already has detectors installed, then the practitioner can choose the closest matching recommended detector spacing to predict real-time crash potential for the corresponding 250 meter section. Moreover, detectors going out of order are common phenomena. In these situations, the results can be valuable to identify the second best detector settings to predict crashes till the faulty detector gets repaired. The paper also introduces Bayesian Network[13), 14)] as a modeling method, which is a highly acclaimed real-time prediction method in the field of Artificial Intelligence and possesses the capability to update itself in real-time.

This paper is organized into six sections. This section, has explained the necessity of the study. The second section explains how the data were prepared and the variables were selected for modeling. The third section provides a brief but self containing introduction to Bayesian Network. The fourth section presents the analysis and results of the models built. The fifth section explains how the model can be used in real life. Lastly, the paper summarizes the contributions of the study along with the limitations and the future scopes.

2. Data Collection, Preparation and Exploratory Analysis

(1) Data Collection

Data were collected from the Shinjuku 4 Tokyo Metropolitan Expressway (in-bound traffic only), Japan, under the jurisdiction of the Tokyo Metropolitan Expressway Company Limited. The length of the expressway is approximately 14 kilometers for the direction bound for downtown Tokyo. It has mostly two lanes in each direction and the in-bound direction accommodates 50 detectors, 6 entry and 3 exit points. This study collected data from two separate databases –the crash and the detector database. The time period for the data collection was from December, 2006 till November, 2008. The crash data contained 1318 cases with information about date, time (in minutes), location (to nearest 10 meters), crash lane, type of crash and vehicle involvement. The detector data contained 5 minute station level aggregated values of average speed and cumulative flow for each of the 50 detectors for the year round. The detectors produced both speed and flow data correctly in 90.71% times, whereas, they correctly captured speed data during 85.9% of the study period. Flow data were always available when the speed data were available, suggesting that flow is the most reliable output of these detectors.

(2) Data Preparation

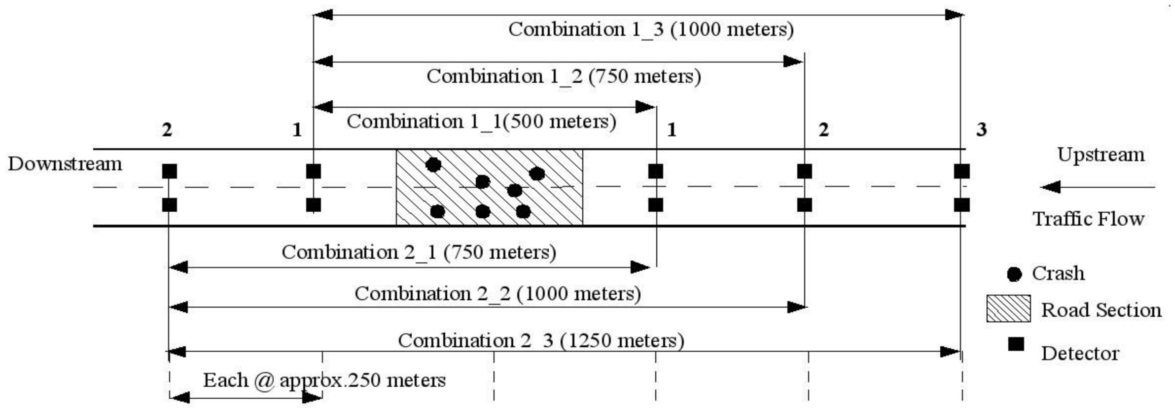


Figure 1: Detector of Combination for Each Section

The total length of the study area was divided into 250 meter sections, which is approximately equal to the existing inter detector spacing. Locations of each crash point, access point as well as the detectors were identified on the road layout. Each crash point was associated with its corresponding section. Data from sections harboring access points, their immediate upstream and downstream sections were not considered in this study as the proposed model is for predicting crashes on basic freeway segments only. Detector data near the access points are supposed to be influenced by merging and diverging traffic conditions and this study recommends to build a separate model to predict real-time crash probability in merging and/or diverging areas. Then, five loop detectors for each section were identified – 2 in the downstream and 3 in the upstream of the flow direction with no detector falling into the merging or diverging traffic area as presented in Figure 1. The detectors were selected as such that the first upstream detector is placed approximately 250 meters upstream from the center of the section in concern; the second detector is approximately 500 meters from the same reference point and so on. Similar convention was followed for the two downstream detectors as well. Thus, 6 different inter-detector spacings were considered for evaluation: 1 with 500 meters (1_1), 2 with 750 meters (1_2 and 2_1), 2 with 1000 meters (1_3 and 2_2) and 1 with 1250 meters (1_3) gap. A higher number of detectors in any direction would have resulted in very few sections with non-overlapping detectors with the merging and diverging traffic conditions.

The next step extracts data from the detector database. For this, it is important to understand the data aggregation process as this is a major modification from the experimental designs of previous studies where detector data were extracted for each individual crash point. As demonstrated in Figure 2, if two independent 250 meters road sections 'A' and 'M' are considered, then the detector combination 1_1 is represented by detector no. 2 and 4; combination 1_2 with 2 and 5 and so on. All the crash points falling into section 'A' will be sharing the same detector settings for each of the six detector combinations. Similarly, for the section 'M', detector 13 and 15 represents combination 1_1; detector 12 and 15 represents combination 2_1 and so on. Now, combination 2_1 does not exist for section 'A' as detector 1 is located within an area flagged as merging traffic. Later, the data were further aggregated based on each of the six detector combinations for all the sections under consideration. At present, the expressway authority stores the aggregated traffic data for each 5 minutes. This study selected a 5 minute time period starting at least 9 minutes before the occurrence of the crash as the condition leading to crash. For example, if a crash had occurred on the 28th August, 2008 at 1:54:00 pm, then a time period on the same day starting from 1:40:00 pm to 1:45:00 pm was classified as a traffic condition leading to crash. The 28th August, 2008 is a Thursday. Continuing with the same example, for the normal traffic condition corresponding to the crash, all the data for the corresponding detectors from 1:40:00 pm till 1:45:00 pm for all Thursdays within the study period were classified as normal traffic condition. Following these definitions, data were extracted for all six detector combinations. The extracted variables from detector database were 5 minute station level cumulative vehicle count and 5 minute average speed of the vehicles. Thus, the model built in this study will predict the risk of formation of a hazardous traffic condition at least 9 minutes before it reaches its peak. This is important from the intervention designing point of view as any intervention requires sufficient amount of time to smooth the hazardous traffic condition back to normal condition. Now, the data were further filtered as there may be other Thursdays where crash occurred within the vicinity of the detectors in a time period closed to 1:40:00 pm. Next, distribution of traffic flow and speed data along with the crash data with respect to different days of the week and hours of day were analyzed which suggested that the traffic volume and number of crashes are lower during the weekends. Traffic volume was also found to be low from 8 pm till 7 am. Thus, crash data as well as the detector data corresponding to the weekends and the aforementioned time period were truncated from the dataset. This decision was reasonable as crashes occurring during these time periods may have relationship with high-speed driving rather than a turbulent traffic condition that just developed through a certain period of time[7]. The final datasets for each detector combinations are: 1_1: 281 (26812), 1_2: 218 (20083), 1_3: 175 (15977), 2_1: 250 (23068), 2_2: 195 (17515), 2_3: 167 (16683) represented as - combination no.: number of crash data points (corresponding non-crash points). The last 30 crash points and their corresponding non-crash points were kept for the model evaluation purpose and the rest of the data were used for model building. It was found that 88.66% of these crashes were rear-end collusions, 5.32% hitting the road furnitures and 4.63% side-wise collusions. This is expected as the expressway has mostly two lanes in each direction and crashes taking place in the sections near the access points were not considered in this study.

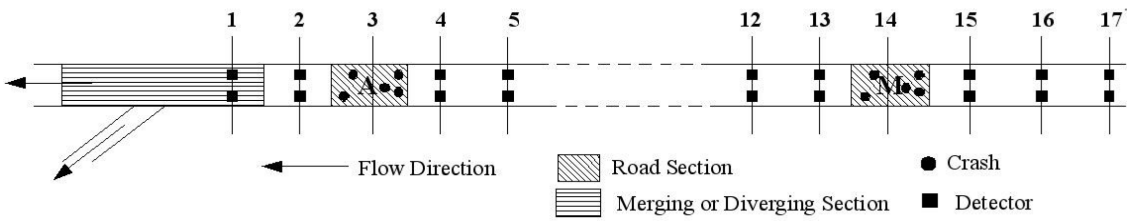


Figure 2: Aggregation of Detector Data for Each Detector Combination

(3) Exploratory Analysis

Exploratory analysis was conducted using the concepts of binomial logistic regression to identify the predictors for modeling. Logistic regression[15] is similar to linear regression but here, a linear model for transformed probabilities is set up (see Equation 1), where logit p = log[p/(1-p)], i.e., the log odds and p is the probability of the occurrence of the event (here, crash).

$$logit(p)=\beta_0+\beta_0*x_1+\ldots+\beta_k*x_k \quad (1)$$

Previous studies mostly used the standard deviation or coefficient of variance of traffic flow data as variables. Hossain and Muromachi[14] emphasized that a universal real-time crash prediction model must not be heavily dependent on speed and occupancy data as these are specific to the type of detectors. They also mentioned that choosing standard deviations or coefficient of variance may be cumbersome from counter measure designing point of view as any measure might increase the dispersion more as compared to the average values, causing false alarms. Thus for this study, traffic volume was considered as a major variable and average values rather than dispersions of traffic flow variables were used as predictors. In this study, the combination of variables tested to construct the six logistic regression models are presented in Table 1. The unit of speed was 5 minute average and that of flow was 5 minute vehicle count.

Table 1: Variable Set for Different Logistic Regression Models

No.	Variables
Model 1	Upstream speed (US_Sp), Upstream flow (US_Fl), Downstream speed (DS_Sp), Downstream flow (DS_Fl)
Model 2	Upstream speed (US_Sp), Downstream speed (DS_Sp)
Model 3	Upstream flow (US_Fl), Downstream flow (DS_Fl)
Model 4	Upstream flow * Upstream speed (US_Fl*US_Sp), Downstream flow * Downstream speed (DS_Fl*DS_Sp)
Model 5	Speed difference between upstream and downstream (Diff_Sp), Flow difference between upstream and downstream (Diff_Fl)
Model 6	Speed difference between upstream and downstream * Flow difference between upstream and downstream (Diff_Sp*Diff_Fl)

The first model deals with all four variables – upstream and downstream speed and flow. The second and the third model considers only speed and flow related variables respectively. The fourth model considers the interaction of speed and flow variables by introducing their products as variables. Model 5 deals with the spatial variation between the speed and flow variables. Lastly, the sixth model focuses on the interaction of the speed and flow variables along the space. Next, these six models were built for all the six detector combinations. However, due to space limitation, only the results of Model 1 and 5 for all six combinations are presented (Table 2).

Table 2: Logistic Regression Model for Variable Selection

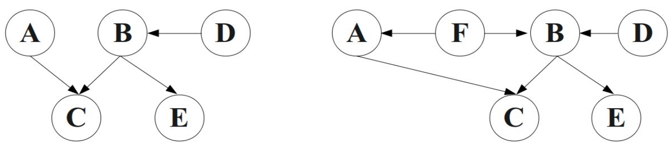
	Combination 1_1							
	Model 1					Model 5		
	(Intercept)	DS_Fl	DS_Sp	US_Fl	US_Sp	(Intercept)	Diff_Fl	Diff_Sp
Coefficient	-3.6854	-0.0012	-0.0075	0.0009	-0.0174	-3.5785	-0.0017	-0.0196
Std. Error	0.2150	0.0019	0.0040	0.0020	0.0053	0.1874	0.0011	0.0028
Pr(>|z|)	<2e-16 ***	0.5500	0.1176	0.6538	0.0010**	<2e-16***	0.1320	4.37e-12***
	Combination 1_2							
Coefficient	-3.5036	-0.0003	-0.0094	-0.0012	-0.0140	-3.6703	-0.0012	-0.0215
Std. Error	0.3357	0.0015	0.0060	0.0023	0.0060	0.2079	0.0013	0.0037
Pr(>|z|)	<2e-16***	0.8234	0.1216	0.6118	0.0196	<2e-16***	0.3810	1.42e-08***
	Combination 1_3							
Coefficient	-3.6666	0.0004	-0.0133	0.0001	-0.0115	-3.6700	-0.0007	-0.0201
Std. Error	0.4121	0.0018	0.0046	0.0002	0.0049	0.2338	0.0015	0.0036
Pr(>|z|)	<2e-16***	0.8181	.0042**	0.9850	.0253*	<2e-16***	0.6460	.0000***
	Combination 2_1							
Coefficient	-3.4530	0.0030	-0.0175	-0.0032	-0.0093	-3.9560	0.0020	-0.0258
Std. Error	0.3121	0.0013	0.0056	0.0020	0.0056	0.1620	0.0011	0.0036
Pr(>|z|)	<2e-16***	.0205*	.0018**	0.1183	0.1044	<2e-16***	.0816.	.0008***
	Combination 2_2							
Coefficient	-3.2494	0.0038	-0.0193	-0.0043	-0.0090	-3.8700	0.0021	-0.0272
Std. Error	0.3480	0.0015	0.0054	0.0023	0.0051	0.1848	0.0013	0.0040
Pr(>|z|)	<2e-16***	.0140*	.0003***	.0657.	.0790.	<2e-16***	0.1140	.0000***
	Combination 2_3							
Coefficient	-4.0647	0.0019	-0.0166	0.0008	-0.0108	-4.0420	0.0015	-0.0235
Std. Error	0.4197	0.0018	0.0055	0.0024	0.0053	0.2032	0.0017	0.0045
Pr(>|z|)	<2e-16***	0.3114	.0027**	0.7530	.0453*	<2e-16***	0.3860	.0000***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

It was observed that conforming to the previous studies based on North American data, mathematical forms of speed were significant for all six detector combinations, whereas, flow was found significant in some models only. It was also observed that the differences of upstream and downstream data were significant. Abdel-Aty et al.[17] discovered that crashes occur in high speed and low speed scenarios. He further suggested that formation and subsequent dissipation of queues causing a backward shock wave in case of high speed scenario and causes driving discomfort which may result in crashes. For low speed scenarios, a disruption in the downstream that propagates a shock wave to the upstream may cause driving errors. With a similar approach but including only rear-end crash data, Pande and Abdel-Aty [18] confirmed that crashes are related to coefficient of variation in speed and average occupancy under extended congestion. The variation between the upstream or downstream can be captured by considering the difference in traffic flow variables between these two locations. This also helps in reducing the number of variables, too. Thus, Diff_Sp and Diff_Fl are selected to be sufficient to develop the real-time crash prediction model.

3. Introduction to Bayesian Network (BN)

The modeling method used in this paper is Bayesian Network (BN), a widely used method in risk prediction for highly uncertain phenomena, specially in the field of military technology, medical science, risk monitoring of nuclear power plants, reliability of software, etc. However, it is still an emerging method in transportation engineering. BN can be defined as an acyclic directed graph (DAG) which defines a factorization of a joint probability distribution over the variables that are presented by the nodes of the DAG, where the factorization is given by the directed links of the DAG[18]. BN is a graphical modeling method represented with a graph and a basic equation. The graph contains two parts – the nodes (variables) and the arcs (their inter-relationship). Figure 3(a) represents a problem domain containing five variables – A, B, C, D and E, where B (child node) is caused by D (parent node, represented as $pa(X_i)$), E is caused by B and C is jointly caused by A and B.



(a) (b)

Figure 3: (a) An Example Bayesian Network (b) Adding New Variables to an Existing Bayesian Network

The inter-relationships of the variables are represented by drawing arcs from the parent nodes to the child nodes. If a BN contains '*n*' number of variables, then the complete problem domain can be represented with Equation 2.

$$P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | pa(x_i)) \tag{2}$$

The probability (or conditional probability) distributions of all the nodes are required to specify a BN. Assuming each variable in this example has two states, the BN is expected to require 2^5-1 = 31 joint probabilities. However, the architecture of BN suggest that each network can be presented with the probabilities of each node who do not have any parent node and the conditional probabilities of the child nodes with respect to their immediate parent nodes only. Thus, Equation 2 can be re-written conforming to this example as Equation 3.

$$P(A,B,C,D,E) = P(A)P(D)P(E|B)P(B|D)P(C|A,B) \tag{3}$$

Now, in future, if a situation arises where the behaviors of variable B and D have changed and may require the model to be calibrated, data for only *P(B), P(D)* and *P(B|D)* are needed to re-calibrate the model. Thus, the same model can be built with data from different time periods. Moreover, in course of time, if a new variable F emerges which influences both A and B, then the model can be modified as presented with Figure 3(b) and Equation 4 requiring only probability tables for *P(F), P(A|F)* and *P(B|D,F)* to be reconstructed.

$$P(A,B,C,D,E,F) = P(F)P(D)P(A|F)P(E|B)P(B|D,F)P(C|A,B) \tag{4}$$

Lastly, if each variable is assumed to have two states and if they are represented with small letters (e.g., state of A as a_1 and a_2), the probability of C being in c_2 state when information about only A, D and E (A = a_1, D = d_2 and E = e_1) are available, can be predicted using Baye's theorem by marginalizing the variables as shown in Equation 5.

$$P(C=c_2 | A=a_1, D=d_2, E=e_1) = \frac{\sum_B \sum_F P(A=a_1, B, C=c_2, D=d_2, E=e_1, F)}{\sum_B \sum_C \sum_F P(A=a_1, B, C, D=d_2, E=e_1, F)} \tag{5}$$

Thus, BN has inherent capability to update the model in real-time, revise the model with partial new data, incorporate new variables by only updating the probability tables of other variables directly connected to the new variables and make inferences even when information regarding all the variables are not available; which are the major qualities required in a suitable method for real-time crash prediction. A detailed discussion on BN can be found in Hossain and Muromachi[13].

4. Model Building and Evaluation

The latest 30 crash data for each of the six detector combinations were kept as validation dataset and the remaining as training dataset. The difference between upstream and downstream flow and speed were chosen as the information variables to predict crash. Thus, BN for each detector combination was build with '*Speed Difference (SD)*' and '*Flow Difference (FD)*' as the parent nodes connected to the child node '*Crash (C)*' based on the hypothesis that speed difference and flow difference between the upstream and downstream traffic independently or jointly influence the crash (Equation 6).

$$P(C,SD,FD) = P(SD)\,P(FD)\,P(C \mid FD,SD) \tag{6}$$

The next step involves building the prior probability tables for P(*Speed Difference*), P(*Flow Difference*) and P(*Crash* | *Speed Difference, Flow Difference*). As the differences in speed and flow are continuous data, it was necessary to make the values discrete to facilitate calculation. Through rigorous trials, the final categories were decided for speed and flow difference (Figure 4). Afterwards, conditional probability table of P(*Crash* | *Speed Difference, Flow Difference*) was constructed. The BN was built using NETICA software[19]. Due to space limitation, output of only Combination 2_1 is shown (Figure 4). It can be observed that speed difference is normally distributed around zero difference between upstream and downstream, however, the flow difference exhibits two distinct patterns – one distributed normally around no flow difference and another one near flow difference around 100 – 110 vehicles in 5 minutes. The later condition suggests that upstream area had more flow than downstream in several occasions and may have caused discomfort to the drivers by creating a shock wave. The value 1.05 in Figure 5 suggests that if no information regarding speed difference or flow difference is available, the road condition has 1.05% probability of having a crash anytime between 7 am and 8 pm during the weekdays (calculated using Baye's theorem) for each 5 minute in a 250 meter road section. Similarly, models were built for detector combination 1_1, 1_2, 1_3, 2_2 and 2_3. Afterwards, each of the six models was evaluated using the validation dataset. As it contained around 100 normal traffic condition entries for each crash prone condition, randomly 2 entries were selected for evaluation. Thus, the validation dataset for each of the models had 30 entries for conditions leading to crash and 60 for normal traffic conditions. These values were run down the model and the corresponding crash risk was calculated (Equation 5 and 6). It is worth mentioning that some of these records did not contain information of speed, however, those probabilities were calculated only using flow data as it is normal to have situations where the detectors may occasionally fail to yield speed data. The average crash risk (e.g., 1.05% for Combination 2_1) for each model was used as the baseline threshold (in ***Bold-Italic font face*** in Table 3) and any crash probability higher than the threshold was classified as a crash prone condition and vice versa. Now, as the average crash risk for each of the detector settings were around 1%, the values were increased by 25% (1.25%) and 50% (1.5%) to observe the prediction success (Table 3).

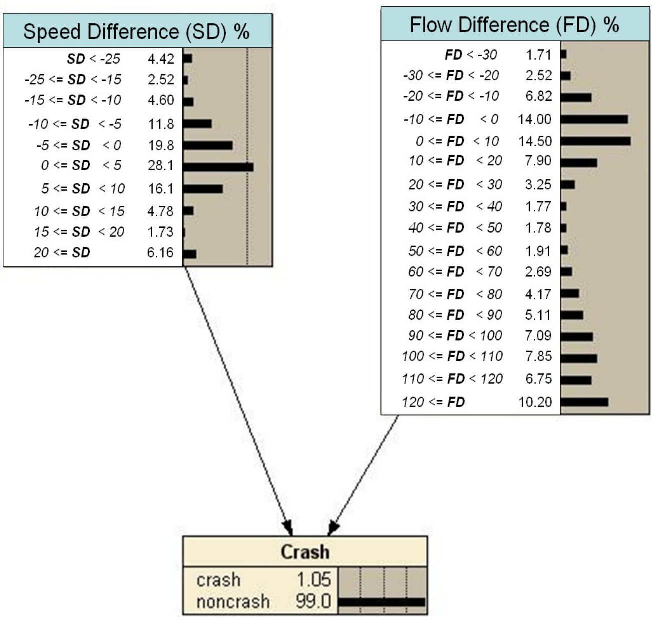


Figure 4: Bayesian Network Model for the Detector Combination 2_1

Table 3: Evaluation of Prediction Success for Different Detector Combinations

Detector Combination	Threshold	Crash	Non-Crash
1_1	***1.18***	50.00%	65.00%
	1.25	43.33%	66.67%
	1.5	30.00%	80.00%
1_2	***1.04***	63.33%	78.33%
	1.25	43.33%	80.00%
	1.5	36.67%	86.67%
1_3	***1.08***	60.00%	76.67%
	1.25	46.67%	78.33%
	1.5	36.67%	83.33%
2_1	***1.05***	63.33%	80.00%
	1.25	53.33%	86.67%
	1.5	36.67%	90.00%
2_2	***1.12***	50.00%	66.67%
	1.25	40.00%	70.00%
	1.5	30.00%	76.67%
2_3	***0.99***	53.33%	65.00%
	1.25	30.00%	68.33%
	1.5	20.00%	70.00%

It can be observed (Table 3) that the crash prediction success decreases with the increased threshold value, but higher thresholds increase the prediction success of the normal traffic condition and thus, reduce the false alarms. Choosing the ideal threshold value is complex and is subjected to the decision of the experts. It is recommended to conduct the cost-benefit analysis by estimating the cost of false alarms as well as the cost of crashes to fix the optimum threshold value. The threshold value can be altered based on time of day, too. The results (Table 3) insists that all the models could predict at least 50% crash prone and 65% normal traffic conditions successfully when the average crash risk was used as the threshold, however, Combination 2_1 and Combination 1_2 had the highest prediction success (63.33%), suggesting that 750 meters detector spacing exhibits the best prediction performance for the study area. However, Combination 2_1 maintained more than 60% and 80% accuracy in predicting crash prone and normal traffic conditions respectively. Furthermore, if the detectors are too closely spaced, they may not inflict sufficient changes in upstream and downstream conditions and thus yield poor detection performance. Similarly, if they are placed over 1000 meters apart, their detection performance may get affected due to external factors. Thus, in a practical scenario, the real-time crash potential can be calculated with Combination 2_1. If any of the detectors in Combination 2_1 experiences problems, then Combination 1_2 can be used for the time being. If that one also produces missing data, then Combination 1_3 and Combination 2_2 can be used. However Combination 1_1 and 2_3 may not be used as they produce low prediction success accompanied with high false alarms.

It is important to mention that the prediction success presented in Table 3 represents capability of the initial model and the results of the model may not be ready for use yet. As mentioned earlier, the proposed model has the inherent capability to learn and calibrate itself in real-time. Every time when new data are evaluated, the model can evaluate the crash risk and by comparing the predicted outcome with the actual outcome, the probability tables can be updated based on the actual outcome. As the initial model was built with limited amount of data, it is normal that the average crash probability (1.05 for Combination 2_1) will be changing in course time as it keeps on learning from every new data. After sometimes, similar to the iteration methods, the crash probability will change very little with new data. At that point, the model will be ready for making proper prediction.

5. Implementation Strategy

Unlike the non real-time crash prediction models, the study did not include different parameters relating to road geometry, e.g., horizontal and vertical alignments, curvature, etc. as predictors. This is due to the fact that the study aims to focus on predicting crashes based on sudden changes in driving condition. Moreover, although the sample size considered in this study is larger than most of the previous studies, it still may not be sufficient to develop different models based on different traffic conditions. The view was shared by several previous studies [1)-3), 8),10)], too. This study expects that the proposed real-time crash prediction model will be employed in hazardous locations and they will be trained in real-time to accommodate the local variation of the traffic condition. Thus, in course of time, every location equipped with these real-time models will have a different model customized with its own location based traffic variable data. This was another major reason for not including road geometry related variables for modeling. The idea is significantly different from the previous studies as they have focused on developing a single model for all parts of the road network and do not consider the possibility of training the models in real time. Thus, this manuscript requires to include an implementation strategy of the proposed model. Implementation of the proposed model can be separated into several steps as follows:

Step 1: The expressway authorities need to decide location(s) to install the real-time crash warning facilities. For existing roads, this can be done by dividing the whole road length into 250 meter sections and calculating the crash frequency (and/or severity) using the black-spot identification method. If a newly proposed road is under consideration then probable black-spots can be identified using conventional crash prediction models.

Step 2: Considering the available budget, the authorities will select the number of detectors and their layout following Table 3. If they decide to install only two detectors per location, then Combination 2_1 should be chosen. If budget permits installing two more detectors, then Combination 1_2 can also be setup for the same location. Thus, if Combination 2_1 goes out of order or fails to yield data, the model for Combination 1_2 can be used temporarily. Moreover, these two combinations also help in achieving Combination 2_2 as it shares one detector from both Combination 2_1 and 1_2.

Step 3: The threshold value for decision making can be decided based on the discussion of the previous section.

Step 4: The model needs to be updated in real-time as long as we do not achieve a stable average probability of crash, as explained in the previous subsection.

6. Conclusion

The major difference between the previously developed and the newly proposed model is the viewpoint from which they were built. When the former attempts to find the best way to predict real-time crash potential for expressways with existing detectors, the later answers where and how to layout the detectors to develop real-time crash warning systems. Moreover, the previous studies were mostly developed using North American interstate freeway data. Those roads normally have higher number of lanes and lower number of access point and detectors as compared to the urban expressways outside North America. This study was conducted on Shinjuku 4 Tokyo Metropolitan Expressway, one of the busiest in Japan, which has mostly two lanes in each directions and is densely populated with detectors. This enabled in testing various detector combination, which was not possible in the previous studies (except Abdel-Aty *et al.*[10)]). The data used were quite latest, too (December, 2006 - November, 2008). The study is timely as many emerging economies outside North America are now heavily investing in the transportation sectors resulting in many new expressways in their mega cities. It is impractical to equip the whole expressway network with detectors to begin with, as it involves huge initial investment as well as regular expenditure for maintenance. The expressway authorities may benefit from this research by building real-time crash warning systems for hazardous and/or strategically vital road sections.

The study introduced two new innovations in the methodology, too. First, it binds the prediction results with both time and space. The space constrain is new (as per the knowledge of the authors) as previously developed models predicted crash probability for a space roughly referenced from existing detector locations. This study yields crash risk for specifically predefined 250 meter road sections. Secondly, the paper suggests the concept of updating the model in real-time, whereas the previous models brought the dimension of 'real-time' by only feeding the model with real-time traffic flow data. Real-time crash prediction model development requires both crash data and their corresponding detector data. In many cases, the detector data are not archived for long period of time, resulting in low sample size for modeling. Thus the prediction success is often low and exhibits high false alarms, too. This is true even for this study. However, a model that can update itself in the future will have the opportunity to produce acceptable prediction success in course of time.

This study can also be considered as one of the earliest implementations of Bayesian Network in the field of transportation engineering. Application of BN facilitated higher flexibility for the future upgradation of the model. Some of its inherent benefits include, i) the ability to make inference regarding any variable in the model, ii) making inferences even when information about only one variable is available, iii) indifferent to the correlation among information variables, iv) understanding the phenomena from the model outcome, v) updating the model with limited effort (by simply updating the probability tables), vi) easily modifying the model by introducing new variables which can be accomplished by redrawing the graph, calculating the probability tables of the new variables and only re-calculating the probability tables of the existing variables which are direct parents or children of the new variables. Existing variables can be dropped in the same fashion, too. Apart from this, the major benefit of using BN was its capability to be learn and update the model in real-time as soon as new data is fed into the system.

The study identified the difference between upstream and downstream 5 minute cumulative flow and average speed as the most suitable variables for the model building. The validation results suggest that one of the six models (Combination 2_1) could predict 63.33% crash prone situations with less than 20% false alarms. These results are much better[1)-3), 6), 7), 9)] or as good as[10)] most of the previous studies. Out of order detectors are part of regular events in expressways. For this, the study also recommends a cost sensitive implementation method. If the budget is the minimum then the authorities can opt for Combination 2_1. If higher reliability is required, i.e., making decent prediction even when the detectors are failing to yield data, two more detectors can be placed following the configurations of Combination 1_2.

For transferability, the paper suggested that the models developed should not be directly implemented in the field to formulate counter measures or instigate warnings. At first, it needs to be calibrated with field data by iterative methods. When the model will be fed with new data, it will make predictions. Checking the prediction with the actual outcome, the model needs to be updated in real-time, which will result in a change in the average crash probability. When the average crash probability becomes stable, the model will become ready for use.

Regarding the limitations, the paper did not explain the physics behind crash and treated the problem as a classification problem where the main concern was, if the data are like this, than how well it can be associated with crash prone or normal traffic condition. An in-depth data mining is recommended to develop hypothesis based on the real-time traffic flow data and test those with different experimental settings. The model is also developed for basic freeway segments only. A separate model is recommended to be built with the data from the locations near the access points. The study has utilized two detectors at a time for crash prediction. It I will be interesting to examine how the prediction success of a model increases with the increase in number of detectors used.

Acknowledgement

The authors would like to acknowledge the Tokyo Metropolitan Expressway Company Limited for facilitating this research.

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Optimum Detector Spacing for Real-Time Monitoring of Hazardous Locations on Urban Expressways*

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This paper evaluates the optimum detector spacing to monitor the crash risk of hazardous locations on urban expressways in real-time. For this, crash data and traffic flow data (flow and speed) were collected for two years (December, 2006 to November, 2008) from 30 loop detectors on Shinjuku 4 Tokyo Metropolitan Expressway, Japan. Six different detector spacings were evaluated and Bayesian Network was used as the modeling method. The 5-minute cumulative flow difference and average speed difference between upstream and down stream detectors were identified as suitable predictors. The optimum detector spacing was identified and an implementation strategy was presented.