

Development of a freeway crash duration prediction model

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Abstract

The detection of incidents and the subsequent incident response activities and traffic management activities have long been known to have a significant impact on the resultant magnitude of incident induced delay. Efforts to reduce incident induced delay have tended to focus on reducing the time to detect incidents (i.e. automatic incident detection) and to provide appropriate and swift emergency response. However, efforts to develop traffic management strategies in response to incidents are often hampered by a lack of knowledge of how long the incident is likely to exist. This lack of knowledge also is problematic for disseminating information to travellers about the incident.

In practice, traffic management personnel, police, etc. are able to provide rough estimates of the duration of incidents on the basis of experience and the known characteristics of the crash (e.g. number of vehicles involved, type of vehicles, etc.). The purpose of this work is to examine the feasibility of developing a model that permits the prediction of crash duration on the basis of observable crash characteristics. Such a model could be integrated within the traffic management centre (TMC) software to assist operators in selecting appropriate traffic management response strategies and in the provision of information to drivers.

The examination of the potential to develop a crash duration prediction model is done on the basis of field data for an urban freeway (the QEW) in Toronto Canada. Field data are obtained from two unrelated databases: the provincial

crash database and the freeway traffic management system incident log database. It is found that linking these databases is a complex problem that has a significant influence on the explanatory power of the crash duration prediction model.

Keywords

Incident duration, duration prediction model, integrated database, database matching process, statistical models

1 Introduction

Most large urban centres in North America have freeways as primary surface transportation corridors. Over the past several decades there has been a continuing trend of increasing congestion on these freeways resulting in significant direct and indirect costs to businesses, commuters, and the environment. For example, a recent mobility study conducted in the U.S. estimates the cost of traffic congestion in terms of wasted fuel and lost productivity for the entire U.S. for 2001 to be \$69.5 billion, a 7% increase from the previous year [1]. While some of this congestion is a result of demand exceeding the capacity supplied by the transportation system, the literature indicates that the majority (approximately 60%) of congestion is caused by incidents, such as crashes, spilled load, stalled vehicles, debris, etc., that causes a temporary reduction in the capacity of a portion of the road network. [2]. Therefore, efforts to diminish the effects of non recurrent congestion will have a significant impact on mitigating freeway congestion.

Most major urban centres in North America have responded to these increases in freeway congestion by developing Traffic Management Programs (TMP) to reduce the effects of non recurrent congestion. The programs typically include the deployment of field traffic surveillance equipment (e.g. loop detectors, CCTV cameras, etc.), traffic control equipment (e.g. ramp meters), traveller information systems (e.g. changeable message signs, highway advisory radio), and an emergency dispatch centre (e.g. police, fire, paramedic).

Given the large portion of total traffic congestion that is caused by incidents, most TMPs have focused their operations to mitigate incident effects as much as possible, especially the duration of an incident. Incident duration is often described in terms of a number of distinct phases, namely, detection, response, treatment and dissipation of effects as illustrated in Figure 1 [3].

The Highway Capacity Manual considers as part of the incident duration the queue dissipation time after the incident has been removed from the roadway. However, not all researchers or practitioner agree on this definition. Some authors [e.g. 4, 5] do not consider the time for the effects of the incident to dissipate as part of the incident duration. Other researchers [6] have suggested that an incident does not have to go through all the phases defined in Figure 1.

Irrespective of the definition one adopts to describe the duration of an incident, it is clear that the length of time that the freeway capacity is reduced has a significant influence on the delay caused by the incident. Consequently, the expected duration of an incident is an important factor that influences the type of traffic management strategy to implement and the type of information that should be provided to travellers.

Currently there does not appear to be a systematic means of estimating incident duration in real-time. TMC operators are usually able to provide some insight as to the expected duration of an incident on the basis of their personal experience and observable incident characteristics (e.g. number of vehicles involved). However, the reliability of this method is unknown and likely varies significantly as a function of the operator, their level of experience, etc. Furthermore, given

the absence of knowledge of the reliability of the operator based estimates of incident duration, incident duration estimates made this way are rarely disseminated to the public and are used for internal purposes only.

Incident duration is expected to depend on a number of incident characteristics such as: the type of road on which the incident has occurred, weather, number of lanes blocked, time of day, type of vehicles involved (i.e. automobiles, trucks or buses), number and severity of personal injuries, involvement of hazardous materials, whether or not a load has been spilled and if so the type, quantity, and location of the spilled material, and response time of personnel dispatched to the incident site. Previous studies have shown that different factors are important for estimating incident duration. For example, Garib et al. [7] calibrated a log linear regression model and found that the log of incident duration is dependent on six variables, namely: number of lanes affected, number of vehicles involved, truck involvement, time of day, time of Police arrival, and weather conditions. In another study, Giuliano [8] used a series of ANOVA tables on a highly categorized database to identify which factors influenced incident duration. Her research developed separate models for incidents and accidents using the log of duration as the dependent variable to evaluate 12 different factors suspected to influence duration. The author's findings show that duration is a function of the type of incident, number of lanes closed, and time of day.

The majority of work described in the literature that addresses the issue of predicting incident duration has focussed on developing models that assume complete knowledge of incident characteristics. As such these models are not

generally suitable for real-time application as certain incident characteristics are often not known when the incident first occurs. For example, the number and severity of personal injuries are certainly not known until at least after the time when medical personnel arrive on the scene, and may not even be known until several hours after the injured persons arrive at a hospital.

The research described in this paper has three main objectives:

1. Develop an integrated database including crash duration and crash characteristics.
2. Identify factors contained within the integrated database that are useful for predicting crash duration
3. Develop a static statistical model as a precursor to developing models that can be used to estimate crash duration in real-time.

This paper is organized as follows. The next section describes the study methodology. Section 3 describes the field data sources and database integration process that was developed and applied to match crash records from different data sources. Section 4 describes the calibration of the crash duration prediction models. Conclusions and recommendations are provided in Section 5.

2 Study Methodology

The methodology adopted in this study consisted of 4 sequential stages as illustrated in Figure 2. The research started with an extensive review of the literature to identify other studies that have examined predictive relationships for

incident duration. At the conclusion of this phase, we decided to define the scope of our research to examine duration of only crashes, and not consider other types of incidents. Therefore, in the remainder of this paper, we refer to crash duration models rather than incident duration models.

The second phase attempted to assemble a database for Ontario crashes that contained information on the characteristics and environmental conditions associated with each crash. Unfortunately, there is no single existing database that contains all of this information, and therefore it was necessary to integrate several separate databases. This data integration, which presented a range of challenges, is described fully in the next section.

We elected to adopt an incremental approach to developing crash prediction models in the sense that we first develop temporally static models assuming full knowledge of all crash and environmental characteristics. The characteristics of these static models provide insights to the appropriate means of developing real-time models that explicitly consider the temporal aspect.

Consequently, the third phase consisted of formulating and calibrating static crash duration prediction models on the basis of the data contained within the integrated database developed in phase 2. The results from this phase are described in Section 4 of this paper.

The fourth phase, which is not described in this paper, consists of formulating and calibrating real-time crash duration prediction models.

3 Development of the Crash Duration Database

The development of the crash duration database began with an assessment of available data sources. We were not able to identify any existing databases that contained all of the information we required to develop the crash duration models and therefore we proceeded to identify data sources that could be integrated to provide a single database capable of supporting the proposed research. Given our location, we elected to utilize data from the Province of Ontario, though it is worth noting that similar data sets to those used for Ontario are available in most other provinces and states and the methodologies we used would be equally valid for application to data from these other locations.

3.1 Description of Field Site

Existing crash databases in the Province of Ontario do not contain information detailing crash duration. Therefore it was necessary in this study to obtain this data from another source. The only source that provides this information is freeway traffic management system (FTMS) incident logs. Therefore, our field site from which we could obtain data was restricted to provincial highways operating under an FTMS. After consulting with the Ontario Ministry of Transportation, it was decided to select a 19 km section of the Queen Elizabeth Expressway (QEW) in Mississauga between Royal Windsor Drive and Highway 427 (Figure 3) for two main reasons:

1. Historical incident log data were available for this section for a period of 5 years.¹
2. MTO staff felt that the data for this section were likely more reliable than from other FTMS covered highway segments as a result of fewer construction activities, etc.

The FTMS operating on the 19 km section of the QEW illustrated in Figure 3 includes 15 CCTV cameras (indicated by the yellow solid circles in Figure 3) and 53 loop detector stations.

3.2 Description of Data Bases

The FTMS maintains an electronic log of all incidents detected by FTMS incident detection algorithms or by TMC personnel, and those reported to the TMC by emergency personnel. The incident log maintains a record of a number of incident attributes including the type of incident (accident, disabled vehicle, roadwork, debris, other, unconfirmed events), when detection occurred, any changes to the status of the incident, the time the incident was cleared, etc.

¹ Note, for this study, we made use of only 3 years of data for calibrating the crash prediction models. The remaining 2 years of data were reserved for future model validation.

Incident log data was obtained from MTO for the 19 km test section for 3 years (1999 – 2001)².

The original format of the incident logs is an ASCII text file containing blank spaces between lines. Furthermore, the incident logs contain entries for all incidents, not just crashes. A custom Visual Basic program was written to convert the incident logs from ASCII format to MS Access database format and to extract only those entries from the incident logs that were designated as crashes and that occurred within the 19 km section defined in Figure 3. This resulted in a total of 587 crashes remaining within the Incident Log database.³

MTO maintains a crash database entitled the Accident Data System (ADS) that contains data for all reported vehicle collisions for the entire province. In the event of a motor vehicle accident it is mandatory for police to be called to the scene whenever there is personal injury or property damages exceed a specified value. In this event, the attending police officer completes a motor vehicle accident report (MVAR) form. If there are no personal injuries and property

² A summary form of the detailed incident logs were obtained from MTO. The detailed logs were not available at the time of this study. The summary form does not included information such as the lane block pattern.

³ Analysis of the Incident Log database revealed that crashes are only recorded in the database for weekdays between the time of 6 AM and 9 PM implying that the traffic management centre was only staffed during these times.

damages are estimated to be less than the specified value, then the involved parties can present their statements at a collision reporting centre and a self-reported accident (SRA) form is completed. Data that are entered into ADS are obtained from police reports and from self reported collision reports.

The ADS database consists of three separate data tables entitled *b*, *d*, and *i*. Table *b* contains general information about the crash. Table *d* contains information about involved vehicles and drivers. Table *i* contains information about injured persons. With this structure, there are generally multiple records in Tables *b*, *d*, and *i* for each individual crash event (Figure 4). This data structure is not convenient for our use so we restructured the database to create a single data table with one record for each crash event. Furthermore we extracted only those records pertaining to crashes that were reported to have occurred on the QEW (not the ramps) between Royal Windsor Drive and Highway 427. To be consistent with the Incident Log database, only crashes that were reported to have occurred on weekdays between the time of 6 AM and 8 PM were considered.

ADS data were obtained from MTO for the 19 km test section for 5 years (1997 – 2001). Only data for the years 1999, 2000, and 2001 were used in the matching process. This resulted in 1,184 crashes – approximately two times the number of crashes recorded in the Incident Log database. It is not clear why so many crashes are absent from the Incident Log database, but it is suspected that the missing crashes were minor events that were either not detected by the FTMS or

were not confirmed by the operators and therefore were not included within the Incident Log database.

3.3 Database Integration Process

The ADS contains a great deal of information regarding the accident type, number of involved persons, number and severity of injuries, road and weather conditions, driver characteristics, etc. However, the database does not contain any information that defines directly the duration of the accident. Consequently, there is a need to match records in the FTMS Incident Log database with records in the ADS for the same crash event. Unfortunately, there is no direct link between these two databases and there is no unique crash event identifier present in both databases that can be used to directly carry out the record matching process. Consequently a more elaborate matching process is required to integrate these two databases.

The integration of the FTMS Incident Log database and the ADS database is illustrated in Figure 5.

Since there is no unique crash event identifier that can be used to match crash records in the Incident Log database and the ADS a method of matching the records was devised. Both databases contain descriptors of crash attributes that can be used in the matching process. A review of the fields in each database revealed that there are 4 descriptors of the crash that are common to each database (date, time, location, and direction).

However, it must be emphasized that the values for these fields in each database are obtained from different sources. For example, consider the *time* field which is intended to reflect the time at which the crash occurred. The entry in the ADS database is obtained from either the reporting police officer (MVAR) or the individual(s) involved in the crash (SRA). This time is typically an approximation and is unlikely to be accurate to more than the nearest 10 minutes. In contrast, the time reported in the Incident Log database is the time when the record is created in the on-line database. The record may be generated from an automatic incident detection algorithm, in which case the time may be a minute or so later than the true crash occurrence time. In the case that the record is generated by an operator, the time lag may be longer. It seems unlikely that the recorded time would precede the actual time of occurrence.

Figure 6 illustrates the fields used to match crash events from the ADS database and the Incident Log database. The units of measurement for data, time and direction are the same in both databases. The measurement of location is conducted differently in each database. The ADS database describes the location of the crash in terms of provincial linear highway reference system (LHRS) number and an offset. Appropriate use of this system permits the accurate reference of a crash location to the nearest meter.

In the Incident Log database, crash locations are referred to in terms of the location of the nearest upstream loop detector station. Loop stations are located on average approximately 500m apart, with some variability along the network (from a minimum of 280m to a maximum of 1,250m). Consequently, the

location referencing scheme induces a maximum error that can range from as little as approximately 270m to approximately 1,240m. The error associated with locations from the ADS database is unknown but is likely to be larger for self reported crashes than police reported crashes.

Given the uncertainty associated with the error distributions associated with the 4 matching fields and the different databases, the matching process developed consisted of a composite error index (Equation 1).

$$E_{A_i B_j} = \gamma_D (D_{A_i} - D_{B_j})^2 + \gamma_T (T_{A_i} - T_{B_j})^2 + \gamma_V (V_{A_i} - V_{B_j})^2 + \gamma_X (X_{A_i} - X_{B_j})^2 + e_1 + e_2 + e_3 \quad (1)$$

where:

$E_{A_i B_j}$ = composite error calculated between crash record i from the

ADS database and record j from the Incident Log database

A_i = i^{th} record in the Incident Log database

B_j = j^{th} record in the ADS database

D = date of crash as recorded in the database

T = time of crash occurrence as recorded in the database (hours)

V = recorded direction of travel for lanes in which crash occurred
(Eastbound = 0; Westbound = 1)

X = recorded location of the crash (km)

γ_D = weighting factor for date deviations

γ_T = weighting factor for time deviations

γ_V = weighting factor for direction deviations

γ_x = weighting factor location deviations

e_1, e_2, e_3 = heuristic discrepancy error

As indicated in Equation 1, the reported location of the crash is defined in terms of distance (km) from a predefined origin. The ADS and the Incident Log databases rely on location referencing systems that are not directly comparable. Therefore, each location referencing system was transformed to provide the crash location in terms of the distance from a fixed origin located at the western extent of the study area.

The last three terms in Equation 1 (i.e. e_1 , e_2 , and e_3) permit the inclusion within the matching process the expectation that self-reported crashes generally have a shorter duration than do police reported crashes. If the crash duration associated with a particular match falls within the limits specified in Table 1, then the value of the discrepancy error term is greater than zero; otherwise the value = 0.

The intervals were determined subjectively on the basis of a review of the crash data and opinions of personnel at MTO who are responsible for the ADS database and the Incident Log database.

The matching process proceeds by sequentially stepping through the crashes in the Incident Log database, and for each record attempting to identify the corresponding crash record in the ADS database that minimizes the composite error as defined in Equation 1.

In addition to the crash duration, the integrated database contained 35 fields describing the crash, roadway, and environmental conditions (Table 2). These

fields represented the characteristics that could be used as independent variables in the development of a crash duration model.

Initial values (Table 3) for the weighing coefficients (γ_D , γ_T , γ_V , γ_X) and the discrepancy errors (e_1 , e_2 , e_3) were determined subjectively. Using these values, the integrated database contained 298 crash records. The mean crash duration was 42.5 minutes with a standard deviation of approximately 65 minutes. The distribution of crash duration, illustrated in Figure 7, was found to be approximately log-normal.

The next section describes the development of a crash duration model and includes a sensitivity analysis of the effect of the weighting coefficients and the discrepancy errors on the performance of the crash duration models.

4 Development of a Crash Duration Model

A number of model structures are available by which to establish the relationship between crash duration and independent variables. We elected to begin the model development assuming a first order linear model and conduct the calibration of the coefficients of the independent variables using least squared regression.

The statistical analysis software package SAS was used for all model calibrations. The step-wise approach was adopted for determining the independent variables that should be included within the models. The F-test was used to decide whether an independent variable made a significant contribution to the model's ability to explain the variance observed in the data. A level of

significance of 15% was chosen for adding and removing independent variables to/from the model.

The resulting model consisted of 6 independent variables (*SRA*, *Truck*, *Rollover*, *EmergencyEquipment*, *Damage4*, and *Alignment2*) plus a constant. All coefficients are statistically significant at the 95% level, however, the explanatory power of the model is rather poor as indicated by $R^2 = 0.22$. Furthermore, for the explanatory factors (i.e. alignment and damage,) the model includes only a single category (i.e. *alignment2* and *damage4*) while other categories are ignored.

In the interest of improving the explanatory power of the model, and to explore the effect of the weighting factors used in the composite error function (Equation 1) a sensitivity analysis was conducted.

For each set of weighting coefficient values considered, a step-wise regression analysis was conducted as described above. This sensitivity analysis revealed that the use of the heuristic discrepancy error terms (e_1 , e_2 , e_3) introduces bias into the crash duration analysis database by discouraging matches for self-reported crashes ($SRA=1$) of long duration and discouraging matches for police reported crashes ($SRA=0$) of short duration. As a result of these findings, the heuristic discrepancy error terms were removed from the composite error expression for all further analyses.

It was also found that the maximum permissible error (E_{A,B_j}) has a strong influence on the number of successfully matched crashes (i.e. number of records

in the crash duration analysis database) and the explanatory power of the resulting crash duration model. As shown in Figure 8, as the maximum permissible error increases, the number of records in the crash duration analysis database increases but the explanatory power of the linear regression model (as indicated by the R^2) significantly decreases.

For a very small maximum permissible error (e.g. 0.05) the explanatory power of the linear regression is rather good ($R^2 = 0.53$). However, for this case the database contains only 43 crashes and an examination of the model revealed a lack of a physical basis for the independent variables included in the model. These observations tend to imply that the higher explanatory power of the model for very low values of the maximum permissible error is an aberration rather than a statistically and physically valid result.

5 Conclusions and Recommendations

This paper has presented a study that has attempted to develop a static crash duration prediction model. A crash duration database was developed from two separate databases by matching crash records that minimized a composite error term. Linear regression models were calibrated using the resulting crash duration analysis database through the use of step-wise regression.

The results from this study have lead to the following conclusions:

1. Existing provincially maintained accident databases do not include information on the duration of the event. Consequently, the

development of a crash duration prediction model requires the integration of two or more separate databases.

2. The integration of the provincial accident database (ADS) and the FTMS incident log database represented a much more challenging problem than originally anticipated. A heuristic crash record matching technique was developed that estimates a composite error considering reported crash location, direction of traffic flow in lanes, date and time of day.
3. The number of matched records is highly dependent on the weighting coefficients in the composite error function.
4. The best first order linear regression models were determined using step-wise regression. The explanatory power of these models (R^2) varied from 0.1 to 0.58 depending on the weighting coefficients chosen for the composite error function.
5. The current matching process appears to lack sufficient constraints to provide a reliable crash duration analysis database. It is expected that the availability of more detailed incident logs will provide additional crash characteristics that can be incorporated within the composite error function and provide more accurate matches.
6. The explanatory power and the statistical and physical reliability of the best first order regression models of crash duration appear to be rather poor. While other regression model forms (e.g. higher order linear;

non-linear; etc.) may provide better results, it appears that improvements to the matching process may be necessary before crash prediction models can be calibrated that have practical value.

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Tables

Table 1: Coefficients for heuristic discrepancy error terms from
Equation 1

Discrepancy error	Police reported crash (MVAR)	Self-reported crash (SRA)
e_1	$0 \leq CD < 10$	$CD > 120$
e_2	$10 \leq CD < 20$	$60 < CD \leq 120$
e_3	$20 \leq CD < 30$	$30 < CD \leq 60$

CD = crash duration in minutes

Table 2: Fields within the integrated crash database

#	Variable	Category	#	Variable	Category
1	VehNum	Continuous	19	alignment2*	Straight on hill
2	damage0*	Unknown	20	alignment3*	Curve on level
3	damage1*	None	21	alignment4*	Curve on hill
4	damage2*	Light	22	EmergencyEquipment	Binary
5	damage3*	Moderate	23	weather1*	Clear
6	damage4*	Severe	24	weather2*	Rain
7	damage5*	Demolished	25	weather3*	Snow
8	class1*	Fatal injury	26	weather4*	Extreme conditions
9	class2*	Non fatal injury	27	SRC	Binary
10	class3*	Property damage only	28	ejection	Binary
11	light1*	Daylight	29	truck	Binary
12	light2*	Dawn	30	loaded	Binary
13	light3*	Dusk	31	TowedVeh	Binary
14	light4*	Dark	32	Rollover	Binary
15	surface1*	Dry	33	FixedObject	Binary
16	surface2*	Wet	34	Direction**	Binary
17	surface3*	Snowed-frezed	35	PeakTime	Hour of day
18	alignment1*	Straight on level			

* Binary “dummy” variables

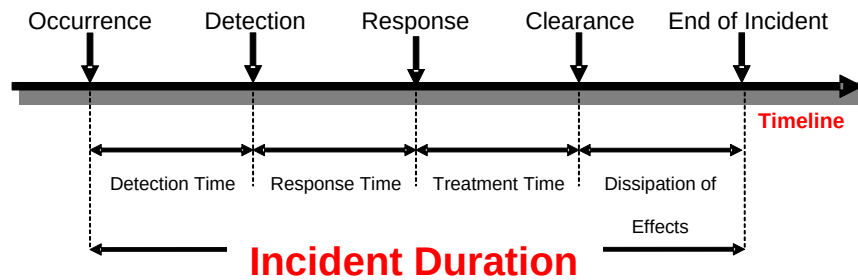
**Direction: 1 if westbound; 0 if eastbound

“Binary”: 1 if event occurred; 0 if event did not occur

Table 3: Weighting coefficient values

Weighting coefficient	Value
γ_D	10
γ_T	160
γ_V	10
γ_X	1
e_1	10
e_2	7
e_3	3
$Max E_{A_i B_j}$	10

Figures



Occurrence is the time when the incident occurred. In practice, this time is typically not known.

Detection is the time when the TMC is made aware (via automatic incident detection systems or through other mean) that an incident has occurred. In many TMP systems detection time is the time when the TMC personal confirms that an incident has taken place. Detection is typically accomplished by way of visual confirmation via CCTV cameras.

Response is the time when responding agencies (e.g. police, maintenance crews, fire and/or medical personnel) arrive at the incident site.

Clearance is the time when the travel lanes of the roadway have been cleared of vehicles and/or debris.

End of Incident is the time when the queue that resulted from the incident has dissipated.

Figure 1: Definition of incident stages (from ref. 3)

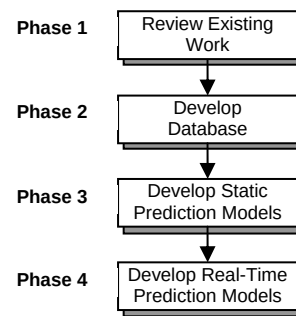


Figure 2: Study approach



Figure 3: Data collection site on the QEW in Mississauga, Ontario
(Source: [9])

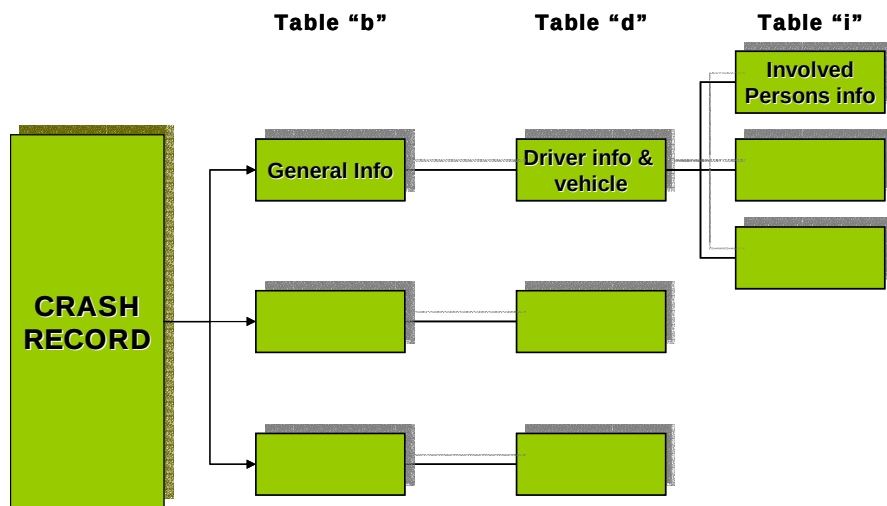


Figure 4: Structure of ADS database

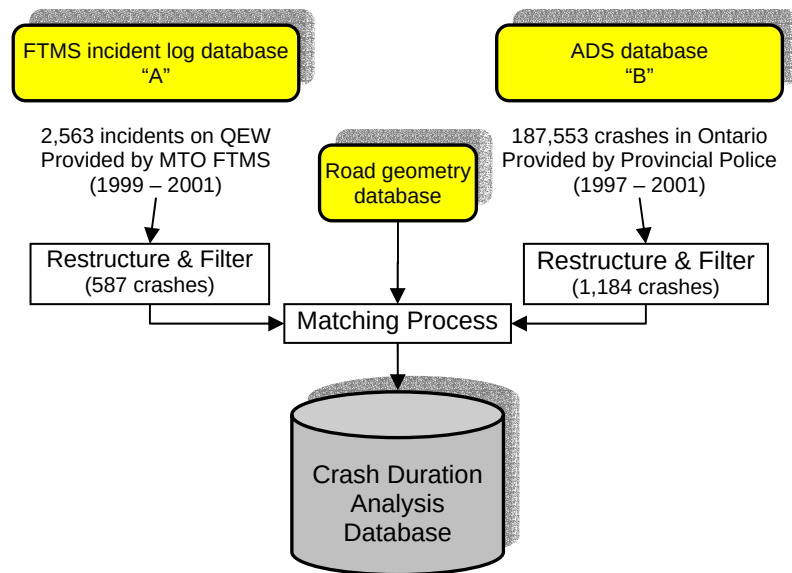


Figure 5: Layout of Crash Duration Analysis Database

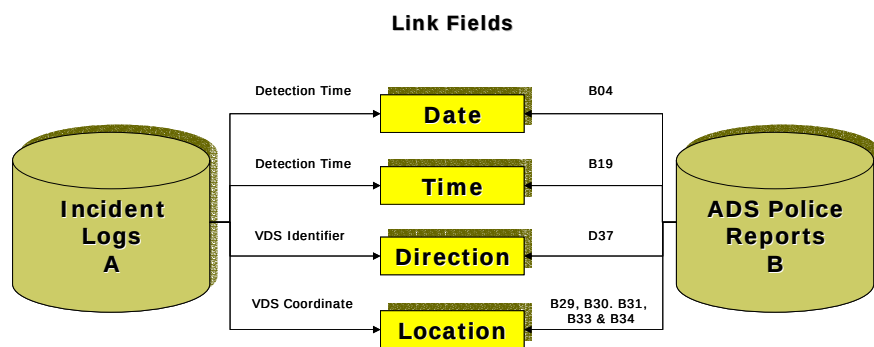


Figure 6: Fields used in the matching process to link the databases

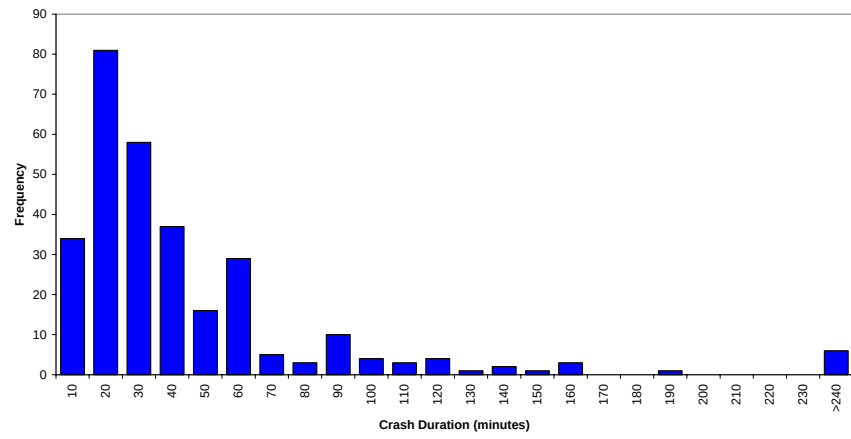


Figure 7: Distribution of crash duration for default weighting coefficients

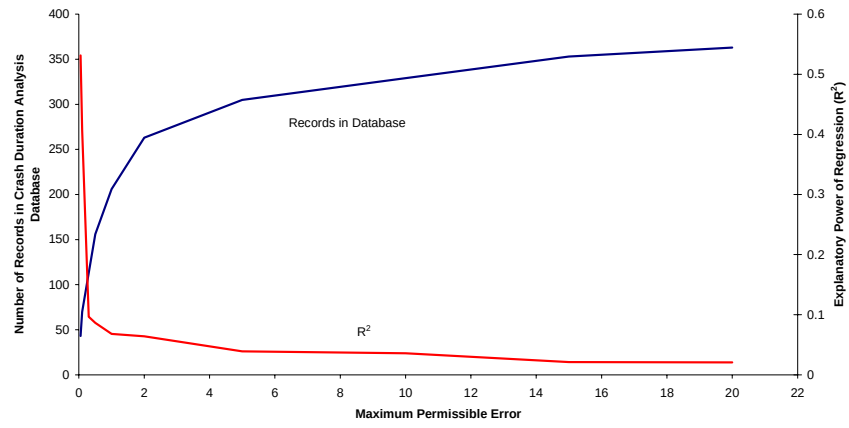


Figure 8: Effect of maximum permissible error on the size of the crash duration analysis database and the resulting regression model