

THE TRAFFIC CONFLICTS TECHNIQUE: AN ACCIDENT PREDICTION METHOD

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A traffic conflicts technique was developed by General Motors as a method of measuring accident potential and is based on tabulation of evasive maneuvers as evidenced by brake-light indications and lane changes. For accident potential at intersections, 20 specific conflict classifications are defined. As a result of an FHWA-financed research program, Ohio became involved in the evaluation of the GM technique. At the time that the federal program ended, Ohio decided to pursue its own evaluation of the technique. This was prompted by a conviction that the theory behind the conflicts technique was sound and by a desire to find an accident prediction technique for use in Ohio. An accident projection technique is useful if it reflects the accident trends of the subject area. Early tests indicated that the algorithm published by FHWA could not be easily calibrated for Ohio data trends. Although Ohio data were used in generation of the FHWA method of accident prediction, it was felt that the data from the states of Virginia and Washington were of such volume and different nature as to bias the resulting algorithm. During 1972 and the first half of 1973, the Ohio data base was enlarged from 196 projects (more than 400 approaches) to 410 projects providing 922 approaches, of which 611 were usable for analysis purposes. A series of regression models was applied to this enlarged data base in an attempt to find a reliable accident prediction model. As a result of this analysis, accident prediction algorithms were developed that provide a mean accuracy of ± 1.1 accidents per year and a 75th percentile accuracy of ± 1.8 accidents per year. In addition, substantial insight into the workings of the conflicts technique has been obtained.

•A TRAFFIC CONFLICTS TECHNIQUE was developed by General Motors Research Laboratories to evaluate intersection operation. The basic premise of the conflicts technique is that the number of evasive maneuvers and brake-light indications can be used both to estimate the number of accidents that will occur over a given period of time and to evaluate the operational problems of the subject intersection. A GM procedures manual (2) gives details of the actual counting procedure.

During 1969, the Federal Highway Administration negotiated contracts with the states of Ohio, Virginia, and Washington to conduct an evaluation of the traffic conflicts technique. Under the federal program, each state was to conduct conflicts counts at a minimum of 100 intersections both before and after some engineering improvement. These counts were to be made over a 1-year period during which each state would conduct its own evaluation of the technique and forward it along with the data collected to FHWA for statistical analysis.

The stated purpose of the program was to determine whether conflicts counts conducted at the state level could provide information useful in determining safety improvement needs. In addition, the combined data from the various states would be utilized by FHWA to determine whether any correlation existed between conflicts and accidents.

As a result of the federal analysis program (1), 1,306 approaches were counted and analyzed. The results of this analysis are provided below.

All three states found that the conflicts technique provided the information needed for the design of safety improvements. Indeed, where accident data were available, the conflicts count not only verified the accident analysis but also provided insight into the conditions precipitating accidents.

The basic conclusions drawn from the federal program are summarized as follows:

1. The data compiled in the study tended to support the hypothesis that conflicts and accidents are associated;
2. On the basis of the experience of the three states, it appeared that safety deficiencies at intersections could be pinpointed more quickly and reliably by using the GM technique than by using conventional methods;
3. The GM technique may be particularly valuable at low-volume, rural intersections where the accident reporting level is low;
4. The traffic conflicts technique, because of its usefulness in pinpointing intersection problems more precisely, should lead to low-cost remedial actions;
5. The technique can be applied with minor modification to locations other than intersections;
6. The effect of intersection improvements may be demonstrated from conflicts counts taken shortly after completion of a spot improvement; and
7. The general surveillance information obtained during the collection of conflicts count data may be valuable in improving the overall operations of intersections.

Thus, previous efforts have shown the traffic conflicts technique to be a potentially valuable tool for the evaluation of intersection operation. Of particular interest to the state of Ohio was the possible application of the technique to the prediction of accident rates at newly improved intersections. To pursue this application, we began an in-house analysis program upon termination of the FHWA program.

CONFLICTS ANALYSIS PROGRAM

In February 1972, a program of conflicts analysis was initiated by the Traffic Studies Section of the Ohio Department of Transportation. Initial steps of this program were acquisition of the data base management programs from FHWA and enlargement of the Ohio data base.

The programs obtained from FHWA consisted of data base edit/update, card re-formatting, and correlation analysis. In addition, the Ohio data file maintained by FHWA was obtained. After several modifications were made to the FHWA programs to make them compatible with our computer system, a major file update was begun.

This program of data compilation, coding, keypunching, editing, and, finally, master file updating increased our data base from the 196 projects obtained during the FHWA study to 356 projects of current data by November 1972. By May 1973, all available conflicts counts and the latest available accident data had been placed in the master file and numerous minor errors were corrected, giving some 611 usable data points.

Under the initial Ohio conflicts analysis program, we decided that attention would be directed to the possible relationship between intersection accidents and conflicts. Although we were interested in other possible applications of the technique, such as pinpointing operational problems and freeway analysis, we felt that prediction of accidents at intersections would provide a much more valuable tool for the traffic engineer. In addition, we felt that the basic theories of the conflicts technique could be tested most effectively by such an analysis program.

For an accident projection technique to be useful, it must reflect the accident trends of the area to which it will be applied. Thus we decided that only Ohio data would be used in the analysis. After several initial tests of the expanded Ohio data base against projections using the algorithm proposed by the FHWA study, it became apparent that the FHWA algorithm was not sufficiently sensitive to accident trends in Ohio. Although Ohio data were used in the generation of the FHWA algorithm, it was felt that the urban

nature of the Washington and Virginia data used in the development of these equations biased the equations toward urban accident trends. Because the Ohio data are pre-dominately rural in nature, new relationships that would be more sensitive to rural conflict trends needed to be developed. Thus, the ultimate objective of Ohio's analysis program was to generate prediction equations for accidents based on the data collected in a conflicts study within Ohio.

In addition, it was hoped that insight might be gained into potential alterations or improvements in the conflicts count technique. In particular, attention was to be given to the utilization of any additional parameters such as cross-street volume and percentage of commercial vehicles not included in the previous analyses.

Procedure

The procedure used for this project can be broken into the following three basic phases:

1. Update data base to reflect all conflicts counts and accident data available,
2. Determine relationships among various measures of conflicts, exposure, accidents, and so forth to establish variables for use in prediction equations, and
3. Generate accident prediction equations and verify them against data obtained after cut-off date (final output was to be a report consisting of the results of this study and a user's manual for predicting accidents from conflicts counts).

Data Base Update

As stated earlier, before the initial data base was modified, several programming modifications were necessary. These changes in the edit/update program corrected for those differences between the FHWA computer and that of the Ohio Department of Transportation. Once these changes were completed, approximately 15,000 records were added to the data base. This addition of data ensured that all available conflicts counts and accident data were on the master file, thus providing the largest data base possible.

Data Analysis

Although some preliminary analysis was done while the data base was being built, serious analysis began November 7, 1972. This analysis was obtained through use of BMD02R, SAS, and our own GENPLOT programs. BMD02R is a multiple regression program developed by the Health Science Computing Facility at UCLA (4). This program was used for the initial analysis phase.

Output from the program consists of variable means and standard deviation, covariance matrix, correlation matrix, linear regression coefficients, and residual plots.

The statistical analysis system (SAS) is a group of statistical routines developed by the University of North Carolina for work such as that under discussion (3). Once obtained and on-line, SAS provided more useful, efficient, and informative output than BMD and was used almost exclusively during the later phases of the analysis.

The third program, GENPLOT, is a general plot and polynomial regression program that has been used to check for data trends, to plot data, and to generate least squares fits for the data.

A total of 11 dependent and 26 independent variables were included in the data analysis phase. In addition, data were classified according to various combinations of the following groups.

1. Average daily traffic range (ADT),
2. Conflict type,
3. Environment,
4. Intersection type,

5. Major to minor route volume ratio (split), and
6. Intersection control (signalized versus unsignalized).

Table 1 gives the classification systems tested, and, as can be seen, results of the analysis were somewhat discouraging. Although an occasional particular data subset gave correlations as high as 0.36 to 0.37, the given classifying system did not provide acceptable correlation factors for other subsets. Typically, R^2 for the regressions was far from the initially desired minimum of 0.3.

It was suspected that the rural and retail strip nature of the data contributed to the low correlations found in this initial phase. In most cases, the number of accidents per year on any given approach varied between 0 and 4, resulting in rather large standard deviations (approximately 2.5) in the accident rates as compared to the mean of about 2.2. Efforts at normalizing the data with exposure originally resulted in little or no improvement.

In mid-December of 1972, a major breakthrough was made in predicting accidents at unsignalized intersections. This breakthrough resulted when volume split was introduced as a variable in conjunction with normalizing accidents by ADT. At this point, it was found that, if the total observed cross volume was divided by the observed volume on the counted approach, this volume split became a critical variable. Also, when accidents are expressed in terms of accidents per 2 years per 1,000 ADT, the regression equations generated for unsignalized approaches were more reliable. The net result of these changes in the prediction model was a mean accuracy of about ± 2 accidents per year with a standard deviation of 0.2. An investigation of those points where our prediction error was greater than six accidents per 2 years revealed that several assumptions made earlier in the analysis phase were invalid. A new analysis of the data was made and resulted in development of a new, larger data base and even more reliable regression equations. After a regression model for unsignalized approaches was obtained, the next step was to find a model for signalized approaches. After some initial investigations and another update of the data base, a series of SAS runs was made to obtain regression equations.

The result of these final SAS runs was a set of equations for both of the individual control classes (signalized and unsignalized) and all data combined. Data points were classified by environment, intersection type, and accident type and were tested for possible use in the new models.

Finally, regressions were run on both raw accidents per 2 years and accidents per 2 years per 1,000 ADT. Although the environment and intersection type classifications appeared to provide good equations for some of the data, neither was consistent enough over all the data points to justify its use. In the end, it was decided that classification into signalized and unsignalized was sufficient.

Upon comparison of the projected accident rates to the actual accident data, the resulting error was within acceptable limits. Plots of this error are shown in Figure 1. It should be noted that, upon investigation of those points with the greatest prediction error, certain common characteristics were found.

1. Bad data point—In several cases it was found that accident records had been attributed to the wrong approach. In one case the correction of the coding error reduced the average prediction error over four approaches from roughly eight accidents per 2 years to about three accidents per 2 years.

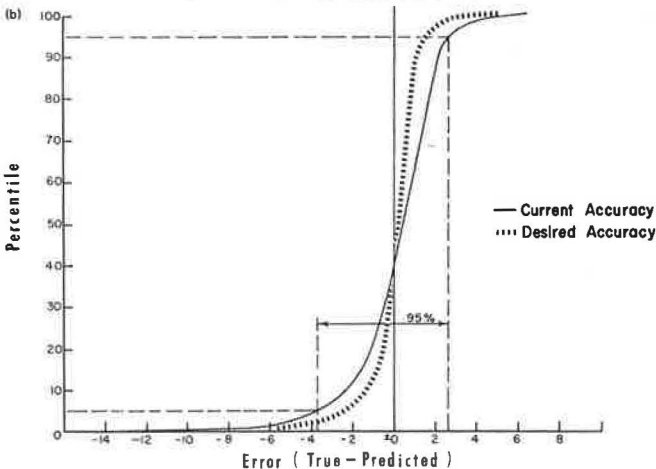
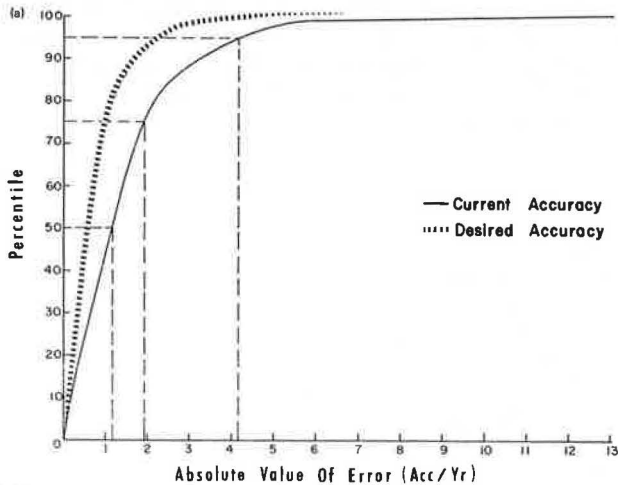
2. More than one approach lane—In most of the conflicts counts taken in Ohio, only one approach lane was provided on each leg of the intersection. In several cases studied where more than one lane existed on a given leg, the prediction error for that leg was high. This may be attributed to the sampling of only one lane for conflicts at such locations. It is suggested that, in future evaluations and regression runs, the number of approach lanes be included as either a variable or a classification criterion.

3. Combination of high volume and high speed—At several locations a high-volume, high approach speed leg had a poor prediction. A prime example of this is I-280 and Walbridge Road in Wood County. At this location, an at-grade intersection is signalized on the I-280 main line. The resulting interruption of flow on I-280 produced 31 accidents in 2 years. When a conflict count was run at the intersection, a rather low

Table 1. Classification systems tested.

Classifications	General Results			
	Sample Too Small	Poor	Average	Good
ADT range			X	
0 to 2,000		X		
2,001 to 7,000		X		
7,001 to 12,000			X	
More than 12,000	X			
Conflict type		X		
Weave			X	
Cross				X
Opposing				X
Rear end			X	
Environment			X	
Rural			X	
Retail strip		X		
Residential	X			
Intersection type			X	
T and Y	X			
Right angle			X	
Skew		X		
Volume split (unsignalized)		X		
Intersection control				X
Signalized				X
Unsignalized (including flasher)				X

Figure 1. Prediction error distribution for (a) absolute value and (b) true versus predicted value.



conflict-per-opportunity ratio was observed resulting in a prediction of only three accidents per 2 years. It is obvious from investigation of this and similar cases that our current prediction equations cannot be applied to such abnormal locations. As such, the reader is cautioned to apply the current algorithms with care.

4. Alteration during accident period—Ordinarily, accident data are recorded for a period 2 years before the conflicts count and 2 years after the count. In several cases an improvement was made during this period, and the resulting change in operation of the intersection naturally had an effect on the accident trends. When an accident projection was made from the conflict count, the error was often high in such cases. During any further analysis or attempts at generating accident trend equations, care will be taken to adjust the accident report period to reflect the operational characteristics sampled by the conflict count.

5. Unusual geometrics—The final basic type of poor prediction point was that generated at an intersection with unusual geometrics. Such a location might be found at a ramp junction, where a jug-handle is used for left turns. Because most of the data used in the regressions were from T and cross intersections, other types of intersections are not predicted well. Any location where "other" is coded as the intersection type should be excluded from analysis with the algorithms developed by this program.

Generation of Accident Prediction Equations

As stated earlier, after a substantial number of classification systems had been investigated, we decided that a simple division into signalized and unsignalized intersections would provide the most reliable accident prediction equations. The variables chosen for inclusion in the equations and the equations themselves are provided below. (The reader is cautioned that the blind use of these equations, as with any empirical model, may well produce poor results. Should anyone care to apply the results of our research in other states or under other than primarily rural conditions, he is encouraged to attempt to calibrate the basic model by analyzing data collected in his area.)

The variables used by Ohio were chosen by the SAS forward selection method of multiple linear regression (3) and are defined below.

<u>Variable</u>	<u>Definition</u>
ADT	Average daily traffic (in thousands) calculated from the conflict count
SPLIT	Ratio of the sum of the counted cross-street volumes to the counted approach volume
OPOPP	Opposing conflict opportunities
RROPP	Rear-end conflict opportunities
TTOPP	Total observed conflict opportunities
CPT	Total conflicts per 10 opportunities
OPCON	Opposing conflicts
TTCO	Total conflicts
OCPO2	Square of opposing conflicts per 10 opportunities
RATE	Accidents per 2 years per 1,000 ADT
AP2Y	Accidents per 2 years

The general form of the prediction equation for accidents at signalized approaches is

$$AP2Y = A + B \times ADT - C \times CPT - D \times D \times RROPP + E \times OCPO2 + F \times TTOPP - G \times OPOPP$$

Unsignalized approaches use the following equation form:

$$\begin{aligned} \text{RATE} &= A + B \times \text{SPLIT} - C \times \text{ADT}^{1/2} - D \times \text{SPLIT}^2 + E \times \text{ADT} \\ &\quad - F \times \text{OPOPP} + G \times \text{OPCON} \\ \text{AP2Y} &= H + \text{RATE} \times \text{ADT} \end{aligned}$$

In these equations, ADT is that value obtained from the conflict count. Although this often differs from the true ADT for the particular route, two limitations dictated that ADT be calculated from the count sheets. First, ADT is not normally available for the local streets and county roads counted in the conflicts program. Second, we felt that the traffic flow rate existing during the count period should be used to normalize the data inasmuch as the count day is very likely not to be an average day. In future analysis we hope to improve our predictions by using true ADT in the prediction equation.

In addition, the number of conflicts and opportunities used in the equations are those counted during a standard 10-hour period (ten 15-minute counts). Detailed descriptions of the count procedures, data reduction, and accident prediction algorithm may be found in other publications and in the Ohio Conflicts Procedure Manual, which will be published in 1974.

COMMENTS AND CONCLUSIONS

As a result of Ohio's analysis of the traffic conflicts technique, our traffic engineers have been provided with a means of determining the accident potential of a newly improved intersection, thus facilitating before and after studies. In addition to the accident prediction technique, Ohio has gained insight into the workings of the conflicts technique and an appreciation of the many possible applications of the theory of conflicts. The Appendix shows the kind of data collected in a conflict count and how they can be used in accident prediction.

Among the areas planned for future study is use of a modified conflict technique to evaluate freeway signing in gore areas. A pilot project run in 1973 has shown promise for the technique in evaluating the flow and safety of various areas of flow conflict such as freeway weave and gore sections. In addition, Ohio plans to conduct more research into the basic intersection analysis application to verify the equations we now have and improve on them to give more accurate before and after projections.

Thus, Ohio has conducted substantial research into the application of the traffic conflicts technique to accident prediction at rural intersections and has shown the method to be a potentially useful engineering tool. With some future development and "polishing" of the prediction algorithm, the basic model should provide an easily calibrated means of projecting the accident rates at newly constructed and improved intersections. Also, analysis of freeway sections may be simplified to some extent through application of a modified conflicts technique, and evaluation of conflicts data may well provide valuable input to the designing of new facilities and upgrading of existing ones. Indeed, conflicts may well help us move closer to preventive rather than remedial traffic engineering.

REFERENCES

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3. Service, J., Barr, A., and Goodnight, J. A User's Guide to Statistical Analysis System. Dept. of Statistics, North Carolina State Univ., Aug. 1972.
4. Dixon, W. J. Biomedical Computer Programs. Univ. of California Press, Los Angeles, 1967.

APPENDIX

SAMPLE CALCULATIONS

This Appendix is intended to show exactly what sort of information is gathered in a conflicts count and how it is used to predict accidents. Figures 2 and 3 show sample calculations for signalized and unsignalized accident rates. (Conflict counts are recorded on data sheet C, and volume counts are recorded on data sheet D.)

The variables tested for possible use in the regression equations are listed below.

<u>Variable Name</u>	<u>Interpretation</u>
ADT	Average daily traffic in thousands
ADT2	Square root of ADT
ADT3	ADT squared
APVOL	Counted approach volume
APYR	Accidents per year
AP2Y	Accidents per 2 years
CADT	Cross volume
CCPO2	CRCPO squared
CPT	Total of WVCPO, OPCPO, CRCPO, and RRCPO
CPT2	CPT squared
CRACC	Cross accidents
CRCON	Cross conflicts
CRCPO	Cross conflicts per 10 opportunities
CROPP	Cross conflict opportunities
NCTS	Number of 15-minute counts taken
OCPO2	OPCPO squared
OPACC	Opposing accidents
OPCON	Opposing conflicts
OPCPO	Opposing conflicts per 10 opportunities
OPOPP	Opposing conflict opportunities
RATE	Accidents per 2 years per 1,000 ADT
RCPO2	RRCPO squared
RRACC	Rear-end accidents
RRCON	Rear-end conflicts
RRCPO	Rear-end conflicts per 10 opportunities
RROPP	Rear-end conflict opportunities
SPLIT	Ratio of CADT/ADT
SPLT2	SPLIT squared
TTCO	Total conflicts
TTOPP	Total conflict opportunities
WCPO2	WVCPO squared
WVACC	Weave accidents
WVCON	Weave conflicts
WVCPO	Weave conflicts per 10 opportunities
WVOPP	Weave opportunities

Figure 2. Signalized intersection accident projection.

A. ADT. (data sheet D)

1. Total All Fields except Field 4 = 1777 =APVOL

2. $\frac{APVOL * 0.0066}{NCTS}$ = 1172.8 =ADT

B. CPT

1. Data Sheet C.

(a) Total Fields 1, 2 & 3, "No. Vehs." columns = 16 =WVOPP

(b) Total Fields 1, 2 & 3, "No. Confs." columns = 0 =WVCON

(c) Total Fields 4 & 5 "No. Vehs." columns = 205 =OPOPP

(d) Total Fields 4 & 5 "No. Confs." columns = 0 =OPCON

(e) Total Fields 6 thru 10, "No. Vehs." columns = 0 =CROPP

(f) Total Fields 6 thru 10, "No. Confs." columns = 0 =CRCON

(g) Total Fields 11 thru 22 = 44 =RRCON

2. Data Sheet D

(a) Total Fields 1, 2, 3, 5, 6, 10 thru 14, (-)Minus Field 4 = 934 =RROPP

3. (a) $\frac{WVCON}{WVOPP} * 10$ = + 0 =WVCPO

(b) $\frac{OPCON}{OPOPP} * 10$ = + 0 =OPCPO

(c) $\frac{CRCON}{CROPP} * 10$ = + 0 =CRCPO

(d) $\frac{RRCON}{RROPP} * 10$ = + 0.4711 =RRCPO

4. WVCPO + OPCPO + CRCPO + RRCPO = 0.4711 =CPT

C. RROPP (see B, 2, (a)) = 934 =RROPP

D. OCPO2 (see B, 3, (b)) = 0 =OCPO2

1. $(OPCPO = \frac{0}{10})^2$ = 0 =OCPO2

E. TTOPP (see B, 1, & B, 2)

1. WVOPP = 16

2. OPOPP = 205

3. CROPP = 0

4. RROPP = 934

5. WVOPP + OPOPP + CROPP + RROPP = 1155 =TTOPP

F. OPOPP (see B, 1, (c)) = 205 =OPOPP

G. AP2Y

1. +11.6345 * (ADT = 1172.8) = + 136449

- 0.0503 * (CPT = 0.4711) = - 0.0237

- 0.0321 * (RROPP = 934) = - 29.9814

+ 0.0387 * (OCPO2 = 0) = + 0.0000

+ 0.0285 * (TTOPP = 1155) = + 32.9175

- 0.02255 * (OPOPP = 205) = - 4.6228

+ 1.6153

Algebraic Total = Accidents per 2 Years = 13.5498 =AP2Y

H. Confidence Intervals: APYR = AP2Y / 2.0 = 6.78

1.

Percentile	X	APYR - X	APYR + X
50th	1.50	<u>5.28</u>	<u>8.28</u>
75th	2.40	<u>4.38</u>	<u>9.18</u>
90th	3.70	<u>3.08</u>	<u>10.48</u>
95th	4.60	<u>2.18</u>	<u>11.38</u>

Figure 3. Unsignalized intersection accident projection.

A. SPLIT

1. APVOL (Data Sheet "D")
 - (a) Total all fields except field 4 = 522 =APVOL
2. CROPP (Data Sheet "C")
 - (a) Total of fields 6 thru 10, "No Vehs" Columns = 683 =CROPP
3. $\frac{CROPP}{APVOL} =$ 1.3084 =SPLIT

B. SPLT2 (see A, 3 above)

1. $(SPLIT = \underline{1.3084})^2 =$ 1.7119 =SPLT2

C. ADT (see A, 1, (a))

1. $\frac{(APVOL = \underline{522})}{NCTS} * 0.0066 =$ 0.3132 =ADT

D. ADT2 (see C, 1)

1. $\sqrt{(ADT = \underline{0.3132})} =$ 0.5596 =ADT2

E. OPOPP (Data Sheet "C")

1. Total Fields 4 & 5, "No Vehs" Columns = 152 =OPOPP

F. OPCON (Data Sheet "C")

1. Total Fields 4 & 5, "No Confs" Columns = 0 =OPCON

G. APZY

1. RATE

(a) +17.7731 * (SPLIT = <u>1.3084</u>) =	<u>+23.2542</u>
- 1.6785 * (SPLT2 = <u>1.7119</u>) =	<u>- 2.8734</u>
+18.2544 * (ADT = <u>0.3132</u>) =	<u>+ 5.7173</u>
-36.7045 * (ADT2 = <u>0.5596</u>) =	<u>-20.5338</u>
- 0.0264 * (OPOPP = <u>152</u>) =	<u>- 4.0128</u>
+ 0.8385 * (OPCON = <u>0</u>) =	<u>+ 0</u>
	<u>+ 22.3568</u>
<hr/>	
Algebraic Total = Accident Rate =	<u>23,902.1</u> = RATE
2. APZY
 - (a) $[(RATE = \underline{23,902.1}) * (ADT = \underline{0.3132})] + 0.36 =$ 7,846.2 =APZY

H. Confidence Intervals: APYR = APZY / 2.0 = 3.92

1.

Percentile	X	APYR - X	APYR + X
50th	1.10	<u>2.82</u>	<u>5.02</u>
75th	1.75	<u>2.17</u>	<u>5.67</u>
90th	2.70	<u>1.22</u>	<u>6.62</u>
95th	3.80	<u>0.12</u>	<u>7.72</u>