Predicting Pedestrian Crosswalk Volumes

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The measurement of pedestrian volumes for use in determining signal warrants or calculating accident exposure has traditionally been accomplished by manual counting. Some efforts have been directed to the development of mechanical devices and analytical modeling. None of these developments have yet enjoyed widespread success and acceptance. In an effort to reduce the costs and resources to produce manual pedestrian counts, a sampling technique was developed using expansion models to predict hourly pedestrian volumes, thus reducing manpower requirements and data collection costs. The procedure was developed from data collected in Washington, D.C., that included over 18,000 5-min pedestrian count intervals. The resulting expansion models were validated with data not used to develop the models. The models and the procedures for applying them were deemed valid. There was strong intuitive evidence that this method may be applicable in other cities even though this aspect has not yet been tested.

The measurement of pedestrian volumes is considerably more difficult than the measurement of vehicle volumes. When compared to vehicles, pedestrians are less confined to marked traffic lanes; frequently tend to form groups; object to being controlled, observed, or measured; and display a great curiosity for unfamiliar objects and situations. In part, because of this variability and unpredictability of pedestrian movements, most pedestrian studies have used manual counts at specific sites for limited periods of 1 to 10 hr to obtain pedestrian volume data. Although this technique is labor intensive and expensive, past studies have not generally concerned themselves with developing more efficient data collection techniques.

The purpose of this study was to develop an optimum pedestrian sampling scheme using small count intervals to predict hourly and multihourly pedestrian volumes. With such a technique developed, savings in time and resources would be obtained to be applied with the two primary uses of these data: (a) evaluation of traffic signal warrants and (b) exposure data to be used in conjunction with accident or conflict data to produce accident rates or hazard indices.

PEDESTRIAN VOLUME MEASURING TECHNIQUES

Although manual counting is the most prevalent method of collecting pedestrian volume data, mechanical counting devices and analytical models have been developed for measuring pedestrian volumes. Cameron (*1–3*) describes an automatic pedestrian counter that was developed and refined during 1971 and 1972 in Seattle, Washington. The automatic pedestrian counter was used to record pedestrian volumes for a downtown employee population, a downtown shopper population, and a mixed population of employees, shoppers, visitors, and residents. Cameron concluded that the automatic pedestrian counter could be used to provide a reliable, economic data base for planning and designing pedestrian movement systems.

Mudaly (*4, 5*) describes a computer-based infrared pedestrian data acquisition system. The combined hardware-software instrumentation system enables pedestrian flow conditions at any point in a pedestrian traffic stream to be sampled, event by event, stored on magnetic cassette tape, and analyzed remotely by a digital computer. A photocell detector senses infrared reflections off the human body and clothing from a linear lamp. The effectiveness of the technique was evaluated by observation and by manually and automatically recording count comparisons. The error between observed number of pedestrians and automated count number was found to be approximately 5 percent.

Although automatic pedestrian counters have been developed, they have not been widely accepted and used. The mechanical counter developed and used in Seattle, Washington, has not been reported as being used outside that city and has not been used there on a regular basis. The computer-based infrared system first reported in 1979 and then again in 1980 has not been found in the literature since that time. It appears that this is not an area of active interest or current research and development.

Mathematical models for predicting pedestrian volumes have been developed, but they suffer from various deficiencies and limitations (*6–9*). Most models are site specific (i.e., they are limited to the area for which they have been developed and no record has been found of any attempt to generalize models from one city to another). The accuracy of the models depends on the amount and type of input data. Data collection costs increase rapidly as the amount and complexity of data increase. Finally, the reported models have not been tested over an extended period of time and temporal effects could have a significant influence on their accuracy.

Manual counting procedures using direct observation is the method most commonly used by cities to gather pedestrian volume data for routine use. Continuous counting procedures and sampling procedures are generally employed in this method. Pedestrian counts are generally conducted in accordance with procedures that are widely recognized and accepted but which may vary from city to city. Several research studies have also used manual counting procedures. However, these pedestrian volume counts were usually included as part of a larger study and were not the main focus of the research. Several studies have used some form of sampling for pedestrian volume data collection. Manual pedestrian counting procedures currently in use are both costly and labor intensive.

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METHODOLOGY

Short-term vehicle counts of 5, 6, 10, or 15 min are routinely used to estimate hourly and daily vehicle volumes. In most cases the accuracy of the expanded counts is adequate for their intended use such as analysis of maximum flow rates, flow variations within peak hours, capacity limitations, and peak hour volume characteristics. One of the major uses for pedestrian volume data is to determine whether or not revised Warrant 3, the minimum pedestrian volume warrant for the installation of traffic signals, as specified in the *Manual on Uniform Traffic Control Devices* (MUTCD) is satisfied. To make this determination, a knowledge of hourly pedestrian volumes for the highest volume hour (at least 190 pedestrians) or 4 hr (at least 100 pedestrians per hour) during the day is required. In view of this requirement and considering the variable nature of pedestrian activities, pedestrian counts are usually made continuously for a 10- to 12-hr period. This technique provides great accuracy, but is labor intensive and therefore expensive.

The expansion model developed in this study uses a sampling technique to predict hourly pedestrian volumes, thus reducing manpower requirements and data collection costs. For this method, a short-term count is taken within each hour (or multihour) of the study period and expanded, based on the length of the count period, to predict the total count for the hour(s). In this way hourly volume counts may be determined for the entire study period. The accuracy of the expanded counts is determined by the length of the count period and the position of the count period within the hour(s). For example, a 5-min count may be selected for a given crossing site. It could be specified that this count be made for the first 5 min of each hour, the last 5 min of each hour, some 5-min period within the hour, or for a randomly chosen 5-min period within each hour. This study investigated sampling schemes with sampling periods of varying length, occurring at differing positions within the hour, in order to determine an optimum procedure.

DATA COLLECTION

The data for this study were the number of pedestrians observed crossing at either an intersection or midblock crossing during 5-min intervals. Data were collected in Washington, D.C., during July 1986 at eight intersections and six mid-block locations. The principal criterion for site selection was land use, because this is usually the dominant factor in the generation of pedestrian trips. The sites by name, primary land use, and type of crossing are given in Table 1. A mixture of signalized and unsignalized locations was obtained. Care was taken to select locations with significant pedestrian volumes so that an adequate amount of data could be collected within the resources of the study.

All pedestrian crossings were counted at each site during each 12-hr data collection period. These 12-hr samples consisted of continuous counts that were made at each site by one or two data collectors (depending on the level of pedestrian activity). The counts were made on weekdays for the 12-hr period from 7 a.m. to 7 p.m. Pedestrian volumes were recorded in each crosswalk at 5-min intervals. Three days of data were recorded at each site.

TABLE 1 SITES SELECTED

Site	Land Use	Type of Crossing
Connecticut Ave. at National Zoo, N.W.	R	M
14th & E Sts., N.W.	O	I
14th & U Sts., N.W.	Rs	I
23rd & H Sts., N.W.	S	I
Jefferson Dr. & 7th St., S.W.	C	I
12th & Monroe Sts., N.E.	Rs	I
15th St. & Constitution Ave., N.W.	R	I
1st St. & Independence Ave., S.E.	C	I
Connecticut Ave. & DeSales St., N.W.	O	M
Howard University on Georgia Ave., N.W.	S	M
Connecticut Ave. & Woodley Road, N.W.	Rs	I
17th St., N.W. between Constitution & Independence Aves.	C	M
4200 block Massachusetts Ave., N.W.	Rs	M
7th St. south of D St., S.W.	O	M

NOTE: C = cultural/entertainment, I = intersection, M = midblock, O = office/retail, R = recreation/parks/zoo, Rs = residential (multifamily), and S = schools/institutions.

DATA ANALYSIS

A data base of 18,432 5-min intervals of pedestrian counts was produced that in turn permitted a complete and thorough analysis of any combination of variables. For model development, 10 sites were randomly selected from the 14-site data base. The remaining four sites were used to validate the models. Only the first data set (one 12-hr day of data per site approach) was used for both modeling and validation. Thus, 408 hr of observations were used in the expansion modeling and 120 hr in the validation.

The sampling interval times investigated were 5, 10, 15, and 30 min. All of these sampling intervals were analyzed for the first, middle, last, and random positions in the time frame being predicted.

In reviewing the data distributions for use in the 1-hr prediction models, all variables showed positive skewness. (Normality of data is a requirement in regression.) The skewness values associated with each interval and position variable are shown in Table 2. For a sample size greater than 250, the critical skewness value ($B1$) at a 98 percent confidence level is 0.13. The original data for all variables had skewness values greater than 3.

To adjust these data in order to produce a normal distribution, the logarithms were calculated for all observations for all variables. Table 2 also shows the skewness values for the logarithmic transformation. All variables except for last 10-min, first 15-min, and last 15-min events are less than the critical value of 0.13; thus, at the 98 percent confidence level, these variables constitute a normal distribution. As for the three exceptions, they are slightly skewed to the negative side of the normal distribution. However, regression was performed on all variables while recognizing that these three exceptions were not normally distributed.

From the regression analysis of 1-hr modeling, Table 3 was constructed to evaluate the count intervals and the position of the events within the interval. For all count intervals, the middle event produced the better model because it exhibited the highest coefficient of determination (R^2) and the lowest standard error about the mean (SE_y). Also, it was apparent that

TABLE 2 SKEWNESS VALUES FOR 1-HR MODEL VARIABLES

Time Interval and Position Within Hr	Original Data Sample Size	Original Data Value	Transformed Data Sample Size	Transformed Data Value
Total hr	408	3.80	408	−0.06
First 5 min	402	4.07	358	0.02
Middle 5 min	404	3.88	366	−0.02
Last 5 min	404	3.81	374	−0.04
Random 5 min	404	4.09	370	0.03
First 10 min	408	4.00	394	−0.08
Middle 10 min	404	3.78	396	−0.08
Last 10 min	404	3.84	393	−0.19[a]
Random 10 min	404	5.07	394	−0.07
First 15 min	408	3.90	402	−0.16[a]
Middle 15 min	404	3.86	399	0.02
Last 15 min	404	3.68	400	−0.21[a]
Random 15 min	404	3.45	401	−0.10
First 30 min	408	4.01	408	−0.08
Middle 30 min	404	3.88	404	−0.01
Last 30 min	404	3.71	403	−0.04
Random 30 min	404	3.86	403	−0.00

NOTE: Not all samples will have 408 observations because of missing data or logarithms of observations with counts of zero.
[a]Exceeded critical skewness value of 0.13.

as the count interval increased from 5 to 10 to 15 to 30 min, the prediction models became better. This was expected since the variation among count intervals decreased as the count interval increased. Therefore, based on the R^2 and SE_y values, the middle event count intervals were selected as the best predictors of 1-hr counts.

TABLE 3 COEFFICIENTS OF DETERMINATION AND STANDARD ERROR OF ESTIMATES FOR 1-HR MODELS

Variables Correlated with Total Hr	R^2	SE_y
First 5 min	0.72	0.26
Middle 5 min	0.77	0.22
Last 5 min	0.75	0.24
Random 5 min	0.73	0.25
First 10 min	0.80	0.22
Middle 10 min	0.86	0.18
Last 10 min	0.82	0.20
Random 10 min	0.70	0.27
First 15 min	0.85	0.19
Middle 15 min	0.91	0.15
Last 15 min	0.88	0.17
Random 15 min	0.90	0.15
First 30 min	0.94	0.12
Middle 30 min	0.96	0.09
Last 30 min	0.94	0.12
Random 30 min	0.95	0.11

NOTE: All F- and t-statistics were significant at $p = 0.0001$.

The expansion models developed for the middle event of the four count intervals follow:

5 min: $V1 = 19.91\ I5^{0.7862}$ (1)

where $V1$ is 1-hr prediction and $I5$ is the middle 5-min count.

10 min: $V1 = 9.82\ I10^{0.8465}$ (2)

where $I10$ is the middle 10-min count.

15 min: $V1 = 5.75\ I15^{0.8996}$ (3)

where $I15$ is the middle 15-min count.

30 min: $V1 = 2.37\ I30^{0.9625}$ (4)

where $I30$ is the middle 30-min count.

As stated earlier, the larger the count interval for the middle event became, the better the volume prediction became. However, all models are presented in order to give the user the option of choosing the desired degree of accuracy. The user may need only a rough 1-hr estimation, thus using a middle 5-min count is adequate. If a more accurate 1-hr estimation is desired, a middle 30-min count may be required.

Models were also developed for 2-, 3-, and 4-hr volume counts using the same procedures discussed previously. Thus, only a brief description of each of these models will follow. Because the random sampling scheme produced the poorest results for the 1-hour modeling, this scheme was not used for the modeling of 2-, 3-, and 4-hr volumes. Also, the "middle event" was defined as the middle period of the time interval being modeled.

Skewness values were determined for the observations of the first, middle, and last count interval variables. Again, all variables had positive skewed distributions, and the logarithm was taken to correct this skewness. A few variables still exhibited skewness; however, as before, regression was used on all sampling schemes.

Using R^2 and SE_y, the sampling scheme models were evaluated to find the optimum counting event. The values of R^2 and SE_y for each set of multihour models are presented in Table 4. Reviewing this table showed the middle event of all counting intervals to produce the better models. Also, as the count interval increased, the expansion models' predictability improved. Based on these results, the middle event produced the best predictor of multihour volumes, which corresponded to the findings with the 1-hr models. The equations for the three multihour expansion models based on the middle event follow:

5 min: $V2 = 43.04\ I5^{0.7686}$ (5)

10 min: $V2 = 20.89\ I10^{0.8226}$ (6)

15 min: $V2 = 14.65\ I15^{0.8241}$ (7)

30 min: $V2 = 6.14\ I30^{0.8918}$ (8)

where $V2$ is the 2-hr volume prediction.

5 min: $V3 = 60.19\ I5^{0.7851}$ (9)

10 min: $V3 = 32.15\ I10^{0.8184}$ (10)

15 min: $V3 = 17.38\ I15^{0.8842}$ (11)

30 min: $V3 = 9.44\ I30^{0.8901}$ (12)

where $V3$ is the 3-hr volume prediction.

TABLE 4 COEFFICIENTS OF DETERMINATION AND STANDARD ERROR OF ESTIMATES FOR 2-, 3-, AND 4-HR MODELS

Variables Correlated with 2-, 3-, and 4-Hr Counts	2-Hr		3-Hr		4-Hr	
	R^2	SE_y	R^2	SE_y	R^2	SE_y
First 5 min	0.67	0.27	0.61	0.29	0.58	0.30
Middle 5 min	0.74	0.24	0.75	0.23	0.85	0.17
Last 5 min	0.70	0.25	0.68	0.26	0.51	0.31
First 10 min	0.70	0.26	0.43	0.33	0.59	0.30
Middle 10 min	0.84	0.19	0.81	0.20	0.86	0.17
Last 10 min	0.78	0.22	0.75	0.23	0.67	0.27
First 15 min	0.73	0.25	0.68	0.27	0.63	0.28
Middle 15 min	0.86	0.18	0.85	0.18	0.91	0.14
Last 15 min	0.80	0.22	0.78	0.23	0.72	0.26
First 30 min	0.83	0.20	0.75	0.24	0.72	0.25
Middle 30 min	0.92	0.14	0.90	0.15	0.90	0.15
Last 30 min	0.86	0.18	0.84	0.20	0.76	0.23

NOTE: All F- and t-statistics were significant at $p = 0.0001$.

$$5\text{ min: } V4 = 62.43\ I5^{0.8113} \quad (13)$$

$$10\text{ min: } V4 = 44.89\ I10^{0.7618} \quad (14)$$

$$15\text{ min: } V4 = 27.13\ I15^{0.8087} \quad (15)$$

$$30\text{ min: } V4 = 15.57\ I30^{0.8134} \quad (16)$$

where $V4$ is the 4-hr volume prediction.

In summary, this analysis effort produced good expansion models based on the evaluation of the parameters R^2 and SE_y. Additionally, four observations were made:

- The middle event for any counting interval of any hour or multihour expansion model was determined to be the best sampling scheme with respect to position. This phenomenon indicated that the position of a count during any time period was important in order to produce an accurate expanded count.
- As the counting interval increased, the volume prediction became more accurate. Because small count intervals have more variation from one interval to the next, the potential for extracting a nonrepresentative count for the time period being predicted is high. Thus, a larger count interval will reduce this variation and produce a better representation of the time period.
- As the sampling period increased (from 1 to 2 to 3 to 4 hr), the prediction became less accurate based on the four sample count intervals (5, 10, 15, and 30 min) used in this study. This result was due to the variation that exists with small sample intervals.
- The different volume distributions of the 10 sites used in this analysis did not affect the outcome of the position of the counting interval. This observation was based on the high values of R^2 for the middle event. Thus, these expansion models were reliable in predicting volumes regardless of the volume distribution patterns.

VALIDATION

As stated earlier, four sites were excluded from the modeling effort for use in validating the models developed. These sites produced 120 observations for the 1-hr models, 60 observations for the 2-hr models, 40 observations for the 3-hr models, and 30 observations for the 4-hr models. All four counting intervals were studied for each model.

The purpose of the validation study was to investigate the accuracy of the models using data that were not included in the development of the models. Even though these four sites were from the same city from which the models were developed, their volume distribution patterns were all different. As was observed in the development of the models, the middle counting interval produced the best models regardless of the volume distributions. The 14 sites produced six 12-hr distribution patterns. These patterns are shown in Figure 1. Therefore, the hourly or multihourly observations contained in these four sites are intuitively representative of any observation that could have been taken from any site in any city.

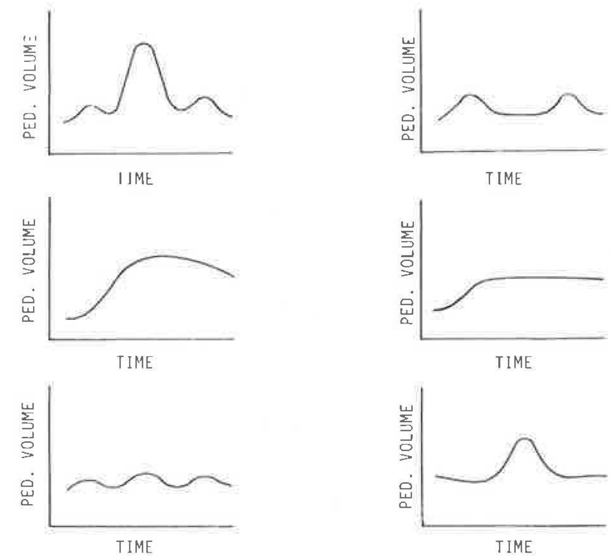

FIGURE 1 12-hr distribution patterns.

The average percent differences between predicted and actual counts were calculated for each count interval expansion model and are presented in Table 5. The table clearly shows that the percent error (average percent difference) decreased as the count interval increased. As found earlier, the models also became more accurate as the count interval increased.

TABLE 5 PERCENT ERROR BASED ON THE FOUR VALIDATION SITES FOR 1-, 2-, 3-, AND 4-HR EXPANSION MODELS

Predicted Volume (hr)	Count Interval (min) 5	10	15	30
1	31.2	27.1	18.9	11.9
2	34.5	28.7	23.6	20.6
3	33.2	31.0	28.0	23.6
4	33.6	28.4	27.4	23.5

NOTE: All percentages are in ± values.

In terms of accuracy of the models developed, the following example compares the percent error (Table 5) to the SE_y of the 1-hr model for a 5-min count of 10 pedestrians. By use of the

1-hr, 5-min model (Equation 1), the hour volume predicted was 122 pedestrians. The SE_y for this equation (0.22) produced a volume range of 202 to 73 pedestrians. For the percent error factor (31.2 percent), the volume range was 160 to 84 pedestrians. Therefore, based on the validation data set, predictions made by the model were within the parameters set forth by the regression modeling analysis.

APPLICATION OF PEDESTRIAN COUNTING PROCEDURE

The application procedure contains four steps. Each step is described and its implementation is illustrated with an example.

Step 1: Select Type of Application

To evaluate signal warrants, there must be hourly counts by crosswalk. However, because the pedestrian volume warrant is based on the number of pedestrians crossing the highest volume crosswalk exceeding a stated minimum for each of 4 hr or 1 peak hr in a given day, it is only necessary to determine which crosswalk has the highest volume and count that one. Therefore, the user must make a sample count during each of at least 4 hr or 1 hr on a given day.

For exposure data applications, a daily total pedestrian volume count for the crossing or entire intersection is usually required. Therefore, samples may be taken every hour, every 2 hr, every 3 hr, or every 4 hr depending on the level of accuracy desired.

Step 2: Select Count Interval

The sample count interval (5, 10, 15, or 30 min) is established by the user's selected application, desired level of accuracy, and the use of the percent error (prediction range factors) developed in the previous section. For the signal warrant application, only 1-hr predictions are used. For exposure data, 1-hr or multihour predictions may be used.

The values in Table 5 are percentages that indicate the expected degree of accuracy of an expanded sample crosswalk count. For example, a 5-min sample count of an hourly volume is less accurate than a 30-min count because the percent errors are 631.2 percent and ±11.9 percent, respectively.

Step 3: Collect Data

Through careful scheduling, greater economies in time and resources may be achieved. Not only will time be saved at a specific site by sampling, but also that time saved may be used to sample additional sites. As discussed in the previous section, the selected count interval (5, 10, 15, or 30 min) must be positioned in the middle of the period to be sampled (i.e., 1 hr, 2 hr, 3 hr, or 4 hr). For example, a 10-min sample for the period 8 to 9 a.m. would be from 8:25 to 8:35 a.m.

In order to schedule a data collector to cover more than one site, the period from which the sample is drawn is simply redefined for each site. For example, given three sites within 10-min travel time of one another, a 10-min count interval is selected, sampling 1-hr periods. The schedule for the first hour might be as follows:

Site	*Period (a.m.)*	*Sample Count (a.m.)*
1	7:40–8:40	8:05–8:15
2	8:00–9:00	8:25–8:35
3	8:20–9:20	8:45–8:55

If for some reason the hourly volume counts for one site are to be compared with the hourly volume counts at other sites, the periods and sample count times must be the same and more than one data collector would be required.

Step 4: Compute Estimated Volumes

Select from Equations 1–16 the expansion model that corresponds to the period (1, 2, 3, or 4 hr) and count interval (5, 10, 15, or 30 min). For example, the model for a 3-hr period and a 15-min count interval would be:

$$V3 = 17.38\ I15^{0.8842}$$

Substitute the sample count, I, in the model selected and perform the calculation to obtain the expanded period count. For example, a sample count of 20 would predict an expanded 3-hr volume of 246.

$$V3 = 17.38\ (20)^{0.8842} = 246$$

Note that the predicted volumes correspond to the period selected in accordance with the application selected in Step 1 (i.e., the 1-hr models produce 1-hr volumes, the 2-hr models produce 2-hr volumes, and so on).

CONCLUSIONS AND RECOMMENDATIONS

The modeling effort resulted in good pedestrian volume prediction models based on R^2 and SE_y. In all cases, the middle interval position event produced the best model regardless of the size of the count interval. However, it was apparent that the larger the count interval, the better the volume prediction.

Additional findings were as follows. As the multihour volume period increased, the multihour prediction became less accurate. This was a result of the increase in variation of the counting intervals as the 1-hr volumes increased to 4-hr volumes. Also, the models for the middle counting intervals were not affected by the different volume distributions that existed for the hour or multihour volume counts. This was evident by the constant result of the middle event being the best predictor of pedestrian volumes.

A validation study was conducted using the middle count models. The purpose of this study was to determine the prediction error of the expansion models. Findings of this validation reflected the earlier findings in the modeling effort. As the count interval increased, the percent error decreased; thus, the better the volume prediction. Also, as the prediction of hourly volumes increased to multihour volumes, the percent error became larger and was reflected in the modeling effort by the decrease of R^2 and increase of SE_y.

Regardless of the findings of the modeling approach, one question will arise for studies constrained by using data in only one city: Are these models valid in other cities that have different characteristics? The answer, at present, is unknown. However, the hourly models were derived with approximately 400 hourly observations and validated with 120 observations. This means that there were possibly 400 different 1-hr volume distributions in the modeling derivations and 120 different distributions in the modeling validations. Thus, the potential of encompassing many of the typical 1-hr distributions is good.

As for the multihour models, the sample sizes were less than for the 1-hr models. Confidence in the reliability and validity of these models was not as great as it was in the 1-hr models. Therefore, additional research would improve these multihour models.

Additional research on these models could take two approaches. To test the validity of the models developed in this study, data should be collected at several sites for several cities throughout the country. These data then would be input into these models. The validity would be tested by comparing the percent errors calculated in this study with the percent errors calculated for the additional data. If these percent errors are found to be statistically the same, then the models developed here would be valid.

The second approach would test the models' reliability. In testing model reliability, models would have to be developed for various cities and then compared with the models of this study. The models developed in this study would be reliable for use in other cities if the models developed for other cities had the following characteristics: positively skewed data (corrected by logarithmic transformation), optimum counting intervals occurring at the middle event, and regression equations and parameters similar to those of this study.

In conclusion, promise has been shown for the use of expansion models in predicting pedestrian volumes. As presented in the application section of this report, the ease and cost reduction in the use of these models is clear. With the additional research conducted in other cities, these models could prove to be beneficial in the prediction of pedestrian volumes for use in signal warrants and exposure data applications.

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