Model of Turning Movement Propensity

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A model is described for determining the seed or propensity matrix from which turning flows at an intersection can be estimated to match given inflow and outflow volumes, using the biproportional method when intersection-specific counts are unavailable. Normalizing counts to standard inflow and outflow totals is demonstrated to reveal a striking similarity in underlying propensities across intersections. Functional class is shown to be a poor explanator of different propensities. Propensity is modeled as a function of angle, competing short cuts, presence of dead-end approaches, and grid density. Estimates made using the propensity model seed are found to have prediction errors of about 6 percent of inflow volume, compared to errors of 4 percent for estimates that use an intersection-specific count as seed.

Turning counts at intersections are needed for a variety of reasons, including signal design, capacity analysis, safety design, and impact analysis. The traditional way of measuring these movements is manual, that is, to have one or more persons count vehicles at the intersection. The cost of doing manual counts is prohibitive for some applications, such as making statewide forecasts of intersection capacity needs and a variety of either preliminary or long-range analyses. For such analyses, inflow and outflow volumes at each approach are often known (or estimated) from traffic counts made with automatic traffic recorders (ATRs) that use a pressured tube laid across a roadway. The availability of these inflow and outflow volumes has set the stage for the development of estimation methodologies that distribute the flows among the various possible turning movements. If the turning movements are represented as an origin-destination (O-D) matrix, the incoming approach volumes are then row totals and the outgoing volumes are column totals. In order to estimate turning movements at an intersection, a seed matrix representing an initial guess of the turning movements is mathematically balanced to make its row and column totals match the ATR-measured approach volumes.

Estimation of O-D matrices that agree with summary data such as row and column totals has been a fruitful area of study for the last decade. For example, Van Zuylen (*1*), Mekky (*2*), and Hauer et al. (*3*) deal with turning movements at a single intersection; Van Zuylen and Willumsen (*4*), Bell (*5*), and Geva et al. (*6*) deal with trip matrices on road networks; Ben Akiva et al. (*7*), Simon and Furth (*8*), and Furth (*9*) deal with passenger trips along a bus route; and McNeil and Hendrickson (*10*) deal with general matrix estimation. Of the various methods proposed for estimating O-D matrices, one method that is generally acknowledged to yield good results is the biproportional method. Ben-Akiva et al. (*7*), who review three methods (including the biproportional method) based on a seed matrix, find that they give similar results. The mathematical tractability of the biproportional method makes it therefore the preferred method.

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BIPROPORTIONAL METHOD

Given a seed matrix of propensities or prior estimates $((p_{ij}))$, and a set of desired row and column totals, the biproportional method produces a matrix of estimates $((t_{ij}))$ given by

$$t_{ij} = A_i B_j p_{ij} \tag{1}$$

where A_i and B_j are row- and column-specific factors whose values are set so as to ensure that the estimated row and column totals match the given row and column totals. Unfortunately, there is no closed-form solution for the A_is and B_js. One method for solving for the t_{ij}s is as follows. Beginning with the seed matrix, factor each row so that its total matches the given row total. Then factor each column to match the given column total. Because this factoring will upset the row totals, repeat the process, balancing each row, then each column, until all row and column totals match. It can be proven that the procedure will eventually converge. Let α_i^k equal the balancing factor applied to Row i in Iteration k, and let β_j^k equal the balancing factor applied to Column j in Iteration k, and suppose that procedure converges in K iterations. The estimate for Cell (i,j) will be

$$t_{ij} = p_{ij}(\alpha_i^1\alpha_i^2 \ldots \alpha_i^K)(\beta_j^1\beta_j^2 \ldots \beta_j^K) \tag{2}$$

The ultimate row and column factors are then

$$A_i = \alpha_i^1\alpha_i^2 \ldots \alpha_i^K \text{ and } B_j = \beta_j^1\beta_j^2 \ldots \beta_j^K \tag{3}$$

and with this substitution it is clear that Equation 2 is of the form of Equation 1. Therefore, this method yields a biproportional solution.

Hauer et al. (*3*) provide a theoretical basis for the method, interpreting the seed as a matrix of expected values, and the resulting matrix as the most likely realization of a random process governed by this seed that matches the given row and column totals. (This logic is the reverse of the usual maximum likelihood logic, in which expected values are estimated from a realization or sample of a random process.) Another interpretation is that the method agrees with a gravity model theory of travel. The seed matrix represents propensities (inverse impedances) for travel between the various O-D pairs, and each propensity is multiplied by an origin-specific factor (representing the origin's capacity to generate trips) and a destination-specific factor (representing the destination's capacity to attract trips). These origin and destination factors are not exogenously specified, but are uniquely implied by the new productions and attractions of the various origins and destinations.

PAST ATTEMPTS AT SELECTING A SEED MATRIX

Biproportional estimates of turning flows depend on the seed matrix. Schaefer (*11*) summarizes reported estimation accuracy using different sources of seeds. The best accuracy is found when the seed is based on intersection-specific counts. These counts might be old counts, counts done for a short period, or counts done in a different period of the day. The author's research, based on data from 14 intersections in eastern Massachusetts, confirms the high degree of accuracy attainable using such seeds. Not all intersections had the necessary data (e.g., an old count), and some intersections supplied data for both an a.m. peak and a p.m. peak hour. The results, presented in Table 1, express accuracy in terms of relative root mean-squared (RMS) error, that is, the square root of the mean-squared prediction error divided by the mean inflow. The relative RMS error for seven intersection-specific seed types tested is shown to be small, between 4 and 7 percent for left, straight, and right movements. Of particular interest is the satisfactory accuracy obtained using 15-min counts as a seed. These counts could be made by the technician that lays down the ATR equipment at little additional cost when ATRs are the source of inflow and outflow volumes. Furth (*12*) provides more detail on this study of intersection-specific seeds.

The main intent, however, is to deal with the far more common case that old counts at an intersection are unavailable, and resources prohibit the collection of even short-period counts. In order to deal with this situation, a variety of seed types have been tested. As reported by Schaefer (*11*), they include two naive approaches: (a) equal propensities for all movements, and (b) the use of arbitrary standard propensities such as 25/50/25 (left/through/right) or, following the 1965 *Highway Capacity Manual* (*13*), 10/80/10. A third approach is to use mean proportions derived from a city-specific sample of intersections. For example, Mountain and Steele (*14*) used average proportions (18.2 percent left, 66.0 percent through, 15.8 percent right, with left-hand rule of road) in the Merseyside, England, metro area and found better estimation accuracy than using the two naive methods.

A fourth approach is to classify intersections and use average proportions for each class, based on a sample of intersections in each class. This approach was followed by Hauer et al. (*3*) using Toronto data. They originally examined five classes of intersections, corresponding to Toronto's grid network: central business district (CBD), arterial-arterial, collector-collector, and two orientations of arterial-collector (depending on whether the arterial ran north-south or east-west). The distinction by orientation was dropped in the final model. The final model, with four intersection classes, has five types of approaches (because an arterial-collector intersection has two types of approaches), and average movement proportions were calculated for each approach type. These proportions are reproduced in Table 2. The striking differences between these proportions would seem to justify the notion that the approach types are very different from one another, and that therefore

TABLE 1 ESTIMATION ACCURACY FOR INTERSECTION-SPECIFIC SEED SOURCES

Seed Source	Root Mean Squared Error as a Fraction of Mean Inflow Volume			Total number of cases
	Left	Through	Straight	
15-min count, same period	5%	6%	6%	39
15-min count just outside period	4%	4%	4%	41
15-min count in opposite period	6%	7%	5%	22
15-min count in opposite period, transposed	5%	5%	5%	22
recent 60-min count, same period	5%	5%	5%	24
recent 60-min count, opposite period, transposed	6%	6%	6%	41
old 60-min count, same period	4%	5%	4%	41

TABLE 2 TORONTO CLASSIFICATION SCHEME

Approach Type	Proportion Left	Proportion Straight	Normalized Propensity Left	Normalized Propensity Straight	Number of Approaches in Sample
CBD	0.10	0.78	0.10	0.78	92
Arterial to arterial	0.12	0.76	0.12	0.76	83
Arterial to collector	0.04	0.91	0.13	0.71	52
Collector to arterial	0.30	0.38	0.14	0.71	53
Collector to collector	0.10	0.70	0.10	0.70	3

using a different seed for each intersection class should dramatically improve estimation accuracy. However, no comparison was made of accuracy using four classes versus a single class. The next section will demonstrate that there is reason to believe that the four Toronto classes are not as different as they appear to be.

VALUE OF NORMALIZING MATRICES

An important feature of the biproportional method is that the solution is invariant to a biproportional adjustment of the seed matrix. A biproportional adjustment of the seed has the form

$$q_{ij} = p_{ij}C_iD_j \tag{4}$$

where C_i is a strictly positive row-specific factor and D_j is a strictly positive column-specific factor. Another way of stating this property is that two seed matrices are equivalent (in terms of results) if one is a biproportional adjustment of the other.

In order to prove this result, suppose matrices $((p_{ij}))$ and $((q_{ij}))$ are both used as seeds and are updated to the same set of row and column totals. The solution using $((q_{ij}))$ as the seed is given by

$$t'_{ij} = q_{ij}A'_iB'_j = p_{ij}(C_iA'_i)(D_jB'_j) \tag{5}$$

where A'_i and B'_j are the implicit row and column adjustment factors, whereas the solution using $((p_{ij}))$ as the seed is given by Equation 1:

$$t_{ij} = A_iB_jp_{ij} \tag{1}$$

It is clear that one solution to Equation 5 is for $C_iA'_i = A_i$ and $D_jB'_j = B_j$, in which case $t'_{ij} = t_{ij}$. Then, since the biproportional method is known to yield a unique solution, this solution is it.

Therefore, because seed propensities are not unique, they can be manipulated biproportionally for the convenience of the analyst. One reason to manipulate seeds is to permit a comparison. Matrices $((p_{ij}))$ and $((q_{ij}))$ might appear different even though they produce the same results. Their equivalence is visible, however, when they are manipulated to a common set of row and column totals. For example, the normalized Toronto seeds are shown next to the inflow proportions in Table 2. Normalized straight propensities for all five types of approaches are between 70 and 78 percent, and except for the collector-collector approach, which had only three observations in the sample, the left and right propensities are nearly equal. These results suggest that Hauer et al. (*3*) could have used one seed for all approach types and obtained nearly as good a fit. They also demonstrate that the differences in turning proportions between functional classes are attributable mainly to the different inflow and outflow volumes they carry, rather than to intrinsic differences in turning propensity.

Another striking example is shown in Figure 1. Part (a) shows the turning movements at an intersection in suburban Boston. Just east of this intersection is an interchange with a major freeway, and just north of it is a large industrial park, strongly skewing the flows. In Figure 1b, these flows have been normalized so that all inflow and outflow volumes equal 100. As this second figure indicates, the underlying propensities at this intersection are quite normal—roughly 20/60/20 at all four approaches—showing that the unusual traffic pattern, in this case anyway, is not caused by unusual turning propensities, but to unusual productions and attractions.

Other comparisons of normalized counts have revealed strong similarities between a.m. and p.m. peak propensities, a tendency for left and right propensities to be equal, and a tendency for through propensities at the four legs of an approach to be equal.

VARIATION AMONG MASSACHUSETTS INTERSECTIONS

A total of 105 four-way intersections were examined in eastern Massachusetts. Most intersections are from the Boston suburbs; none are from the downtowns of Boston or other central cities. Counts were obtained primarily from consulting firms and local governments. Most of the count data include both an a.m. peak and a p.m. peak count, yielding 201 peak-hour counts altogether. As shown in Figure 2, the 804 approaches they comprise exhibit wide variety in the proportion of through volume. When normalized, however, the distribution tightens significantly, with about 75 percent of the approaches reflecting a through propensity between 50 and 80 percent.

The results of Figure 2 indicate that there is far more similarity in propensity than might have been suspected from intersections with such widely varying turning patterns. Nevertheless, significant differences in turning propensities

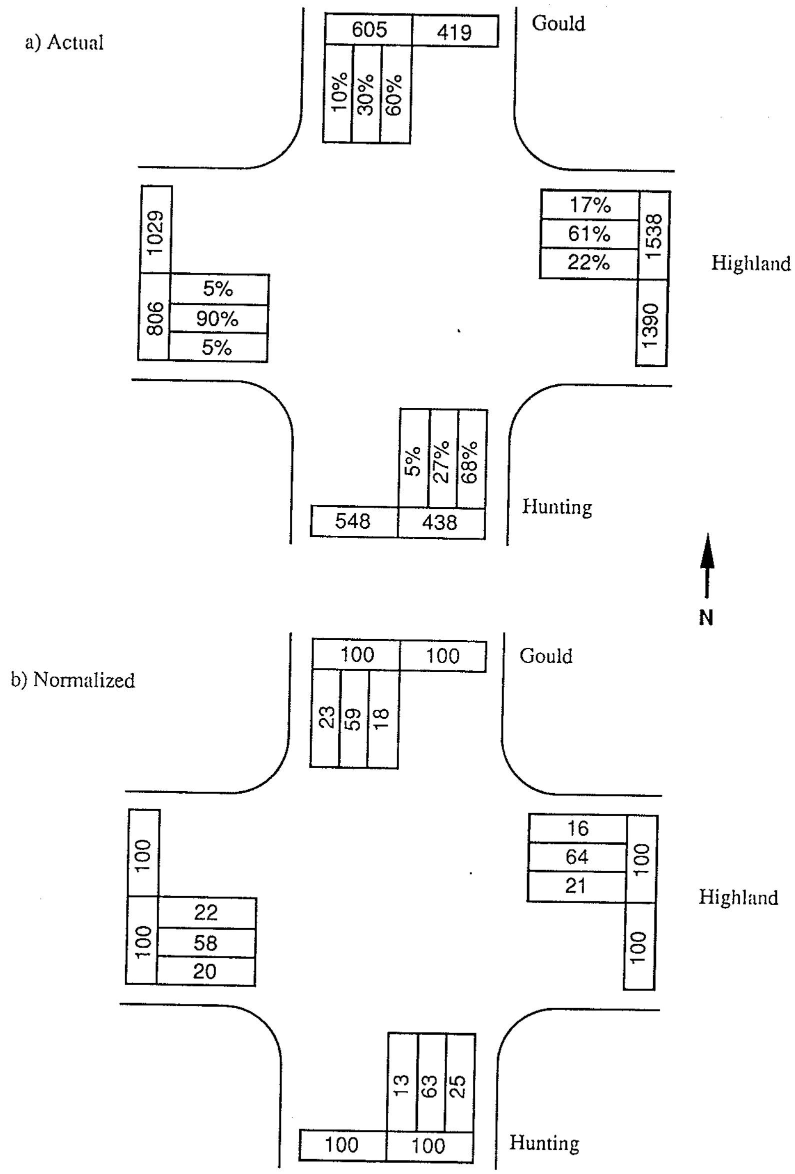

FIGURE 1 Example of actual versus normalized count.

still persist. One goal was to explain the differences in underlying propensity and to develop a propensity prediction model that accounts for these factors.

A classification analysis similar to that done in Toronto was performed to study the effect of functional class. The 804 approaches were divided into five groups by entering volume, roughly corresponding to major arterial, minor arterial, major collector, minor collector, and local street. They were further subdivided into four groups by the average entering volume of the cross street, the two smallest groups having been combined. All 20 categories were well represented in the sample. The mean percentages of the inflows going left, straight, and right for each category are presented in Table 3. There are significant differences, as expected. The farther above the diagonal, the smaller the proportion going straight, to a low of 21 percent for local street at major arterial, versus a high of 84 percent for major arterial at local street or minor collector. The distribution of normalized counts is presented in Table 4. The normalized straight volumes are much more similar across categories, ranging from 56 to 68 percent. Left and right volumes are usually equal to one another. Although there are slightly higher straight propensities on the higher-volume roads, there is no clear pattern, because the highest straight propensities are associated with major collectors, not with arterials.

These results suggest that approach volume, and its relative, functional class, is not a very good determinant of turning propensity, at least in eastern Massachusetts. The similarity between classes is encouraging, demonstrating some consistency in what otherwise appears as a highly chaotic phenomenon. However, the variation within the classes is still significant. For each class, the standard deviation of the normalized propensities was calculated. They are similar across classes; about 15 percent (in absolute percentage points) for the straight

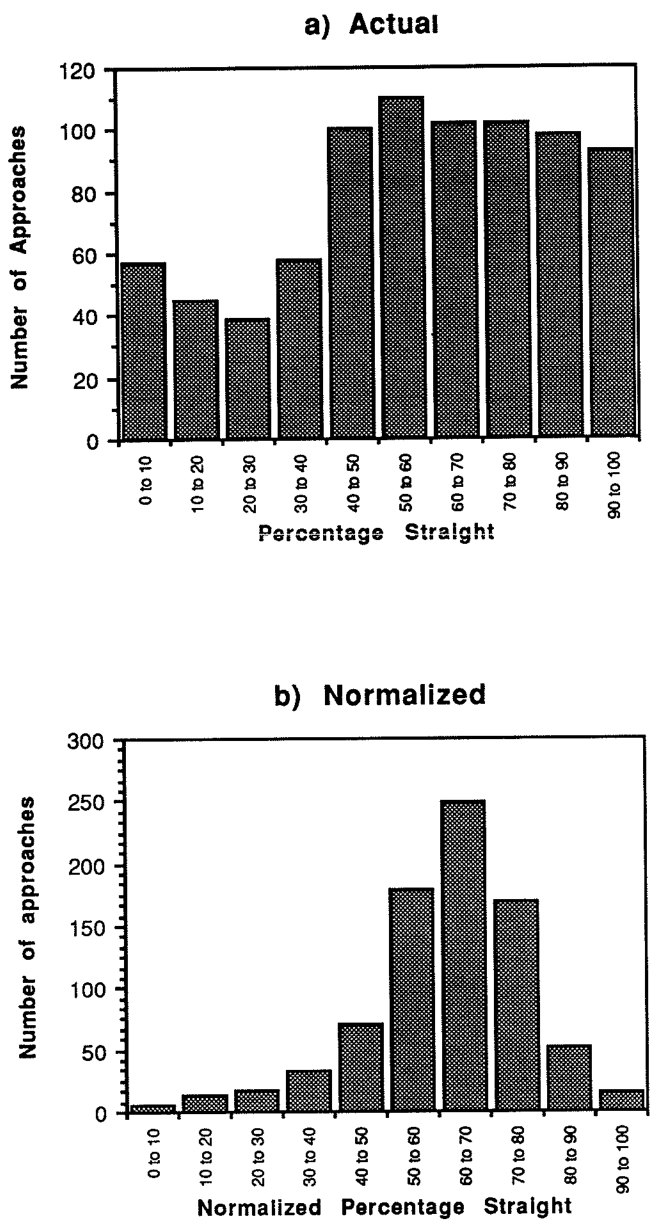

FIGURE 2 Distribution of actual and normalized percentage straight volume.

movements and about 12 percent for the turns. (One can generally expect one-third of the observations to lie outside a range of one standard deviation.) Furthermore, the results shown in Figure 2 indicate that although most approaches have normalized straight volumes in the 50 to 80 percent range, many approaches are still outside this range. This high degree of variation argues against using as seed either a single category or as many as 20 categories on the basis of functional class or approach volumes.

FACTORS AFFECTING TURNING PROPENSITY

The data set of normalized counts was studied in detail to find factors that correlated with propensities. Intersections with particularly low or high straight propensities were examined carefully. Several clear patterns that proved consistent with theories of travel behavior emerged. This preliminary analysis consequently suggested four factors that influenced propensities: the presence of dead-end approaches, the presence of diverting short cuts, angle, and grid density.

First, intersections with low normalized straight volumes tended to be those for which one approach was a dead end or other no-through street (e.g., a horseshoe). The fact that a driver enters the intersection traveling in a given direction is usually an indication that he or she wants to continue in that direction, implying a higher propensity for going straight than for turning. If a driver approaches an intersection from a dead end, however, his entering direction has no bearing on his desired direction, and so a much smaller straight propensity is expected. (Some approaches that were classified as dead ends actually had more than one means of egress, e.g., a shopping mall or a horseshoe, which explains why the estimated straight propensity for dead-end approaches is as high as it is, about 50 percent.) The transpose is also true; the propensity to go straight is lower if the facing approach is a dead end.

Second, intersections with high normalized straight volumes tended to be those for which other streets provided shortcuts that divert the turns that otherwise would have been expected. An example of competing shortcuts is the intersection shown in Figure 3, where there are strongly competing shortcuts for each possible turn, and normalized straight volumes are between 94 and 96 percent on the four approaches.

Third, a group of intersections with unusually low normalized straight volumes was those for which the angle for a straight movement was outside the range of 180° ± 45°. As stated earlier, the fact that a driver approaches an intersection in a given direction usually indicates that he or she desires to continue in that direction. Therefore, movements at an angle far from 180°, whether the movement is nominally a turn or a through movement, can be expected to have a smaller propensity than a standard 180° straight movement. Angles, of course, are also important factors when there is asymmetry between left- and right-turn propensity.

Finally, there is good reason to believe that the propensity for going straight should be sensitive to grid density. In dense grid areas, intuition suggests that drivers turn more often per mile. However, because a dense grid offers more opportunities to turn, drivers will actually turn less often per intersection, according to both Hauer's Toronto data (*3*) (see Table 2) and the Massachusetts data. The propensity to turn would be lower where the grid is dense than, say, at an isolated rural intersection, which may be the only chance in several miles to change direction.

MODEL DEVELOPMENT

A data base of 95 intersections, with a single peak-period count for each intersection (a.m. when available) was prepared for the model development effort. Those intersections excluded from the original set of 105 intersections had freeway ramps, turning restrictions, and other unusual features. With each intersection were coded the presence of dead ends, the strength of diverting shortcuts for each corner of the inter-

TABLE 3 TURNING PERCENTAGES CLASSIFIED BY APPROACH VOLUME

Approach Vol		Cross Street Avg One Way Volume 0 - 250	251 - 500	501 - 750	751+
0-120	L	25.5	32.0	31.1	46.4
	S	54.3	37.4	40.0	21.3
	R	20.2	30.5	29.0	32.3
	(n)	46	33	13	30
121 - 250	L	14.9	23.1	29.3	29.7
	S	64.3	49.3	42.2	26.5
	R	20.8	27.6	28.5	43.8
	(n)	30	42	25	20
251 - 500	L	14.1	16.2	22.8	29.6
	S	70.5	65.0	49.7	43.4
	R	15.4	18.8	27.5	27.0
	(n)	56	72	52	46
501 - 750	L	12.7	15.8	21.8	27.2
	S	76.6	69.3	57.6	52.8
	R	10.7	14.9	20.6	20.0
	(n)	28	52	48	43
751+	L	7.6	14.2	18.5	20.6
	S	84.4	69.5	61.8	51.1
	R	8.0	16.3	19.7	28.3
	(n)	38	53	46	31

Key: L=left, S=straight, R=right, (n)=number of approaches

TABLE 4 NORMALIZED TURNING PERCENTAGES CLASSIFIED BY APPROACH VOLUME

Approach Vol		Cross Street Avg One Way Volume 0 - 250	251 - 500	501 - 750	751+
0-120	L	22.0	20.6	18.0	23.6
	S	55.8	59.2	59.9	55.9
	R	22.1	20.2	22.1	20.5
	(n)	46	33	13	30
121 - 250	L	22.5	17.9	19.1	18.8
	S	57.2	60.8	59.1	58.8
	R	20.3	21.3	21.8	22.4
	(n)	30	42	25	20
251 - 500	L	17.4	15.5	17.4	17.0
	S	61.1	67.7	63.2	65.8
	R	21.5	16.8	19.4	17.2
	(n)	56	72	52	46
501 - 750	L	22.2	18.7	19.1	19.5
	S	55.9	63.4	64.5	62.9
	R	21.9	17.9	16.4	17.6
	(n)	28	52	48	43
751+	L	18.1	20.4	18.2	18.1
	S	61.1	60.2	62.4	61.5
	R	20.8	19.4	19.4	20.4
	(n)	38	53	46	31

Key: L=left, S=straight, R=right, (n)=number of approaches

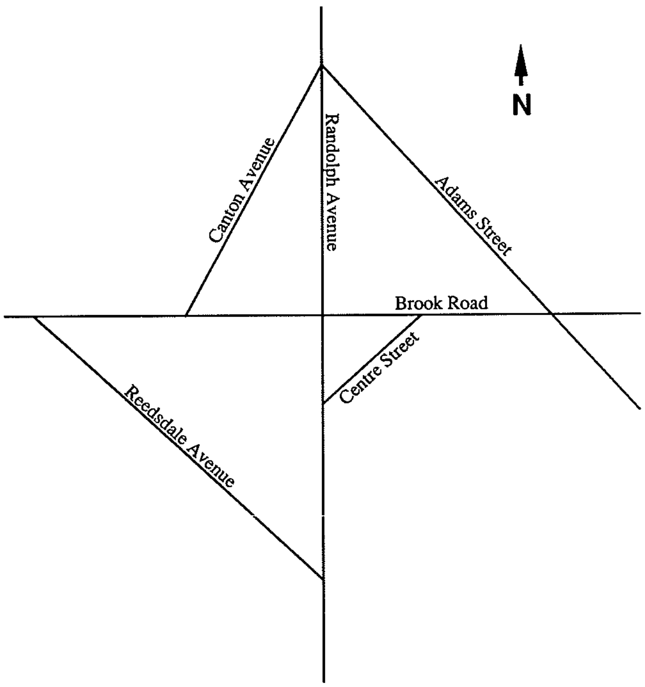

FIGURE 3 Example of competing shortcuts (Randolph Avenue at Brook Road, Milton).

section, a binary variable indicating the grid density, and the intersection angles. In determining angles, curved approaches were treated as lines joining the intersection of interest with the approach's next intersection with a through street. These factors were determined for the most part from maps. However, some local knowledge was useful, particularly in determining the strength of a diverting shortcut, where there is a degree of subjectivity.

Diverting shortcuts, where they existed, were classified at four levels. A Level 4 diversion implies that nearly all expected turns are diverted away from the intersection. Levels 3, 2, and 1 indicate increasingly weaker competition. In assigning a level of diversion to a corner of an intersection, the following factors were considered:

1. The distance of the shortcut from the intersection. The closer the shortcut, the stronger the competition.
2. The land use between the shortcut and the intersection. The greater the development, the weaker the competition, because trips generated between the shortcut and the intersection won't be able to use the shortcut.
3. How well known the shortcut is. Maps may reveal a wonderful shortcut that may turn out to be a dirt road, or a narrow road connecting two broad roads that carry mostly long-distance travelers unacquainted with local side streets.

No formula for assigning a diversion level was developed, because the data required for such a formula would be hard to quantify or obtain. Instead, judgment was relied on to weigh the three factors and assign a value.

First, intersections without dead ends were analyzed. The first analysis centered on normalized straight volumes, therefore ignoring the effect of angle. (Those intersections for which the straight angle was not between 135° and 225° were excluded.) A composite variable DIVAVG was created for each intersection; it is the average diversion level assigned to the four corners, and therefore ranged from 0 (no diversions) to 4 (Level 4 diversion at all four corners). A multiple regression of normalized straight volumes versus DIVAVG and the dense grid dummy yielded the results presented in Table 5. The effect of both variables is positive and significant. The multiple regression enabled the estimation of the straight propensities in the absence of diversion effect, for there were only three intersections in the whole data set that had no diversions or dead ends, and using just those three to estimate pure straight propensity would have been unreliable. According to the regression results, the straight propensity in the absence of dead ends and diversions is about 62 percent in the less dense suburbs, and about 68 percent in the denser suburbs. (There were no CBD data.)

Next, the effect of angle on propensity was modeled. A function was sought with the familiar bell shape, peaking when the angle is 180° with a smooth peak. The chosen function is

TABLE 5 DIVERSION AND GRID DENSITY EFFECT ON STRAIGHT PROPENSITY

RESULTS (n = 63 observations)

Variable	Coefficient	Value	Std. error	t-statistic
NORSAVG	a_0	61.57	1.94	31.7
DGDUMMY	a_1	5.88	2.19	2.7
DIVAVG	a_2	5.05	1.35	3.7

$R^2 = 0.24$; standard error of regression = 8.66

Model: NORSAVG = $a_0 + a_1(\text{DGDUMMY}) + a_2(\text{DIVAVG})$

where NORSAVG = Average normalized straight propensity for four approaches of an intersection

DGDUMMY = 1 if intersection is in a dense grid area, 0 otherwise

DIVAVG = average diversion level assigned to four corners of intersection (diversion level at a given corner lies between 0 and 4)

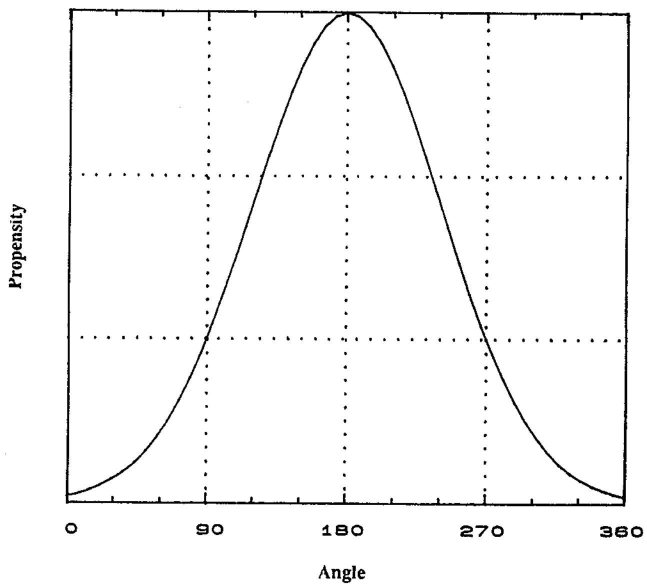

FIGURE 4 Gaussian-angle-based propensity function.

the Gaussian curve shown in Figure 4, given by

$$r(\Theta) = e^{-[(\Theta - 180)/k]^2/2} \tag{6}$$

where

Θ = angle of movement ($0 \le \Theta \le 360$)
$r(\Theta)$ = propensity
k = shape parameter controlling how peaked the distribution is

At a right-angle intersection, the straight propensity is arbitrarily set to $r(180) = 1$, and the propensity of a right or left turn is

$$r(90) = r(270) = e^{-(90/k)^2/2} \tag{7}$$

Another way of expressing the propensity function is to specify the ratio R, the desired ratio of the propensity of a 90° movement to the propensity of a 180° movement. Then the propensity can be expressed directly in terms of R.

$$r(\Theta) = e^{(\ln R)[(\Theta - 180)/90]^2} = R^{[(\Theta - 180)/90]^2} \tag{8}$$

For example, to make left/straight/right propensities equal to 20/60/20, choose $R = 1/3$, which implies that $k = 60.7$. The propensity function drawn in Figure 4 reflects this propensity ratio.

Based on the earlier analysis, the straight proportion for nondense grid areas was about 62 percent, yielding a value of R of 19/62 or 0.306. For dense grid areas, $R = 15/70 = 0.214$. These proportions differ slightly from the values suggested by Table 5 because the multiple regression was highly simplified, with the diversion levels averaged together without consideration of their relative location and the diversion fraction assigned to each diversion level.

The effect of diversions was modeled as causing a fractional reduction in the propensity of the affected movement. Diversion level was treated as a discrete variable, with each diversion level assigned a value representing the fractional reduction in propensity it causes. Values were tested to obtain an improved fit in the multiple regression of average normalized straight propensity versus DIVAVG, where DIVAVG was calculated from assigned fractions rather than from the original diversion level, and the grid density dummy. The resulting fractions are shown in Table 6. A more exact analysis for estimating these fractions, such as maximum likelihood or least squares based on individual movement propensities, was not undertaken, in part for lack of time, but also because the diversion levels are subjectively assigned and therefore approximate.

The final form of the model for non-dead-end intersections is

$$p_{ij} = [1 - D(d_{ij})]R_g^{[(\Theta_{ij} - 180)/90]^2} \tag{9}$$

TABLE 6 CHOSEN CATEGORY MODEL PARAMETERS

	Non-Dense Grid		Dense Grid	
Base Straight Propensity	62%		70%	
Right-to-Straight Propensity Ratio	0.306		0.214	
	Assigned Diversion Level			
	1	2	3	4
Diversion Fraction	0.2	0.4	0.67	0.94
Propensities for Dead Ends and Approaches Opposite a Dead End				
	Opposing Dead Ends		Non-Dead End Opposing Dead End	
Straight Propensity	3%		50%	
Turn Propensity	48.5%		25%	

where

p_{ij} = propensity of a movement from Approach i to j $(i \neq j)$,
Θ_{ij} = angle from Approach i to j,
g = grid type (dense or not dense),
R_g = base ratio of 90° to 180° propensity for Grid Type g,
d_{ij} = level of diversion assigned to movement i–j, and
$D(d_{ij})$ = fractional propensity reduction associated with diversion level d_{ij}.

Intersections with dead ends were split into two groups: those with opposing dead ends and those with a through street opposing a dead end. For the dead-end street and the street facing it, the propensity model was of the form

$$p(\text{straight}) = \text{constant}$$

$$p(\text{turn}) = \text{constant}$$

where different constants are used for each of the groups. For the cross street, the propensity model for non-dead-end intersections was used. Straight and turn propensities were chosen for the two groups so that, when combined with the propensities modeled for the cross street, they yielded normalized propensities that agreed with the group average. Those values are also presented in Table 6.

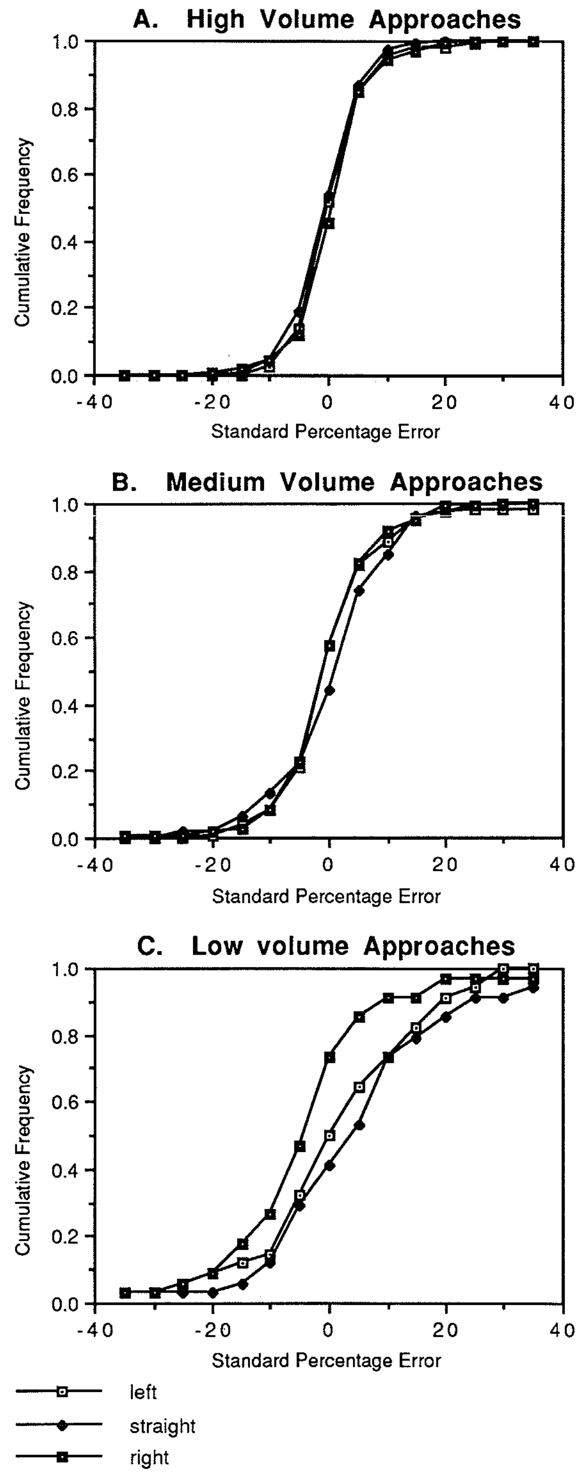

FIGURE 5 Standard percentage error distributions of non-dead-end intersections.

EVALUATION OF PROPENSITY MODEL

In order to evaluate the propensity model, true peak-hour counts were compared with counts predicted by the model for 95 intersections. Distributions of estimation error for left, straight, and right movements at non-dead-end and dead-end intersections are shown in Figures 5 and 6. Errors are expressed as percentages of the inflow volume. The distributions for low-, medium-, and high-volume approaches are shown separately, with thresholds of 100 and 400 vph separating the groups. At the non-dead-end intersections, the error for straight movements at high-volume approaches is within ±5 percent of the inflow volume in 68 percent of the cases, and is within ±10 percent in 93 percent of the cases. This level of accuracy is good for a seed that is not based on counts but only intersection characteristics. Relative errors for left and right movements are similar to those for straight movements. At lower-volume approaches, relative errors are larger, with the fraction of straight volumes estimated to within ±5 and ±10 percent dropping to 52 and 72 percent for medium-volume approaches and 24 and 60 percent for low-volume approaches. The distributions for dead-end intersections seem slightly better, probably because there are fewer degrees of freedom in distributing the vehicle movements. For all intersections combined, the RMS error for left, straight, and right flows was 6, 7, and 6 percent, respectively, of the mean inflow volume. As a basis of comparison, RMS prediction errors were 4 to 5 percent of inflow volume when an intersection-specific count was used as the seed (Table 1).

The overall performance of the propensity model is encouraging. Recognizing the inherent day-to-day variability in flows, the average prediction error caused by the model is probably of the same order of magnitude as the average error inherent in a single day's count. Of course, prediction errors can be unacceptably large at some intersections, and counts will still be needed for uses like signal timing. However, for other purposes, the results suggest that when approach volumes (ins and outs) are known at an intersection, an estimate of turning

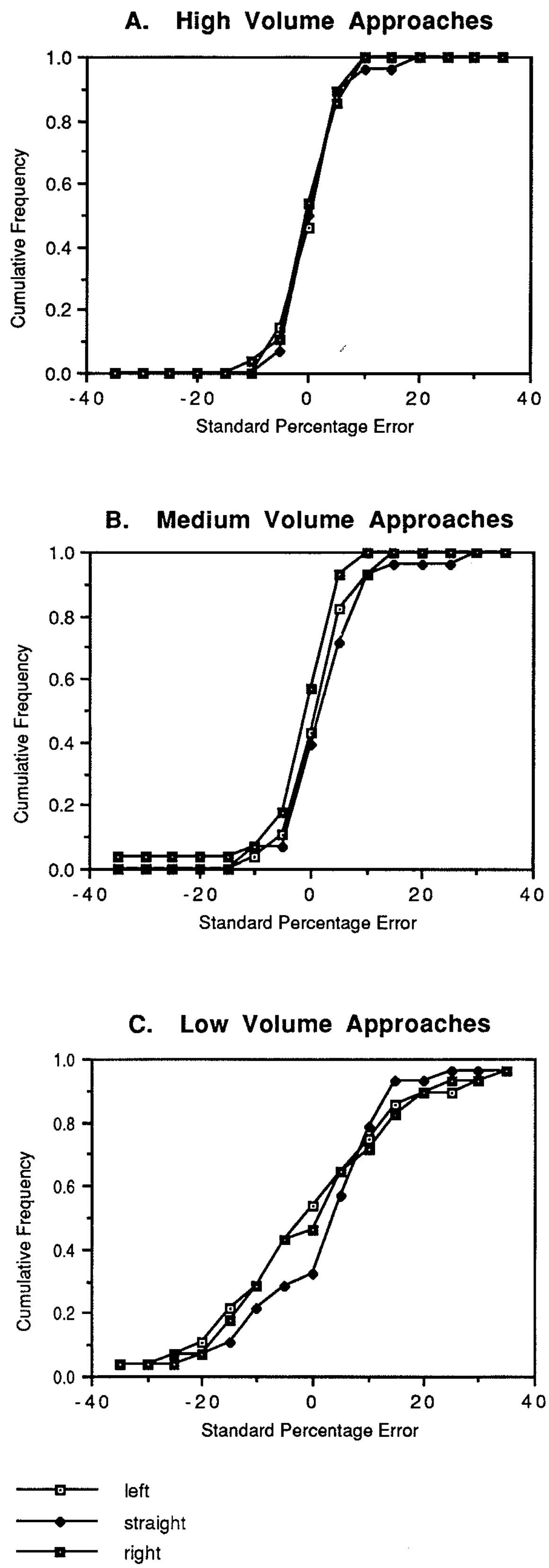

FIGURE 6 Standard percentage error distributions at dead-end intersections.

movements made using data obtained from a map can be almost as reliable as going out and counting the turning movements. If the approach volumes represent a multiday sample, the reliability may surpass that of an actual count. Intersection-specific counts, when available, provide superior estimates to those based on the propensity model.

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