Regularity of Some Detector-Observed Arterial Traffic Volume Characteristics

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An extensive data base was obtained for four two-lane arterial locations in Toronto. The data were 5-min detector counts in each base of each location for a total of 13 291 counts over 77 days. The paper reports on the regularity of the weekday pattern and of the time at which certain flow levels are reached. The patterns are quite regular, and the variance of the time at which specified peak levels are reached is rather small (from 4 to 6 min). A significant correlation between flows in the two lanes is found, particularly at higher volumes. The variation about the average pattern is also studied to assess the merits of using a predictor algorithm. The correlation between present and past variations (and thus future and present variations) is sometimes significant, but this correlation varies within a daily record. Further, it is not necessarily the same magnitude or sign at a given time on different days. It is nonetheless possible to construct a predictor that can extract information. The issue of the utility and the cost effectiveness of such prediction is noted, as is the fact that such an issue can only be resolved by considering the specific control with which the predictor is to be used. The issue of the typicalness or atypicalness of the Toronto regularity of pattern must also be considered.

The regularity of daily traffic patterns is of basic concern when various candidate control strategies are evaluated. At one extreme, if little variation exists from day to day, a time-of-day (minimal response) controller will undoubtedly suffice. At the other extreme, if no discernible pattern exists or if it arrives randomly each day, then a highly responsive control is appropriate.

Between these extremes, there is the possibility of a basic underlying pattern with substantial variation about it. There is also the possibility that on a given day there will be a major deviation from an otherwise extremely regular pattern. To accommodate such possibilities, traffic data can be collected in real time and deviations noted, or a predictor can be established to estimate future values.

Efforts to control congestion should consider (a) the regularity of daily patterns and (b) the regularity of the times at which various flow levels are reached. These considerations provide insight into the utility of minimal response control versus highly responsive control in this flow regime.

An extensive data base was acquired through the courtesy of the Metropolitan Toronto Department of Roads and Traffic. This data base was used to investigate

1. The regularity of the weekday pattern,
2. The regularity of the time at which certain flow levels are reached,
3. The correlation of the flow between lanes on the same approach, and
4. The potential for refining estimates of traffic volumes, based on observation of the deviations from the historic or nominal pattern.

DATA BASE

The Metropolitan Toronto Department of Roads and Traffic provided an extensive data base, consisting of 5-min samples of volume by lane at each of four sites over a 77-day period. The data were collected by computer from September 24 to December 10, 1973.

Figures 1 and 2 show the detector locations for each of the four sites.

The data were acquired from the detectors whenever possible. Table 1 gives the distribution of the samples by day of week and hour of day. Note that all periods of common interest are well covered. The data were output in 5-min counts, and the first counting period was initiated whenever the computer "came up." For simplicity, all data were shifted to standard 5-min periods; the first period was midnight to 12:05 a.m. The time shift thus introduced was uniformly distributed between -2.5 and +2.5 min. This could introduce a standard deviation of $\sigma = 1.44$ min in any time shift estimates.

REGULARITY OF DAILY PATTERN

The average pattern was computed for each day by averaging the volume observed in each time slot. Because the weekdays did not differ substantially, a single average pattern was also computed by aggregating all weekdays at each detector.

Figure 3 shows the average weekday pattern at each

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Figure 1. Location of detectors at site 1 (suburban).

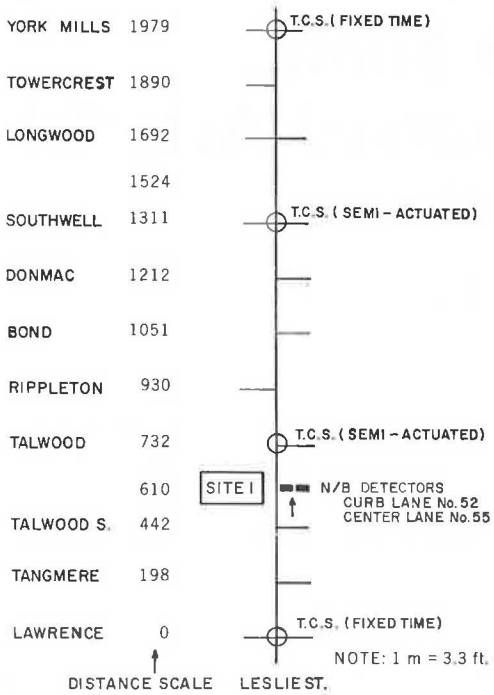

Figure 2. Location of detectors at sites 2, 3, and 4 (central area).

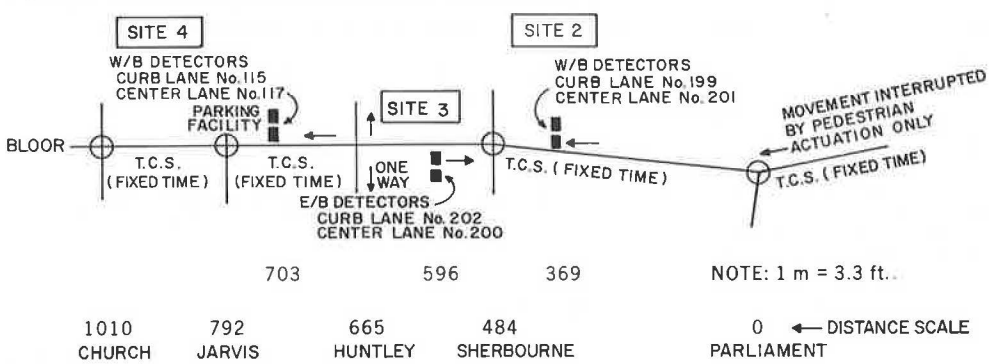

Table 1. Distributions of samples by day and time.

Time	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.	Sun.	Total	Percent
Midnight	115	69	46	38	52	92	104	516	3.9
1 a.m.	69	0	0	12	12	26	83	202	1.5
2 a.m.	96	26	0	12	10	0	72	216	1.6
3 a.m.	96	56	0	35	13	14	72	286	2.2
4 a.m.	97	80	29	68	23	36	79	412	3.1
5 a.m.	129	116	74	89	99	75	96	678	5.1
6 a.m.	143	113	97	109	129	104	113	808	6.1
7 a.m.	144	132	117	120	132	108	120	873	6.6
8 a.m.	139	133	118	120	132	94	65	801	6.0
9 a.m.	135	128	120	120	131	82	0	716	5.4
10 a.m.	136	132	108	104	124	57	0	661	5.0
11 a.m.	132	131	108	96	116	43	0	626	4.7
Noon	67	44	45	47	61	48	0	312	2.3
1 p.m.	131	117	116	81	94	48	0	587	4.4
2 p.m.	133	120	120	86	101	48	0	608	4.6
3 p.m.	141	120	117	97	127	57	2	661	5.0
4 p.m.	144	132	132	120	132	77	24	761	5.7
5 p.m.	144	131	132	120	132	89	29	777	5.8
6 p.m.	118	114	114	100	126	95	72	739	5.6
7 p.m.	57	32	15	45	95	103	106	453	3.4
8 p.m.	15	0	0	1	91	108	117	332	2.5
9 p.m.	8	0	0	7	84	103	120	322	2.4
10 p.m.	52	30	8	45	86	96	119	436	3.3
11 p.m.	70	46	28	57	92	101	114	508	3.8
Total	2511	2002	1644	1729	2194	1704	1507	13 291	100.0
Percent	19	15	12	13	17	13	11	100	

of the four sites. The shaded area indicates the region within which one can expect 95 percent of the observations to fall. This is not a confidence bound on the average. The confidence bound is much tighter. It is an estimate of the fluctuations from day to day within a specified time slot.

Figure 3 shows that, although there is substantial variation most of the time, the peaking is quite sharp, and relatively little variation exists in the time at which certain levels are reached. That is, specified level X is reached at approximately the same time every day. One can even question whether the variation in the vertical dimension is as substantial as it appears: The 95 percent range is on the order of ±120 vehicles/h/lane or ±10 vehicles/lane in a 5-min period. This occurs when the average count is on the order of 40 vehicles/lane in a 5-min period. Further, the distribution is approximately normal, so that the deviations tend to be clustered near zero.

Figure 4 shows the distribution of the times at which certain volumes are reached at site 2. For instance, 720 vehicles/lane is first attained earlier than 6:55 a.m. only 10 percent of the time. By 7:07 a.m., there is a 90 percent chance that 720 vehicles/h/lane has already occurred. Note that the variation is rather small, leading to the conclusion that minimal response policies could be developed with some assurance that the onset of certain levels could be anticipated with some confidence.

It should be noted that there is no protection against statistical rare events, i.e., major deviations from the average pattern. Generally, these can be associated with weather or special community activities.

CORRELATION BETWEEN LANES

If a volume is to be observed, it is necessary to determine whether one lane will suffice or whether two or more lanes must be measured. For the data available, which contained only two-lane approaches, the question reduces to one or both.

It was found that all weekdays could be aggregated for a given site and that a two-regime curve relating total volume to curb-lane volume should be established. The breakpoint was established at 360 vehicles/h in the curb lane, and no data for a curb-lane volume of less than 240 vehicles/h were considered.

Data given in Table 2 show that the total volume is rather strongly correlated to curb-lane volume in the higher flow regime, with correlation coefficients on the order of 0.9 and more. The correlation equation used for the higher flow regime is

$$Y = A + C(X - 30) \quad \text{for } X \geq 30 \tag{1}$$

The correlation equation used for the lower flow regime is

$$Y = A + B(X - 30) \quad \text{for } X < 30 \tag{2}$$

where

Y = total 5-min count,
A = intercept at curb,
B = slope in regime for low flows,
C = slope in regime for high flows, and
X = curb-lane 5-min count.

A least squares fit was performed on the data for each site, with the two curves tied to a common point at the boundary between regimes. The results are summarized in Table 2 and are shown in Figure 5. Note that the slopes of lines in the $X \geq 30$ regime are comparable, except for site 1, the suburban site.

Clearly, the lane split tends to equalize as volume increases. The downtown sites tend to have greater concentrations in the outer (left) lane, although data are certainly not sufficient to identify location as a causative factor.

Based on these fits, the total volume can in fact be computed with some confidence if the calibrated lines are known.

It was determined that the weekend curves are not dissimilar to the weekday curves, within the range of the weekend data.

POTENTIAL FOR PREDICTION

On any given day, the actual pattern differs from the average pattern by some set of discrepancies ϵ_i. At a particular site, let

a_i = average count for time period i,
x_i = actual count for time period i, and
$\epsilon_i = x_i - a_i$.

If the set ϵ_i is serially uncorrelated, then there is no hope for predicting a future value x_j any better than simply saying that its expected value is a_j. If there is some correlation among the ϵ_i, however, then there is information contained in the sequence of past values of ϵ_i. This information may be extrapolated into the future to get some better estimate (i.e., prediction) of a value x_{i+k}.

Predictors may be based on nothing more than historic patterns, they may ignore the historic pattern and project forward based on current trends, or they may project forward a refinement to the historic pattern based on recent (i.e., real time) deviations from the historic pattern. Because the weekday pattern appears so regular (Figures 3 and 4), it appears most fruitful to investigate whether there is any additional information in the set of discrepancies.

The set of $\{\epsilon_i\}$, which is the outcome on any given day, may be viewed as the outcome of a zero-mean process. It is of interest to compute the autocovariance values at one and two lags: $R(1) = E(\epsilon_i \epsilon_{i+1})$ and $R(2) = E(\epsilon_i \epsilon_{i+2})$, as well as the variance $E(\epsilon_i^2)$. If a sample of N data points were available, these could be estimated by

$$\hat{R}(k) = (1/N - 1 - k) \sum_{i=1}^{N-1} \epsilon_i \epsilon_{i+k} \tag{3}$$

$$\hat{\sigma}^2 = (1/N - 1) \sum_{i=1}^{N} \epsilon_i \epsilon_i \tag{4}$$

respectively. If there were M days available, the estimates obtained from equations 3 and 4 for each day could then be averaged to improve the estimate.

The use of equations 3 and 4 assumes, however, that the quantities R(1), R(2), and σ^2 do not change as a function of time within the day. This is not necessarily true.

To ensure that such an assumption is not made unless justified, we used

$$\hat{R}_i(k) = \beta \hat{R}_{i-1}(k) + (1 - \beta)\epsilon_i \epsilon_{i-k} \tag{5}$$

$$\hat{\sigma}_i^2 = \beta \hat{\sigma}_{i-1}^2 + (1 - \beta)\epsilon_i \epsilon_i \tag{6}$$

as estimators, so that, if the quantities of interest do change, it will be reflected in the estimators. β controls both the responsiveness of the estimator to change and the variance (and thus confidence) of the estimate. β = 0.8 was used in the material presented here.

It may be shown that most predictors of interest depend on the quantities above. Indeed, if a predictor is being used such that one has past data through period K - 1 and is computing the values for period K + 1 during period K—the data for which are not yet in hand—then the quantity of interest is $E(\epsilon_{i+2}\epsilon_i)$, which indicates how much knowledge of period K + 1 can be extracted from period K - 1 and before.

The quantities $\hat{\rho}_i(1)$ and $\hat{\rho}_i(2)$ may be computed from

$$\hat{\rho}_i(k) = \left[\hat{R}_i(k) \Big/ \sqrt{\hat{\sigma}_i^2 \, \hat{\sigma}_{i-k}^2}\right] \tag{7}$$

Therefore, the autocovariance values are indeed functions of the time of day, and they should be treated as such. Moreover, there are times when they are sufficiently high that they can indeed be used effectively to refine the estimate of a future volume x_{i+k}.

Of course, it must be recognized that the effectiveness, while real, may not be cost effective. If $\hat{\rho}_i(2) \simeq 0.7$, the variance reduction is on the order of $(0.7)^2 \simeq 0.5$ or 50 percent. The standard deviation is thus reduced to $1/\sqrt{2}$ or 0.707 of its former value. Recall that the 95 percent bounds were ±120 vehicles/h/lane for a mean of about 480 vehicles/h/lane. They would now be reduced to ±0.707(120) or ±85 vehicles/h/lane. The net tightening of the range is (120 - 85)/12 = 3 vehicles per lane per 5 minutes. The question is whether this added precision is worth the cost.

Figure 3. Average weekday pattern and variation of individual flows.

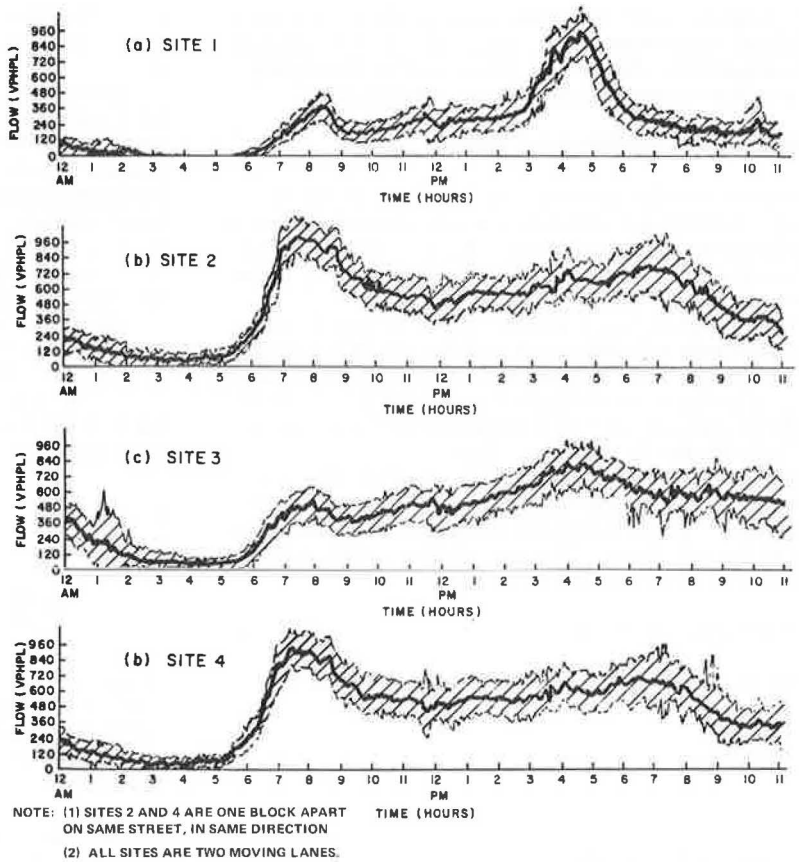

Figure 4. Times at which certain levels are reached (site 2).

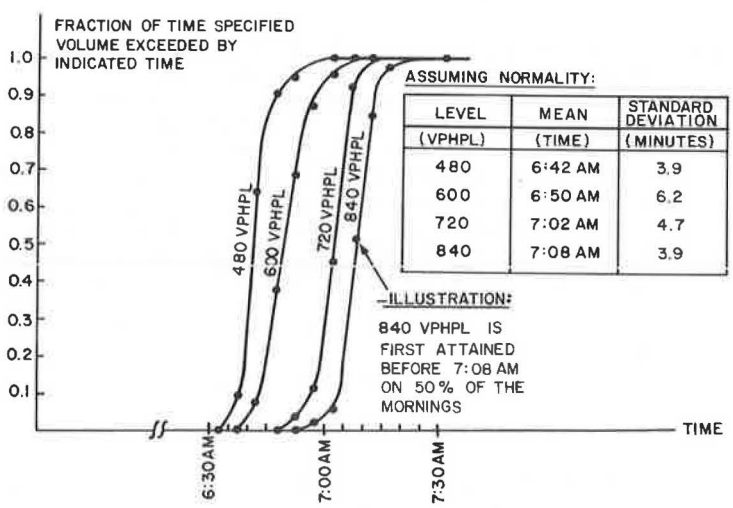

Figure 5. Least squares fit of total count as a function of curb-lane count, weekdays only.

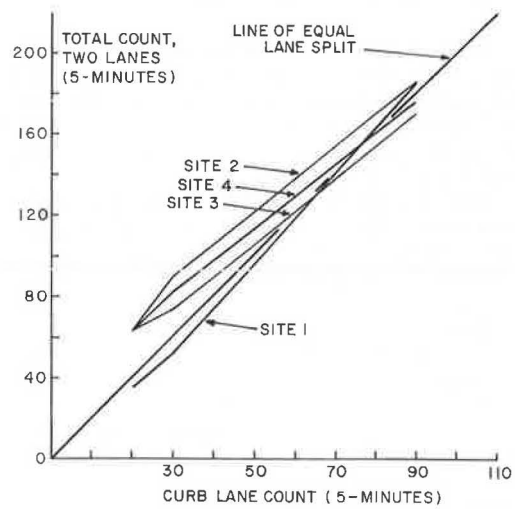

Table 2. Summary of correlations, weekdays only.

Site	Regime	Correlation: Total to Curb	Correlation: Center Lane to Curb	Sample Size	Slope in Regime	Intercept at Curb (vol = 30)
1	Low	0.67	0.37	2936	1.7	52.6
	High	0.98	0.93	3416	2.2	
2	Low	0.63	0.46	1640	2.5	89.4
	High	0.95	0.76	6311	1.6	
3	Low	0.27	0.08	1912	1.2	74.4
	High	0.88	0.59	6124	1.6	
4	Low	0.49	0.32	1633	2.1	23.5
	High	0.92	0.62	6400	1.5	

The correlations not only vary with time but also do not have comparable values at the same clock times from day to day. The indication is that, if a person decides to undertake a refined prediction of future volume levels, it should be undertaken with on-line estimation of the predictor coefficients. These coefficients vary with time. Moreover, this variation cannot be specified a priori from historic data as a simple or even complex function of time.

Note that this last conclusion can only be reached through a data base such as that used herein. Many daily sets $\{\rho_t(k)\}$ must be observed. Note also that the averaging of many sets $\{\hat{\rho}_t(k)\}$ or $\{\hat{R}_t(k)\}$ will not produce a better estimate of the true temporal correlations. Indeed, it will obscure it, for the average will tend to zero or at least to small values.

DISCUSSION OF RESULTS

The data were of particular interest because of the implications for the control of congested and oversaturated street networks (1). In regard to control of congested traffic flow, the following can be said about the Toronto data.

1. Because the daily pattern at a specific site is quite regular, minimal response (i.e., preplanned) signal control can be considered as a viable approach.
2. The times at which specific higher volumes are first reached is even more regular, and the initiation of those levels can be anticipated with some confidence. Although preplanned switching can be used with confidence, the variability that does exist lessens the benefits of multiple, rapid switches.
3. Single-lane detection provides good indications of the total approach volume, at least on two-lane approaches.
4. Variations about the average pattern are serially correlated, so that some information can be extracted from past variations to enhance volume predictions.

These results support the use of minimal response policies in many applications. Further, both these remarks and the discussion below are based on regularity as observed in Toronto. This has not been conclusively demonstrated to be the general pattern. Neither, however, are there strong arguments that it is atypical.

Before remarks are made about the entire range of flow levels exhibited in the data, two types of responsive systems must be distinguished: actuated equipment and coordinated system control algorithms. The time frame of the data studied herein (i.e., 5-min) is relevant only for the second type, and the remarks address only such systems.

It should be observed that the information contained to this point relates only to the inherent variability of the traffic flow and to potential for refining traffic predictions. It was noted that a two-step predictor can sometimes reduce the variance by 50 percent. This can result in a reduction in the deviation from the mean of 25 to 17.5 percent of the mean when the 95 percent range of volume values is considered.

It does not follow, however, that this reduction is important. The control algorithm may just not need such a precise prediction of volume. Even if there is some benefit to such added precision, there is the question of cost effectiveness: The detectors cost money, as does the maintenance of the detector system. Further, there are computation burdens on the computer system and storage requirements for intermediate results.

Because of these considerations, use of such predictors must be evaluated in terms of the cost effectiveness of the control function delivered, with predictor and control effectiveness integrally related. It is clear at this point that meaningful results can be obtained with only minimal response policies. It remains for advanced control projects such as the UTCS program to determine the cost effectiveness of various predictor-control policy combinations.

If open loop policies are used, however, two problems remain: (a) potentially severe impacts due to the rare event that would be ignored and (b) determining the average pattern, which may change slowly over time (i.e., months or years). The first problem can be addressed by limited surveillance, not for on-line adaptations but for a quality control chart type of monitoring on whether the average pattern assumed is indeed applicable.

The second problem can likewise be addressed by detectors placed for surveillance, and not necessarily for on-line control purposes. Such detectors could be sampled systematically, not all necessarily on the same day, so as to update average stored patterns.

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