Improved Estimation of Traffic Flow for Real-Time Control

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A critical review of the most widely accepted demand prediction algorithms is presented. Based on data collected at four intersections, sensitivity analysis of the best existing algorithms indicates that very little improvement in their performance could be achieved. A new, simpler algorithm, which requires considerably less information and fewer computations, is subsequently proposed and compared with the best of the existing algorithms. The results suggest that for 5-min prediction the second-generation Urban Traffic Control System predictor (UTCS-2) is usually better. However, in cycle-by-cycle prediction the proposed algorithm is considerably (as much as 41 percent) better than the best of the existing algorithms.

The problems associated with computerized signal control are numerous, ranging from demand prediction algorithms to reliability analysis, detector placement, and safelock design. In recent publications (1-3), traffic models and signal control strategies have been developed.

The major objective of this study is to determine the most reliable prediction algorithm suitable for implementing a recently developed (3) real-time control policy for critical intersections. This determination depends on two basic criteria: (a) algorithm performance and (b) the ability of the selected algorithm to estimate average arrival flow rates on a cycle-by-cycle basis. The second criterion is required for the implementation of a policy such as that mentioned above.

A critical review of the most widely accepted demand prediction algorithms is performed first. This review includes a summary of performance characteristics in which emphasis is placed on the effectiveness and drawbacks of each algorithm from the limited tests found in the literature. Potential improvements to the best existing algorithms, suggested in the literature, are discussed, and sensitivity tests are performed that indicate the extent of improvement in algorithm performance that could be expected to result from such changes.

Subsequently, a new demand prediction algorithm is proposed and compared with the second- and third-generation Urban Traffic Control System (UTCS) predictors (4,5), which were found to be the best (for the purposes of this study) among the existing algorithms. The current-measurement and historical-average predictors are also included in the comparisons. The comparison tests are based on 10 data sets collected at four intersections over a three-month period. These tests are more extensive and detailed than previous ones in that they include both isolated and coordinated intersections controlled by pretimed or actuated signals.

The major findings can be summarized in three parts:

1. The test results of a comparison of the performance of UTCS-2, UTCS-3, historical average, and current measurement are in agreement with previous studies (6,7). More specifically, the 5-min predictions of both UTCS-2 and UTCS-3 track the trend of the actual values of the volume measurements, and both improve the prediction in comparison with using the current measurement as the predicted value. However, in both cases the predicted values time-lag the actual measurements. The test results also show that UTCS-2 performs consistently better than UTCS-3. However, UTCS-2 provides less information or very little additional information over historical averages.

2. The sensitivity analysis performed here on UTCS-2 and UTCS-3 parameters indicates that not much improvement in expected UTCS performance could be achieved by varying the parameters away from the values recommended in the literature (6,8). These observations reinforce the need for the development of simpler and more accurate demand prediction algorithms.

3. An algorithm is proposed that, in its simplest form, degenerates to a moving average. The tests show that, when few data are available, the moving average is the most accurate method. When more detailed data are available, the complete algorithm performs at least as well as or better than a moving average.

BACKGROUND

Review of Demand Prediction Algorithms

The existing demand prediction algorithms fall into three general categories: (a) the second generation, (b) the third generation, and (c) algorithms developed after the third generation. The second generation is designed for control intervals on the order of 5-15 min, and the third generation is designed on a cycle-by-cycle basis.

Second-generation algorithms are older and typically require extensive historical data as reference. They use current traffic measurements to correct for the traffic deviations from the average historical pattern. Second-generation UTCS (UTCS-2) (4), ASCOT (9), and ASCOT-RTOP (10) all belong to this category.

Third-generation algorithms (5,7), generally more recent than the second generation, were developed with the objective of making predictions based on current traffic measurements only. However, the third-generation UTCS (5), the best-known algorithm in this category, requires a "representative" data set for estimating prediction coefficients. This assumption is in conflict with the idea of "highly responsive control software" (i.e., the third-generation control software) for which the predictor was designed (7).

The Baras-Levine algorithms (11-13), which constitute the most recent approach to demand prediction, fall in the third category. These algorithms are based on the hypothesis that, in contrast with previous assumptions, the data from traffic sensors represent a point process that is not Poisson. They therefore use point-process techniques to develop improved filter-predictors for use in traffic-responsive (nearly real-time) computer control of urban traffic. Their algorithm, F/P I (13), is aimed primarily at critical intersection control and is based on a time-varying Markov chain model that represents a linearization and discretization of nonlinear traffic dynamics. F/P I was found to be more accurate and more informative than ASCOT by its authors (13). It needs, however, more computation time. In addition, unlike algorithms in the previous two categories, the Baras-Levine algorithm

Table 1. Algorithms tested and evaluated.

Algorithm	Description
UTCS-2	$\hat{v}_t = m_t + \gamma(m_{t-1} - f_{t-1}) + (1-\alpha)\sum_{s=0}^{t-1} \alpha^s (f_{t-s-1} - m_{t-s-1}) + \gamma(1-\alpha)\sum_{s=0}^{t-2} \alpha^s (f_{t-s-2} - m_{t-s-2})$
UTCS-3	$\hat{v}_t = \gamma_1 f_t + (1-\gamma_1)\left[\hat{\mu}_0 \alpha^t + (1-\alpha)\sum_{s=0}^{t-1} \alpha^s f_{t-s-1}\right]$
Historical average	$\hat{v}_t = m_t$
Current measurement	$\hat{v}_t = f_t$
Proposed	$\hat{v}_t = a_1 f_t + a_2(f_t - f_{t-1}) + a_3 \left(\sum_{k=1}^{N} f_{t-k}/N\right) + a_0$

predicts queue size at an intersection rather than demand.

Both second-generation and third-generation demand prediction algorithms are the results of extensive research. However, the elaborate formulas they offer leave much to be desired. Other researchers have postulated a number of factors that, in their opinion, have apparently hampered the success of demand prediction algorithms. One factor brought forward by Kreer (8) is that the vehicles that are measured should be the same ones that are affected by the resulting change in control action; the only types of control that might satisfy this requirement (but might also result in increased computation costs) are critical intersection control and vehicle-actuated modes of control (8). To be sure, a major reason for the apparent failure in solving the traffic-control problem is that no predictor built to date is adaptive to the changing, underlying traffic-flow process. At coordinated networks, treating demand prediction as an open-loop process is another reason, intimately related to the first one, for this failure. In recent research by Mengert, Brown, and Yuan (7), it was proposed to use the Trigg and Leach method (14), a smoothing algorithm, and another technique that they developed to make UTCS-2 and UTCS-3 adaptive. Significantly, preliminary tests did not reveal substantial improvements. Box-Jenkins-type analyses and other estimation techniques such as Kalman filtering may, however, promise future improvements (7).

Of the five algorithms presented above, only UTCS-2 and UTCS-3 have been chosen for further analysis and testing. The Baras-Levine algorithm (13) could not be included, since it cannot be used for demand prediction. Neither version of the ASCOT algorithm (1,10) has been chosen for three basic reasons:

1. ASCOT is a second-generation technique and as such cannot respond to traffic on a cycle-by-cycle basis; testing two similar techniques (i.e., UTCS-2 and ASCOT) could not be justified unless one were significantly different from the other.
2. ASCOT has data requirements that are significantly greater than those of any of the algorithms reviewed.
3. ASCOT requires extensive instrumentation that is not available in most real systems.

Two more algorithms have been included in comparison tests and performance evaluation. The historical average, one of the two algorithms, assumes that the volume during any specified time period equals the smoothed historical volume for that period as obtained from earlier observations. The second algorithm, the current measurement used as the predicted value, assumes that the volume during any given time period (in this case, 5 min or one cycle) is the same as that during the previous time period. As a result of this assumption, prediction inherently lags behind observation by at least one time period. This method has the simplest data requirements.

Finally, the proposed algorithm assumes prediction to be a linear function of the current volume, the difference between the current and previous volume, and an average volume during the previous three to five time periods. All algorithms tested and evaluated in this work are presented in Table 1 and explained in the following sections.

UTCS-2

The second-generation UTCS, UTCS-2, predicts the next-control-interval (on the order of 5-15 min) traffic volume at each detector location in real time based on the measurements from the same location only. The algorithm makes use of both smoothed historical traffic data and current traffic-volume measurements from the vehicle detector.

The UTCS-2 set of equations has been presented elsewhere (4). The complexity of the solution, however, which is of major interest to this study, is usually not shown. By solving the difference equations of UTCS-2 (4), it can be shown that UTCS-2 results in the following demand prediction equation:

$$\hat{v}_t = m_t + \gamma(m_{t-1} - \gamma f_{t-1}) + (1-\alpha)\sum_{s=0}^{t-1} \alpha^s (f_{t-s-1} - m_{t-s-1}) + \gamma(1-\alpha)\sum_{s=0}^{t-2} \alpha^s (f_{t-s-2} - m_{t-s-2}) \quad (1)$$

in which

$$m_t = a_0 + \sum_{i-1}^{k} [a_i \cos(2nit/N) + b_i \sin(2nit/N)] \quad (2)$$

and

$$\gamma = \left\{(n-1)\sum_{s=1}^{n-1}\left[f_s - m_s - (1-\alpha)\sum_{p=0}^{s-1}\alpha^p(f_{s-p-1} - m_{s-p-1})\right] \times \left[f_{s-1} - m_{s-1} - (1-\alpha)\sum_{p=0}^{s-2}\alpha^p(f_{s-p-2} - m_{s-p-2})\right]\right\} \div (n-2)\sum_{i=1}^{n}\left[f_s - m_s - (1-\alpha)\sum_{p=0}^{s-1}\alpha^p(f_{s-p-1} - m_{s-p-1})\right]^2 \quad (3)$$

where

- $\hat{v}_t$ = predicted volume at time t;
- m_t = historical volume at time t;
- f_t = measured volume at time t;
- d_t = empirical adjustment at time t;
- α = constant computed off-line from representative volume data of the location in question (e.g., for the UTCS system in Washington, D.C., α was 0.2);
- γ = smoothing coefficient (e.g., for the UTCS system in Washington, D.C., γ was 0.9);
- a_0, a_i, b_i = coefficients (computed off-line) of Fourier series approximation of historical traffic patterns for each measurement location;
- k = user input parameter determining the fidelity of Fourier series approximation, usually the result of a trade-off between Fourier series accuracy and storage space and computation effort (in general, for more rapidly varying functions, higher values of

k should be used; k-values from 6 to 20 have been used in past applications);

n = number of sample points of the representative data set; and

N = total number of time intervals in the representative data set (e.g., for 15-min intervals, the data for a 24-h day will consist of 96 intervals).

It can be seen that the UTCS-2 prediction equation (1) is a function of

$$\hat{v} = \hat{v}\,[m(t), f(t), n, \alpha] \tag{4}$$

where

$$m = m(a_0, a_i, b_i, k, N, t; i = 1 \text{ to } k) \tag{5}$$

UTCS-3

The predictor for the third-generation UTCS software, UTCS-3, predicts traffic volume two control intervals into the future. Like UTCS-2, UTCS-3 forecasts the volume at each location in real time based on measurements from the same location. However, it is different from UTCS-2 in that the prediction process relies solely on current-day measurements (no historical traffic pattern is required for prediction). By solving the difference equations of UTCS-3 (5), it can be shown that UTCS-3 results in the following demand prediction equation:

$$\hat{v}_{t+j} = \gamma_j f_t + (1 - \gamma_j)\left[\hat{\mu}_0 \alpha^t + (1 - \alpha) \sum_{s=0}^{t-1} \alpha^s f_{t-s-1}\right] \tag{6}$$

in which

$$\gamma_j = \left\{(n-1) \sum_{s=1}^{n-j} \left[f_s - \hat{\mu}_0 \alpha^s - (1-\alpha) \sum_{p=0}^{s-1} \alpha^p f_{s-p-1}\right] \times \left[f_{s+j} - \hat{\mu}_0 \alpha^{s+j} - (1-\alpha) \sum_{p=0}^{s+j-1} \alpha^p f_{s+j-p-1}\right]\right\} \div (n-1-j) \sum_{s=1}^{n} \left[f_s - \hat{\mu}_0 \alpha^s - (1-\alpha) \sum_{p=0}^{s-1} \alpha^p f_{s-p-1}\right] \tag{7}$$

where

$\hat{v}_{t+j}$ = predicted volume for time (t + j) at time t;

γ_j = extrapolation constant computed off-line from representative volume data of the location in question;

f_t = measured volume at time t;

μ_t = exponentially smoothed volume measurement, also referred to as "coarse prediction of volume"; and

α = smoothing coefficient [a value of 0.95 has been used in past applications (6)].

It can be seen that the UTCS-3 prediction equation (5) is a function of

$$v = v\,[\hat{\mu}_0, f(t), n, \alpha] \tag{8}$$

Comparative Evaluation and Drawbacks of UTCS-2 and UTCS-3

Both UTCS predictors are based on single-location traffic measurements. Both use the linear combination of residues (differences between traffic measurements and either historical data or smoothed traffic data) as the basic feature for prediction. The second-generation predictor requires historical data as the reference. The third-generation predictor does not require historical data, makes predictions based on current traffic measurements (7), and can be applied to undersaturated links only (5).

The drawbacks of UTCS-2 (7) led to the development of UTCS-3. Major UTCS-2 drawbacks are related to its high reliance on historical data: Traffic volume can vary substantially, depending on various external (with respect to algorithm) factors (e.g., weather conditions, special events, developments in other modes of transportation, and even the traffic-control change itself). UTCS-2 is not responsive to such changes. Because of this reliance on historical data, UTCS-2 is not readily transferable across systems and therefore is not practical. A large data base is required for the historical data. This data base consumes computer storage space and must be updated periodically off-line. Furthermore, an analysis conducted early in the UTCS project in which "simulated" traffic data were used indicated that historical data were not always necessary to achieve good prediction.

As can be seen from a comparison of Equations 1-3 and Equations 6-8, UTCS-2 prediction is indeed a function of two time-dependent functions (more accurately, a function of the difference of two time-dependent functions): measured volume f(t) and historical volume m(t). UTCS-3 prediction, on the other hand, is a function of f(t) only. The constants to be predetermined are n, the number of sample points of the representative data set, and α, the smoothing coefficient; these constants are needed irrespective of the UTCS predictor specification chosen.

A small number of past performance tests comparing UTCS-2 and UTCS-3 (6,8) have indicated that UTCS-3 is not capable of achieving a performance as high as that of UTCS-2, which was consistently better--i.e., had both a lower mean square and a lower mean absolute value error. In addition, UTCS-2 had a larger portion of small-magnitude errors than UTCS-3 (6). Time-lagging is a serious drawback of both algorithms, but it is especially obvious with UTCS-3, where it is inherently two time intervals long and cannot be compensated for. One result of this inherent time lag is that, when there is a detector outage, UTCS-2 provides reasonably good values during the outage and is available as soon as vehicle detector operation is restored whereas UTCS-3 will not provide predicted volumes until two time intervals after the vehicle detector is restored.

RESEARCH APPROACH

For testing the demand prediction algorithms, 10 data sets were collected at six locations in the Minneapolis-St. Paul metropolitan area during October, November, and December 1979. The details are summarized in Table 2, which shows that the selected locations include both coordinated and isolated intersections under pretimed or actuated control.

Two error measurements were computed for each data set and algorithm: (a) mean square error (MSE), which penalizes large prediction errors, and (b) mean absolute error (MAE), which indicates the expected typical error for an individual prediction. These error measurements, which have been established in the literature for comparing prediction performance (6,7), are defined as follows:

$$\text{MSE} = [\Sigma(\text{measured volume} - \text{predicted volume})^2]/N \tag{9}$$

$$\text{MAE} = [\Sigma|\text{measured volume} - \text{predicted volume}|]/N \tag{10}$$

where N is the total number of predictions.

In using current UTCS algorithms, all of the

Table 2. Summary of data-set characteristics.

Location	Data Set	Approach Classification	Control Policy	Date and Duration
Oak Street, S.E., and Delaware Avenue, northbound	1	Coordinated	Semiactuated	5-min intervals, 3:00-6:30 p.m., 15 days in Oct.-Nov. 1979
Oak Street, S.E., and Washington Avenue, S.E., westbound	2	Isolated	Pretimed	5-min intervals, 3:00-6:30 p.m., 15 days in Oct.-Nov. 1979
Oak Street, S.E., and Washington Avenue, S.E., eastbound	3	Coordinated	Pretimed	5-min intervals, 3:00-6:30 p.m., 15 days in Oct.-Nov. 1979
Oak Street, S.E., and Washington Avenue, S.E., southbound	4	Coordinated	Pretimed	5-min intervals, 3:00-6:30 p.m., 15 days in Oct.-Nov. 1979
Union Street, S.E., and Washington Avenue, S.E., westbound	5	Coordinated	Pretimed	Nov. 13, 2:45-3:50 p.m., 40 cycles
	6	Coordinated	Pretimed	Nov. 14, 8:30-9:35 a.m., 39 cycles
	7	Coordinated	Pretimed	Nov. 14, 3:55-5:00 p.m., 33 cycles
	8	Coordinated	Pretimed	Nov. 15, 7:30-8:35 a.m., 38 cycles
Fifth and Excelsior, Hopkins	9	Isolated	Pretimed	Dec. 3, 3:50-4:55 p.m., 45 cycles
	10	Isolated	Pretimed	Dec. 4, 3:40-4:55 p.m., 45 cycles

necessary constants were obtained from the literature (6,7) except the smoothing constant, α, in which case the steady-state α value was found and used. Historical averages were formed by using data from seven days. The Statistical Package for the Social Sciences regression package (15) was used to determine constants where needed by the formulas.

All tests for which results are presented later in this paper are valid for comparison among prediction algorithms. Since the data used for testing were collected at a number of locations, nothing can be concluded regarding the relation between control policy and prediction accuracy.

PROPOSED ALGORITHM

Because of the disadvantages of the existing algorithms already described and some additional problems discussed later in this paper, it was decided that a new algorithm should be developed. In addition to meeting the objectives set forth in the introduction, the new algorithm should avoid arbitrary methods of treating the data and should instead be based on theory in as straightforward a manner as possible. It should be flexible enough to become part of closed-loop traffic control once the demand prediction was incorporated into the traffic process. It should also be simpler and at least as accurate as UTCS-2 or, in cycle-by-cycle prediction (of most interest to the project objectives), UTCS-3.

The proposed algorithm uses the volume during the next time period as the predicted variable; the current volume, the difference between current volume and previous volume, and the average volume during the previous three, four, or five time periods are the independent variables. The algorithm can be derived by using data from one or more previous days and used for demand prediction on the following day. On-line derivation is also possible.

The prediction equation is

$$\hat{v}_t = a_0 + a_1 f_t + a_2 (f_t - f_{t-1}) + a_3 \left(\sum_{k=1}^{N} f_{t-k} \Big/ N \right) \tag{11}$$

where N is the number of time periods considered (N = 3, 4, and 5 are suggested values) and a_1, a_2, and a_3 are control coefficients that can be found by using standard regressive techniques to best fit the measured data for the location in question.

From the above it can be seen that the proposed algorithm is a function of

$$\hat{v} = \hat{v}\,[f(t), a_i, N; i = 0 \text{ to } 3] \tag{12}$$

It can also be seen that the algorithm is simpler in form than either UTCS-2 (Equations 1 and 2) or UTCS-3 (Equations 6 and 7). It should also be noted that the prediction equation (Equation 11) is of the general form

$$\hat{v}(t) = a_0 + a_1 f(t) + a_2 [df(t)/dt] + a_3 \int f(t)dt \tag{13}$$

and could be treated as a proportional-plus, derivative-plus integral control problem if the traffic system were closed-loop--i.e., if the demand estimates were used to set the traffic signals controlling the flow f(t). The benefits expected from such a general treatment are known in system analysis and well documented in the literature (16,17).

In an open-loop application, such as at isolated intersections, the accuracy of the proposed algorithm depends directly on the regularity of the traffic data trend--i.e., on the similarity between the trend of the data used for the determination of the control coefficients and that of the actual measurements. This implies that the algorithm should be used during periods compatible with those during which data were collected. Updating algorithm coefficients will further improve accuracy. However, extensive historical data are not required by the algorithm. In a closed-loop application, the algorithm would keep its present form. The coefficients a_i could then be determined through analytic methods well established in the theory of dynamic optimal control (16-18).

A simpler version of the algorithm introduced above is obtained for $a_0 = 0$, $a_1 = 0$, $a_2 = 0$, $a_3 = 1$ in Equation 11:

$$\hat{v}_t = \sum_{k=1}^{N} f_{t-k} \Big/ N \tag{14}$$

which is the moving average. As demonstrated later, this version can achieve high prediction accuracy, as good as or slightly worse than that of Equation 11, but it is inherently slow in responding to abrupt demand changes. In the absence of such changes, and in the absence of any previous information on a particular intersection, this most simple version would be preferable to all others.

TEST RESULTS

In this section, sensitivity tests on certain parameters of the two best existing demand prediction algorithms are first performed. The tests indicate that the performance improvement achieved by varying these parameters is negligible. The proposed algorithm is then tested, evaluated, and compared with the other algorithms given in Table 1. Two prediction intervals--5 min and cycle-by-cycle--are considered by using the data set given in Table 2.

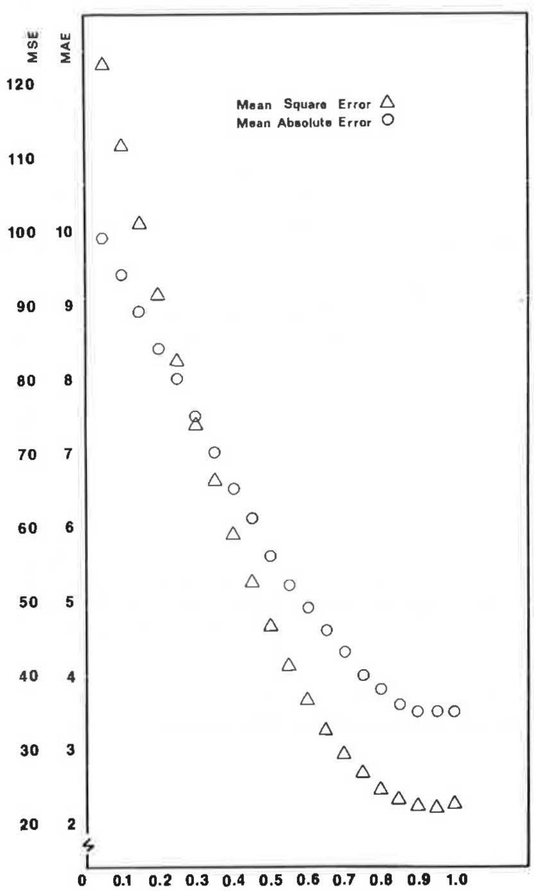
Sensitivity Analysis and UTCS-2 and UTCS-3 Possible Improvements

It has been proposed elsewhere (7) that a potential improvement to UTCS-3 performance lies in computing the parameter γ_j on-line by using a formula that

Table 3. Prediction errors for range of α values in UTCS-3 (data set 1).

α	Error (vehicles/5 min/lane) MSE	MAE
0.05	123.3	10.0
0.10	112.3	9.5
0.15	102.0	9.0
0.20	92.3	8.5
0.25	83.2	8.1
0.30	74.7	7.6
0.35	66.9	7.1
0.40	59.8	6.6
0.45	53.3	6.2
0.50	47.4	5.7
0.55	42.1	5.3
0.60	37.5	5.0
0.65	33.5	4.7
0.70	30.2	4.4
0.75	27.5	4.1
0.80	25.4	3.9
0.85	24.0	3.7
0.90	23.2	3.6
0.95	23.0	3.6
1.00	23.5	3.6

Figure 1. Prediction errors for range of α values in UTCS-3: data set 1.



is different from Equation 7. Such a change would make γ_j a time-varying function adaptive to the latest trend of the traffic deviations. By following similar reasoning, α, the smoothing constant in both UTCS-2 (Equation 3) and UTCS-3 (Equation 8), can be made adaptive by using the Trigg and Leach method (14).

To obtain an indication of the extent to which UTCS performance could be improved through such changes, a sensitivity analysis was performed. First, error sensitivity with respect to changes in α was analyzed. For each α value, a total number of sample points n was chosen so that α achieved a steady-state level. For any data set, errors were then recorded for a complete range of α values.

The tests led to two major conclusions:

1. Around the best α values (i.e., when errors are lowest), errors are not very sensitive to changes in α (see Table 3 and Figure 1). This may be verified, for example, from Table 3, where the MSE elasticity with respect to α can be found to be very low: $e\alpha(\text{MSE}) = 0.16$; in the same table, it can be seen that $e\alpha(\text{MAE}) = 0$.
2. Values of α and γ previously recommended for UTCS-2 and UTCS-3 (6,7) were used, and they performed quite well. Performance was worse when any α or γ values other than the ones recommended from the Washington, D.C., application (6,7) were used with UTCS-2 (see Table 4). Performance improved by, at most, 2.8 percent for "best" α values in the UTCS-3 application (see Table 5).

These sensitivity-analysis results indicate that, if methods for calculating α and γ were improved, the improvement of UTCS performance would be insignificant. This can be concluded since, for the locations examined, error sensitivity to α and γ changes around values recommended in the literature was very low. These results are strengthened when it is observed that the locations examined had quite different properties and were controlled by different policies. These results also support the need for a better demand prediction algorithm.

Five-Minute Prediction

Data sets 1-4 (Table 2) were used in these tests. Five algorithms were tested: UTCS-2, UTCS-3, current measurement, historical average, and the proposed algorithm. Use of UTCS-3 for one-time-step, 5-min prediction was possible (6) by considering 5 min as one time step and by setting j = 1 in Equation 6. The coefficients developed for the proposed algorithm and the test results are summarized in Tables 6 and 7, respectively.

The proposed versions in Table 6 follow the form of the prediction introduced previously by Equation 11. The two errors, MSE and MAE, for the five algorithms are presented in Table 7 in two ways. The value for each error is given so that conclusions on algorithm performance can easily be drawn; evi-

Table 4. Prediction errors for varying α and γ values in UTCS-2.

Data Set	MSE (vehicles/5 min/lane) $\alpha = 0.9^a$, $\gamma = 0.2^a$	$\alpha = 0.9^a$, $\gamma = 0.4$	$\alpha = 0.8$, $\gamma = 0.2$	$\alpha = 0.8$, $\gamma = 0.4$	MAE (vehicles/5 min/lane) $\alpha = 0.9^a$, $\gamma = 0.2^a$	$\alpha = 0.9^a$, $\gamma = 0.4$	$\alpha = 0.8$, $\gamma = 0.2$	$\alpha = 0.8$, $\gamma = 0.4$
1	13.1	14.3	14.0	15.6	3.0	3.0	3.0	3.0
2	61.8	61.9	64.2	65.9	6.4	6.4	6.4	6.5
3	51.4	51.1	52.6	59.4	6.1	6.3	6.2	6.5
4	19.1	21.8	21.0	24.3	3.4	3.7	3.6	3.9

[a]Value recommended from past applications (6, 7).

Table 5. Prediction errors for varying α values in UTCS-3.

Data Set	MSE (vehicles/5 min/lane) $\alpha = 0.95$[a]	MSE (vehicles/5 min/lane) $\alpha = 0.85$	MAE (vehicles/5 min/lane) $\alpha = 0.95$[a]	MAE (vehicles/5 min/lane) $\alpha = 0.85$
1	23.0	22.5	3.6	3.5
2	89.5	88.2	7.7	7.6
3	84.8	83.3	7.5	7.5
4	30.8	30.1	4.3	4.3

[a]Value recommended from past applications (6, 7).

Table 6. Proposed algorithm versions (5-min prediction).

Proposed Version	Control Coefficient a_0	a_1	a_2	a_3	No. of Time Periods (N)
1	11.748	0.521	0	0	-
2	16.713	0.517	0	0	-
3	20.061	0	0.067	0	-
4	18.375	0	0	0.457	3
5	16.962	0	0	0.497	4
6	14.254	0	0	0.573	5
7[a]	0	0	0	1	3
8[a]	0	0	0	1	4
9[a]	0	0	0	1	5

[a]Corresponds to the moving average.

Table 7. Prediction errors of five types of prediction algorithms for 5-min prediction.

Data Set[a]	Algorithm	MSE Value	MSE Difference from UTCS-3 (%)	MAE Value	MAE Difference from UTCS-3 (%)
1	Current	23.5	0.9	3.6	0.0
	UTCS-3	23.3	-	3.6	-
	UTCS-2	13.1	-44	3.0	-17
	Historical	12.8	-45	3.0	-17
	Version 1	19.0	-18.5	3.2	-11.1
	Version 7	22.5	-3.4	3.7	2.8
	Version 8	23.1	-0.9	3.8	5.6
	Version 9	24.5	5.2	4.0	11.1
2	Current	92.9	3.8	7.6	-1.3
	UTCS-3	89.5	-	7.7	-
	UTCS-2	61.8	-31	6.4	-17
	Historical	65.0	-27	6.7	-13
	Version 2	89.4	-0.1	8.0	3.9
	Version 7	117.3	31.1	8.5	10.4
	Version 8	126.8	41.7	8.6	11.7
	Version 9	122.9	37.3	8.3	7.8
3	Current	87.1	2.7	7.6	1.3
	UTCS-3	84.8	-	7.5	-
	UTCS-2	51.4	-39	6.1	-19
	Historical	55.8	-34	6.2	-17
	Version 4	71.0	-16.3	7.3	-2.7
	Version 5	71.3	-15.9	7.2	-4.0
	Version 6	73.4	-13.4	7.3	-2.7
	Version 7	67.5	-20.4	6.8	-9.3
	Version 8	61.5	-27.5	6.3	-16.0
	Version 9	63.5	-25.1	6.4	-14.7
4	Current	34.8	13.0	4.7	9.3
	UTCS-3	30.8	-	4.3	-
	UTCS-2	19.1	-38	3.4	-21
	Historical	16.9	-45	3.4	-21
	Version 3	24.8	-19.5	3.8	-11.6
	Version 7	26.8	-13.0	4.0	-7.0
	Version 8	24.8	-19.5	3.7	-14.0
	Version 9	24.3	-21.1	3.8	-11.6

[a]As in Table 2.

dently, lower errors indicate better algorithm performance. In addition, each algorithm is compared with UTCS-3, and the deviation of its error with respect to that of UTCS-3 is presented. A positive deviation means that the algorithm in question has an error greater than that of UTCS-3 and is therefore less desirable than UTCS-3. A negative deviation implies that the algorithm has an error smaller than that of UTCS-3 and is therefore more desirable. The best-performing algorithm in 5-min prediction, UTCS-2, was not chosen as a basis for comparison since it could not be used in cycle-by-cycle prediction.

The following conclusions can be drawn from the test results and the relative performance comparisons given in Table 7:

1. For any data set, at least one version of the proposed algorithm performs substantially (as much as 21 percent) better than UTCS-3.
2. The proposed algorithm does not always perform as well as UTCS-2 or the historical average. This is especially true for the isolated location (data set 2), where the mean absolute error is 25 percent higher than that of UTCS-2. A probable reason for the superior performance of UTCS-2 in this case is the importance of historical data for 5-min prediction in isolated locations.
3. Versions 7-9 of the proposed algorithm, which degenerate to a moving average of three to five previous periods, exhibit performance very similar to that of the complete algorithm.
4. By increasing N (the number of time periods considered for an average) from three to five in the proposed algorithm, performance is not significantly affected.
5. For all locations, UTCS-2 errors are lower than UTCS-3 errors.
6. For all locations, the errors of the historical algorithm are lower than the errors of UTCS-3. At two of the four locations, the historical algorithm also performs better than UTCS-2; however, for all locations, the difference in performance between the historical algorithm and UTCS-2 is not significant.
7. For all locations, prediction from the current measurement alone is worse than that of either UTCS-2 or UTCS-3.

Figures 2-4 show the performance of four of the algorithms tested for data sets 2, 3, and 4, respectively. The historical average has not been plotted together with the rest of the algorithms, since it exhibits behavior very similar to that of UTCS-2. The conclusions cited above can also be drawn from these figures.

Cycle-by-Cycle Prediction

Both coordinated and isolated intersections, corresponding to data sets 5-10 in Table 2, were used in the cycle-by-cycle prediction tests. Three algorithms were tested: UTCS-3, current measurement, and the proposed algorithm. The two historically based algorithms investigated for 5-min prediction--i.e., historical and UTCS-2--could not be used for cycle-by-cycle prediction since signal cycles did not begin and end at the same times each day.

The coefficients developed for the proposed algorithm and the test results are summarized in Tables 8 and 9, respectively. Coefficients for versions 7-9 (Table 6), which correspond to the moving average, are derived on-line. Coefficients for versions 10-12 (Table 8) are derived from data set 6--i.e., a period adjacent to the prediction period of data set 8. Coefficients for versions 13-15 (Table 8) are derived from the combined set of data sets 5-7--i.e., from periods not compatible with the prediction period of data set 8; for this and the previous test only, the deviation and prediction periods were chosen to be different so that the performance of the algorithm under less than ideal conditions could be examined. Finally, coefficients

Figure 2. Five-minute volume: data set 2.

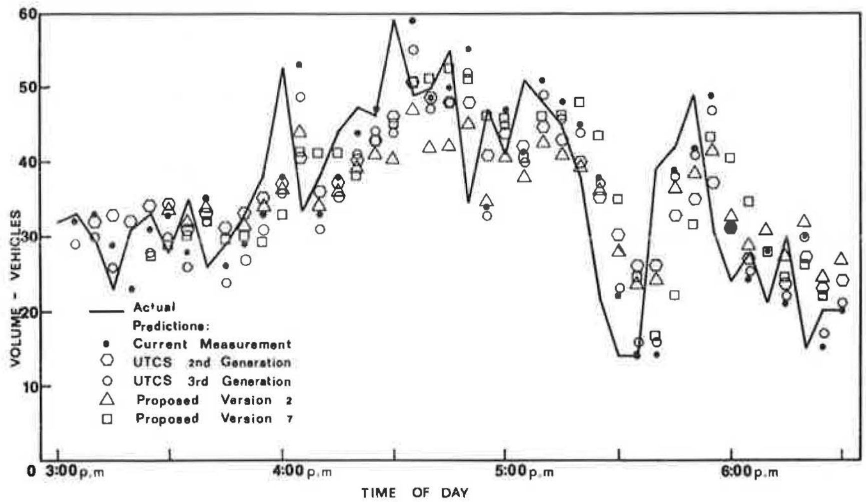


Figure 3. Five-minute volume: data set 3.

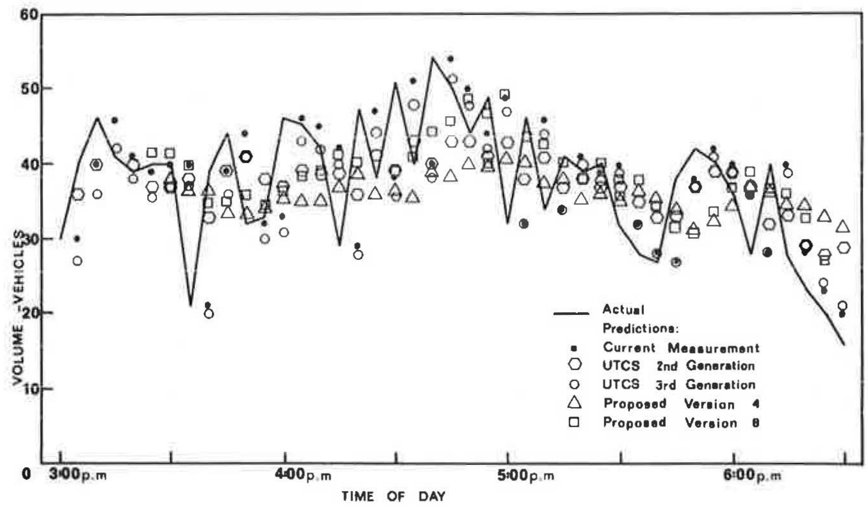
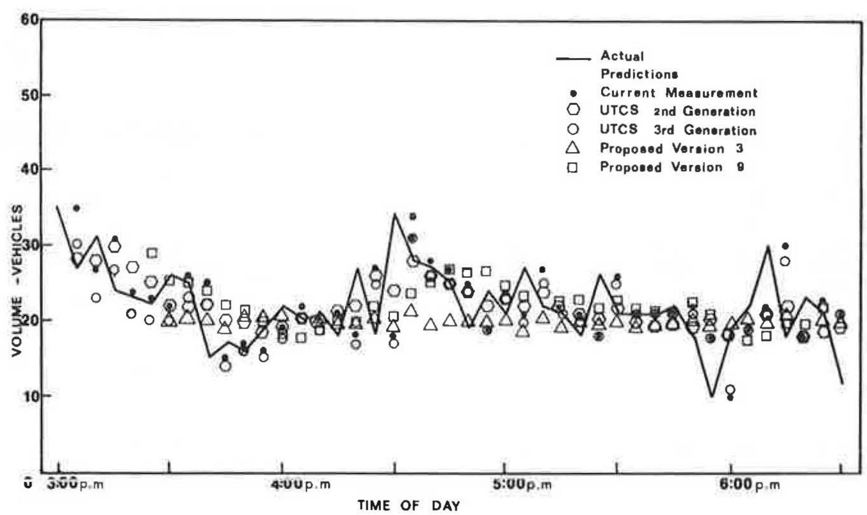


Figure 4. Five-minute volume: data set 4.



for versions 16-18 (Table 8) are derived from data set 9--i.e., a period almost identical to the prediction period. Here, the algorithm was expected to perform best.

The following conclusions can be drawn from the test results and the relative performance comparisons given in Table 9:

1. At all times, at least three versions of the proposed algorithm are substantially (as much as 41 percent) better than UTCS-3. These versions correspond to the moving average. As in the case of 5-min prediction, the unsatisfactory UTCS-3 performance can be attributed, at least in part, to the occasional congestion at the test sites.

Table 8. Proposed algorithm versions (cycle-by-cycle prediction).

Version	Control Coefficient a_0	a_1	a_2	a_3	No. of Time Periods (N)
10	7.435	0	0	-0.359	3
11	9.759	0	0	-0.781	4
12	11.053	0	0	-1.014	5
13	2.044	0	0	0.762	3
14	1.597	0	0	0.818	4
15	1.265	0	0	0.861	5
16	6.839	0	0	0.277	3
17	8.030	0	0	0.149	4
18	8.098	0	0	0.143	5

Table 9. Prediction errors of three types of prediction algorithms for cycle-by-cycle prediction.

Data Set[a]	Algorithm	MSE Value	MSE Difference from UTCS-3 (%)	MAE Value	MAE Difference from UTCS-3 (%)
5	Current	13.14	26	2.98	21
	UTCS-3	10.44	-	2.47	-
	Version 7	7.77	-26	2.22	-10
	Version 8	7.19	-31	2.13	-14
	Version 9	6.94	-34	2.12	-14
6	Current	4.70	10	1.71	9
	UTCS-3	4.27	-	1.57	-
	Version 7	3.74	-12	1.55	-1
	Version 8	3.20	-25	1.44	-8
	Version 9	3.20	-25	1.43	-9
7	Current	7.44	2	2.04	-2
	UTCS-3	7.33	-	2.09	-
	Version 7	6.01	-18	2.03	-3
	Version 8	6.12	-17	2.03	-3
	Version 9	6.04	-18	2.07	-1
8	Current	9.43	22	2.51	15
	UTCS-3	7.74	-	2.18	-
	Version 7	5.07	-34	1.78	-18
	Version 8	5.21	-33	1.76	-19
	Version 9	4.60	-41	1.68	-23
	Version 10[b]	6.20	-20	1.99	-9
	Version 11[b]	8.30	7	2.37	9
	Version 12[b]	9.37	21	2.55	17
	Version 13[c]	6.52	-16	1.98	-9
	Version 14[c]	5.90	-24	1.83	-16
	Version 15[c]	5.79	-25	1.84	-16
5-8	Current	8.75	17	2.32	12
	UTCS-3	7.47	-	2.08	-
9	Current	17.02	15	3.19	7
	UTCS-3	14.82	-	2.97	-
	Version 7	9.22	-38	2.47	-17
	Version 8	8.70	-41	2.48	-16
	Version 9	9.22	-38	2.53	-15
10	Current	8.53	7	2.44	7
	UTCS-3	7.99	-	2.29	-
	Version 16[d]	5.43	-32	2.00	-13
	Version 17[d]	5.31	-34	1.97	-14
	Version 18[d]	5.31	-34	1.97	-14
	Version 7	6.20	-22	1.99	-13
	Version 8	6.30	-21	2.06	-10
	Version 9	6.02	-25	2.02	-12

[a]As in Table 2.
[b]Equations derived from data set 6.
[c]Equations derived from data sets 5-7.
[d]Equations derived from data set 9.

2. From data sets 9 and 10, it can be verified that the more sophisticated versions of the proposed algorithm (versions 16-18) perform even better than the moving average. Therefore, the best performance is obtained when the algorithm is derived from data collected, on an earlier day, during a period identical to the prediction period.

3. When the algorithm is derived from data collected during periods incompatible with the prediction period, in most cases performance is still considerably (as much as 25 percent) better than UTCS-3. In such cases, however, the moving average offers a slightly better prediction than the more sophisticated versions and is therefore preferable.

4. The performance of the proposed algorithm is not affected by the approach type (i.e., coordinated or isolated).

5. For all data sets, the current measurement predictor is least desirable.

Figures 5-8 illustrate the performance of the three algorithms in cycle-by-cycle prediction of data sets 5, 8, 9, and 10, respectively. For data set 8, Figure 6 shows three versions of the proposed algorithm--one that uses a data set from the previous day (version 10), one that uses three data sets from the previous and the current day (version 15), and one that is equivalent to a moving average (version 9) using four data sets. For data set 9, Figure 7 shows the proposed version equivalent to a moving average whereas, for data set 10, Figure 8 shows both that version and the complete proposed algorithm. The conclusions derived from Table 9 and cited above could also be drawn from these figures.

As Figure 8 shows, the proposed algorithm achieves superior performance by weighing a constant average, describing volume trend during the same period on a previous day, much more heavily than cycle-by-cycle traffic fluctuations. This suggests that the assumption of average arrivals frequently used in practice for isolated intersections is not unreasonable. In contrast, in Figures 3 and 6 and in Table 8 it is seen that this assumption is unreasonable for coordinated intersections.

Finally, it should be noted that, as Tables 7 and 9 indicate, the improved performance of the proposed algorithm over UTCS-3 is much more noticeable in cycle-by-cycle than in 5-min prediction.

CONCLUSIONS

The test results of the previous section suggest that in 5-min prediction, for all locations, UTCS-2 performs better than UTCS-3 and that both are superior to the current measurement for prediction. The results also indicate that predictions based on historical data alone are as good as and frequently better than UTCS-2 predictions. The results are consistent with previous findings and lead to the conclusion that computations and data requirements can be significantly reduced by choosing the historical algorithm over either UTCS-2 or UTCS-3 for 5-min prediction. The results also indicate that, in 5-min prediction, at least one version of the proposed algorithm performs better than UTCS-3 in all cases; however, it does not always perform as well as UTCS-2.

In cycle-by-cycle prediction, which was of the greatest interest in this study, UTCS-2 and the historical algorithm cannot be used. From the remaining three algorithms, again the current measurement performs worse than UTCS-3 while the moving-average version of the proposed algorithm performs better than UTCS-3 in all cases. When the proposed algorithm is derived from data collected on an earlier day during a period identical to the prediction period, it performs better than all algorithms examined. However, the complete version of the proposed algorithm has certain disadvantages in comparison with the moving-average version: (a) It may need to be updated frequently, (b) it requires that data be collected on at least one previous day, and (c) it performs best when used during a specified time of day, which makes it necessary to develop more than one equation for each day (a minimum of

Figure 5. Flow rate: data set 5.

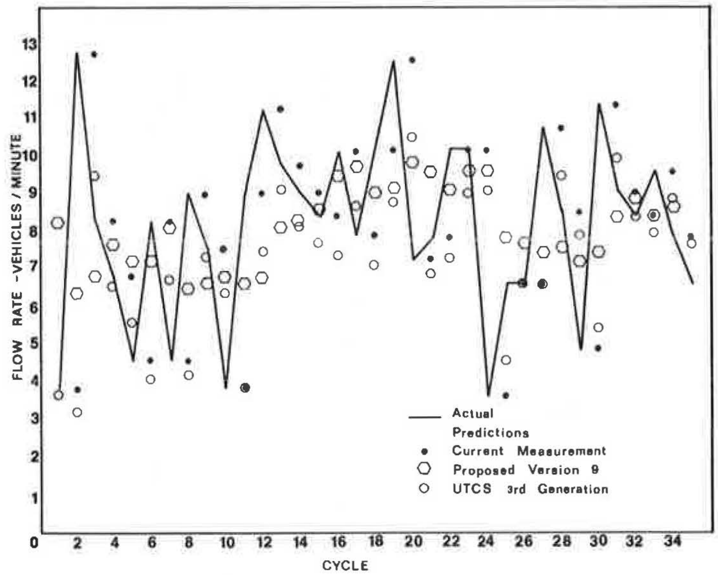


Figure 6. Flow rate: data set 8.

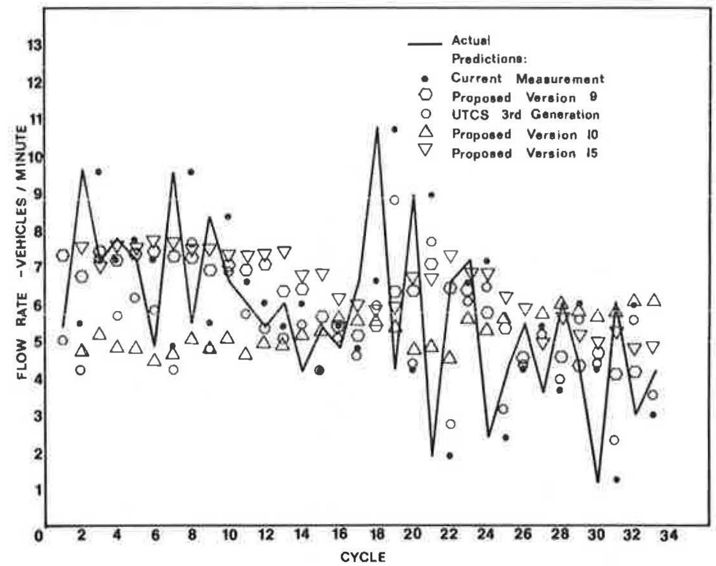


Figure 7. Flow rate: data set 9.

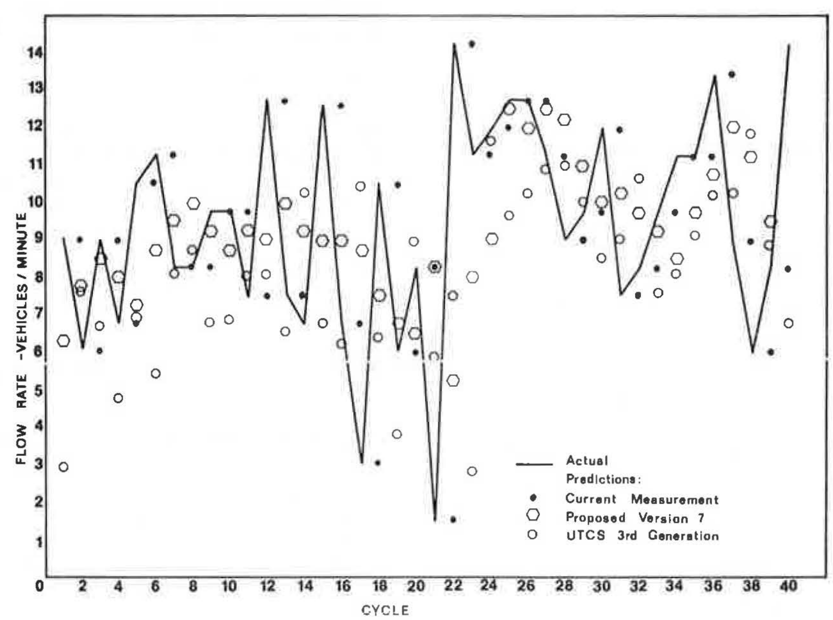
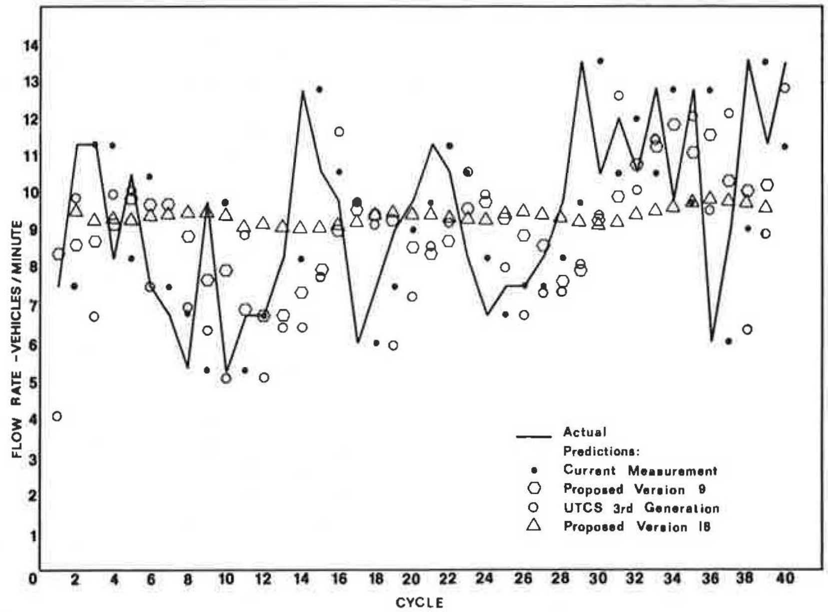


Figure 8. Flow rate: data set 10.



three equations for each peak and off-peak period would be required).

Despite these criticisms, the proposed algorithm has significant advantages over existing algorithms. It does not need extensive historical data as UTCS-2 and the historical average do, and it can be applied in cycle-by-cycle prediction whereas UTCS-2 and the historical average cannot. Furthermore, it performs better (as much as 41 percent better for the versions examined) than the UTCS-3. It should also be pointed out that it could easily be optimized at a later date by using established optimal-control-theory methodologies.

The moving-average version of the proposed algorithm will usually offer prediction that is more accurate than that offered by the best existing algorithms. It achieves such performance with minimal data, since volume or flow-rate measurements from the previous three intervals are sufficient. It is therefore recommended that the moving-average version of the proposed algorithm be used initially, especially if little is known about the demand characteristics of a particular intersection. If more information on demand is available, it is desirable to use the complete proposed algorithm.

ACKNOWLEDGMENT

We would like to acknowledge financial support from the Program of University Research of the U.S. Department of Transportation.

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Discussion

Nathan H. Gartner

The authors have conducted a comprehensive review of algorithms for short-range traffic-volume prediction of the type that were used in second- and third-generation UTCS control strategies. They also investigate a newly proposed, rather simple algorithm that in its general form calculates the predicted volume as a linear combination of the current (measured) value, the difference with respect to the previous value, and the moving average (analogous to the proportional-plus, derivative-plus integral controller). The authors tested this algorithm on a number of data sets covering 5-min intervals and single-cycle intervals (presumably, in the 1- to 2-min range). Judging by two forms of mean error criteria--MSE and MAE (Equations 9 and 10)--results indicate that, for the shorter, cycle-by-cycle predictions, the proposed algorithms perform better than the other algorithms that were tested.

The results and conclusions of the paper are veritable and confirm ideas obtained from previous studies on the use of prediction algorithms in traffic control. This discussion is only peripherally concerned with the particular results and methodology of the paper; it is primarily directed toward the ulterior objective of the study, that of implementing real-time traffic-control strategies.

Real-time traffic control is designed to provide an increased degree of responsiveness to changing traffic flows. The expectation is that intersection performance can be improved by capitalizing on this variability. Yet extensive field tests with the UTCS system and elsewhere show that such expectations did not materialize (19,20). The more responsive the strategy that was tested, the less effective was its performance. In analyzing these results, one may erroneously conclude that a library of signal-control plans generated off-line by using historical data (from another day, perhaps another year, but for the same daily period) is more effective than controls generated on-line by using very recent data (the past few minutes). However, a closer examination of these studies reveals that it is not the rationale that has failed (i.e., that traffic-responsive control should provide benefits over fixed-time control) but the models and procedures that were implemented that failed to produce the desired results.

Real-time traffic-control strategies that rely on predicted volumes are not truly responsive: They do not respond to actual traffic conditions but to hypothetical conditions. The traffic-flow process and the optimization procedure used in deriving the control plans form an inseparable closed-loop control system. The signal controls can only be effective if an accurate model is used in the optimization. Yet these strategies use an abstract model that is calibrated by the predicted volumes. Predictions are inherently inaccurate, and therefore the models cannot take account of the short-term fluctuations to which they are supposed to respond. In essence, by aggregating and averaging the data, the prediction algorithms destroy the information content that is most important for real-time control.

A good demonstration of the inadequacy of short-term volume predictions for their intended use is provided by the extensive data sets analyzed by the authors and shown in Figures 2-8. In all cases, the discrepancies between predicted and actual values are very substantial. The shorter the prediction interval, the larger are the relative discrepancies. [The authors should also calculate the mean relative error values of the type 1/N Σ (error/measured value).] A most telling example is shown in Figure 8, where the best predictor turns out to be an almost fixed value, notwithstanding the highly variable cycle-by-cycle flow rates. It is clear that one cannot conceivably derive a responsive strategy from such a prediction.

Furthermore, suppose one could predict the flows in each cycle with complete accuracy (i.e., with a zero mean error value). Even then the resulting real-time control strategy might be ineffective. For example, the following numbers represent vehicle arrivals for two cycles, grouped into 5-s intervals, on a signal-controlled approach with a 60-s cycle time:

Cycle	Vehicle Arrivals
1	1 1 2 1 1 2 0 2 0 0 1 1
2	0 1 0 0 1 1 2 1 2 1 1 2

During both cycles, the flow is the same (12 vehicles), yet the optimal control strategy for each should be entirely different because of the different distribution of the arrivals within the cycle.

To summarize, I offer the following conclusions:

1. Reliable estimates of future traffic volumes can only be obtained for lengthier time periods (of several minutes). These estimates can then be used to derive steady-state-type control strategies (e.g., first-generation traffic-responsive control).
2. The quality of predictions should not be judged merely by their average closeness to the actual values; rather, they should be evaluated in terms of the ultimate objective--the effectiveness of the control strategies that they produce.
3. Estimates of volumes for very short periods (e.g., cycles) are unreliable and cannot be used to provide effective real-time control. Therefore, there is a need to develop real-time traffic-control strategies that move away from the use of predicted average volumes and rely mostly on actual flows.

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Samir A. Ahmed

The authors have provided a needed critique of several predictor models that have been proposed for real-time control of street intersections. It is true, as the authors have pointed out, that one of the major reasons for the unsatisfactory performance of real-time signal-control systems is the lack of a predictor model that describes the dynamic behavior of the traffic-flow process. The paper does not, however, substantiate the important points made on how a predictor model should avoid arbitrary methods of treating the data and instead be based on a solid theoretical foundation.

Predictor models can be categorized into two general categories: ad hoc models and point-process models. Ad hoc models (e.g., moving-average models, exponential smoothing models, and adaptive exponential smoothing models) propose arbitrary weighting schemes to be assigned to the current and previous observations on the variable of interest. The primary advantage of these models is their ease of implementation, and their major weakness is their inherent lack of a general approach for choosing among alternative weighting schemes. The proposed models described in this paper (Equation 11) and the rest of the models given in Table 1 are in this category. In using these models, much is left to the personal judgment of the engineer or investigator who must assume any special knowledge of the control system under consideration.

The other category of models--point-process models--forms a broad class of potential models for representing the stochastic nature of many physical processes. The eventual form of the predictor model is determined by the properties of the observations on how a process actually behaves and, among other linear predictor models, the resulting forecasts are optimal in terms of having minimum MSE (21). In addition, in view of the recent developments in the joint analysis of interrelated processes, it is possible to construct point-process models for predicting several processes observed in different parts of the control system.

To compare the prediction errors resulting from ad hoc models and point-process models, I applied three ad hoc models and a point-process model that has been developed for freeway traffic to a total of 166 data sets obtained from three freeway surveillance systems (22). Forecasts were made for 1 min ahead in time. By using the same error measures described in the paper, the point-process model has been found to be superior to the ad hoc models.

In conclusion, I believe that it is time that some serious research was devoted to the problem of predicting traffic-flow variables for the real-time control of street intersections. Such research should be based on the well-established theory of point-process models.

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Authors' Closure

We would like to thank Gartner for his constructive remarks, which are in close agreement with our views. With regard to Ahmed's comments, we observe the following.

As pointed out from the outset, the objective of this study was to test the existing models in order to select the most appropriate one for easy field implementation subject to the stated criteria. The development of the models was incidental and resulted from the need to simplify the prediction process. The simple predictors emerged as at least as accurate as and frequently better than the most complex ones.

With respect to the argument that prediction models fall into the two categories suggested by Ahmed, one can argue that, under a more comprehensive classification, models can be grouped as (a) descriptive or correlative, (b) causal, and (c) normative. Most efforts to date belong to the first category. Their inherent weakness is lack of attention to causal analysis and use of rather arbitrary and complex statistical methods to best describe the system modeled. Our attempt at capturing the basic causal relations within the system analyzed represents only a first modest step in entering the second category. We insisted on keeping our models simple in form, yet we included all major terms that would make sense to a traffic practitioner. Furthermore, the models can be simply transformed to become part of the complete feedback system analysis in either the time or the frequency domain, once the complete traffic system is modeled. Since an understanding of the causal relations governing the whole traffic system is currently lacking, it is our belief that a jump into normative interpretations would be premature at this stage. Since such an understanding is lacking, results from normative analysis would not offer substantial improvements and therefore would not be cost effective. To be sure, Ahmed's findings (22) are, in effect, consistent with this statement. For example, they indicate that a simple moving average could be as accurate as the method he proposed.

As for Ahmed's final conclusion, we again feel that the emphasis should not be on the exact statistical treatment of the problem. We believe that demand prediction should not be treated as a point process without using more valuable information that is currently ignored, information related to traffic dynamics. More specifically, a detailed traffic model should be developed for analyzing traffic flow in signalized links. Demand prediction would, then, be greatly simplified, since information from upstream detectors would be used. In addition, a traffic model is needed to identify the tail end of the queue and predict arrivals there. In short, complete dynamic traffic-behavior analysis is more crucial than exact statistical treatment of the prediction method.

Finally, the methods proposed by Ahmed and Cook (22) do not appear to be overwhelmingly superior, and their successful and cost-effective application to interrupted-flow conditions remains to be tested.