Use of Predicted Vehicle Arrival Information for Adaptive Signal Control—An Assessment

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Adaptive signal control at individual intersections relies on detectors to provide advance vehicle arrival information for real-time optimization of the signal operations. As much as 25 sec of advance information may be needed to achieve near optimal operations if flow rates reach about 700 vehicles per hour per lane (vphpl). However, it is often impossible or impractical to place detectors far enough from the intersection to provide the desired amount of information. The use of predicted data becomes a tempting alternative under the circumstance. In this paper, computer simulation is used to assess the desirability of using predicted data in combination with the data provided by the detectors for signal optimization. Three predictors are compared and one is chosen to assess the impact of using the predicted data. It is found that reliance on limited advance arrival information provided solely by the detectors is more desirable than using predicted data to increase the amount of advance information.

Adaptive signal control represents a class of signal control strategies that share three basic characteristics: (a) use of detectors placed upstream of the intersection for early detection of the arrivals of vehicles; (b) use of the advance arrival information obtained by the detectors as a primary basis to determine and implement the optimal signal switching sequence on a real-time basis; and (c) if predicted arrival data are used to supplement the arrival data obtained by the detectors, the prediction period extends into the future only for a very short period of time (e.g., less than 1 min).

Adaptive control (as defined in the preceding paragraph) differs from traffic-actuated control in that the latter does not have real-time optimization capabilities. The former also deviates from the predominant reliance of Urban Traffic Control System (UTCS) strategies *(1)* on predicted flow pattern for signal optimization. Several adaptive control strategies have already been tested. These include Miller's strategy *(2)*, a strategy referred to as Modernized Optimization Vehicle Actuation (MOVA) *(3)*, and the SCOOT signal optimization technique *(4)*. The tests results are encouraging.

Miller's strategy was tested at an intersection by de la Breteque and Jezequel *(5)*. This strategy resulted in approximately an 18 percent reduction in time-in-queue delays in comparison with fixed-time signal operations. The corresponding improvement over two versions of traffic-actuated control varied from negligibly small to about a 17 percent reduction in delays when the total input volume increased from about 1,200 to 2,900 vehicles per hour (vph). When the total input flow dropped below 1,200 vph, the traffic-actuated operations became more efficient.

MOVA was tested by the Transport and Road Research Laboratory, Great Britain *(3)*. This test involved three sites for six peak-hour patterns and four off-peak patterns. The MOVA produced an increase of 7 percent in delays over vehicle-actuated signal operations for one morning peak-hour pattern. For the remaining nine flow patterns, however, the MOVA brought about delay reductions ranging from 5 to 27 percent. The SCOOT optimization technique was also tested by the Transport and Road Research Laboratory *(4)*. It reduced delays by an average of about 12 percent during the workday in comparison with fixed-time signal operations.

More efficient adaptive control strategies will certainly emerge in the years ahead. The advancement in microprocessor technology would further open up opportunities for experimentation with various control strategies. These opportunities, in turn, raise many issues concerning the detector deployment, optimization procedure, and other problems related to the development of adaptive control. One such issue is whether the use of predicted arrival data is desirable from the viewpoint of the control efficiency.

This issue arises when detectors alone cannot provide a desired amount of advance vehicle arrival information for signal optimization. Longer distances between the intersection and the detectors would allow the detectors to provide more advance information. If such information can be used without error for signal optimization, there will be more advance arrival information available, and the better the resulting control efficiencies will be *(6)*. In reality, however, it may not always be practical to place detectors at a considerable distance upstream of the intersection. One potential solution to this problem is to use detectors to provide a portion of the needed information and to supplement such information with data generated by a predictor.

If the predicted data can be used effectively to achieve a high control efficiency, then there will be a greater flexibility in the placement of detectors for adaptive control. This would in turn enhance the applicability of adaptive control. The purpose of this study is to analyze the potential impact of using predicted arrival data for signal optimization. The analysis is limited to the control of individual intersections.

CONTROL STRATEGY

The adaptive control strategy analyzed in this paper is a modified version of a strategy described in an earlier study by Gartner *(7)*. The strategy relies on one detector in each lane to

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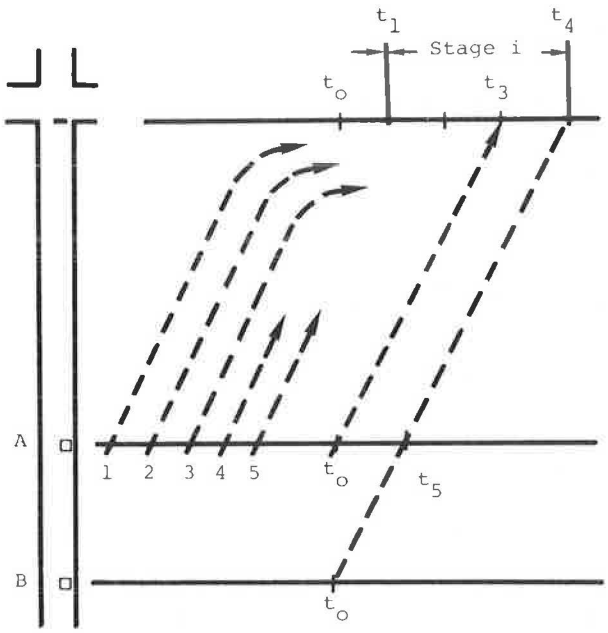

FIGURE 1 Relationship among detector location, arrival information, and optimization stage.

scan the presence of vehicles and thereby determine the vehicle arrival times at the various detector locations. Referring to Figure 1, let t_0 represent the time at which an optimization process should be initiated so that an optimal signal switching sequence can be determined and implemented by t_1 for a future time interval between t_1 and t_4. The future time interval for which an optimal switching sequence is to be determined is referred to as an optimization stage. The length of such a stage is denoted as stage size. The switching sequence for a stage represents a series of green intervals, signal change intervals, and red intervals for each signal phase. Such a sequence may encompass less than one signal cycle or more than one cycle.

In Figure 1, the optimal switching sequence for the time period up to t_1 has already been determined and implemented. Vehicles 1, 2, and 3 are three vehicles that are not expected to enter the intersection by t_1 through the use of the implemented switching sequence. They have been detected and considered in the previous optimization process. In contrast, Vehicles 4 and 5 are vehicles detected after the previous optimization process has begun and before the current optimization process is initiated at t_0. The expected movements of Vehicles 1, 2, and 3, as well as those of additional vehicles detected before t_0, will have to be considered in the current optimization process.

Let t_3 represent the expected arrival time at the stop line of a vehicle that is detected at t_0 by the detector located at Point A. If the interval between t_3 and t_4 is long enough to have additional arrivals, then the detector located at Point A will not be able to provide sufficient advance arrival information for signal optimization. This is because the detector at Point A still has not detected any possible arrivals between t_0 and t_5 at the detector location when the optimization process begins at t_0. There are two options to deal with this problem if one chooses to keep the stage size unchanged. One option is to move the detector further upstream to Point B. This is not always feasible or desirable. Another option is to use a predictor for vehicle arrival times between t_0 and t_5 at Detector Location A.

When the needed arrival information at the detector location is available, a traffic model is used to estimate the traffic conditions that are expected to exist between t_1 and t_4 when alternative signal switching sequences are implemented. Each alternative switching sequence can be evaluated in terms of delay, degree of saturation, or other measures of effectiveness. The optimal switching sequence is one that produces the best signal operations in terms of the specified measure of effectiveness.

In this study, delay is used as the measure of effectiveness. The traffic model used for estimating the delay is, in fact, a microscopic simulation model. Given a signal switching sequence and a vehicle arrival pattern, it can estimate the traffic conditions downstream of the detectors and produce an estimate of the vehicle delay in each traffic lane. A comparison of the delays estimated from this model with those calculated from Webster's formula *(8)* when optimal fixed-time switching sequences are implemented for random arrival patterns is shown in Figure 2. Further tests of this model have been performed on the basis of observed traffic-actuated signal operations at six intersections. The delays estimated from the model for these operations are within 10 percent of the observed values.

Any traffic model used in an adaptive control process for estimating delays and other flow conditions would invariably yield errors in its estimates. In order to analyze the impact of such errors, the traffic model used in this study allows the perceived movements of detected vehicles either to duplicate exactly or to deviate from specified conditions. This model is perhaps too cumbersome for actual implementation in an adaptive control process. Nevertheless, it makes controlled comparisons of various features of adaptive control possible. The

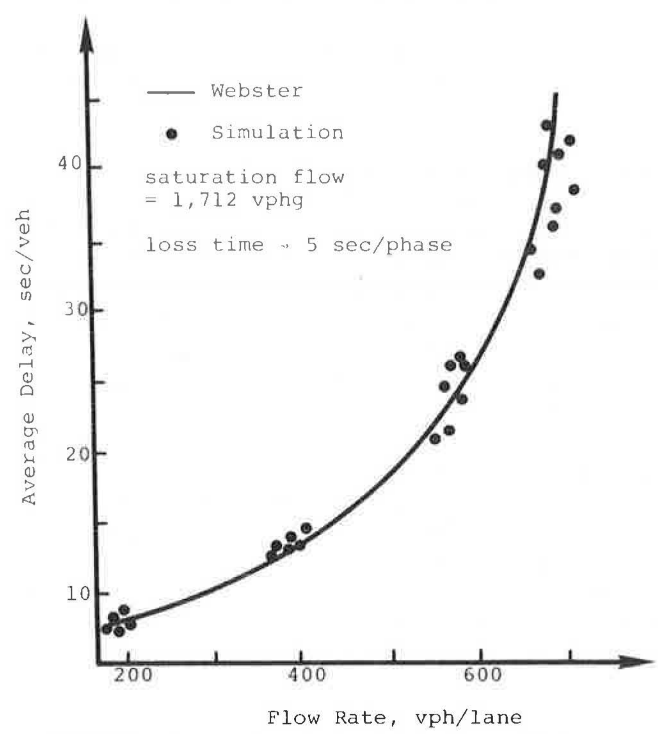

FIGURE 2 Comparison of simulated delays with delays estimated from Webster's formula.

selection and use of a traffic model for adaptive control is a subject that warrants further studies.

In order to generate alternative signal switching sequences for evaluation, each optimization stage is divided into small subintervals of equal lengths. In each subinterval, only one signal phase or phases without conflicting movements are given the right of way. The transfer of the right of way requires the use of a signal change interval. Each alternative switching sequence is first generated with a simple algorithm in the form of a series of integer numbers. Each of such numbers denotes the phase which is to receive the right of way in a given subinterval.

Every alternative right-of-way allocation sequence is then used to construct a signal switching sequence in the form of a series of green interval, signal change interval, and red interval. Not all the right-of-way allocation sequences would result in a feasible signal switching sequence, which has the following characteristics: (a) provides for signal change intervals of a specified length, (b) has green intervals longer than a specified minimum, and (c) has green intervals not longer than a specified maximum after a call for the right of way by a vehicle in a competing phase is received. Only the feasible switching sequences are evaluated to determine the optimal switching sequence. Figure 3 shows an example of the relationship between a right-of-way allocation sequence and a signal switching sequence.

After the optimal switching sequence is determined, the tail portion of that switching sequence is truncated and only the remaining portion is implemented. For example, the optimal switching sequence for the time interval between t_1 and t_4 in Figure 1 may be implemented only up to t_3. In this case, the next optimization stage will begin at t_3 instead of t_4. As a result, successive optimization stages will overlap. The use of overlapped optimization stages removes some uncertainties created by the inherent inability of the optimization process to consider all future vehicle arrivals in a single optimization stage.

Simulation analyses *(6, 9)* of this adaptive control strategy have revealed several important characteristics. First, for flow patterns with flow rates reaching approximately 700 vph per lane, there is no significant advantage of obtaining more than 25 sec of advance information. Therefore, there is no need to use an optimization stage longer than 25 sec. Second, the truncation of the tail portion of the optimal switching sequence for each stage can improve the control efficiencies. The size of the truncation, however, can be limited to about 15 sec. Third, dividing each optimization stage into smaller subintervals can provide better control efficiencies. The use of subintervals shorter than 3 sec, however, has little additional beneficial impact on the control efficiencies. Fourth, the use of a constant average discharge headway for each individual queueing position in order to estimate the flow conditions downstream of the detectors will not significantly reduce the control efficiencies. Last, errors in the vehicle arrival information can seriously reduce the control efficiencies. This characteristic is of particular concern when predicted arrival data are to be used for the signal optimization.

PREDICTION OF ARRIVALS AT DETECTOR LOCATIONS

Prediction Problem

Referring to Figure 4, let $t_1, t_2, \ldots, t_i, t_{i+1}, \ldots,$ and t_k denote the detected arrival times of a series of vehicles at a detector location. Let t_k represent the last detected arrival before T_1. T_1 is the beginning of a time period in which arrival times are to be predicted. The prediction period as defined by T_1 and T_2 has a length of H_2 and the elapsed time between t_k and T_1 is H_1. The prediction problem is that of using the detected arrivals to predict the arrivals in the prediction period.

It is extremely difficult to predict the individual vehicle headways in order to determine the corresponding arrival times for adaptive control. A more practical approach is to predict the number of arrivals during the prediction period and then use the estimate to determine the arrival times by assuming a constant headway between the predicted arrivals. This approach was adopted in this study.

It should be noted again that the optimization stages overlap. As a result, predictions may have to be made repeatedly for certain time intervals (e.g., between T_3 and T_2).

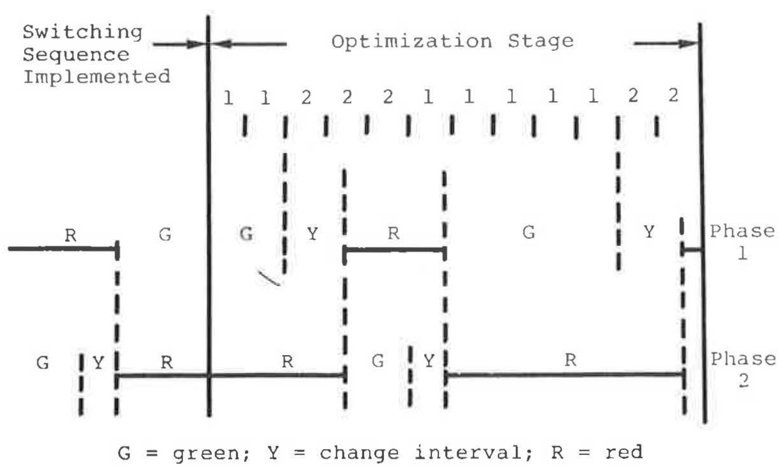

FIGURE 3 An example of right-of-way allocation scheme.

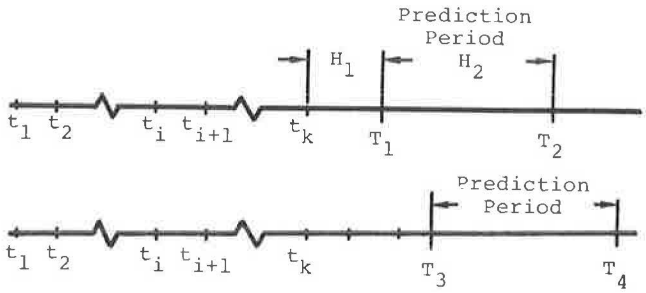

FIGURE 4 Schematic of vehicle arrival prediction problem.

Predictors

Three predictors were tested for their abilities to predict the arrival times at the detector locations. The first predictor was based on the simple exponential smoothing technique *(10)* and can be represented by the following equation:

$$S_T = \alpha y_T + (1 - \alpha) S_{T-1} \tag{1}$$

where

S_T = flow rate in vehicles per second predicted in period T for the prediction period,
α = smoothing constant, and
y_T = observed flow rate in vehicles per second in period T.

The initial value of this predictor, S_0, can be based on the average flow rate of the first few detected arrivals or be set equal to an assumed value. Various combinations of S_0 were used in this study to progressively reduce the prediction errors. The observed flow rate y_T can be determined on the basis of the number of detected arrivals over a specified period before the prediction period. A rather short sampling period of 10 sec was used in this study to determine y_T. Longer sampling periods were found to be unable to produce significantly better predictions.

The second predictor was based on the double exponential smoothing technique *(10)*. This predictor requires repeated applications of the following equations:

$$S_T = \left(2 + \frac{\alpha}{1 - \alpha}\right) F_T - \left(1 - \frac{\alpha}{1 - \alpha}\right) E_T \tag{2a}$$

$$E_T = \alpha\, y_T + (1 - \alpha)E_{T-1} \tag{2b}$$

and

$$F_T = \alpha\, E_T + (1 - \alpha)F_{T-1} \tag{2c}$$

where α, y_T, and S_T are as defined in Equation 1.

The initial values E_0 and F_0 for this predictor can be determined by applying a regression analysis to historical data or can be assigned subjectively. In this study, E_0 was set equal to the average flow rate as represented by the first five detected arrivals, and F_0 set equal to zero. This nonexisting F_0 implies a lack of a definitive upward or downward trend in the arrival rate at the beginning of an arrival pattern.

When a predicted flow S_T was obtained, the average headway h during the prediction period was determined as $1/S_T$. Then, the first arrival in the prediction period was assumed to take place at $T_1 + h$ (Figure 4), and the following arrivals were assumed to be spaced at a constant headway equal to h.

The third and last predictor is in the form of a heuristic algorithm and is referred to as pattern search predictor for convenience. This predictor attempts to match the arrival pattern detected just before the prediction period with the arrival pattern detected earlier in order to predict the arrivals. It is based on the knowledge that the first arrival in the prediction period would have a headway of at least H_1 in relation to t_k (Figure 4). Given this knowledge, the last several arrival times (e.g., t_i through t_k) can be scanned to identify every pair of successive arrivals that has a headway of at least H_1. Let such a pair of arrival times be denoted as t_i and t_{i+1}, then the number of vehicles arriving between $t_i + H_1$ and $t_i + H_1 + H_2$ (Figure 4) can be determined. Every pair of such arrivals would thus form a sample from which the average number of arrivals over a period of H_2 can be estimated.

This estimated average can then be used as the predicted number of arrivals in the prediction period. Let this predicted number of arrivals be denoted as N. Then the average arrival headway in the prediction period can be determined as $h = H_2/(N + 1)$, and the first arrival time in the prediction period can be assumed to be $T_1 + h$. Subsequent arrivals were assumed to have a constant headway in this study.

Prediction Errors

Let t_j be the actual arrival time of the jth vehicle and p_j be the predicted arrival time of the same vehicle. Thus, the prediction error was measured as $p_j - t_j$ if either p_j or t_j or both p_j and t_j were within the prediction period. On the other hand, if both p_j and t_j were outside the prediction period, then the discrepancy between t_j and p_j was irrelevant to the optimization stage being considered, and, therefore, was set equal to zero. The prediction errors were synthesized into mean absolute error and mean square error.

Evaluation of Predictors

Eight vehicle arrival patterns were used for the evaluation of the predictors. Each of the arrival patterns was represented by a sequence of arrival times. Three of the patterns were actual arrival sequences recorded respectively in Potsdam, Watertown, and Syracuse, New York.

Each of the patterns covered a period of approximately 40 min. Two other patterns were approximations of reported flow patterns *(11, 12)*. The remaining arrival patterns were hypothetical random hourly arrival patterns with flow rates ranging from 200 to 800 vph.

The Watertown and Potsdam patterns were similar. The arrivals in these two patterns were not random but slightly cyclic in nature. In contrast, the Syracuse pattern was distinctively cyclic, with a single long headway followed by a number of very short headways. Parts of the headway sequences in the Syracuse pattern and the Watertown pattern are shown in Figures 5 and 6, respectively. The two approximate patterns were each represented by a sequence of 5-min flow rates. The vehicle arrivals for each 5 min were assumed to be random. These approximate patterns are shown in Figure 7.

In testing the three predictors, it was assumed that 25 sec of advance information was to be obtained for the signal optimization. The detectors could provide only 10 sec of the needed information. Therefore, the predictors were used to supply 15 sec of advance information.

The resulting prediction errors are shown in Table 1. None of the predictors was able to consistently produce the smallest prediction errors. For most of the flow patterns examined, the mean square errors and the mean absolute errors produced by the various predictors differed very little. Under these circumstances, the simple exponential smoothing technique appeared to be the most desirable because of its simplicity. The best smoothing constants for this predictor were found to be in the range of 0.01 to 0.03.

Regardless of the predictors used, the prediction errors decreased as the flow rate increased. All three predictors had difficulties providing reasonably accurate predictions for the highly cyclic Syracuse pattern. The prediction errors can certainly be reduced by using a predictor that accounts for the cyclic nature of the arrival pattern. However, it should be noted that the number of arrivals in between any two successive long headways as shown in Figure 5 varied from 10 to 27. Therefore, an even more complicated predictor will not be able to avoid making large prediction errors for this pattern.

The mean absolute errors shown in Table 1 were deceptively small for all but the Syracuse pattern. A better insight into the nature of the prediction error is provided by Figure 8. For both frequency distributions of the prediction errors shown, approx-

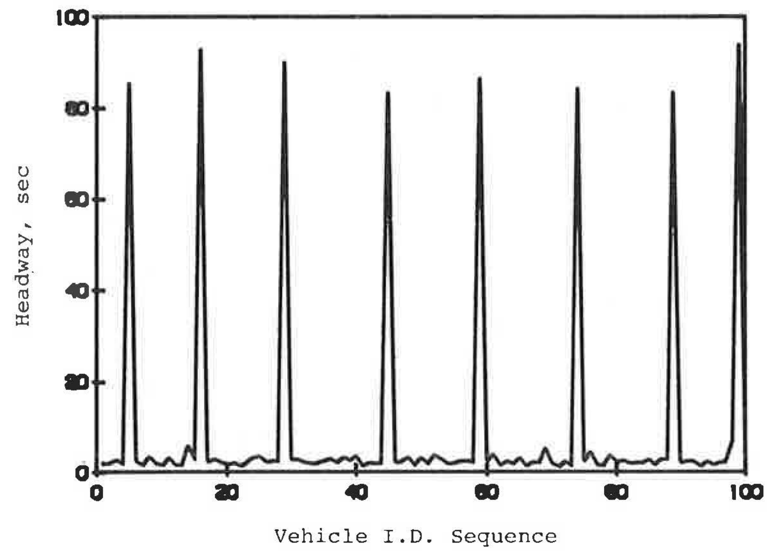

FIGURE 5 Sample arrival headway sequence of the Syracuse pattern.

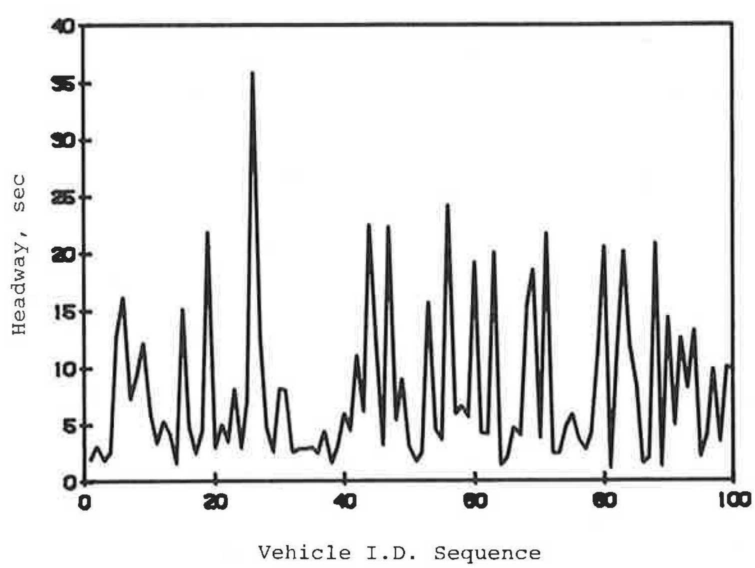

FIGURE 6 Sample of arrival headway sequence of the Watertown pattern.

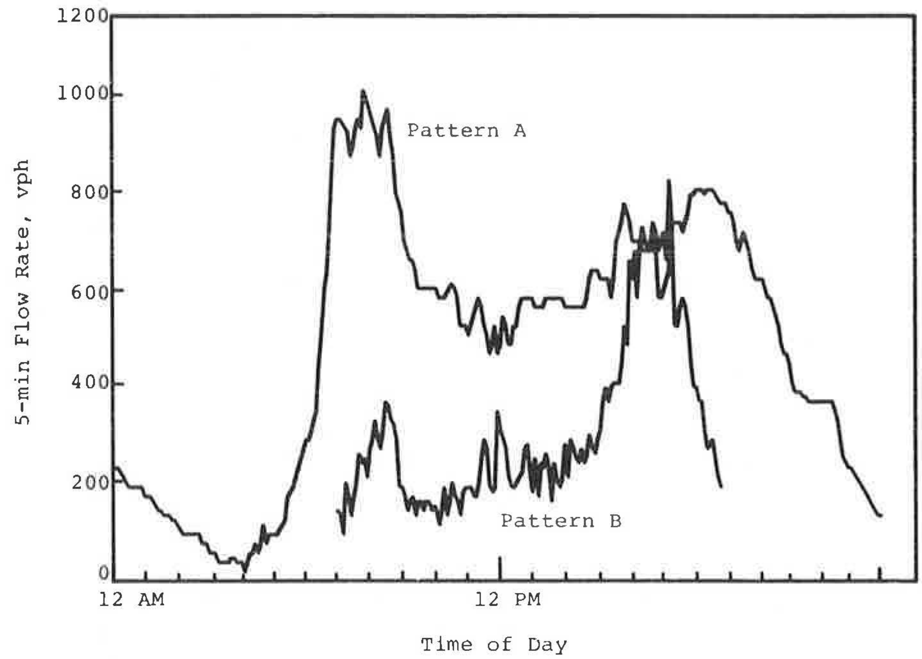

FIGURE 7 Five-min flow rates of approximate arrival Patterns A and B.

TABLE 1 PREDICTION ERRORS

Flow Pattern	Mean Absolute Error (sec) Simple Exponential	Mean Absolute Error (sec) Double Exponential	Mean Absolute Error (sec) Pattern Search	Mean Square Error (sec) Simple Exponential	Mean Square Error (sec) Double Exponential	Mean Square Error (sec) Pattern Search
Potsdam	8.0	10.2	8.2	177.6	281.4	208.6
Watertown	5.0	6.5	5.5	69.9	101.7	88.8
Syracuse	18.6	22.5	17.4	715.0	1,088.6	1,049.7
Random						
200 vph	6.4	6.8	6.4	153.0	144.9	160.8
400 vph	5.4	5.3	4.5	70.6	65.7	53.4
600 vph	4.3	4.3	4.3	42.3	38.2	43.0
800 vph	3.7	3.5	3.4	27.7	25.3	26.6
Approximation						
A	6.8	6.8	5.9	131.0	137.9	117.2
B	5.2	5.3	6.2	93.0	112.3	211.8

imately 70.5 percent of the errors were less than 6 sec, and about 3 percent were greater than 20 sec.

IMPACT OF USING PREDICTED DATA

Eight scenarios of signal control were analyzed through simulation to examine the impact of using predicted data for the signal optimization:

1. Flow Pattern A
   a. Scenario 1: Adaptive control with 25-sec advance information by detectors, 5-sec subintervals, 15-sec stage truncation.
   b. Scenario 2: Adaptive control with 10-sec advance information by detectors, 15-sec advance information by the simple exponential smoothing predictor, 5-sec subintervals, 15-sec stage truncation.
   c. Scenario 3: Adaptive control with 10-sec advance information by detectors, 5-sec subintervals, 5-sec stage truncation.
   d. Scenario 4: Optimal pretimed control.
2. Flow Pattern B
   a. Scenario 1: Adaptive control with 20-sec advance information by detectors, 2.5-sec subintervals, 10-sec stage truncation.
   b. Scenario 2: Adaptive control with 10-sec advance information by detectors, 10-sec advance information by the simple exponential smoothing predictor, 2.5-sec subintervals, 10-sec stage truncation.
   c. Scenario 3: Adaptive control with 10-sec advance information by detectors, 2.5-sec subintervals, 10-sec stage truncation.
   d. Scenario 4: Optimal pretimed control.

All the scenarios were based on a two-phase signal operation for an isolated intersection. Each signal phase had two traffic lanes. The simulated signal operation lasted for 50 min. The

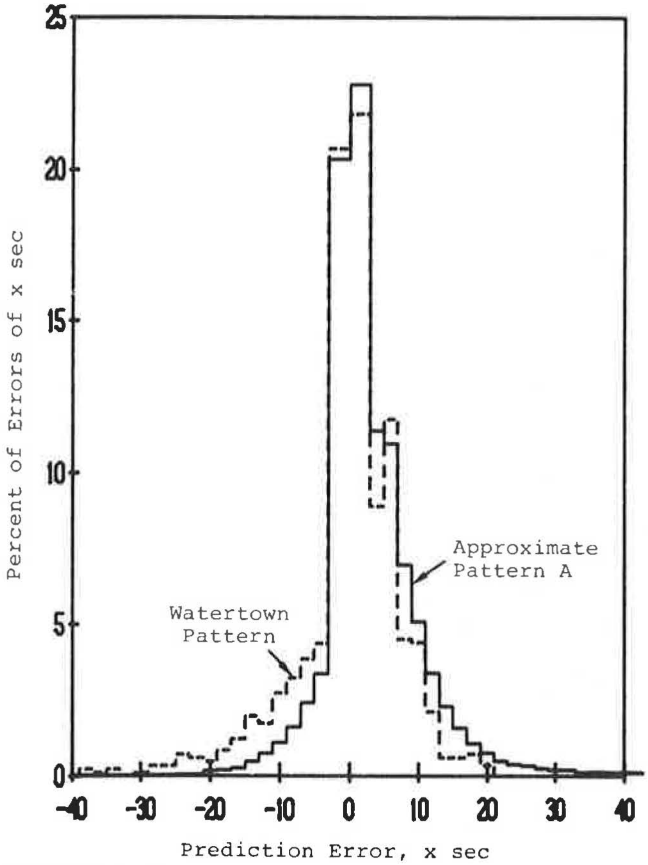

FIGURE 8 Frequency distributions of prediction errors produced by the simple exponential smoothing predictor.

simple exponential smoothing predictor was used to provide needed predictions of vehicle arrivals.

The basic elements of a simulation model used for the analysis are shown in Figure 9. This model used a traffic simulator to simulate the actual movements of the vehicles at an intersection. Such movements interacted with the detectors placed in the approach lanes. The arrival times of the approaching vehicles identified by the detectors were input into the signal optimization process described previously. The resulting adaptive control operations were then evaluated by the traffic simulator. The delays estimated from the traffic simulator and the traffic model of the optimization process were identical if the same vehicular movements and signal switching sequences were used for analysis.

Two flow patterns, denoted as Pattern A and Pattern B, were used in the simulation analysis. Pattern A had equal flow rates in all the traffic lanes. Each phase in Pattern B had a critical lane flow that was twice the flow in the other lane. The critical lane flows of both phases, however, were equal. The vehicle arrivals in both Pattern A and Pattern B were random.

To isolate the impact of using the predicted arrival data, the movements of vehicles downstream of the detectors, anticipated by the traffic model of the adaptive control strategy, were made identical to simulated actual movements. This implies that the simulated adaptive control operations could use the advance arrival information to accurately estimate the flow conditions downstream of the detectors.

The results of the analysis are given in Figures 10 and 11. These figures show that the adaptive control became more effective relative to the pretimed control when unequal lane flows were present in each signal phase. In Scenario 1 the adaptive control reduced the delays of the pretimed control for Pattern A by 8 sec per vehicle (18 percent) when the critical lane flow was 700 vph, and by 4 sec per vehicle (44 percent) when the critical lane flow was 200 vph. In contrast, the corresponding reductions for Pattern B were 13 sec per vehicle (33 percent), and 6 sec per vehicle (66 percent). It should be noted that these magnitudes of delay reduction may diminish to some extent in real-life situations because the vehicle movements downstream of the detectors may not be susceptible to accurate estimation.

Improvements over the pretimed control could still be achieved through the adaptive control when only 10 sec of advance arrival information was available from the detectors (Scenario 3) (see Figures 10 and 11). However, such improvements were much smaller than those attained when a larger amount of advance arrival information was available (Scenario 1).

The use of predicted data in combination with the data provided by the detectors (Scenario 2) generally resulted in poor control efficiencies. Such control efficiencies were in most cases unfavorable when compared with the efficiencies resulting from the use of 10 sec advance information. Under light flow conditions, the use of the predicted data rendered the adaptive control ineffective in realizing an improvement over the pretimed control. When the flow rates increased, the control efficiencies based on the predicted data could become even poorer than the efficiencies of the pretimed control. These characteristics indicate that the adaptive control strategy has a low tolerance for the errors in the arrival sequences used for the signal optimization.

Therefore, it appears that the prediction of vehicle arrivals at the detector locations is not an effective means of increasing the magnitude of the advance arrival information. If detectors cannot be deployed to provide sufficiently long-term (e.g., 20 to 25 sec) advance information, it would be more desirable to rely on relatively short-term (e.g., 10 sec or less) advance information than to rely in part on predicted data. There are, however, several drawbacks of relying on short-term advance information provided by a single detector. One drawback is that it becomes more difficult to develop a simple adaptive control strategy that would produce significant improvements over various existing modes of signal control. Another drawback is that the application of the related adaptive control strategies becomes restrictive when frequent lane changes, large speed variations, and the presence of auxiliary turning lanes are present downstream of the detector.

The performance of the adaptive control strategy described previously was not compared in this study with various types of traffic-actuated controls. In comparison with pretimed operations, traffic-actuated operations can be rather efficient under light flow conditions *(5, 13, 14)*. When the flow rates increase, however, traffic-actuated operations approach pretimed operations. Therefore, the real advantage of adaptive control over traffic-actuated control lies in the regulation of moderate to heavy flow movements. Figure 12, which is a reproduction of the result of a field test *(5)*, underscores this potential of

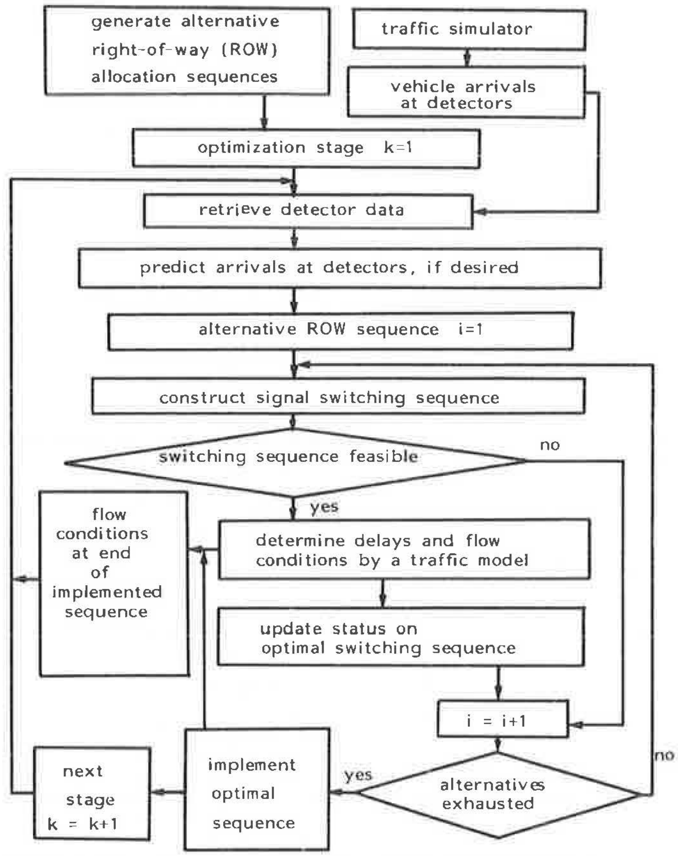

FIGURE 9 Simulation of adaptive signal control operations.

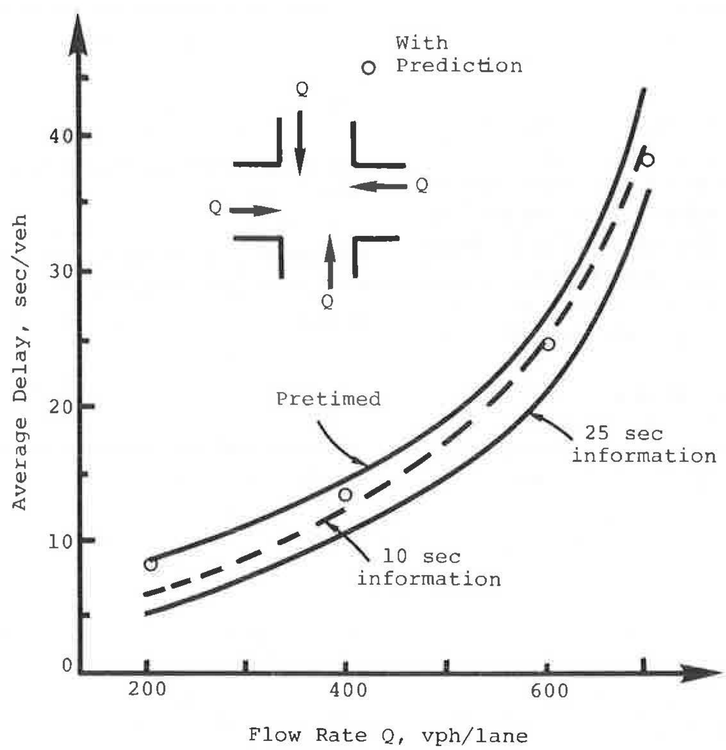

FIGURE 10 Comparison of delays produced under various scenarios of control for flow patterns with equal lane flows.

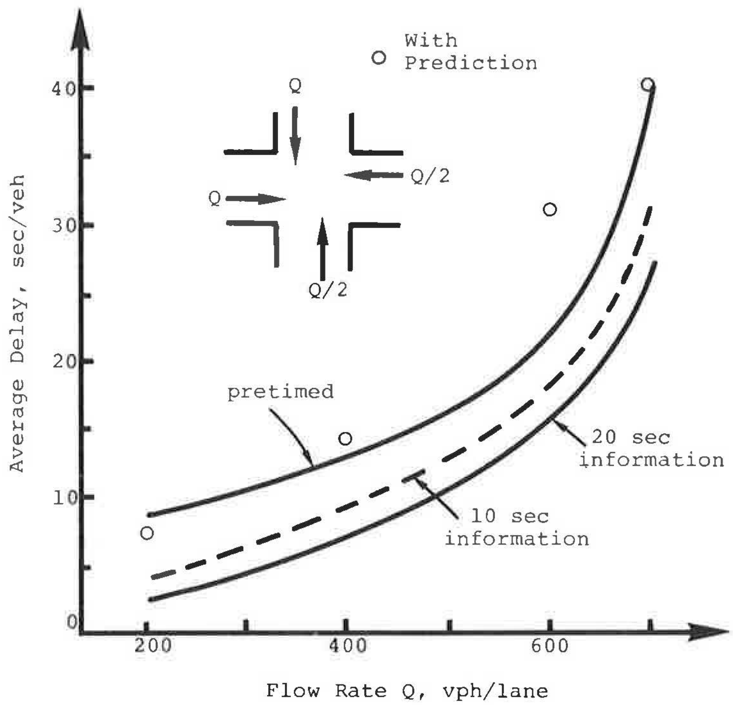

FIGURE 11 Comparison of delays produced under various scenarios of control for flow patterns with unequal lane flows.

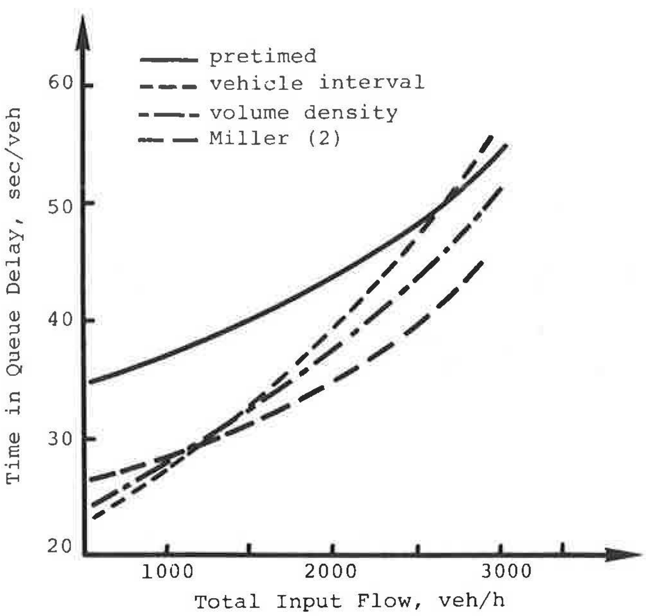

FIGURE 12 Field measurements of delays produced by four control strategies.

adaptive control. The challenge is to develop an adaptive control strategy that would produce significant improvements over the best existing traffic-actuated control under all traffic conditions. One way to meet this challenge is to develop hybrid adaptive control strategies that incorporate certain adaptive control logics into existing or modified traffic-actuated control strategies. The MOVA strategy *(3)* represents a step in this direction.

CONCLUSIONS

The predictors tested in this study yielded comparable prediction errors for a variety of flow patterns. The prediction errors increased as the flows became lighter. The mean absolute errors for all but one extremely cyclic arrival pattern were between 3.7 and 8.0 sec when the simple exponential smoothing predictor was used. About 70 percent of the corresponding predictor errors produced by this predictor were less than 6 sec. Prediction errors longer than 20 sec were rare but did exist. The adaptive control strategy is vulnerable to such prediction errors. Unless much more accurate predictions can be made, it is more desirable to rely on a limited amount of accurate arrival information than to use predicted data in an attempt to increase the magnitude of the advance information.

Adaptive control strategies that rely on a single detector in each approach lane lack a feedback mechanism for minimizing information errors. As a result, they may have difficulties maintaining a high level of control efficiencies over time. Their applications are restricted if frequent lane changes, large speed variations, and a wide range of vehicle types are present downstream of the detectors. This weakness can be eliminated by hybrid adaptive control strategies that provide existing or modified traffic-actuated strategies with real-time signal optimization capabilities.

ACKNOWLEDGMENT

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REFERENCES

1. *Evaluation of UTCS Control Strategies—Executive Summary.* Report FHWA-RD-76-149. FHWA, U.S. Department of Transportation, 1976.
2. A. J. Miller. A Computer Control System for Traffic Networks. Presented at Second International Symposium on the Theory of Traffic Flow, London, England, 1963.
3. R. A. Vincent and C. P. Young. Self-Optimizing Traffic Signal Control Using Microprocessors—The TRRL 'MOVA' Strategy for Isolated Intersections. *Traffic Engineering and Control,* Vol. 27, No. 7/8, 1986, pp. 385–387.
4. P. B. Hunt, D. I. Robertson, R. D. Bretherton, and M. C. Royle. The SCOOT On-Line Traffic Signal Optimization Technique. *Traffic Engineering and Control,* Vol. 23, No. 4, April 1982, pp. 194–196.
5. L. de la Breteque and R. Jazequel. Adaptive Control at an Isolated Intersection—A Comparative Study of Some Algorithms. *Traffic Engineering and Control,* July 1979, pp. 361–363.
6. F. B. Lin. Efficiency and Information Availability in Adaptive Control of Individual Intersections. *Traffic Engineering and Control,* Vol. 26, No. 9, Sept. 1985, pp. 434–439.
7. N. H. Gartner. OPAC: A Demand-Responsive Strategy for Traffic Signal Control. In *Transportation Research Record 906,* TRB, National Research Council, Washington, D.C., 1983, pp. 75–81.
8. F. V. Webster. *Traffic Signal Settings.* Road Research Technical Paper 39. Transport and Road Research Laboratory, Crowthorne, England, 1958.
9. F. B. Lin and D. Cooke. Potential Performance Characteristics of Adaptive Control at Individual Intersections. In *Transportation Research Record 1057,* TRB, National Research Council, Washington, D.C., 1986, pp. 30–33.
10. B. L. Bowerman and R. T. O'Connell. *Time Series and Forecasting.* Duxbury Press. North Scituate, Mass., 1979.
11. W. McShane and K. Crowley. Regularity of Some Detector-Observed Arterial Traffic Volume Characteristics. In *Transportation Research Record 596,* TRB, National Research Council, Washington, D.C., 1976, pp. 33–37.
12. J. B. Kreer. A Comparison of Predictor Algorithms for Computerized Traffic Control Systems. *Traffic Engineering,* Vol. 45, No. 4, April 1975, pp. 51–56.
13. F. B. Lin and S. Shen. Assessment of Traffic-Actuated Signal Controls. In *Proc., Transportation Toward the Year 2000,* Vol. 3, International Transport Congress, Montreal, Canada, 1984, pp. A41–A62.
14. P. J. Tarnoff and P. S. Parsonson. *NCHRP Report 233: Selecting Traffic Signal Control at Individual Intersections.* TRB, National Research Council, Washington, D.C., 1981.

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Effect of Traffic Mix, Volume, and Geometrics on the Trip Time of Passenger Cars and Trucks on Urban Freeways

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The objective of this paper is to investigate and quantify the relation between the average travel time per unit distance experienced by passenger cars, trucks, and other vehicles and the prevailing volumes of passenger cars and trucks on urban freeway sections. This macroscopic relation is examined for freeway sections exhibiting four types of geometric and operational characteristics (pipe, diverge, merge, and weave sections). The models are calibrated for each type of section using the FHWA 1982 data set on urban truck freeway characteristics, thereby providing the basis for the systematic testing of (a) the effect of geometrics on the relative effects of passenger cars and trucks on freeway performance, and (b) the relative sensitivity of the service quality experienced by passenger cars and trucks to the components of the traffic stream. These questions are of current practical interest to agencies contemplating truck-related highway improvements. The results indicate that the coefficients of the respective volume components vary significantly across section types, yielding volume effect truck passenger car equivalents (pces), in terms of impact on average travel time, which differ markedly from one type to another. This suggests that the undifferentiated treatment of pces for certain geometric and operational conditions may not be appropriate.

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The effect of trucks on traffic flow characteristics has long been a subject of interest to traffic and transportation engineers. The principal mechanism for capturing the effect of trucks relative to that of passenger cars has been the concept of passenger car equivalents (pces), which is widely adopted and consistent with the *Highway Capacity Manual* (HCM) *(1)*. Nevertheless, the