Abridgment

Developing a Predictor for Highly Responsive System-Based Traffic Signal Control

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A prediction methodology must be designed to provide the traffic control policy with accurate and reliable information. The design of the control policy, the precision afforded by the surveillance system, and the formulation of the prediction algorithm must be considered interactively and explicitly. From the onset, this was the approach used in the third generation control (3-GC) in the urban traffic control system (UTCS). This paper reports on the predictor development aspects of that work (1). The prediction algorithm described is intended to be applicable only for undersaturated links. The congested flow control acts on link content rather than anticipated volumes.

Previous approaches to developing a prediction methodology were based heavily on acquiring detailed historical patterns of traffic volume on a link-specific basis in the belief that these patterns were strongly repetitive on a day-to-day basis. At the time this work was undertaken, no large data base was available, particularly none that confirmed the high degree of traffic regularity desired over short time periods of 3 to 6 min. Further, experience in the UTCS test bed argued for the lack of diurnal regularity on such a time scale. Results of work by McShane and Crowley, in a paper in this Record, indicate that considerable regularity does exist, at least in some cities. In view of the past work and the unavailability of the required data base, a totally different approach was explored.

The basic idea was to develop a methodology that did not depend on historical data. This approach implies not that traffic patterns lack any degree of repetition from one day to the next but, rather, that it would be preferable not to depend strongly on such regularity of demand in this project.

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Three data bases consisting of five test cases were collected for this activity (Table 1).

DEVELOPMENT OF PROCESS MODELS

The process model is a mathematical description of the variation of link-specific traffic volume over time. As such, it forms the basis for development of the prediction model. That is, by knowing the form of the process, one may postulate appropriate prediction models.

The results indicated that little benefit would be derived by correlating volume on the study link to total volume on upstream links. The refinement of identification by phase is also not justified. Thus, link volumes are related to their own past history in the development that follows.

Two techniques were considered for eliminating the nonstationarity of the data over a day: (a) detrending the data and (b) differencing the volume data. A first-order autoregressive model was found to be sufficient on either basis.

PREDICTION MODELS

Development and Analysis

The prediction algorithm is processed during time step (i + 1) by using data acquired during the prior time steps [i, (i + 1), and so on] to predict the required parameter

Table 1. Description of data bases.

Data Base	Description	Test Case
L Street, Washington, D.C.	A gentle rising trend with pronounced fluctuations from one control period to the next	A
E Street, Washington, D.C.	A gentle falling trend with	
	Moderate fluctuations	B
	A sharp reversal	C
Park Avenue, Greenlawn, N.Y.	Pronounced peaking with moderate fluctuations with	
	A sustained peak	D
	A fall-off from the peak	E

Table 2. Values of the variance of the prediction error.

Predictor		Test Case						
No.	Title	A	B	C	D	E	Sum	Rank
1	Stochastic volume	1.00	1.00	1.00	1.00	1.00	5.00	1
3	Differences	1.17	1.02	1.80	1.07	1.09	6.15	3
4	Average of mean	1.24	1.38	1.50	1.21	1.22	6.55	4
5	Linear extrapolation of mean	1.13	1.00	1.77	1.03	1.03	5.96	2
6	Parameter estimation on volume	1.08	1.13	3.66	1.23	1.18	8.28	7
7	Parameter estimation on variation about mean volume	1.18	1.35	2.56	1.00	1.02	7.11	6
8	Last known volume	1.13	1.09	2.30	1.03	1.03	6.58	5

for time step (i + 2). Hence, because there are two steps to be spanned in the prediction process, from i to (i + 2), we are concerned with developing a two-step predictor.

Evaluation

Consistent with the concept of a first-order process describing the volume sequence, a number of predictor models were formulated (Table 2), and the variance of the prediction errors was noted as follows:

Test Case	Variance	Test Case	Variance
A	288	D	78.5
B	82.1	E	115
C	103		

Predictor 1 is superior to the others over all data bases. Inspection of Table 2 reveals that, for all but one data base, there is little disparity in results among predictors 1, 3, 5, and 8—the latter being the nonpredictor. The exception, test case C, demonstrates an important advantage of predictor 1 over its competitors: its ability to cope with extreme conditions.

The stochastic volume model is a linear filtering model operating on volume measurements taken on the subject link. The computing requirements of this model are very attractive.

Use in Control Policy

The countermeasure in the control policy to predictor errors is the provision of some excess green to cushion against predictor underestimates (i.e., so that congestion is not brought on by inadequate green). If too much cushion must be provided, control flexibility is lost. In test case E, predictor 1 underestimates by three or four vehicles 5.9 percent of the time and by more than four vehicles 8.8 percent of the time. If one provides a cushion of excess green for three vehicles, there is a 0.059 + 0.088 = 0.147 probability that an individual cycle will exceed this cushion. This can be judged acceptable for the purposes of control. Most situations do not require so high a cushion for comparable probability.

The final model recommended was predictor 1: exponentially smoothed trend with a first-order two-step predictor of the variation from the trend having parameter α_j. Work by McShane and Crowley with substantially more data has since indicated that it may be best to continually adjust α_j on-line.

DISCUSSION OF RESULTS

Subsequent to this study, two extended sets of data became available for comparing the efficacy of the selected 2-GC and 3-GC predictors. To afford a comparison with the 2-GC data on a common basis (2) requires that 3-GC predictor data be analyzed for one time step into the future, inasmuch as the only 2-GC predictor data available are for the one time-step prediction.

Basically, the 2-GC predictor provides slightly more accuracy than the 3-GC predictor under conditions in which the traffic flow exhibits a regular behavior. We have not studied the condition in which traffic behavior for the study period departs significantly from the historical trend (e.g., weekends, holidays, inclement weather). As indicated, there is a small practical difference between the two predictor models. However, the 3-GC predictor requires less storage and computational time.

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