FORECASTING FREEWAY AND RAMP DATA FOR IMPROVED REAL-TIME CONTROL AND DATA ANALYSIS

VOLUME I: SUMMARY REPORT

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16. ABSTRACT

The current project addressed two major weak points of the existing WSDOT ramp control system. One weak point in the system is the fact that it reacts to the problem (congestion), rather than preventing the problem. The other weak point in the system is its reliance on detector data that may be in error. Both of these problems can be minimized by developing methods to accurately predict short-term traffic data. By predicting the onset of congestion early enough, the ramp metering system can act to prevent or delay occurrence of the problem. Also, if a detector has failed or is malfunctioning, the data from the detector can be estimated from short-term predictions based on neighboring detectors.

At the beginning of the current project, the researchers had hoped that the same model would provide a basis for both forecasting congestion (for predictive ramp control) and replacing erroneous data (predicting actual values). However, the best congestion or breakdown flow forecaster (the pattern recognition method) does not provide a basis for data prediction. The best method for filling in missing detector data turned out to be multivariate time series analysis.

Several pattern recognition and time series models were tested for further development. In both cases, the simpler models turned out to be the best choices, and in both cases, further model testing and development were recommended.

The research on both model types continues in follow-up studies that are expected to lead to incorporation of these models in the new TSMC computer system.

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VOLUME I: SUMMARY REPORT

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SUMMARY

The current project addressed two major weak points of the existing WSDOT ramp control system. One weak point in the system is the fact that it reacts to the problem (congestion), rather than preventing the problem. The other weak point in the system is its reliance on detector data that may be in error. Both of these problems can be minimized by developing methods to accurately predict short-term traffic data. By predicting the onset of congestion early enough, the ramp metering system can act to prevent or delay occurrence of the problem. Also, if a detector has failed or is malfunctioning, the data from the detector can be estimated from short-term predictions based on neighboring detectors.

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The research on both model types continues in follow-up studies that are expected to lead to incorporation of these models in the new TSMC computer system.

INTRODUCTION AND BACKGROUND

THE NEED FOR FREEWAY DATA FORECASTING

Freeway congestion causes public inconvenience, air pollution, excessive fuel consumption, and loss of productivity in the labor force. Expansion of the highway system is costly, environmentally and socially disruptive, and leads to continued low-density development and the resulting reliance on single-occupant vehicles. (In fact, the results of this last impact exacerbates the problems that were thought to be addressed by the expansion.) Efficient operation of the existing system is essential to address these problems.

Because persistent recurring traffic congestion is a problem facing virtually every major metropolitan area in the U.S., and because we have expectations of continued growth in traffic demand with relatively little money available for capital expansion of highway networks (which may actually add to the problem anyway), effective traffic flow management is an important area of research for freeway system operation.

One way of efficiently operating a freeway system is through ramp control. Since 1981, the Washington State Department of Transportation (WSDOT) has used traffic responsive ramp control to alleviate traffic congestion on Interstate 5 north of downtown Seattle. A primary component of the real-time ramp metering algorithm is the "bottleneck" metering rate calculation, which becomes effective when congestion, or breakdown flow, is detected. One of two weak points of the current WSDOT ramp control system is that it reacts to the problem (congestion), rather than preventing the problem. The other weak point in the system is its reliance on detector data. By relying on detector data, the system is responsive to field conditions, but it is likewise susceptible to detector errors. If a detector fails or

malfunctions, the system lacks the capability to accurately estimate the traffic conditions at the site of the detector.

Both of these problems can be minimized by developing methods to accurately predict short-term traffic data. By predicting the onset of congestion before it occurs, the ramp metering system can act to prevent or delay the occurrence of the problem. Also, if a detector has failed or is malfunctioning, the data from the detector can be estimated from short-term predictions based on neighboring detectors.

Preliminary work on two previous WSDOT projects (Nihan, *et al.* (1) and Nihan and Berg (2)) addressed these two aspects of predicting detector data. The first developed a method to determine when detectors were providing erroneous data. The second project developed an improved predictive metering algorithm that predicts the onset of congestion and activates the appropriate control strategy.

The current project was an extension of these two previous projects. The concentrated effort here was on predicting actual traffic data (volume and lane occupancy), rather than simply the onset of congestion. With the results of these predictions, we expected to be better able to estimate and replace erroneous or missing data and therefore help the existing control algorithm to better anticipate problems and act before the problems occur. At the start of the current project, the researchers had hoped that the same model would provide a basis for both forecasting congestion (for predictive ramp control) and replacing erroneous data (predicting actual values). However, the best congestion or breakdown flow forecaster (the pattern recognition method) does not provide a basis for data prediction. The best method for filling in missing detector data turned out to be multivariate time series analysis. Therefore, this method was used (predicting actual volume and lane occupancy values). The project also performed a follow-up

test of the pattern recognition model developed for anticipatory, on-line ramp control and made recommendations on its further development.

RESEARCH OBJECTIVES

The objectives of the current project were to 1) investigate methods of accurately predicting short-term traffic data (volume and lane occupancy), 2) select the most promising prediction methods that could be used for replacing erroneous or unreliable data for the WSDOT freeway management system, and 3) test the predictions on the I-5 north corridor.

These were the original objectives of the project as stated in the proposal. With the added help of student fellowship support from Transportation Northwest (TransNow), the USDOT University Transportation Center for Region X, we were able to expand the original objectives to include two additional goals: 4) perform a follow-up test of the congestion prediction algorithm and its performance as a ramp control tool, and 5) from this test and the test performed by the previous project, make recommendations on the further development of this predictor.

REVIEW OF PREVIOUS WORK

The previous work relevant to the scope of this project can be classified into two areas:

1. Pattern recognition techniques: techniques that identify patterns in previous traffic flows that foreshadow upcoming breakdown flows.
2. Time series analysis techniques: techniques that predict the actual values of future volumes and lane occupancies on the basis of historical traffic data.

A summary of the project's literature review is presented below for these two categories.

PATTERN RECOGNITION TECHNIQUES

Volumes II and III of the technical report present the current literature on pattern recognition techniques as they apply to traffic congestion prediction. The primary task in pattern recognition is pattern classification, which consists primarily of classifying data into two or more pattern classes. For the congestion prediction problem, we needed to devise a decision function for classifying the traffic data from freeway loop detectors into two classes, 1) data patterns that precede uncongested conditions, and 2) those that precede congested or breakdown conditions. The technique does not allow us to forecast the actual values of the expected flow variables, but rather to pinpoint the patterns that lead to breakdown conditions.

A review of the literature on pattern recognition techniques produced a few existing applications of such tools to traffic flow predictions. Tsai and Case (3), for example, applied a pattern recognition approach to an existing incident detection system on the Queen Elizabeth freeway in Ontario. The aim was to reduce false alarm rates while maintaining acceptable detection rates. Consequently, once an incident has been detected by the existing algorithm, the pattern recognition

algorithm was used to distinguish between true and false alarms on the basis of their different duration rate characteristics. Using this pattern recognition approach, they managed to reduce the false alarm rate from its previous value of .09 percent to .06 percent, while holding their true detection rate constant.

Collins (4) applied a computer-based algorithm, PATREG, to identify the traffic disturbances following an incident. The PATREG algorithm used a pattern recognition technique to monitor the average traffic speed in each lane between a pair of detector stations (one immediately downstream from the other). It determined the upper and lower threshold values of speed for those lanes and indicated the occurrence of an incident when the calculated traffic speed fell outside these predetermined threshold values. Bohnke and Pfannerstill (5) have explored the use of pattern recognition for identifying individual vehicles or their platoons through the characteristic wave-form patterns each vehicle produces when passing over an induction loop detector. This use of pattern recognition to identify specific vehicles or platoons is expected to lead to a more effective traffic management and route guidance system.

These initial applications found in the literature suggest the need for a closer look at the potential usefulness of such a methodology to transportation analysts. Although, to date, there are only a few examples of pattern recognition techniques applied to traffic flow predictions, the examples that have been developed indicate that this is a promising area for fairly dramatic minute-by-minute changes that are not as easily predicted by standard statistical techniques (which are much better at forecasting <u>average</u> changes over time). Because pattern recognition techniques can be used to predict impending conditions (such as breakdown flow conditions) they are useful for on-line ramp control. However, they cannot predict the actual level of change to be expected.

TIME SERIES ANALYSIS TECHNIQUES

Volumes IV and V of the technical report provide an exhaustive list of the time series analysis literature as applied to traffic forecasting. Key examples of such studies are summarized in this section.

Time series analysis techniques use historical traffic flow data to forecast specific traffic variables. An example of this is a study by Nicholson and Swan (6) that used historical data to forecast traffic volumes at the Liverpool (UK) Mersey Queensway Tunnel. Researchers used data in 6-minute time slices for 2 hours in the morning and evening commutes for 43 days, not including weekends. The study found that the maximum prediction errors were on the rate of 8-11 percent, with higher errors obtained when the prediction used data compiled from average previous data (12-19 percent error). Nihan and Holmesland (7) explored the use of time series techniques for short-term traffic volume forecasts for a more aggregate time interval. A data set containing monthly volumes on a freeway segment for the years 1968 through 1976 was used to fit a times series model. The resulting model was then used to forecast volumes for the year 1977. With the month of December 1976 as the origin for the forecast, the largest error was 7.5 percent (for the month of September); all other errors were around 5 percent or less.

Ahmed and Cook (8) used time series techniques to forecast freeway volume and occupancy. A total of 166 data sets from three surveillance systems in Los Angeles, Minneapolis, and Detroit was used to develop a model for short-term traffic data forecasts. The Los Angeles data were 20-second volumes and occupancies per lane, and the data from Minneapolis and Detroit were volumes and occupancies aggregated over all lanes at 30- and 60-second intervals, respectively. Levin and Tsao (9) analyzed 20-, 40-, and 60-second occupancy and volume data collected during a morning rush period at two freeway locations, one on the local lanes and the other on the express lanes of the Dan Ryan Expressway in Chicago, Illinois. The 60-second forecasting interval was found to be the most effective

interval. Forecasts of volume data were found to be less variable than those for occupancy data. By the same token, forecasts for the volumes and occupancy on the express lanes were found to be less variable than those on the local lanes.

Another researcher, Gafarian (10), used time series techniques to forecast density. The results indicated that the forecast functions behaved reasonably up to roughly 5-, 10-, and 20-second lead times for the 92-, 305-, and 558-meter test sections, respectively. The correlation time of the density process increased as the physical length of the roadway section increased; thus, if density were measured over long sections, correspondingly long historical records would be required to fit models and forecast the process. For traffic responsive control, the computational task here might become a problem. Also, this analysis some times produced results with unsatisfactory goodness of fit and large errors.

In 1971, Gazis (11) developed a method for estimating the number of vehicles on a section of roadway from speed and flow measurements at the entrance and exit points of that section. This algorithm was tested with data from three adjoining half-mile sections in the Lincoln Tunnel, and the exact counts were compared with those generated by the algorithm. The results indicated that 99 percent of the time the error was below 10 percent; such accuracy had not been previously obtained with flow and speed data. This research was extended in 1975 by Chang and Gazis (12) to include explicit consideration of lane-changing on a multi-lane freeway. They found that the estimation error could be reduced in this fashion. Moreover, as the roadway section became larger, increasing the number of lane changes, the reduction of error was greater.

Okutani and Stephanedes (13) predicted 15-minute volumes on a study link during the day using the traffic flow on the study link, as well as the traffic flows on the other links feeding into it. The predictive models performed well, and they found that increasing the number of 5-minute time intervals ahead of the current

time for which prediction was made from 1 to 9 did not significantly effect the performance. This type of robust quality is highly desirable for long-term predictive models.

Finally, Davis and Nihan (14) designed a time series model to estimate changes in freeway level of service despite missing data. They used historical volume and occupancy data for the dependent variables, plus dummy intervention variables to represent the time periods when certain policy interventions occurred. The results indicated that the time series model can be used to investigate fairly subtle interactions among traffic stream flows, control policies, and external factors. Davis and Nihan also looked at the application of time series tools for estimating OD patterns from traffic volume data. The results for forecasting intersection turning movements (15) and freeway origin-destination (OD) patterns (16) were very promising and further work in this area is progressing. Finally, Davis and Nihan developed preliminary freeway traffic forecasting models that served as forerunners to the time series work presented in this current report. (17)

In reviewing the literature and relying on our previous experience of fitting time series data to volume and lane occupancy data, we found that this technique can be fairly accurate for forecasting average changes over time, but less accurate in obtaining minute-by-minute forecasts. Because the desired product for replacing missing or erroneous data from loop detectors is a good average value of volume and lane occupancy for particular 5-minute periods, this technique appears to be the best suited for application in missing data replacement for freeway control and traffic analysis. It is less suited for predicting minute-by-minute changes to the system, something that is handled better by pattern recognition techniques.

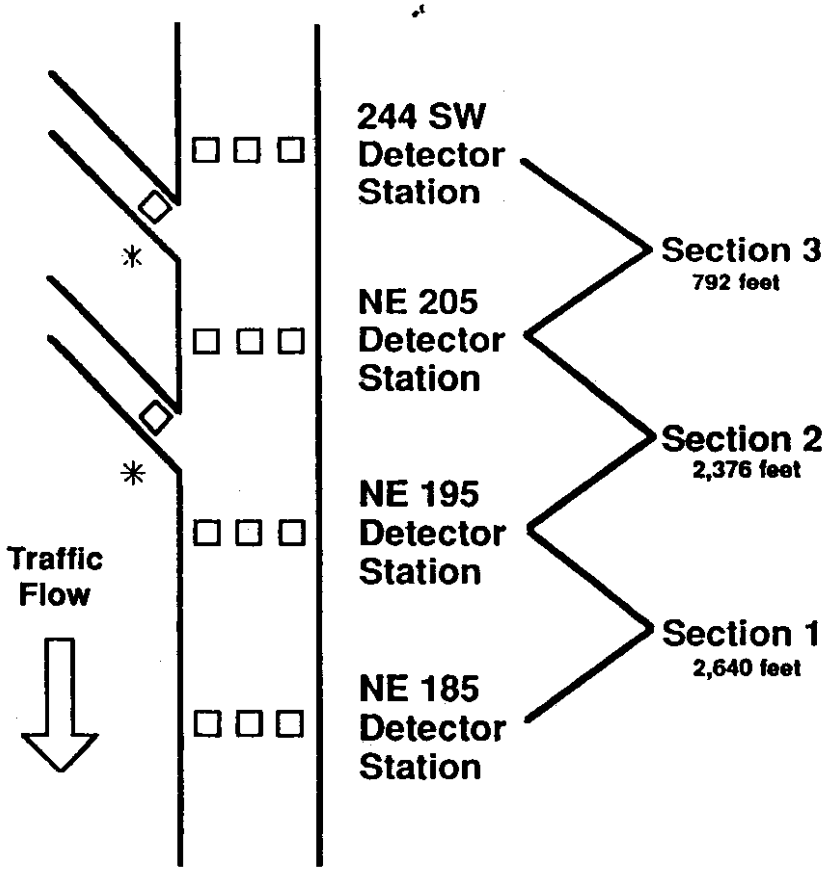
PROCEDURES

The procedures used in this study can be categorized into those developed and used for 1) forecasting expected breakdown conditions (pattern recognition), and 2) forecasting traffic data for missing data replacement (time series). These are discussed below.

FORECASTING EXPECTED BREAKDOWN CONDITIONS (PATTERN RECOGNITION)

Development of the Davis/Nihan Model.

Davis and Nihan (18) developed the first short-term congestion forecasting model based on pattern recognition for application to the WSDOT's real-time ramp metering control system. This simple model used historical 1-minute lane occupancy and storage rate data measured for a routinely congested section of Interstate 5 north of Seattle to classify patterns that reflect impending breakdown conditions versus those that precede uncongested traffic conditions. Testing of several lagged measurements revealed that the variables that best classified the pre-congestion and pre-noncongestion patterns were the occupancy of the test section lagged 1 minute, and the storage rate of the downstream section lagged 2 minutes. This simple model was incorporated on-line at the WSDOT's Traffic System Management Center (TSMC) and evaluated for two separate on-line data collections efforts. These evaluations are discussed in the next section. In developing the model, the research team studied a section of southbound I-5 approximately 12 miles north of downtown Seattle. On this section, congestion routinely begins on weekday mornings and affects traffic flow for several miles upstream. This section was designated as section 2, the section immediately downstream as section 1, and the section immediately upstream as section 3. Figure 1 shows the geometry of this study area. The total length of the three sections was



✳ Ramp Control Signal

Figure 1. Test section of Southbound I-5.

about 1.3 miles. The researchers used 1-minute volume and lane occupancy time series data from each of these sections to develop their predictive model. The approach to model development was a simple form of statistical pattern recognition in which the primary activity was to sort observations into two or more categories (Chen (19)). The 1-minute intervals were sorted into queueing and non-queueing intervals on the basis of observed volume and lane occupancy values for each interval. Queueing intervals were those for which the data met the bottleneck criteria for section 2. The criteria used by the TSMC for bottleneck or breakdown conditions were 1) a positive storage rate for the section, and 2) a lane occupancy for the section $\geq$ 18 percent. Non-queueing intervals did not meet those criteria. Storage rate and occupancy measurements from previous (lag) intervals for sections 1, 2, and 3 were then sorted into those that preceded bottleneck formation and those that did not. A rule based on these lag measurements was developed to discriminate between the two classes of observations using the box-plot feature of the MINITAB statistical package. The researchers evaluated the storage rate and occupancy measurements at time intervals lagged 1, 2, and 3 minutes for sections 1, 2, and 3 to determine which had the greatest ability to discriminate between queueing and non-queueing intervals.

The forecasting algorithm developed by this process is a simple one. Combined values of lane occupancy in section 2 at time t ($OC_2(t)$) and the storage rate for section 1 lagged 1 minute ($SR_1(t-1)$) are the determining factors in forecasting breakdown or queueing conditions for section 2. If $OC_2(t)$ and $SR_1(t-1)$ both indicate an impending "bottleneck," the algorithm forecasts breakdown conditions.

The forecaster's simplicity fits well into real-time process control. It was programmed as a two-step process, as illustrated in Figure 2. First, the computer program

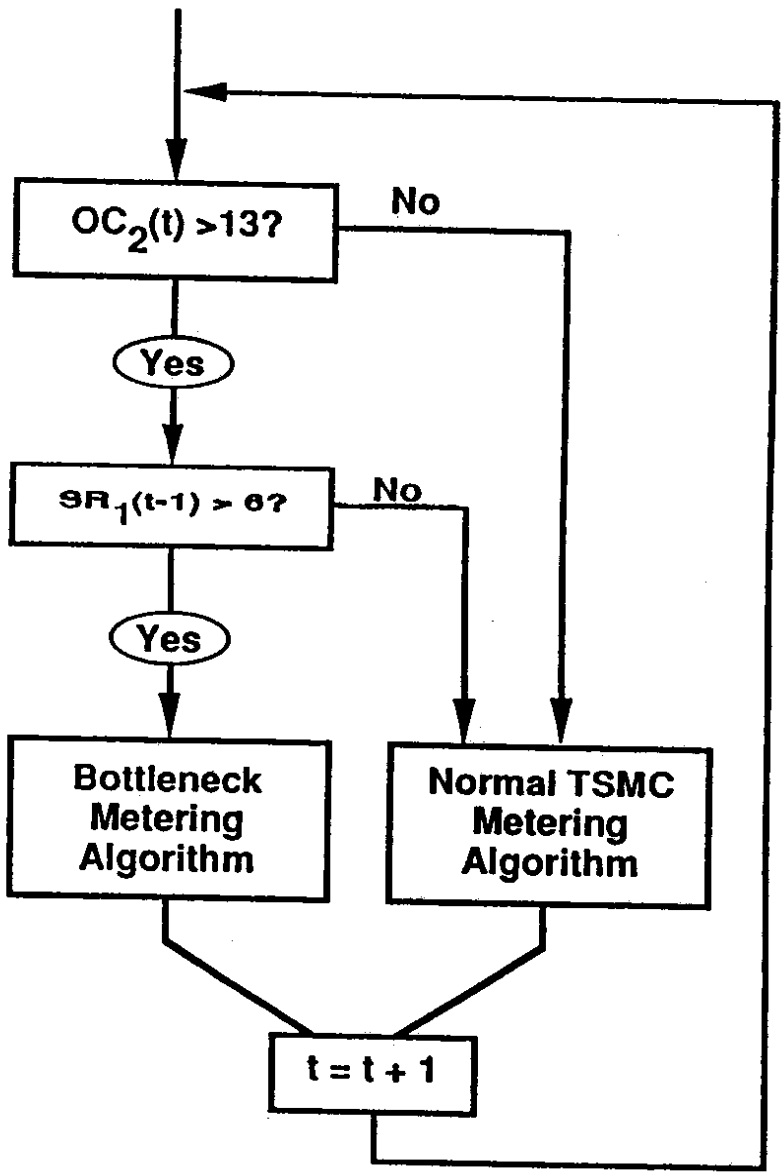


Figure 2. Davis/Nihan Predictive Algorithm

checks the occupancy level at section 2. If the occupancy is above the level that indicates a positive prediction (13 percent), the algorithm checks the storage rate for section 1 from the previous minute. If the storage rate is greater than six vehicles, the algorithm predicts the formation of queueing in section 2 during the next minute and calls the normal bottleneck metering algorithm. This algorithm uses an average storage rate for the metering rate reduction that it distributes over upstream ramps.

Table 1 shows the accuracy of the Davis and Nihan model for each of five days for which data were collected on the system before an on-line performance test.

Table 1. Detection Rates for Pattern Recognition Forecasts

Date	Forecaster*	Percent Correct	False Positives	False Negatives
11/22/88	$SR_1(t-1)$	63	28	49
	$OC_2(t)$	68	24	47
	AND	68	7	73
	OR	63	46	22
11/23/88	$SR_1(t-1)$	71	29	36
	$OC_2(t)$	77	25	0
	AND	92	5	36
	OR	55	50	0
12/13/88	$SR_1(t-1)$	76	23	33
	$OC_2(t)$	57	46	0
	AND	88	11	33
	OR	45	60	0
12/14/88	$SR_1(t-1)$	69	25	48
	$OC_2(t)$	56	58	3
	AND	78	11	52
	OR	45	72	0
12/15/88	$SR_1(t-1)$	67	33	33
	$OC_2(t)$	82	23	0
	AND	89	10	33
	OR	55	47	0

* AND = $SR_1(t-1)$ <u>and</u> $OC_2(t)$
OR = $SR_1(t-1)$ <u>or</u> $OC_2(t)$

Development of Extended Babla/Nihan Model

The Babla/Nihan model was developed to improve the accuracy level obtained with the Davis/Nihan model. This more complicated parametric approach involves the use of loss functions in determining pattern classifications. In this approach, preceding traffic flow conditions are assigned to one of two classes on the basis of a statistical risk calculation that uses a priori probabilities for the two classes. The classes are, as in the Davis/Nihan model, traffic conditions precedent to congested flow and traffic conditions precedent to uncongested flow. Because of the more complicated mathematics of this second model, and because of its ultimate rejection in favor of the simpler approach, the reader is referred to Volume II of this report for a detailed description of the extended Babla/Nihan model.

This extended model and the simpler model were compared by simulation rather than further on-line testing. Freeway volume and lane occupancy data were obtained from the TSMC for calibration and testing of the new (Babla/Nihan) pattern recognition algorithm. One-minute traffic data from the stations in the test section shown in Figure 3 were collected for the morning peak periods of March 28, 29, and 30, 1990. The data collected by the TSMC through loop detectors were in the form of 1-minute volume and occupancy measures at mainline and on-ramp detector stations.

The storage rates for each section (upstream volume minus downstream volume) plus the average occupancy over a section (average occupancy of upstream and downstream stations for that section) were also calculated for the model development. Once the calibration has been completed, TSMC data were used to calibrate an INTRAS simulation model that was then run to compare the performance of the Davis/Nihan model with the Babla/Nihan model. These evaluations are presented in the Discussion Section.

FORECASTING TRAFFIC DATA FROM MISSING DATA REPLACEMENT (TIME SERIES).

Development of Zhu/Nihan Model.

Time series models were developed by Zhu and Nihan to predict volumes and lane occupancies prior to ordinary least squares (OLS) regression for the separate dependent variables V(t) (volume at time t) and O(t) (lane occupancy at time t) against appropriate lagged variables. Spectral analysis was used to determine the appropriate lags for the independent variables. For the test case freeway section (see Figure 3), volumes of the upstream station lagged once and twice, plus volumes for the upstream on-ramp lagged once, were the three variables required to predict a station's volume at time t. A similarly simple model was obtained for predicting lane occupancy for a station at time t.

With data collected at the TSMC for 1-minute time intervals between the hours of 6:00 and 8:00 a.m. on Wednesday, February 23, 1989, the following models were created for testing. (Note: Because a univariate model was selected for the occupancy model, data for only one station was needed for the preliminary test. However, the multivariate volume model required data from upstream and downstream stations, as well as from the on-ramp.)

$$V_d(t) = .42\, V_{up}(t-1) + .60\, V_{up}(t-2) + .25\, V_{on}(t-1) \qquad \text{Equation 1}$$

$$O_{up}(t) = 3.1 + .733\, O_{up}(t-1) \qquad \text{Equation 2}$$

where

V_d = downstream volume (volume at station NE 162nd)

V_{up} = upstream volume (volume at station NE 185th)

V_{on} = on-ramp volume (volume at station NE 175th on)

O_{up} = upstream occupancy (lane occupancy at station NE 185th)

The traffic volume and occupancy data obtained from the TSMC were collected by detectors on the Seattle I-5 freeway segment between 185th and 162nd

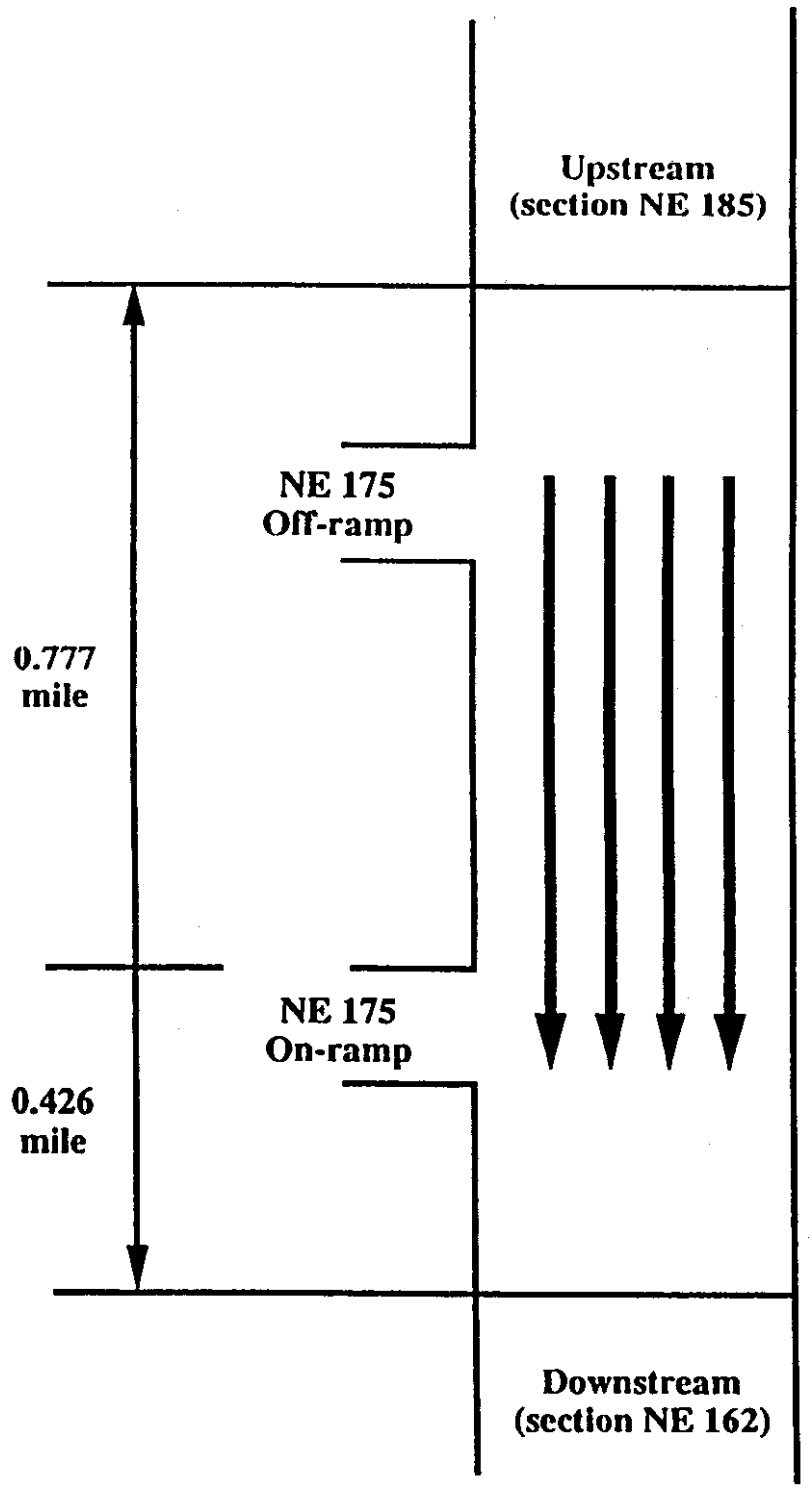


Figure 3. Study Site

N.E. for a peak morning period in February. The data interval was 1-minute, with a total of 122 data points for each section. The first 102 data points were used to build the models shown above, and the last 20 data points were used to evaluate the accuracy of the models and to update the forecasting. Results of this evaluation and its comparison with the Nihan/Knutson model results are covered in the Discussion Section.

Additional Calibration of Simple Model and Development of Extended (Nihan/Knutson) Model

In an effort to develop a more accurate predictor of 1-minute volume and lane occupancies for a freeway station, Nihan and Knutson investigated additional independent variables including downstream storage rates, volume and lane occupancy values, and upstream and on-ramp values. A new set of TSMC data was collected for this study from a freeway section of I-5 a couple of miles upstream of the section used by Zhu and Nihan for their analysis. This section bypasses the city of Lynnwood immediately north of Seattle (see Figure 4).

The selected study site was a freeway section where data had typically been found to be reliable. Reliability is defined in this case as stations that have equipment that rarely breaks down. This stretch of freeway had recurrent peak-hour congestion because of several entrance ramps in a short distance. Coincidentally, this is typical of what is often researched in other parts of the country. This study site was used to calibrate a simple model of the Zhu/Nihan formulation, as well as a new model developed by Nihan and Knutson with additional independent variables. (Hereafter, the Zhu/Nihan model will be referred to as the simple time series model and the Nihan/Knutson model will be referred to as the extended time series model.) The section of the study site required for the old model was 2.13 miles (11,244 feet) in length, encompassing 212th Street SW through 244th Street SW, while the extended model was 1.46 miles (7,675 feet) in length, encompassing one less station, 220th Street SW through 244th

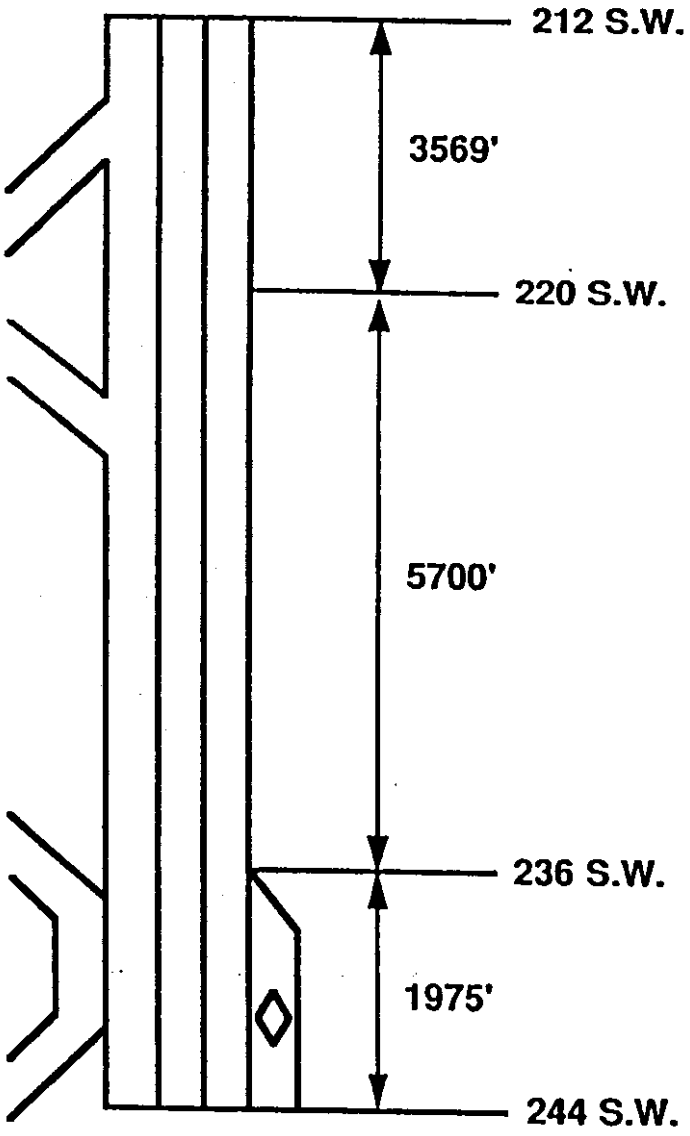


Figure 4. Study Site.

Street SW. Both had two entrance ramps (220th Street SW and 236th Street SW) and one exit ramp. In the final 1,925 feet of the section just under the 236th Street overpass, a high occupancy vehicle (HOV) lane was added as lane four (the left lane). The segment served suburban commuters en route to employment centers in the CBD and other suburban communities for the duration of the study period.

As with the initial study described in the preceding section, data were obtained electronically by WSDOT's loop detectors. A loop embedded in each lane at a particular location records both volume and lane occupancy. A group of loops at one location constitutes a data station; vehicle counts were aggregated at each station to provide the data used in this study. Data can be incremented in 1-, 5-, 15-, or 16-minute blocks for study. As before, the data used in this study were set in 1-minute increments.

Data obtained on February 11 and April 17, 1991, were used for model calibration and evaluation. Two hours of data were collected in 1-minute increments for each day from 6:15 a.m. to 8:15 a.m. at the following stations: 212th Street SW, 220th Street SW, 236th Street SW, 244th Street SW (all on the main line of I-5), the entrance ramp from 236th Street SW, and the exit ramps to 220th Street SW and 244th Street SW. The weather for the first day included cloudy skies, light rain, and good visibility, and the roadway was bare and wet. The second day was partly cloudy with good visibility.

New Calibration of Simple (Zhu/Nihan) Model

Of the 120 data points collected, the first 90 available data points were used to obtain an equation for the simple model and then used to forecast the final 30 points. The model developed here started out as an attempt to determine whether Zhu and Nihan's methods could be applied to other sections of I-5. In keeping with the original goals of this research, it was necessary to find time-lags of upstream

stations that significantly affected the data station in question (downstream station 236th Street SW).

The general form of the simple model is that downstream volume can be expressed as a function of upstream volumes lagged at appropriate time increments. In other words,

$$V_d(t) = \sum_{k=0}^{K_1} a_k V_{up1}(t-k) + \ldots + \sum_{\ell=0}^{L_1} b_\ell V_{on1}(t-\ell) + \ldots + z(t)$$

where Equation 3

V_d = downstream volume,

V_{upi} = upstream volume, station i,

V_{onj} = upstream volume, on-ramp j,

K_i = maximum number of travel increments to traverse section from upstream station i

L_j = maximum number of travel increments to traverse section from on-ramp j

a_k, b_ℓ = constant coefficients

$z(t)$ = error term

Use of Zhu and Nihan's dependent variable set shows that the simple model has significant variables at 212th Street SW (lag 1), 220th Street SW (lags 1 and 2), and the entrance ramp from 220th Street SW (lags 1 and 3). Therefore the forecasting equation for the simpler model was as follows:

$$V_{236}(t) = .186\ V_{212}(t-1) + .281\ V_{220}(t-1) + .491\ V_{220}(t-2) + .456\ V_{on}(t-1) + .598\ V_{on}(t-3)$$ Equation 4

Development of Extended (Nihan/Knutson) Model

In theory, the above method should have forecast traffic volumes relatively well because what was truly being forecast was the critical lags. Unless the vehicles

upstream exited to 220th (a small percentage not accounted for), the traffic volumes at upstream stations would indeed pass the station for which a forecast was desired. However, queueing that might occur downstream from the study section could affect this forecast as well. It is well known from shock wave theory that such breakdown conditions can have major effects both upstream and downstream of the congested location. Consequently, backward-forming and forward-recovery shock waves were considered to be important in the development of an extended forecasting model.

To account for the effects of shock waves on the volume forecast model, additional dependent variables (upstream lane occupancies and upstream and downstream storage rates) with appropriate lags were introduced to the simple model formulation. Using the first 90 points of the study site data described above, the extended model forecasting equation was calibrated with the least squares methodology, as with the simpler model. In the extended model, significant variables were found to be volume at 220th Street SW (lags 1 and 2), lane occupancy at 220th Street SW (lag 1), the upstream storage rate (lags 1 and 3), and the downstream storage rate (lag 2). The extended model forecasting equation for the study site was as follows:

$$V_{236}(t) = 41.28 + .472\, V_{220}(t-1) + .226\, V_{220}(t-2) - .312\, O_{220}(t-1) - .311\, SR_{up}(t-1) - .153\, SR_{up}(t-3) - .138\, SR_{dn}(t-2) \qquad \text{Equation 5}$$

where

O_{220} = lane occupancy for station 220,

SR_{up} = upstream storage rate = $V_{220} - V_{236}$,

SR_{dn} = downstream storage rate = $V_{236} - V_{244}$.

The results of the evaluation of the simple and extended time series models are discussed in the next section.

DISCUSSION

COMPARISON OF PATTERN RECOGNITION MODELS

The Davis/Nihan and Babla/Nihan models were compared with the existing WSDOT ramp metering system through simulation testing with INTRAS software (see Volume II). Tables 2 and 3 give the results of an accuracy check on the models and a summary of the comparative simulation results. These comparisons showed that, although the Babla/Nihan model achieved a slightly higher system-wide average speed and lower system-wide total delay, the accuracy of its predicting capability was not better than that of the simpler Davis/Nihan model. Given that one of the future objectives of the development of these models was on-line incorporation in the TSMC's computerized ramp control system, the simpler Davis/Nihan model was selected for further development.

In addition to the simulation tests, two sets of on-line performance tests were performed on this model. The first on-line test was conducted during the development of the model, and these evaluations are described in Nihan and Berg (2). The second on-line data collection process with this algorithm was evaluated during the current study. This evaluation and its comparison to the results of the first on-line test are described in detail in Volume III of the technical report.

The researchers determined that the chosen pattern recognition model (Davis/Nihan) produced acceptable predictive accuracy, but it required additional study to determine how its use could have a greater impact on overall system performance. One area of possible future study is alternative control strategies for responses to the model's prediction of upcoming congestion. Another potential area of study is the possibility of further model development for longer term forecasts. A final suggested study area is determination of the overall effect of a larger number of stations being incorporated into the on-line testing.

TABLE 2

RESULTS FROM APPLICATION OF DAVIS/NIHAN AND BABLA/NIHAN MODELS ON TSMC DATA

TYPE OF DATA	PERCENT CORRECT	PERCENT FALSE POSITIVES	PERCENT FALSE NEGATIVES
Davis / Nihan model applied to lightly congested data	92	5	36
Davis / Nihan model applied to highly congested data	68	7	73
Babla / Nihan model applied to a.m. peak data of South-bound I-5	75	10	52

TABLE 3

RESULTS FROM APPLICATION OF DAVIS/NIHAN AND BABLA/NIHAN MODELS BY SIMULATION USING INTRAS

	WSDOT EXISTING ALGORITHM	DAVIS/NIHAN ALGORITHM	BABLA/NIHAN ALGORITHM
Average mainline speed, mph	23.8	28.0	25.3
Average speed system-wide, mph	20.2	19.6	20.9
Total veh-miles travelled on mainline	7726	8340	8132
Total veh-miles travelled system-wide	8100	8604	8488
Veh-min. of mainline delay	10970	8757	10327
Veh-min. of delay system-wide	14985	16778	14854
Mainline volume in veh/ln/hr	1452	1568	1529
Total number of vehicles output from all on-ramps	1264	866	1189
Total gallons of fuel consumed system-wide	1678	1779	1722
Veh-miles travelled per gallon of fuel consumed system-wide	4.83	4.84	4.93

COMPARISON OF TIME SERIES MODELS

Tests of the Zhu/Nihan model conducted during model development (see Volume IV of the technical report) indicated that an average forecast error of less than 10 percent could be expected (although individual minute forecasts could be much higher). This appears to be a very promising result for missing data replacement requirements when loop detectors are malfunctioning or out. The extended (Nihan/Knutson) model had slightly better accuracy (see Volume V of the technical report), but this was counter-balanced by the additional number of independent variables needed. The researchers decided that the additional complication did not sufficiently improve the accuracy of the predictive model to warrant the additional resources required for system-wide implementation.

Table 4 summarizes the error measurements for the initial Zhu/Nihan model calibrated for the test section shown in Figure 3 (test section A) and the corresponding measurements for the Zhu/Nihan and Nihan/Knutson models calibrated for the test section shown in Figure 4 (test section B). Two basic error measurements were established as effective for use in comparing the forecasting methods. The mean absolute error (MAE) indicates a typical error for individual forecasts, while the mean squared error (MSE) penalizes large prediction errors. They are defined as follows:

$$MAE = [\Sigma \ |(\text{actual } V(t) - \text{forecast } V(t))| \ ] / N \qquad \text{Equation 6}$$

$$MSE = [\Sigma \ (\text{actual } V(t) - \text{forecast } V(t))^2 \ ] / N \qquad \text{Equation 7}$$

where N = number of predictions

Additionally, sometimes percentages or relative values should be used rather than absolute numbers, since absolute numbers may be difficult to evaluate (i.e., it is hard to distinguish the difference in effects of a vehicle error of magnitude E on two different actual volumes: error of 15 vehicles on actual volume of 30 vehicles is different than on an actual volume of 115 vehicles). Therefore, the percentages of

the mean absolute error values (MAE%) were also computed, as were the relative values of the squared error. These were given as follows:

$$MAE\% = [\Sigma\ |(\text{actual } V(t) - \text{forecast } V(t)/\text{actual } V(t))|\ ] / N \times 100 \quad \text{Equation 8}$$

$$MSE_{rel} = [\Sigma\ \{(\text{actual } V(t) - \text{forecast } V(t)/\text{actual } V(t)\}^2\ ] / N \quad \text{Equation 9}$$

Table 4

COMPARISON OF MODELS

	Zhu/Nihan (Test section A)	Zhu/Nihan (test section B)	Nihan/Knutson (test section B)
Mean Actual V(t)	95.6 veh/min	49.9 veh/min	49.9 veh/min
Standard Deviation	11.5	3.5	3.5
MAE	7.3 veh/min	5.2 veh/min	4.3 veh/min
MAE%	8.2%	9.9%	9.0%
MSE	75.1 veh/min	43.7 veh^2/min	31.4 veh^2/min
MSE_{rel}	0.86	0.89	0.64
EMAX%	27.8%	27.5%	30.6%

Finally, another error term, Emax%, was also used. This represented the maximum percentage of error noted for any particular minute for the forecast data sets. This type of error is important for setting up criteria for determining when an incident or data collection error may have occurred. It can be used in cases where the predicted volume exceeds some preset maximum error. When this happens, some type of malfunction or incident may be assumed to have happened.

A serendipitous result was found in the model testing conducted during the current study in that the data collected by the TSMC for the Volume V report (test section B) included a time period during which an incident occurred. Both models flagged the incident very well and then, after a few minutes of updating, returned to the same level of forecasting accuracy for the new traffic situation.

APPLICATION AND IMPLEMENTATION

ON-LINE FREEWAY CONTROL

The simple pattern recognition model developed by Davis and Nihan has acceptable accuracy and looks promising as an on-line addition to the current computerized ramp control algorithm. Additional development is required before this can occur. The area of alternative ramp control strategies for responses to predicted congestion, as well as the impact of longer term forecasts and possible further model development, will be studied before final decisions for implementation are made.

Once these have been determined, plans for incorporation of the improved algorithm into the new computer system at the TSMC should be able to proceed. Further testing of this model for inclusion in several parts of the system will be continuing in a follow-up study and is expected to result in a model system that can be incorporated into the WSDOT overall system.

MISSING DATA REPLACEMENT

Of the two models developed for testing during this study, the simpler Zhu/Nihan model was considered the best choice for implementation. As with the other models, however, this model is site-specific and station-specific in that it was fit to historical data for a certain section of freeway. This is not as serious a problem as it might appear, since the simple model contains only three explanatory variables and is recursively fit to new data. Therefore, it can be easily incorporated at several sections along the freeway without large computer requirements.

Continued development of this model is needed before it can be successfully incorporated into the TSMC system. This is planned in a follow-up study and is expected to produce a set of recursive models that can be applied to various freeway segments.

CONCLUSIONS AND RECOMMENDATIONS

Of the various types of models tested for forecasting freeway flow, the researchers found that pattern recognition models were best for predicting on-coming congestion on a minute-by minute-basis. However, these models could not be used to forecast the actual values of volume and lane occupancy for the expected congestion. Rather, they proved to be most sensitive to upcoming peaks and valleys in freeway flow without the capability of specifying the actual numbers.

Time series models, on the other hand, were found capable of predicting actual values of volume and lane occupancy, but were not as sensitive to the minute by minute changes. These models were better at predicting the average values of these variables over time, i.e., future moving averages.

Consequently, a major conclusion of this study was the choice of pattern recognition models for use in on-line freeway control and time series models for use in missing data replacement. The study determined that a pattern recognition model could best be used for forecasting congestion of breakdown conditions 1 or 2 minutes before they occurred, and, with this forecast, to alter the ramp control algorithm to head off the expected breakdown conditions. The researchers also concluded that an off-line time series model would provide the best forecast for situations in which malfunctioning loops reduced in bad data or missing data for a particular freeway station. Such a model could be used to replace the defective data for 5-minute (or larger) data intervals.

Of the pattern recognition models tested, the simplest model developed by Davis and Nihan had acceptable accuracy and was most promising as an on-line addition to the current computerized ramp control system. However, additional development will be required before the model can be incorporated into the new computer system. Two recommended areas of model development include 1) investigation of the impacts of longer term forecasts and the trade-offs in accuracy,

and 2) investigation of alternative ramp control strategies, including incorporation of the model in several test sections along the freeway at once.

Of the time series models developed for testing during this study, the simpler Zhu/Nihan model was considered the best choice for implementation. Further testing and refinement of this model, including an additional look at the possible inclusion of downstream variables, plus testing of the model on several sections of the freeway system, are recommended.

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