Predictive Algorithm Improvements for a Real-Time Ramp Control System

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16. ABSTRACT

The purpose of this project was to determine the feasibility and evaluate the usefulness of a predictive ramp-metering algorithm, an algorithm that anticipates bottlenecks (a bottleneck being a reduction in the traffic capacity of the freeway) one to two minutes before their occurrence. The predictive algorithm was tested on-line in the Washington State Department of Transportation's ramp-metering central computer.

The predictive algorithm's accuracy in predicting bottlenecks on-line was very good, with a correct prediction rate of almost 80 percent. The measured increase in volume and decrease in occupancy during a portion of the morning peak period showed that the predictive algorithm reduced the number and/or severity of bottlenecks on the freeway test section.

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SUMMARY

The purpose of this project was to determine the feasibility and evaluate the usefulness of a predictive ramp-metering algorithm, an algorithm that anticipates breakdown conditions one to two minutes before their occurrence. The predictive algorithm was tested on-line in the Washington State Department of Transportation's ramp-metering central computer.

The predictive algorithm's accuracy in predicting breakdown conditions on-line was very good, with a correct prediction rate of almost 80 percent. The measured increase in volume and decrease in occupancy during a portion of the morning peak period showed that the predictive algorithm reduced the frequency and/or severity of breakdown conditions on the freeway test section.

The quantification of the on-line test of the predictive algorithm was clouded to a degree because of the time frame of the on-line test (spring and summer), the size of the "before" and "after" data sets, and the fact that the on-line test was subject to external factors that could not be controlled, e.g., driver behavior and equipment breakdowns. Further testing will help resolve this issue.

CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

In summary, the algorithm developed to predict and respond to freeway congestion conditions met its objectives: identification of impending breakdown conditions and the adjustment of ramp-metering rates to reduce the impact of the congestion. The quantification of the on-line test of the predictive algorithm was clouded to a degree because of the time frame of the on-line test, the size of the "before" and "after" data sets, and the fact that the test was on-line and subject to external factors that could not be controlled, e.g., driver behavior and equipment breakdowns.

The predictive algorithm appeared to have reduced the frequency and/or severity of breakdown conditions in the test section, as measured by an increase in volume and a decrease in occupancy, during some of the time periods. These time periods corresponded to lightly congested conditions on the freeway. During heavily congested time periods results were insignificant. Because the predictive algorithm was designed for lightly congested flow, these results were expected.

Unfortunately, the lack of "after" data and the time frame of the data collection effort, both uncontrollable factors, raised some doubt about the degree of the predictive algorithm's effectiveness. Only further testing can resolve this issue.

Results of the advance queue override data analysis proved inconclusive. The facts that this technique looked only at a single point on the on-ramp, that the lack of a covariable made intervention analysis impossible, and that the data sets were small are obvious deficiencies. However, to accurately obtain queue data would require time-intensive effort. Queue data could be collected by either video recordings or floating car studies, both personnel intensive methods.

In early test runs of the predictive algorithm, breakdown conditions were predicted, and subsequently occurred, before initiation of the ramp-metering system in the a.m. peak period. Since then, the predictive algorithm messaging program has helped the WSDOT ramp-metering operators better determine when the ramp-metering system should be initiated.

RECOMMENDATIONS

The following are the study's recommendations for future actions regarding the predictive algorithm. No order of importance is implied in the list.

1. Pursue the programming of the INTRAS model (or other models such as FRESIM) to incorporate existing WSDOT ramp-metering strategies. In addition, incorporate the predictive algorithm and test its effectiveness in a controlled setting, i.e., through simulation.
2. Pursue refinements to the predictive algorithm to enable more accuracy, especially for heavily congested flows. Many possibilities could be explored. Instead of a single threshold for occupancy and storage rate values that signal the prediction of congestion, a linear relationship or step function might provide better prediction accuracies, especially for heavily congested traffic. Another improvement might involve different combinations of variables (occupancy and storage rate) or alternative time frames for the variables. Because the prediction of congestion is based on recognition of a pattern that occurs before breakdown conditions occur, the ability to determine alternative variables that also precede the breakdown conditions, such as upstream volume entering the section, may help in substantiating the predicted congestion, particularly during heavily congested periods.
3. Continue the data collection effort for further time series intervention analysis. Future operation of the predictive algorithm should follow an "operant" design. (13) The "operant" design allows the intervention to be

applied many times, thereby enabling volume and occupancy to return to baseline (before) conditions in between the intervention. Any changes due to the intervention then become very apparent.

4. Expand the ability of the predictive algorithm to predict congestion on more than one section of southbound I-5, including sections downstream of NE 195th. One would expect that if a single prediction section shows improvements with use of a predictive type algorithm, multiple prediction sections should create even greater improvements to the freeway system. Obviously, any expansion to the predictive algorithm should be evaluated.

5. The WSDOT should consider using the predictive algorithm as an early warning "prompt" for initiating ramp-metering at the beginning of the peak periods. In its simplest form, this prompt could be an on-screen message alerting an operator to the possible formation of congestion in the ramp-metering system.

6. The predictive algorithm might have some application for incident detection strategies. Because of its ability to quickly detect capacity reducing bottlenecks, it might help in the early detection of incidents.

7. Simulation testing of any new or improved ramp-metering and incident detection strategies should be supplemented with on-line testing. On-line testing in conjunction with simulation testing will either corroborate the strategy or instill serious doubt about its validity.

8. New, real-time ramp-metering computer systems should be designed so that differing strategies can be programmed as a separate program module and activated or deactivated on command.

INTRODUCTION

PURPOSE

The purpose of this project was to determine the feasibility and evaluate the usefulness of a predictive ramp-metering algorithm, an algorithm that anticipates the occurrence of breakdown conditions on a freeway one to two minutes before their occurrence. The Washington State Department of Transportation (WSDOT) expressed a need for this type of algorithm to maximize the efficiency of the existing freeway system.

THE PROBLEM

The Seattle metropolitan region has been ranked as sixth worst in the nation on a congestion severity index, which measures total delay per million vehicle miles of travel. (1) Current projections by the Puget Sound Council of Governments, this region's metropolitan planning organization, are for a 27 percent increase in new residents in the area, which will create a 30 percent increase in vehicle miles of travel by the year 2000. (2, 3) With no new freeways planned and limited financial resources available for highway construction, this region's transportation system will be stretched to its limit.

To address the problem of growing traffic volumes, the Washington State Department of Transportation (WSDOT) has been planning, building, and operating a transportation management system (TMS) since the early 1970s. This TMS, called FLOW, is aimed at maximizing the efficiency of the existing freeway system. Aspects of this TMS effort include the following: (4)

- a surveillance control and driver information (SC&DI) system, consisting of a ramp metering and data accumulation system, a closed circuit television system, a variable message sign system, a highway advisory radio system, and a computer generated graphic freeway display system;

- a high-occupancy vehicle (HOV) lane program. Out of a planned 156-mile, region-wide HOV lane system, 40 miles of lanes are currently in operation;
- a park-and-ride lot program;
- reversible roadway systems on I-5 and I-90;
- freeway flyer stops for express buses;
- arterial signal control systems;
- support for ride-matching services for carpools and vanpools;
- tow truck operations on I-90 and SR-520; and
- an incident management program.

The WSDOT has had tremendous success in improving and maintaining a viable transportation network through the use of FLOW system techniques. However, to maintain this region's mobility in response to future increases in travel, WSDOT will need to expand and advance aspects of the FLOW system. A predictive algorithm for the ramp-metering system is just one way to address this need.

PREDICTIVE ALGORITHMS

As an example of the application of a predictive algorithm, consider the following one-dimensional scenario.

Assume a section of freeway is operating at capacity, and the traffic feeding into the section will maintain operation at capacity for some length of time. If a traffic incident or a recurrent point of congestion causes a breakdown in the traffic stream, a queue will form upstream of the breakdown point, typifying "forced or breakdown flow." (5) For this scenario, assume the breakdown is caused by a recurrent point of congestion, a point where vehicular demand exceeds roadway capacity.

The duration and severity of the breakdown determine the extent of queuing and delays caused to vehicles upstream of the breakdown point. A minor breakdown, with a short and small impact on capacity, may allow traffic flow to recover to capacity quickly.

However, a severe breakdown may affect the capacity through the breakdown point for an extended period.

The 1985 Highway Capacity Manual states that the queue departure rate from a breakdown point may or may not be equal to a roadway's capacity under stable flow conditions. (6) Assuming that vehicles leave the queue at a rate equal to the capacity of the breakdown point under stable flow conditions, if vehicles then continue to enter the queue at a rate equal to or greater than the capacity of the breakdown point, a shockwave moves through the system as vehicles enter and leave the queue. This breakdown and concomitant shockwave may occur over and over until the vehicular demand on the roadway falls below capacity.

Now consider that many of these breakdown points occur on a freeway system, each with its own capacity that may vary because of weather, time of day, and impacts from other breakdown points in the system. While current ramp-metering strategies attempt to ensure demand on the freeway does not exceed capacity, all ramp-metering systems use "real-time," generally one-minute old, or historical data to calculate metering rates. In other words, these systems react to a traffic condition that has already occurred.

Since most urbanized freeways, with or without ramp-metering, have breakdown points associated with a recurrent point of congestion, identification of an impending breakdown and a temporary reduction in demand upstream of the breakdown point could maintain capacity operation at the breakdown point. This capacity operation, could, in turn, increase the overall throughput of vehicles past the breakdown point and reduce travellers' delays by reducing or eliminating the otherwise certain breakdown.

The predictive algorithm attempts to anticipate when a breakdown on a section of freeway will occur and tries to reduce the severity of or eliminate the congestion by restricting upstream on-ramp metering rates and better balancing demand versus capacity.

The predictive algorithm was developed to be most effective in lightly congested flow. In this case, lightly congested was considered to be instances in which small disturbances in the traffic stream might lead to a breakdown of the traffic stream. If the frequency and/or severity of breakdown conditions in the lightly congested flow were reduced, the traffic stream would maintain a more stable flow, thereby increasing vehicle throughput.

RAMP-METERING: LITERATURE REVIEW

RAMP-METERING METHODOLOGY

Ramp-metering has become a proven part of many urban areas' Transportation management systems (TMS). Ramp metering systems currently operate in cities such as New York, Los Angeles, Detroit, Sacramento, Minneapolis, Denver, Chicago, Dallas, Fort Worth and Seattle. (7,8) And the number grows every year.

The basic principle behind ramp-metering is to ensure that demand on the freeway does not exceed capacity. Such a situation is the ideal. Unfortunately, at many times of the day most urbanized areas experience a demand on their freeways that exceeds those same freeways capacities. The result is daily traffic back-ups, i.e. recurrent congestion.

By temporarily storing vehicles on the on-ramps, ramp-metering can smooth the peaks in demand and help reduce freeway congestion. Furthermore, because of the added delay drivers experience while waiting on the metered on-ramp, many divert their shorter trips to parallel arterials, or adjust the time of their trip to avoid the ramp delay. These changes further reduce the peak demand on the freeway.

Another benefit of ramp-metering is reduced congestion at the merge from the on-ramp to the mainline and thus a safer operation. The safety of a freeway corridor increases after implementation of a ramp-metering system because of a decrease in on-ramp-merging conflicts and an increase in the stability of traffic flow on the freeway. (9)

RAMP METERING TECHNIQUES

All of the following ramp-metering techniques provide significant improvements in terms of congestion and travel times, over a condition of no ramp control. However, all metering rate calculations are based on "real-time," generally one-minute old, or historical data. Thus the ramp-metering systems react to historical traffic conditions.

Pretimed Metering

The basic form of ramp-metering consists of a pretimed operation. In this form, the ramp meter operates with predetermined metering rates for a particular control period. These metering rates are determined through analysis of historical traffic data in the control section, i.e., the metering rates are based on traffic congestion related to the time of day.

Traffic-Responsive Metering

In an effort to be more responsive to changing traffic conditions, another form of ramp-metering, traffic-responsive metering, was developed. Through the use of vehicle induction loops and "real-time" processing, traffic-responsive metering calculates metering rates on the basis of current freeway congestion. The traffic-responsive metering scheme has several variations. All are designed to be more responsive to current traffic conditions.

Cities such as Seattle, San Diego and Chicago use a form of the traffic-responsive metering strategy called occupancy control. Here, "real-time" occupancy measurements from vehicle induction loops embedded in the freeway pavement upstream of the on-ramp are compared to a predetermined occupancy versus metering-rate table. A metering rate is selected on the basis of this table for the next control interval.

Another form of traffic-responsive metering is demand-capacity control. In demand-capacity control, metering rates are selected after real-time volume measurements have been compared with predetermined downstream capacities. In this way, the theoretical downstream capacity is never exceeded. Cities such as Detroit and Houston use demand-capacity control with various modifications.

Integrated Traffic-Responsive Metering

Another type of ramp-metering control strategy as defined in the 1985 FHWA "Traffic Control Systems Handbook" is "integrated traffic-responsive" metering. (10) Integrated traffic-responsive metering is "the application of traffic-responsive metering to a series of ramps where metering rates at each ramp are selected in accordance with system, as well as local, demand-capacity restraints." (11) The FHWA has stated that integrated, traffic-responsive ramp-metering strategies are thought to "provide a significant improvement over currently used individual ramp optimization strategies." (12)

Only a few states use a form of integrated traffic-responsive metering; Washington, Minnesota, Colorado, New York, California, Illinois and Virginia. As examples, two integrated traffic-responsive ramp-metering systems from Seattle, WA, and Twin Cities, MI, will be discussed.

In Seattle, WA, the ramp-metering system uses an integrated traffic-responsive metering algorithm, called the bottleneck algorithm, in addition to the occupancy control strategy. (13) The bottleneck metering algorithm sets individual ramp meter rates on the basis of a system-wide control scheme.

The bottleneck algorithm enables the calculation of metering rates in real-time through the use of demand-capacity relationships. The algorithm first determines whether a threshold occupancy level in a section of the freeway has been exceeded. The threshold occupancy level is considered to be the occupancy at which a freeway section is approaching capacity. If the threshold value has been exceeded, volume data are checked to determine whether more vehicles enter than leave that particular freeway section, i.e., whether the vehicles are being stored in the freeway section.

A freeway section is defined as two consecutive loop detector stations on the freeway; the upstream station is the entering station, the downstream station is the exiting station and is used for occupancy threshold determinations. These sections are shown in Figure 1. If the algorithm determines that vehicles are being stored in a freeway section, the upstream on-ramps that influence the particular freeway section are assigned a bottleneck metering rate reduction (BMRR) value. The sum of these individual BMRR values is equal to the number of vehicles being stored in the freeway section in question. The influences of upstream on-ramps on any particular freeway section in question are represented by weighting factors which are treated as operator adjustable variables in the central computer. Each on-ramp's BMRR is subtracted from that on-ramp's previous

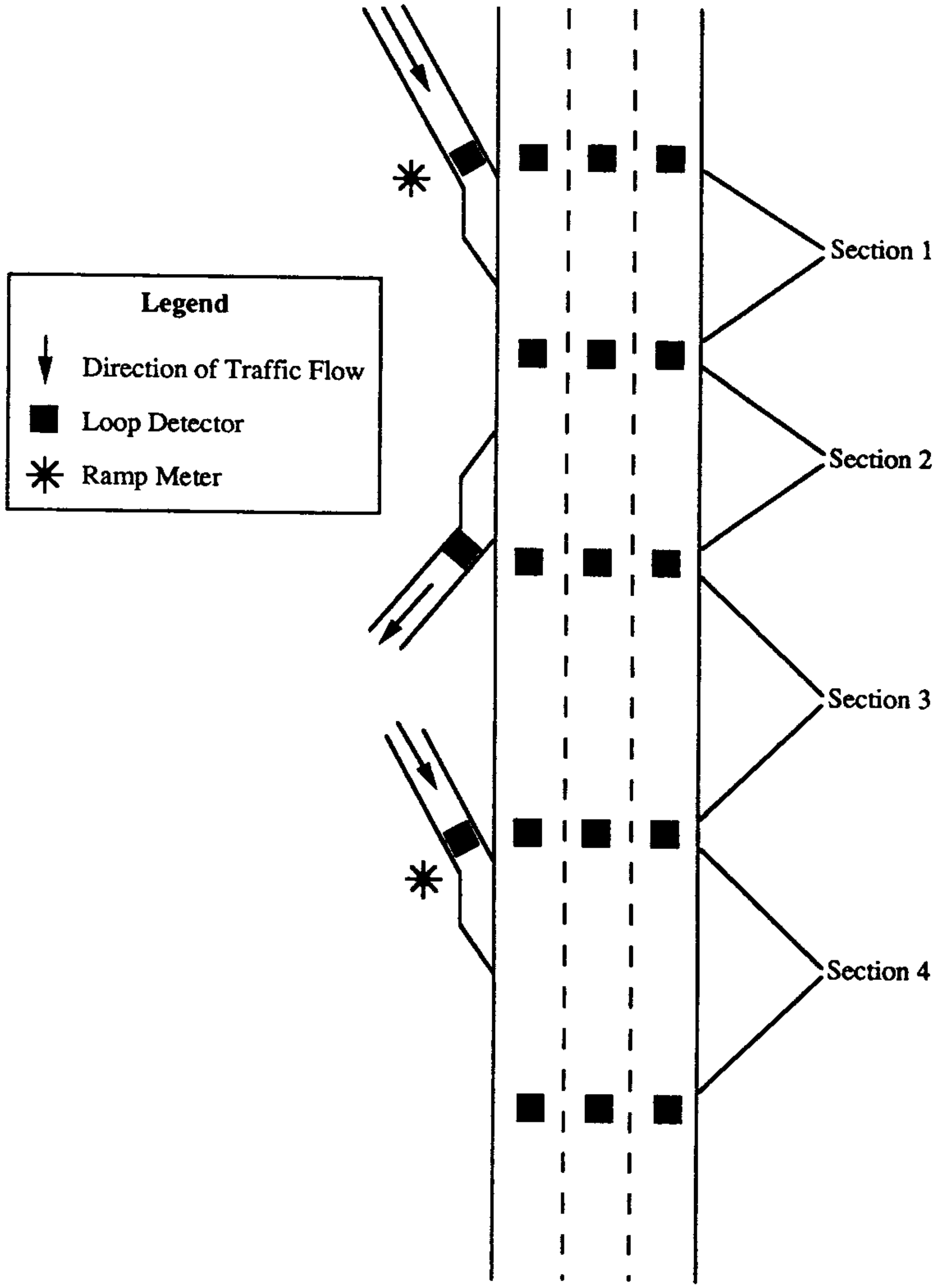

Figure 1. Freeway Sections for WSDOT Bottleneck Algorithm

minute volume and the most restrictive result is selected as the final bottleneck metering rate. All bottleneck metering rate calculations are based on the previous minute's data. (For a more in-depth explanation, see Jacobson, Henry and Mehyar (13)).

In the Twin Cities, MN, a demand-capacity relationship based on downstream loop occupancies calculates metering rates. Up to six downstream loop detector stations can be assigned to a single ramp meter for the calculation of metering rates. Through analysis of historical data, loop occupancies and volume data associated with the capacity of a freeway section have been tabulated. In "real-time" control, occupancy data from these downstream stations are sampled every 30 seconds. The occupancy data are compared to the pre-set metering rate table for a particular ramp meter and the most restrictive rate is selected. (14)

Gap-Acceptance Merge Control

One final type of ramp metering strategy, gap-acceptance merge control, attempts to maximize the volume entering the freeway by looking for "gaps" in the mainline traffic stream. This type of strategy is not currently used in the United States.

RAMP-METERING: STATE OF THE ART

Over the years, researchers have made many attempts to improve upon these basic forms of ramp-metering. The underlying premise for these improvements has been to make the ramp-metering operation more responsive to traffic conditions within the ramp control freeway system.

In the San-Francisco area, a ramp control scheme that used fuzzy set theory for inexact reasoning was tested with the simulation of the ramp-metering system on the San-Francisco/Oakland Bay Bridge. (15) Fuzzy set theory attempts to replicate operator override control of the ramp-metering system during incident conditions by modeling linguistic control rules. These rules are incorporated into the ramp-metering algorithm, called a fuzzy controller, to provide for real-time, responsive control strategies.

Although this technique has not been tested on-line, in simulation testing, the result in most cases was a reduction in passenger hours of travel during incident conditions with the fuzzy controller. Unfortunately, the fuzzy controller tended to dissipate the ramp queues later than the existing control strategies after an incident had been cleared, thereby adding travel time to vehicles in the ramp queue. On-line testing is scheduled for early 1990.

Other attempts to improve ramp-metering systems involve balancing real-time demand on a freeway section with the section's calculated capacity. Improvements in the estimation of space-mean-speed and density have made real-time capacity estimates more reliable. (16, 17, 18, 19) The most recent attempt at this type of metering scheme was conducted in San Diego by Verac, Inc., under contract with the FHWA. (20)

This metering scheme calculates real-time capacities for all freeway sub-sections in the control system by first estimating densities and space-mean-speeds from detector data (volume and occupancy). These real-time capacities are compared with calculated capacities of each freeway section to determine whether adjustments to the ramp-metering rates are needed. The objective is to ensure that the maximum possible demand through each freeway section is accommodated, that is, that real-time capacity equals calculated capacity.

This scheme is inherently sensitive to the density and space-mean-speed estimates as well as the predetermined capacities calculated for each freeway section. Also, origin and destination data are needed for each metered on-ramp in the system. Simulation testing with INTRAS and FREFLO has shown improvements over traditional metering strategies.

Another similar metering strategy developed at the University of California at Berkeley, (21) computes metering rates on the basis of the difference between the traffic volume entering sections of the freeway and the calculated capacity of the downstream section. This method has not been tested on-line.

While all of these approaches to an integrated demand responsive ramp-metering system are improvements over the traditional forms, they all rely on previously collected data, generally one-minute old, to determine ramp-metering rates. None of the strategies present a marked improvement over currently operational metering schemes. The lack of on-line testing may be a sign of their practicality.

No systems currently in operation employ a predictive type of algorithm, whether the prediction is for traffic volume, occupancy, density or other traffic measures, in the formulation of ramp-metering rates in a real-time system. Work in the area of predicting traffic volumes has typically involved short-term predictions of less than one year. (22, 23)

One study from Shinshu University in Japan, (24) involved the prediction of traffic volumes on the basis of previously collected historical data from a study link and from data leading into the study link. Real-time traffic measurements were then used to correct for traffic deviations from the average historical pattern. These predictions were generally made in 5 minute intervals.

SUMMARY

Most ramp-metering operations today base their metering rates on a pretimed rate schedule, time-of-day rate schedule, or on local congestion levels at the metered on-ramp merge. Some operations use a combination of these.

Still, a few others base adjustments on a system-wide metering control scheme. All of these operations use previously collected data, generally one-minute old, when calculating metering rates. Thus they react to freeway conditions after they have occurred.

PREDICTIVE ALGORITHM

INTRODUCTION

The predictive algorithm tested as part of this project was developed at the University of Washington and is described in the paper entitled "Adaptive Forecasting of Freeway Traffic Congestion." (25) A summary of this paper follows.

DEVELOPMENT

The predictive algorithm is based on statistical pattern recognition. (26, 27) In the prediction of congestion, the problem is one of identifying variables that discern breakdown conditions from non-breakdown conditions.

To accomplish this differentiation, one minute summaries of historical data from the Washington State Department of Transportation were analyzed for a portion of the I-5 ramp-metering system as shown in Figure 2. Data sets from both lightly congested and heavily congested time intervals were obtained. Using these data, researchers plotted the difference between traffic entering and leaving a freeway section, referred to as the "IO difference," and that freeway section's average downstream loop occupancy for the past intervals of 1, 2 and 3 minutes. The problem became one of identifying patterns in the volume and occupancy data for sections 1, 2 and 3 which preceded breakdown conditions in section 2. Breakdown conditions in section 2 could easily be identified as meeting the WSDOT definition, i.e., occupancy > 18% and the IO difference was positive. For both the lightly congested and heavily congested data sets the plots enabled the identification of one occupancy variable and one IO variable to be used as predictors.

Results of the analysis showed downstream loop occupancy in section 2, averaged over the past minute, and the IO difference in section 1, lagged two minutes, provided the best predictors of a bottleneck. In testing these variables for their accuracy in predicting breakdown conditions, the lightly congested data set showed promising results. Table 1

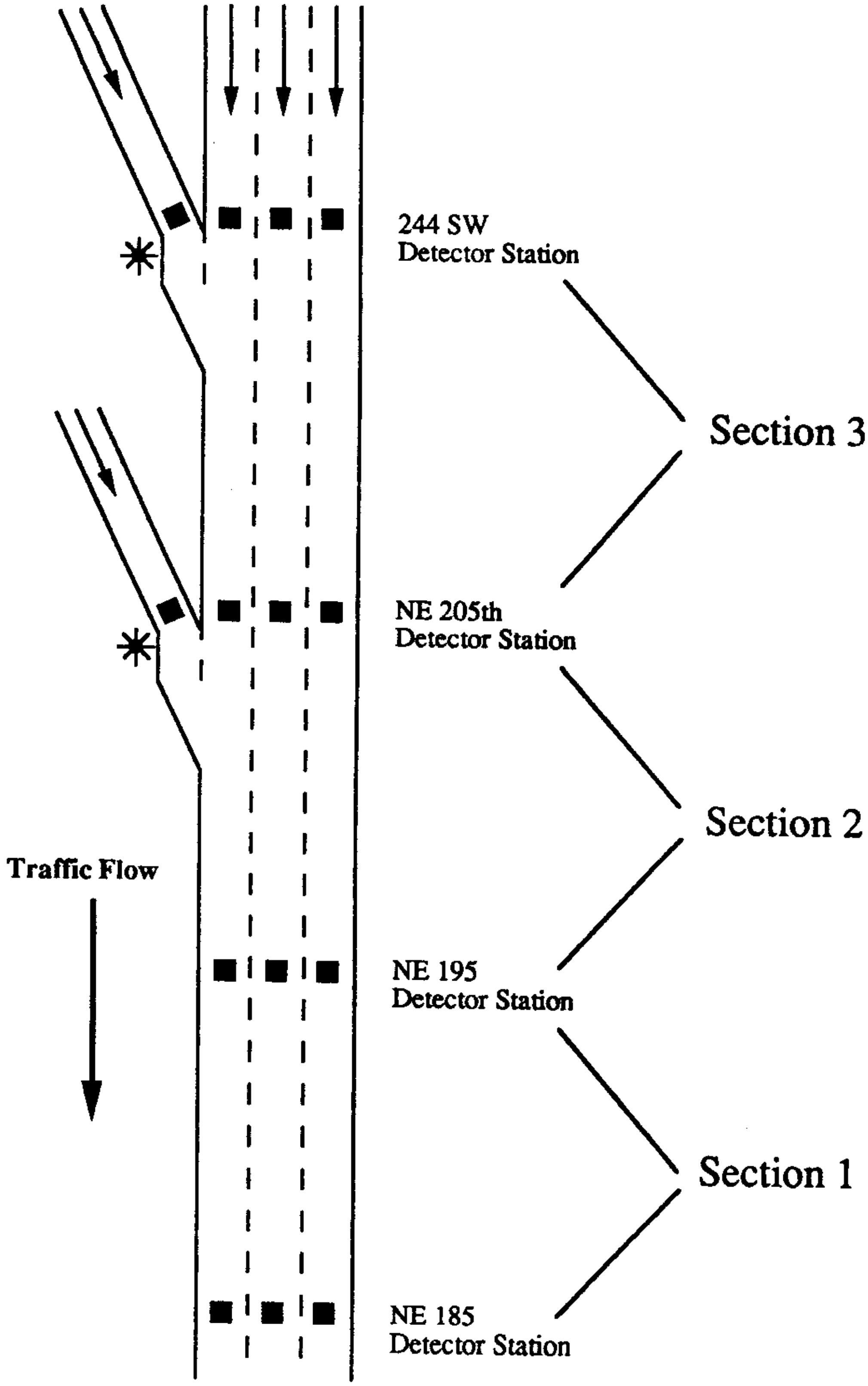

Figure 2. Predictive Algorithm Development Sections

Table 1. Comparison of Predictions

	Percent Correct	False Positive Rate	False Negative Rate
Lightly Congested Data	92	5	36
Heavily Congested Data	68	7	73

compares accuracy figures for both lightly and heavily congested predictions. The "Percent Correct" column gives the unconditional percentage of correct forecasts, while the "False Positive" and "False Negative" columns give conditional percentages. That is, the "False Positive" column gives the percentage of non-queuing (nonbreakdown) intervals which were falsely predicted to show queuing while the "False Negative" column gives the percentage of queuing (breakdown) intervals which were falsely predicted to not show queuing. These conditional rates are more informative than unconditional rates such as the "Percent Correct" because they correct for the high proportion of non-queuing intervals in the available data sample.

In terms of the false prediction's effect on ramp-metering rates, a false positive prediction tends to reduce upstream ramp-metering rates, thereby increasing those on-ramps' queues. On the other hand, a false negative rate, a lack of prediction before a congestion occurred, means the ramp-metering system is simply no better off than it was before: breakdown conditions are identified only after they have occurred and are not predicted in advance. Because of this situation, the false positive rate should be kept to a minimum while the false negative rate is less serious.

The results shown below were considered to be preliminary, and further research is underway to attain more accurate forecasts, especially on the heavily congested data sets.

IMPLEMENTATION

The predictive algorithm was incorporated into the WSDOT's existing central computer system as a third ramp-metering algorithm; the first two were the local and bottleneck algorithms. The predictive algorithm was programmed into the original bottleneck metering algorithm subroutine. This new subroutine generated metering rates on the basis of the real-time storage rate (IO difference) of vehicles in the test section or on the basis of the default storage rate used when a bottleneck was predicted. Because breakdown conditions were determined from the current time interval, while a predicted breakdown was defined as congestion that would occur in one or two minutes, both checks had to be made and compared simultaneously. Then, the more severe condition, calculated or predicted, would control the determination of the metering rate for the next time interval.

Breakdown conditions were predicted only for the section of southbound I-5 between NE 205th and NE 195th. Once the subroutine was pointing at the downstream end (NE 195th) of the test section, the decision process involved in determining the bottleneck/predicted bottleneck metering rate was as shown in Figure 3.

The messages printed consisted of current and historical occupancies and storage rates. The messages were used to determine the accuracy of the predictive algorithm.

The predictive algorithm used was designed to predict breakdown conditions during lightly congested time intervals. This would represent the portion of the peak period where traffic conditions change from free-flow to forced-flow.

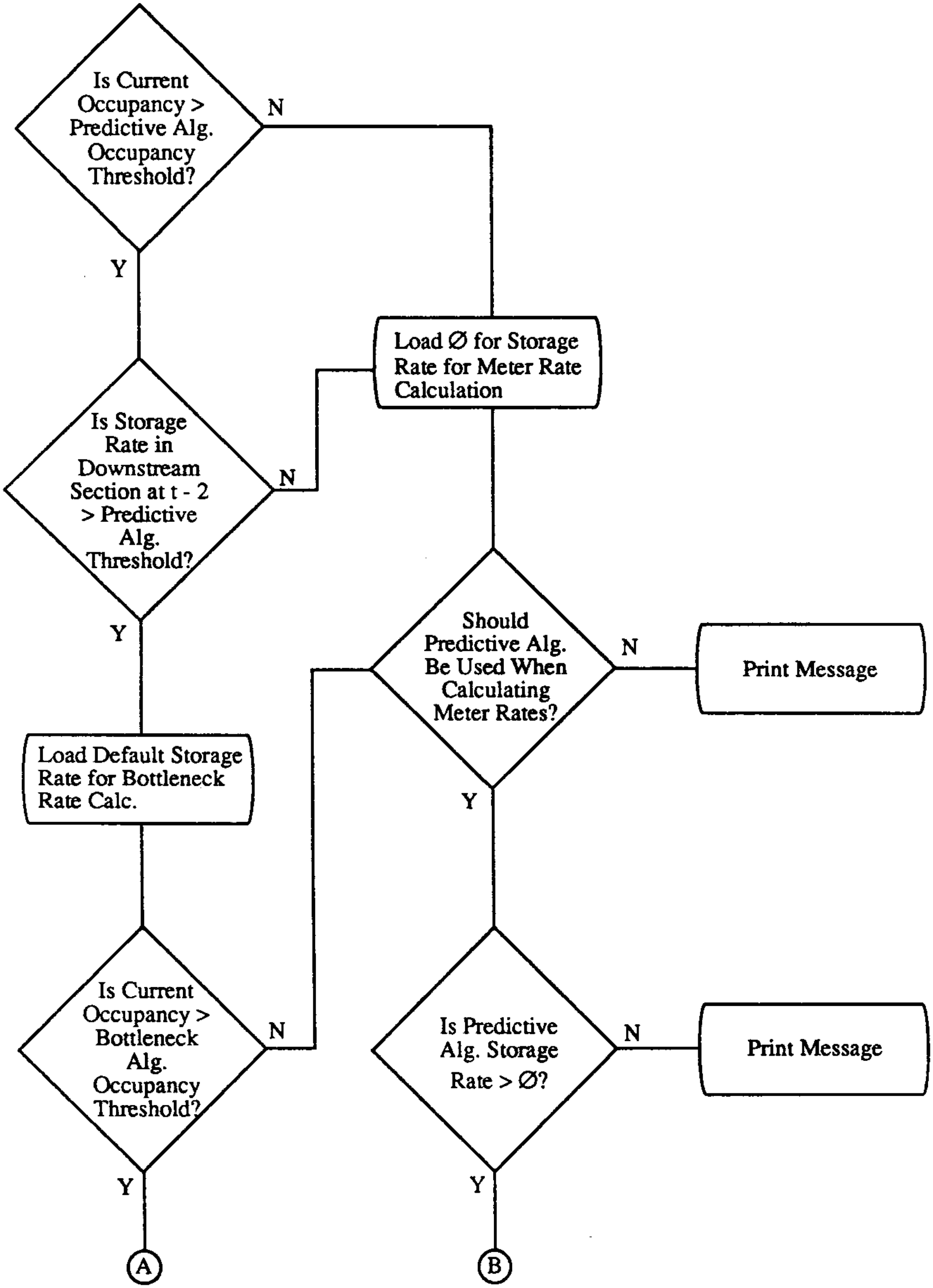

Figure 3. Predictive Algorithm Implementation Decision Process

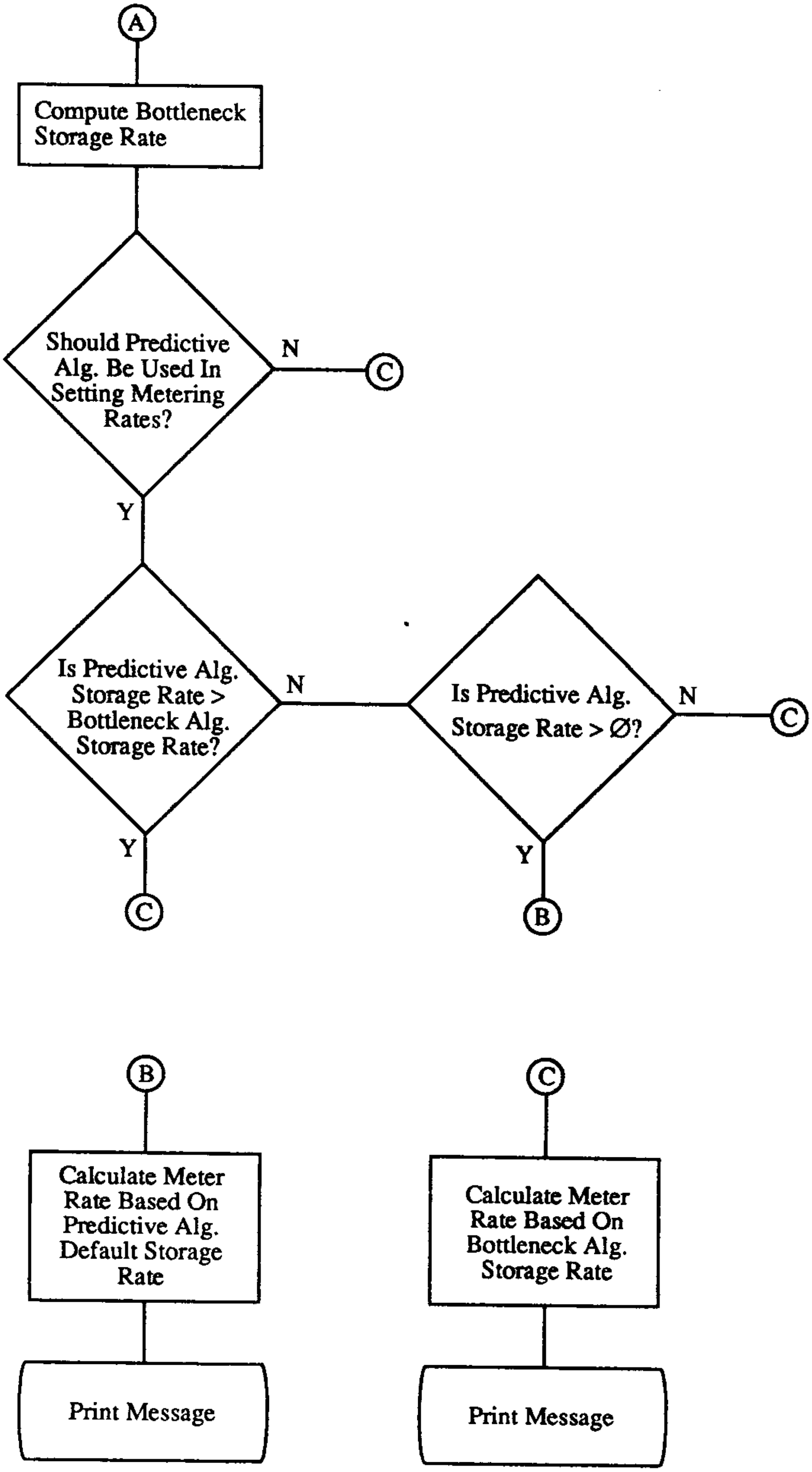

Figure 3. Continued

RESEARCH DESIGN

INTRODUCTION

The research team tested the predictive algorithm on-line by incorporating it into the WSDOT's ramp-metering central computer at the Traffic Systems Management Center (TSMC). Additionally, simulation testing of the predictive algorithm was attempted through use of the Integrated Traffic Simulation (INTRAS) model. However, as of this writing, incorporation of WSDOT's existing control schemes into the INTRAS model was not complete.

ON-LINE TESTING

While simulation testing of a predictive algorithm can provide controlled statistical data to evaluate alternative ramp-metering strategies, on-line testing, in association with existing control strategies, provides an indication of overall system performance because real-life situations are inherent. Positive, negative, and neutral impacts from the predictive algorithm can be determined on the basis of real conditions when on-line testing is conducted.

To allow on-line testing, the predictive algorithm was programmed into the existing Perkin/Elmer ramp-metering central computer system at the TSMC. Prediction messaging was included to determine the accuracy of the predictive algorithm. These messages were saved and printed for later analysis. A comparison was made between the ability of the predictive algorithm to correctly predict congestion and the statistical tests from the before-and-after data to determine how usage of the algorithm translated into highway system performance.

The predictive algorithm was evaluated on only a portion of the southbound I-5 ramp-metering system, as shown in Figure 4. The NE 205th St/NE 195th St section of freeway represents a chronic bottleneck location. The NE 205th on-ramp is generally one

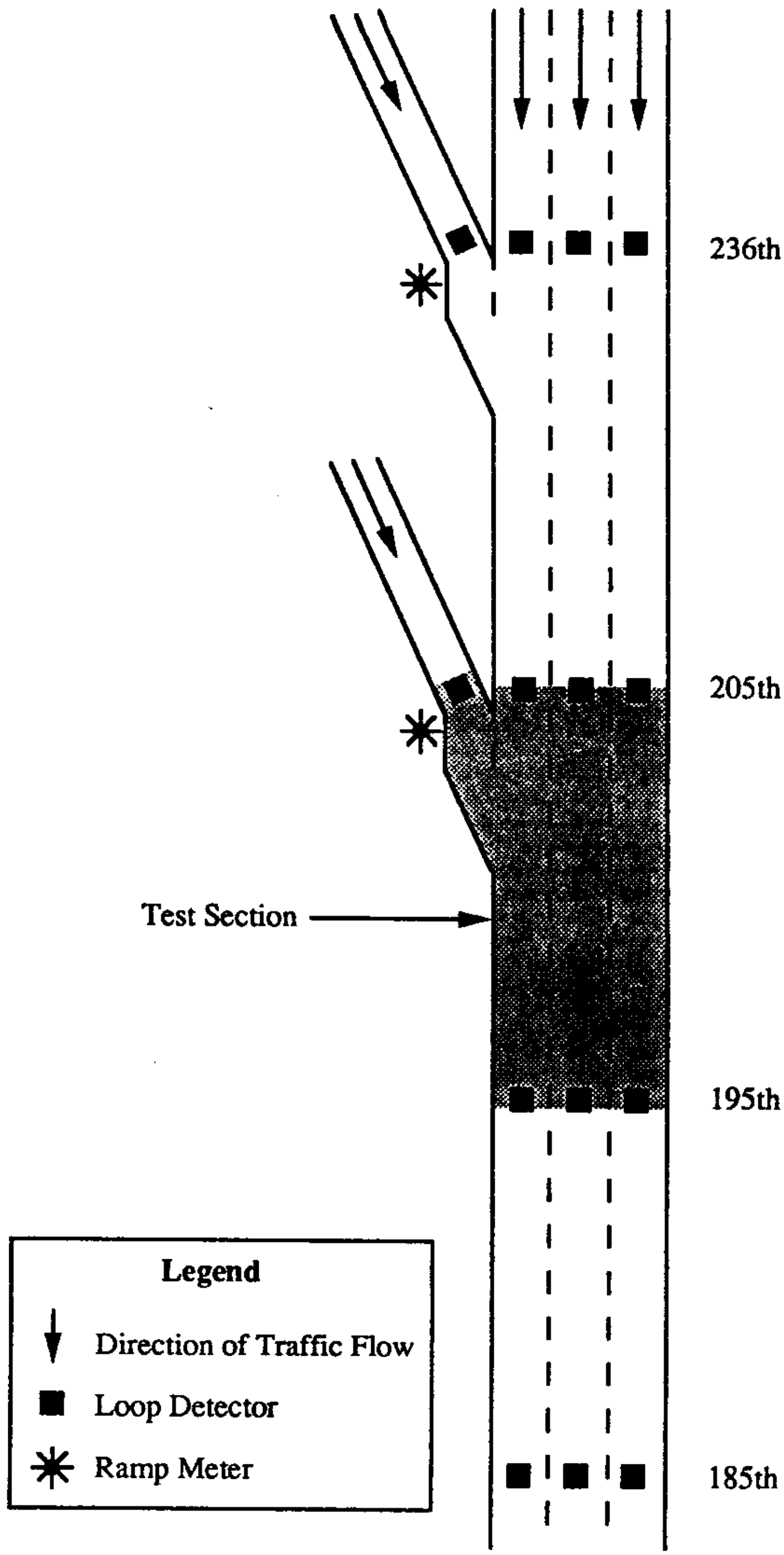

Figure 4. Predictive Algorithm Analysis Section

of the first ramp-metering stations to be initiated in the morning. Data for analysis was collected at mainline stations between 236th St SW and S. Spokane St. Figure 5 shows these stations' locations.

The algorithm was evaluated between 6:00 a.m. and 8:00 a.m. Within this time frame the traffic conditions changed from free-flow to forced-flow conditions through the study section. Typically, the TSMC conducts ramp-metering from 6:15 a.m. to 8:00 a.m. on this section of southbound I-5.

The central computer at the TSMC collects historical data on a continual basis. Both before and after integration of the predictive algorithm, 15-minute intervals of volume and occupancy data were used for evaluation. Volume and occupancy data represented direct traffic measurements from vehicle induction loops in the field.

Data were collected for six weeks before and after implementation of the predictive algorithm. The objective was to obtain at least 30 good data sets for analysis. The "before" data collection period extended from April 26, 1989, until June 20, 1989. The "after" period included June 29, 1989, to August 8, 1989. The "after" period included only 22 days of data because of a lengthy equipment malfunction. This malfunction caused some problems in the analysis, as discussed in the section on Results and Interpretation.

The data were screened before analysis to determine whether extraneous factors had influenced their values. These factors included the following:

- adverse weather conditions,
- blocking incidents as logged by TSMC personnel, and/or
- equipment malfunctions.

On days when one or more of these factors occurred, the data were discarded.

After being collected by the TSMC, the data were down-loaded into the University of Washington's VAX computer system. The statistics package MINITAB (28) was employed to perform a technique known as time-series intervention analysis to determine the effects of the predictive algorithm. (29, 30)

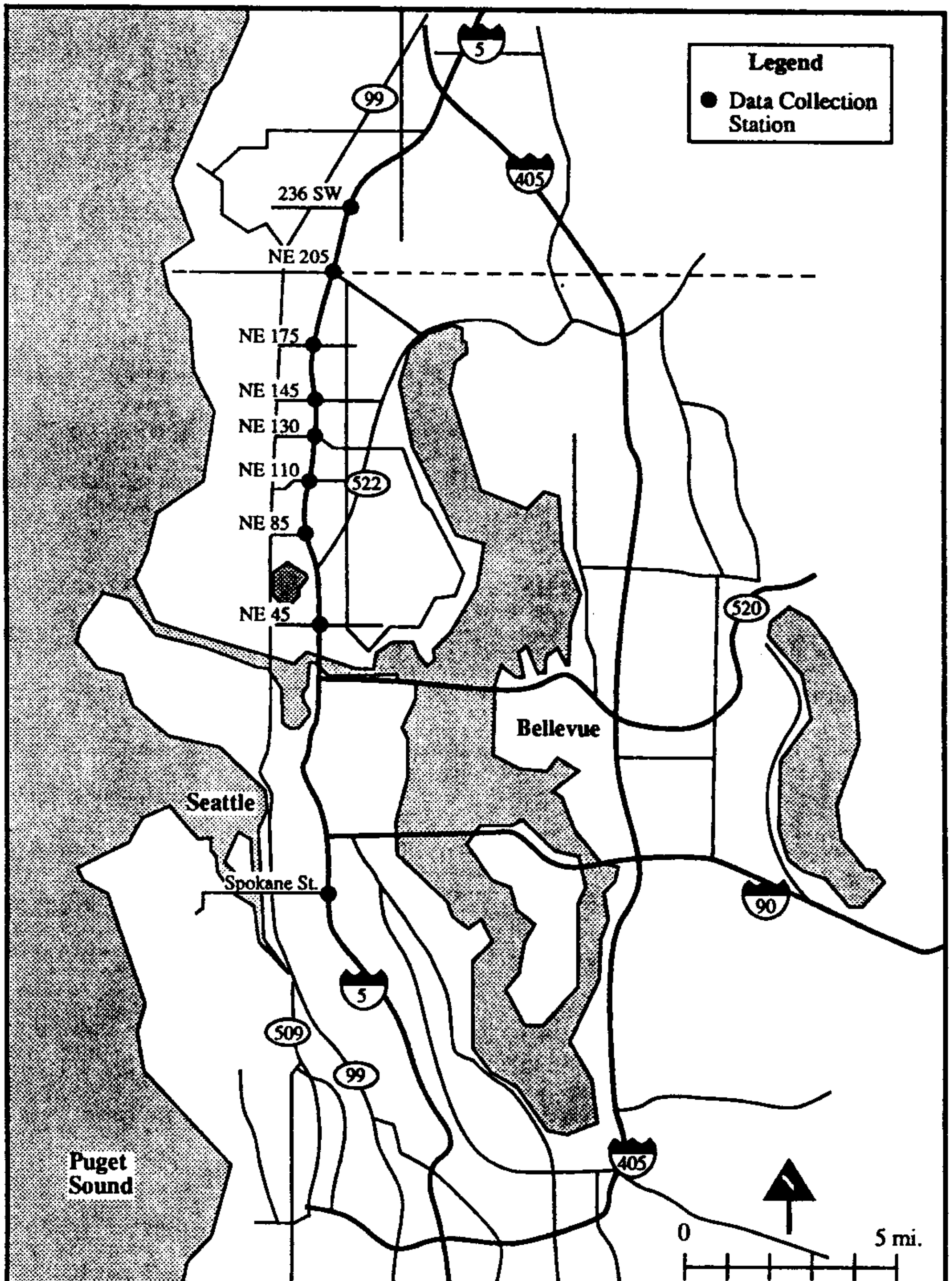

Figure 5. Data Collection Stations

Because the I-5 data sets of volume and occupancy proved to be stationary and random, the time-series intervention analysis became a linear regression analysis with an intervention variable included as one of the independent variables. The intervention variable took on values of either 0 or 1:0 for the time-series data before the intervention, 1 for the time-series data after the intervention. The intervention was the implementation of the predictive algorithm.

Covariables were also included as independent variables in the intervention analysis. The covariables represented the control stations' values and compensated for parameter fluctuations not attributable to the predictive algorithm, e.g., seasonal trends and weather. These control stations were all located downstream, from one to seven miles, from the predictive algorithm test section.

Before the researchers could assume that a simple linear regression model could statistically explain the time-series data, checks on the results were necessary. The two most notable checks involved looking for autocorrelation in the residuals and, because of the seasons included in the data collection, looking for the effect of trends on the time series.

For the time-series intervention analysis, each 15-minute interval between 6:00 a.m. and 8:00 a.m. was first aggregated in terms of volume data and occupancy data for all stations. A linear regression analysis was then performed to determine the coefficients of Equation 1:

$$DV_t = b_0 + b_1 IN_t + b_2 Co(1)_t + b_3 CO(2)_t + \ldots b_i CO(j)_t + u_t, \text{ (Equation 1)}$$

where DV_t = Dependent variable (volume, occupancy) value on day t,

IN_t = Intervention variable; 0 on days before the predictive algorithm was used and 1 on days after the predictive algorithm was used,

$CO(j)$ = Covariable(s) value(s) on day t,

u_t = Regression residual on day t, and

$b_0, b_1, \ldots, b_i$ = Regression coefficients to be estimated.

The coefficient resulting from Equation 1, b_1, is the amount of increase or decrease in the dependent variable value attributable to the predictive algorithm in a particular time period.

When the research team determined that a linear trend was affecting the regression and that this trend was not completely accounted for in the covariable(s), a time variable was included in the regression equation. With this inclusion, the time series, DV_t, could be better described by Equation 2:

$$DV_t = b_0 + b_1IN_t + b_2TR_t + b_3CO(1)_t + b_4CO(2)_t + \ldots b_iCO(j)_t + u_t \quad \text{(Equation 2)}$$

where

DV_t	=	Dependent variable (volume, occupancy) value on day t,
IN_t	=	Intervention variable; 0 on days before the predictive algorithm was used and 1 on days after the predictive algorithm was used,
TR_t	=	The effect of time, represented by a linear trend, on day t,
$CO(j)$	=	Covariable(s) value(s) on day t,
u_t	=	Regression residual on day t, and
$b_0, b_1, \ldots, b_i$	=	Regression coefficients to be estimated.

In Equation 2, TR_t denotes the trend in day t, which is considered to be a linear function of time. This equation describes the time series by an average level, U_t, that will change over time according to the following equation:

$$U_t = IN_t + TR_t + CO(j) \quad \text{(Equation 3)}$$

plus an error term that represents the deviation from the average. (31)

To check for excessive ramp queuing due to the predictive algorithm, data were collected on the status of ramp queuing in the before and after periods. The reasoning behind the queuing check was to determine whether the use of the predictive algorithm restricted ramp-metering rates too severely. If the predictive algorithm reduced on-ramp volumes from their current levels, mainline conditions would improve at the expense of the on-ramps.

All metered on-ramps on southbound I-5 have an advance queue induction loop. This loop is placed where on-ramp queues from the ramp meter can be a maximum length without affecting city arterials. If queues reach the advance queue loop, an override condition, called advance queue override, is enabled, and metering rates are set to a predetermined level until the queue has been dissipated.

By collecting advance queue override status on all southbound on-ramps, the researchers were able to compare those ramps affected by the predictive algorithm with all other on-ramps, and changes in on-ramp queuing could be determined.

RESULTS AND INTERPRETATION

PREDICTIVE ALGORITHM ACCURACY

Before the predictive algorithm was enabled to alter ramp-metering rates, data were collected on the ability of the algorithm to correctly predict breakdown conditions 1 to 2 minutes before their occurrence in an on-line system. Table 2 shows the results of this analysis.

The percentage correct was calculated by first adding the number of times breakdown conditions were predicted and subsequently occurred plus the number of times the predictive algorithm did not predict a breakdown and a breakdown did not occur. This total was then divided by the total number of 20-second intervals in the analysis time frame. The false positive rate was calculated by dividing the number of times the predictive algorithm predicted a breakdown and that breakdown did not occur, by the total number of intervals in which a breakdown did not occur in the analysis time frame. The false negative rate was calculated by dividing the number of times a breakdown occurred but was not predicted by the total number of times a breakdown occurred in the analysis time frame.

One important note: because the predictive algorithm was incorporated into the ramp-metering system for use over the entire range of occupancies, the accuracy results in Table 2 came from a combination of lightly congested and heavily congested data sets.

In general, the results in Table 2 appear favorable and comparable with the rates shown in Table 1. Both tables show a high percentage of correct prediction and a low false positive rate. The high false negative rate was built into the predictive algorithm because of

Table 2 Accuracy of the Predictive Algorithm

Percent Correct	False Positive	False Negative
79.6	7.1	40.8

the variables used in identifying impending congestion and the tradeoff between the false positive and false negative rates. (32) The high false negative rate is not too disconcerting because it means that when breakdown conditions did occur the algorithm missed predicting them 40.8 percent of the time. In essence, a false negative means reverting back to the existing system which reponds once the congestion occurs, so the ramp-metering system is no worse off.

INTERVENTION ANALYSIS RESULTS

Results of the intervention analysis for the three dependent variables, 236th SW, NE 205th and NE 185th, are shown in Tables 3, 4 and 5, respectively. Note that the coefficient represents the actual increase in volume or occupancy due to the intervention (i.e., the use of the prediction algorithm) in each time period. Because of the similarities between the three station's results, each of the time periods will be discussed, rather than each station's analysis.

Table 3. Intervention Analysis for 236th SW

Period	Variable	Coefficient	T-Ratio	Significance
6:00-6:15	Volume	-95.6	-7.49	p<.01
	Occupancy	-1.5	3.55	p<.01
6:15-6:30	Volume*	-11.9	-0.40	INSIG
	Occupancy	-2.4	-2.16	p<.05
6:30-6:45	Volume	39.9	2.35	p<.05
	Occupancy	-1.2	1.30	INSIG
6:45-7:00	Volume	41.6	2.30	p<.05
	Occupancy	-3.4	2.88	p<.01
7:00-7:15	Volume	35.5	2.54	p<.05
	Occupancy	-2.8	1.80	INSIG
7:15-7:30	Volume	-36.7	1.60	INSIG
	Occupancy	-1.5	0.95	INSIG
7:30-7:45	Volume	-14.4	0.49	INSIG
	Occupancy	-2.6	1.40	INSIG
7:45-8:00	Volume	-10.7	-0.28	INSIG
	Occupancy	-0.6	0.36	INSIG

*Includes effects due to time, TR_t

Table 4. Intervention Analysis for NE 205th

Period	Variable	Coefficient	T-Ratio	Significance
6:00-6:15	Volume	-68.0	4.00	p<.01
	Occupancy*	0.8	0.72	INSIG
6:15-6:30	Volume	66.2	4.27	p<.01
	Occupancy	-3.4	-2.91	p<.01
6:30-6:45	Volume*	17.0	0.61	INSIG
	Occupancy	-1.9	-1.95	p<.10
6:45-7:00	Volume	47.8	2.51	p<.05
	Occupancy	-4.2	-3.07	p<.01
7:00-7:15	Volume	8.9	0.54	INSIG
	Occupancy	0.0	0.02	INSIG
7:15-7:30	Volume	-31.6	-1.36	INSIG
	Occupancy	-3.3	-2.04	p<.05
7:30-7:45	Volume	-32.5	-1.11	INSIG
	Occupancy	-2.4	-1.43	INSIG
7:45-8:00	Volume	-16.3	-0.76	INSIG
	Occupancy	-0.1	-0.07	INSIG

Table 5. Intervention Analysis for NE 185th

Period	Variable	Coefficient	T-Ratio	Significance
6:00-6:15	Volume*	-32.9	-1.32	INSIG
	Occupancy*	-0.7	-0.77	INSIG
6:15-6:30	Volume*	15.2	0.58	INSIG
	Occupancy	-2.2	-2.93	p<.01
6:30-6:45	Volume*	1.9	0.06	INSIG
	Occupancy	-2.3	-2.58	p<.05
6:45-7:00	Volume*	-4.2	-0.21	INSIG
	Occupancy	-0.1	-0.04	INSIG
7:00-7:15	Volume*	-30.5	-0.82	INSIG
	Occupancy	-0.9	-1.08	INSIG
7:15-7:30	Volume	2.5	0.10	INSIG
	Occupancy	-2.7	-2.85	p<.01
7:30-7:45	Volume	-9.9	-0.34	INSIG
	Occupancy	0.6	0.68	INSIG
7:45-8:00	Volume	26.5	1.02	INSIG
	Occupancy	-0.7	-0.72	INSIG

*Includes effects due to time, TR_t

Influences on Intervention Analysis

Intervention Versus Trend Effects

Some of the time periods appeared to be better represented in the intervention analysis by a combination of a linear trend and an intervention effect. In most time periods the covariable(s) picked up any effects of trends in the data. However, in some of the time periods the covariable(s) did not account for all of the trend effects in the data. In these instances, a time variable, represented by a linear trend, was included in the analysis, as shown in the intervention analysis tables.

Data Set Size

The data sets used in the intervention analysis totaled 53 samples, including 31 days of "before" data and 22 days of "after" data. The number of "after" days of data proved to be too few. Unfortunately, the problem was unavoidable because of equipment problems. Because of the small size of the "after" data set, the distinction between an intervention and a trend effect was difficult at times. In some instances, what looked to be an intervention could not be substantiated with the lack of "after" data and was therefore considered to include some trend effect that was not picked up by the covariable(s).

Time Of Year

Time of year, as an influence on the intervention analysis, may or may not have been picked up by the covariables because of the location of the covariables' data collection stations, all downstream of the predictive algorithm test section. These stations may or may not have been indicative of the annual trends associated with the test section's traffic conditions.

Initially, the analysis of the predictive algorithm was planned for the months of February through May. Traffic conditions on southbound I-5 are fairly similar during this time period. However, beginning in June and extending through August, weather conditions in the Pacific Northwest become the most favorable for vacations. During this part of the year, the University of Washington and all public schools in the area are out of session, except for students enrolled in summer classes.

Therefore, traffic volumes during the morning peak period in the summer months are generally lighter than during the rest of the year. Additionally, summer brings better weather conditions for driving.

Because of the improved weather conditions and school breaks in the summer months, the researchers expected that traffic conditions would be less congested, especially on the fringes of the peak period, during the months of July and August.

Results: 6:00 to 6:15 a.m.

This time period showed a significant drop in volume at 236th SW because of an intervention. However, this drop was not due to the intervention of the predictive algorithm for two reasons. One, ramp metering was initiated in this time period, generally closer to 6:15 than 6:00. Therefore, the predictive algorithm had not had much time to affect traffic volumes on the freeway. Secondly, the predictive algorithm affected metering rates on a total of six on-ramps. Three of these on-ramps were upstream of 236th SW, but only one of the on-ramps, 220th SW, was routinely initiated before 6:15 a.m. On-ramp volumes at 220th SW averaged 139 vehicles in the 6:00 to 6:15 time period in spring 1989. To assert that the predictive algorithm could, in less than 15 minutes, reduce the volume on this single on-ramp by an average of 95 vehicles is unreasonable.

More plausible is the theory that commuters shifted their travel patterns during the summer months because of the lighter traffic volumes. As traffic volumes decreased because of summer vacations and school breaks and driving conditions improved because of better weather conditions, commuters could leave from home later and still arrive at work on time.

This occurrence was clearly seen at the station farthest north, 236th SW, and was still apparent at NE 205th. However, at NE 185th, the change in traffic volumes had been smoothed out and appeared to be more of a trend rather than an intervention effect. This smoothing is partly due to NE 185th being the farthest downstream station but also due to the three on-ramps between 236th SW and NE 185th.

Occupancy generally did not change during this time period. Except for 236th SW, the changes in occupancy were insignificant and looked to be influenced to a greater degree by trend effects than by an intervention. This change in occupancy was expected in conjunction with the drop in volume.

Results: 6:15 to 6:30 a.m.

In general, volume changes in this time period were mixed. Stations 236th SW and NE 185th both appeared to be affected more by a trend than an intervention, while NE 205th showed a significant increase in volume because of an intervention. The time series plots for volume at 236th SW and NE 205th are shown in Figures 6 and 7, respectively. Through just a visual inspection, these figures show the difficulty in assessing whether a trend or intervention has affected the "after" data. The main problem is the lack of "after" data.

In contrast, occupancy showed no influence of a trend and dropped significantly at all stations. This means that while volume generally increased between the "before" and "after" time periods, significantly in one case, occupancy decreased. On a volume/occupancy curve, this could be represented by a backwards movement along the curve from the congested regime to a more uniform flow regime.

Because volume increased and occupancy decreased in this time period, leading to the conclusion that the predictive algorithm had had some effect on traffic, weather conditions during the analysis time frame were checked to see whether a drastic change had taken place that could explain the effect on traffic. Records kept by the WSDOT (12) stated that weather conditions in both "before" and "after" time periods were predominantly clear and dry. The exceptions were that in the "before" time frame, 5 out of the 31 "before" days

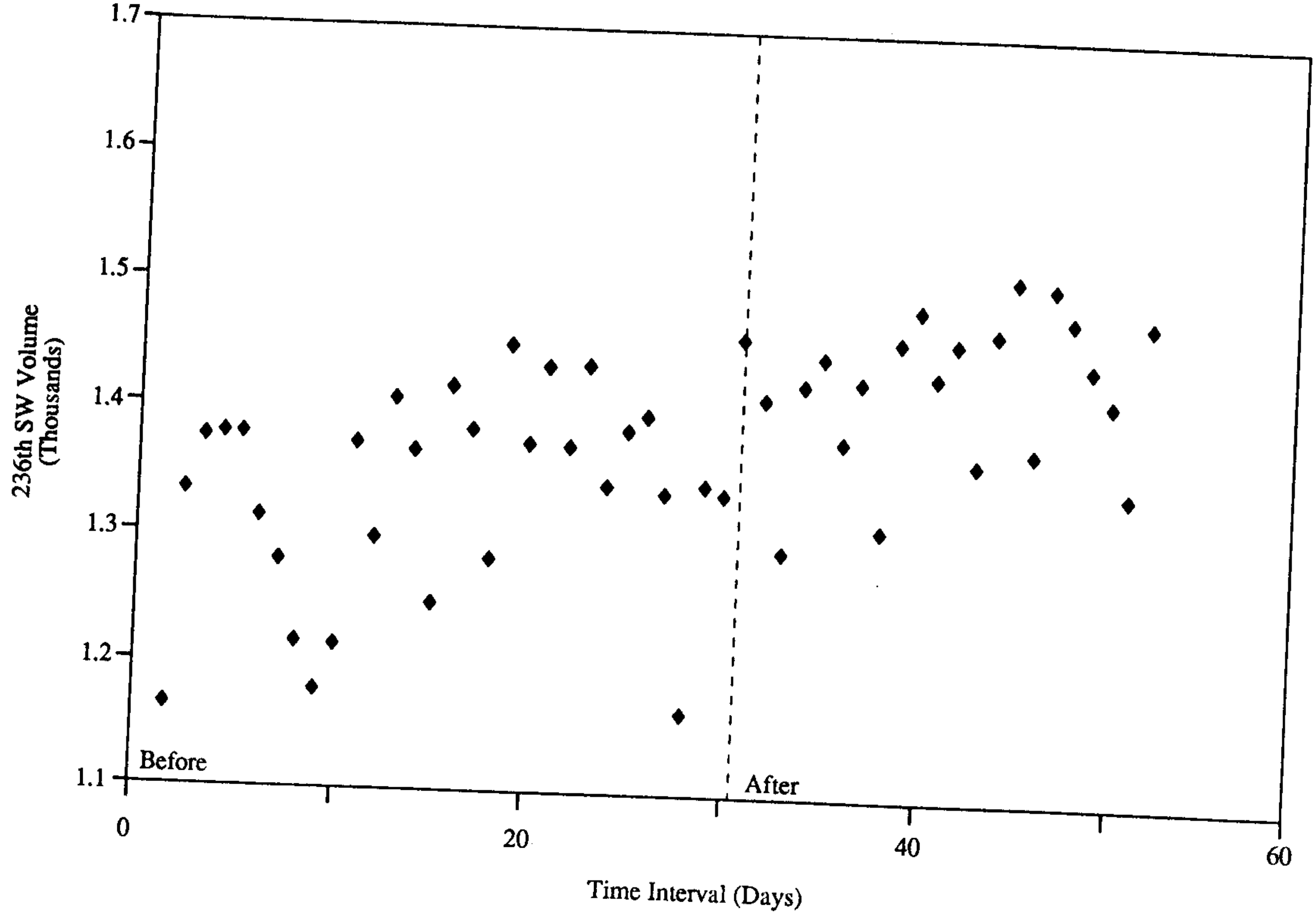

Figure 6. Time Series Plot: Volume 236th SW

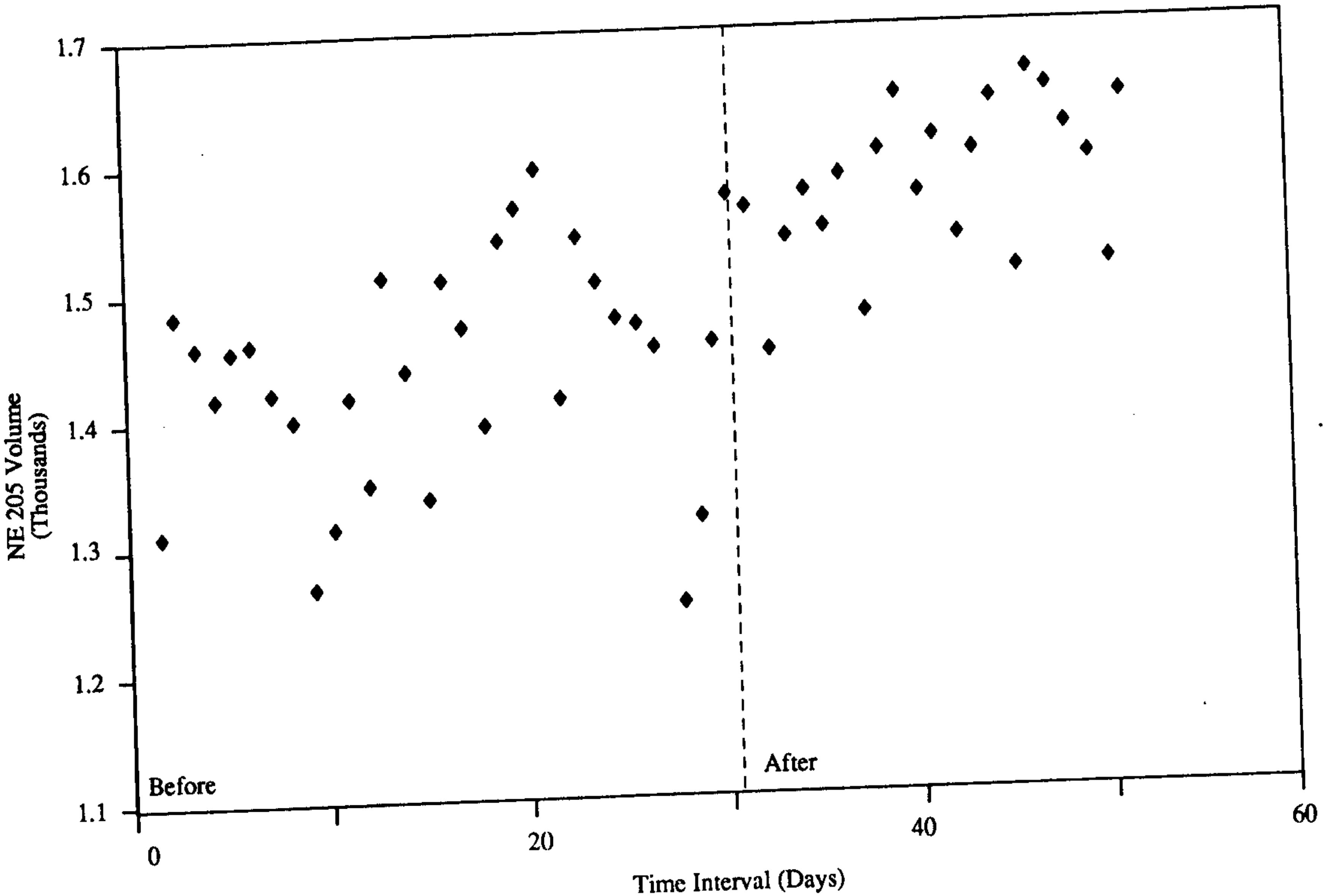

Figure 7. Time Series Plot: Volume NE 205th

had experienced rain in the a.m. peak period, and in the "after" period rain in the a.m. peak period occurred only once. In light of the small number of rain days the researchers judged that the weather had had no influence on the results.

Results: 6:30 to 6:45 a.m.

While both NE 205th and NE 185th still exhibited some influence of a linear trend, 236th SW showed a significant increase in volume because of the predictive algorithm intervention. But even with the need for the additional independent variable representing time as a linear trend, both NE 205th and NE 185th showed an increase, although insignificant, in volume. The effects present because of the linear time variable were also insignificant but had to be included because of the inability of the covariables to completely account for all trend effects.

On the other hand, the covariables completely accounted for all effects from trends in the occupancy data sets. There were significant decreases in occupancy at both NE 205th and NE 185th.

This time period seemed to be at a transition between the trends associated with summer traffic and the more congested and unstable flow associated with non-summer peak period traffic. Some of the variables appeared to have been affected by the predictive algorithm; however, the effects of the linear trend were still apparent.

Results: 6:45 to 7:00 a.m.

In this time period, significant increases in volume and significant decreases in occupancy were found at 236th SW and NE 205th. Basically no change in volume or occupancy occurred at NE 185th.

In this time period, the covariables completely accounted for all trend effects.

The shift in volume and occupancy at 236th SW and NE 205th corresponded to a shift to less congested flow through this section of freeway.

As an example of the changes in traffic occurring during this time period, Figure 8 shows a volume/occupancy curve for NE 205th, both before and after implementation of the predictive algorithm. This curve represents data during a portion of the a.m. peak period, 6:45 a.m. to 7:00 a.m., and therefore shows only the peak in the traditional v/o curve.

The main difference between the two time periods is in the spread of the data points. The "after" time period shows a much tighter grouping of the data points in comparison to the "before" time period. Generally, occupancy values were less than 20 percent in the "after" period. This percentage translated into a more stable flow of traffic at NE 205th through the use of the predictive algorithm to reduce the number and/or severity of bottlenecks between NE 205th and NE 195th. This flow is represented on the v/o curve as a shift backwards, away from the unstable flow regime.

Traffic congestion between 236th SW and NE 205th during this time period appeared to have been reduced by the reduction in bottlenecks between NE 205th and NE 195th and, therefore, vehicle throughput increased. This change is represented as a shift backwards, towards the less congested flow regime, on the traditional v/o curve. However, since NE 185th was already operating at capacity in the "before" data, and no changes occurred downstream of NE 185th to affect its capacity, traffic conditions at NE 185th did not change.

These changes in volume and occupancy during this time period should have meant queuing from NE 185th and continuing upstream. This expectation was substantiated by observations of the 7:00 to 7:15 time period at NE 205th in Table 4. It shows virtually no change in volume or occupancy because of downstream capacity constraints. In essence, a shockwave had moved upstream from NE 185th and, on the average, reached NE 205th by 7:00 to 7:15 a.m.

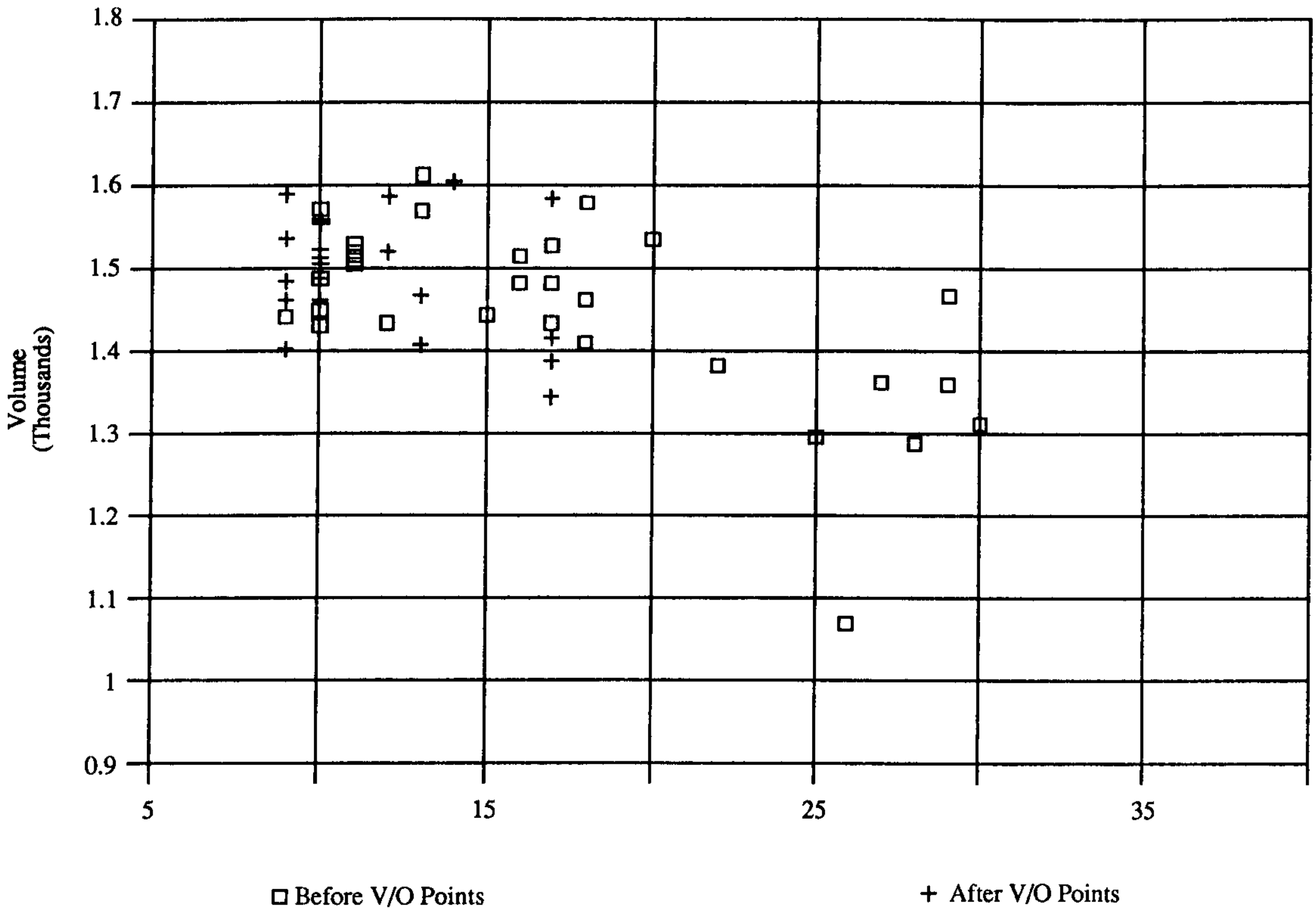

Figure 8. Volume/Occupancy: Plot NE 205th

Results: 7:00 to 8:00 a.m.

Results from the intervention analysis between 7:00 and 8:00 a.m. were very similar for all stations. Virtually all changes were insignificant. Most volume and occupancy values showed insignificant decreases attributable to the intervention, while a few time periods still experienced some trend effects.

The lack of conclusive results during this time frame was expected. The predictive algorithm was calibrated to work best under lightly congested traffic conditions. The 7:00 to 8:00 a.m. time frame was generally represented by heavily congested flow, which reduced the effectiveness of the predictive algorithm. The results confirmed this.

QUEUING RESULTS

Table 6 summarizes the on-ramp queuing results in terms of the mean length of time, standard deviation, and maximum length of time an on-ramp was metered in the advance queue override condition. The data sets used for this analysis included 23 days of "before" data and 18 days of "after" data. These data sets were limited in size because of printer errors and priority conflicts. Significant results with these small data sets are virtually impossible. However, some general observations may be made.

Throughout the entire data collection time frame, the only ramps experiencing the advance queue override condition were the on-ramps upstream of NE 205th. These on-ramps were all directly affected by the predictive algorithm. The on-ramps downstream of NE 205th, the on-ramps that would have been used as covariables in the queuing intervention analysis, never experienced the advance queue override condition during the entire before and after data collection effort. Therefore, conducting an intervention analysis on the queuing data became impossible because of the lack of any covariables.

Table 6. Queuing Analysis

Before Data Set

	On-Ramp Locations																	
	44 SW-l(1)			44 SW-R(2)			220 SW			236 SW			NE 244			NE 205		
End Time	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max
6:15																		
6:30																		
6:45	0.17	0.7	3.0															
7:00	0.30	1.0	4.0										0.13	0.5	2.0			
7:15	0.65	1.6	5.0	0.09	0.4	2.0	0.17	0.5	2.0	0.09	0.4	2.0	0.70	1.3	4.0			
7:30	0.78	1.2	3.0	0.57	1.3	5.0	0.48	1.2	5.0	0.44	0.9	3.0	1.83	2.4	9.0			
7:45	0.26	0.5	2.0	0.04	0.2	1.0	0.83	1.6	5.0	0.04	0.2	1.0	2.26	2.5	7.0			
8:00	0.09	0.3	1.0				0.04	0.2	1.0				0.13	0.3	1.0			

After Data Set

	On-Ramp Locations																	
	44 SW-l(1)			44 SW-R(2)			220 SW			236 SW			NE 244			NE 205		
End Time	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max	Mean	Std	Max
6:15																		
6:30																		
6:45	0.39	1.2	5.0				0.06	0.2	1.0									
7:00	0.33	0.8	3.0				0.17	0.7	3.0									
7:15	0.94	1.6	5.0	0.22	0.6	2.0	0.06	0.2	1.0				1.72	2.2	7.0			
7:30	1.94	1.6	5.0	0.78	1.2	3.0	2.11	3.2	10.	0.11	0.5	2.0	2.11	2.3	6.0			
7:45	1.50	1.9	6.0	0.17	0.5	2.0	1.56	2.4	9.0	0.17	0.7	3.0	2.44	2.3	8.0			
8:00	0.28	0.6	2.0				0.50	1.1	4.0				0.06	0.2	1.0			

Note: All values in minutes. Blanks indicate zero (0).

(1) Left lane of a two-lane on-ramp.
(2) Right lane of a two-lane on-ramp.

It is very difficult to conclusively state that the predictive algorithm affected on-ramp queuing. In general, the mean and maximum length of time an on-ramp was metered in advance queue override increased for both lanes at the 44th SW and the 220th SW on-ramps. The 220th SW on-ramp also experienced advance queue override conditions one-half hour earlier in the "after" time frame. One explanation for these changes could be the shift in departure times associated with the home to work trip during the summer months. If commuters truly left later because of better driving conditions in the summer months, fewer vehicles would have used the on-ramps before metering had been initiated. This situation would have increased queues in later time periods.

The inconclusiveness of these data is demonstrated by the advance queue override data at NE 205th. NE 205th was the closest on-ramp to the predictive algorithm test section, NE 205th to NE 195th. Any prediction of a bottleneck should have reduced metering rates at the NE 205th on-ramp more severely than at any other upstream on-ramp because of NE 205th's proximity to the bottleneck section and, therefore, its greater and more immediate impact on the bottleneck section.

Yet in neither the "before" nor "after" data set was NE 205th metered in advance queue override. Apparently, the predictive algorithm had no impact on ramp queues at NE 205th.

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