EVALUATION OF A PREDICTING ALGORITHM FOR A REAL-TIME RAMP CONTROL SYSTEM

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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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EVALUATION OF A PREDICTING ALGORITHM FOR A REAL-TIME RAMP CONTROL SYSTEM

VOLUME III

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ABSTRACT

EVALUATION OF A PREDICTIVE ALGORITHM FOR A REAL-TIME RAMP CONTROL SYSTEM

by Iris Cabrera-Gonzalez

This report evaluates a statistical pattern recognition-based predictive algorithm that was tested on-line with the ramp metering computer system of the Washington State Department of Transportation in Spring, 1990. The purpose of this algorithm was to forecast bottleneck formation 1 or 2 minutes in advance of its occurrence, and to adjust ramp metering rates in order to avoid or decrease bottleneck formation. The evaluation of this algorithm was conducted by applying multiple linear regression techniques to traffic volumes and occupancy time series data collected by the Washington State Department of Transportation's Transportation System Management Center (TSMC). In addition to the statistical analysis, the accuracy of the algorithm's predicting ability was evaluated using the computer generated prediction messages printed during the study period. The results show that the predictive algorithm was able to correctly predict traffic conditions 80 percent of the time, with a congestion detection rate of 58.6 percent. While the impact of the predictive algorithm was not significant during heavily-congested traffic periods, it had a positive impact on the traffic conditions during those periods when occupancy on the mainline reached values of up to 18 percent.

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1. INTRODUCTION

PROBLEM STATEMENT

The Washington State Department of Transportation (WSDOT) operates a traffic responsive ramp control system on a section of Interstate-5 north of Seattle to cope with recurrent freeway traffic congestion. The system, which is described in detail in the last section of this chapter, operates effectively as long as congestion on the metered freeway section is not excessive. When this freeway section is excessively congested, the only option within this system is to introduce more restrictive metering rates. The system is, thus, reactive rather than anticipatory, which means it is only able to respond to existing traffic conditions rather than anticipate them. To enhance the performance of the WSDOT ramp metering system, predicting capabilities need to be added to the existing real-time control strategy.

At the University of Washington the short term prediction of traffic flow variables for application to the development of predictive algorithms has been the subject of continuous research. Among different approaches tried, pattern recognition techniques have been successfully applied to the development of predictive algorithms. (1,2,3) On the basis of these techniques, an algorithm was developed that forecasts freeway traffic congestion 1 or more minutes in advance of its occurrence. During the spring and summer of 1989, this algorithm was tested on-line at the ramp metering computer system of the WSDOT's Transportation System Management Center (TSMC). In contrast to the controlled conditions of simulated testing, the on-line testing provided an opportunity for the algorithm to perform under real life conditions.

The locations of the study area and freeway section where the algorithm was tested and evaluated are illustrated in Figure 1.1 and Figure 1.2, respectively. The test section consisted of approximately 1.5 miles of Interstate-5 northbound. Within this freeway section, the subsection immediately downstream of the NE 205th St. Station, shown in Figure 1.2, routinely experiences traffic congestion during morning peak periods.

In addition to forecasting traffic congestion, the algorithm adjusted ramp metering rates at the on-ramps upstream of the bottleneck section in order to prevent or decrease the severity of congestion build-up. The forecasting routine and subsequent ramp metering adjustment procedure are shown in Figure 1.3.

The impact of the algorithm's intervention was evaluated using the "time series intervention analysis" technique (4,5), where "intervention" refers to the adjustment of ramp metering rates made by the algorithm during certain days within the study period. Time series intervention analysis has been described in several technical reports, and is discussed further in Chapter 3.

The results of the predictive algorithm's intervention showed that some improvement of traffic conditions was obtained. The validity of these results may have been affected, however, by three factors:

- the type of time series intervention design,
- the time frame of the data collection effort, and
- the relatively small size of the "after" data set,

These factors are discussed further in Chapter 2.

In summary, even though the predictive algorithm's intervention seemed to have had a significant impact on the traffic conditions, the factors mentioned above may have affected the results. Therefore, additional research to address those problems was done.

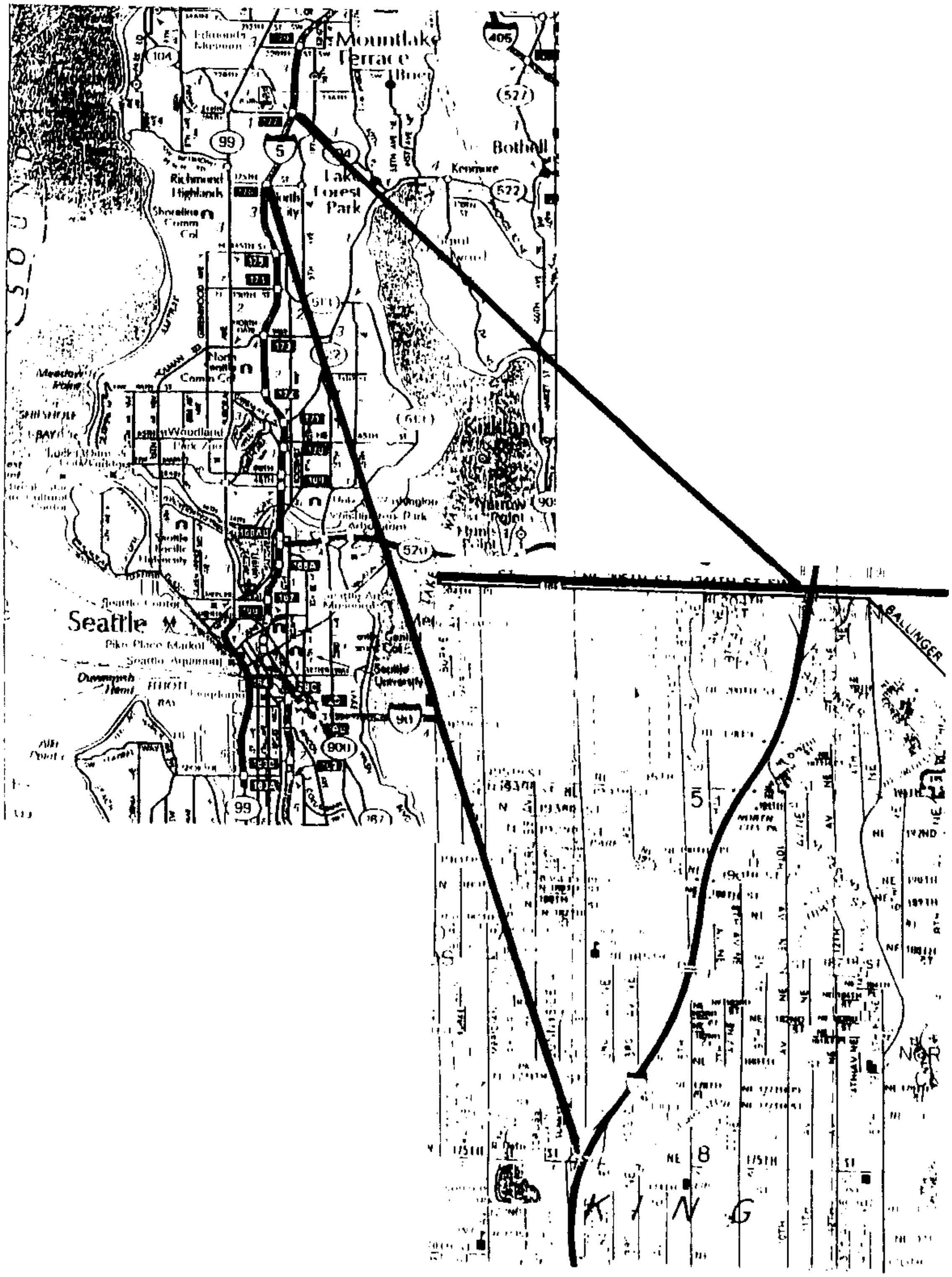

FIGURE 1.1 GENERAL LOCATION OF STUDY AREA

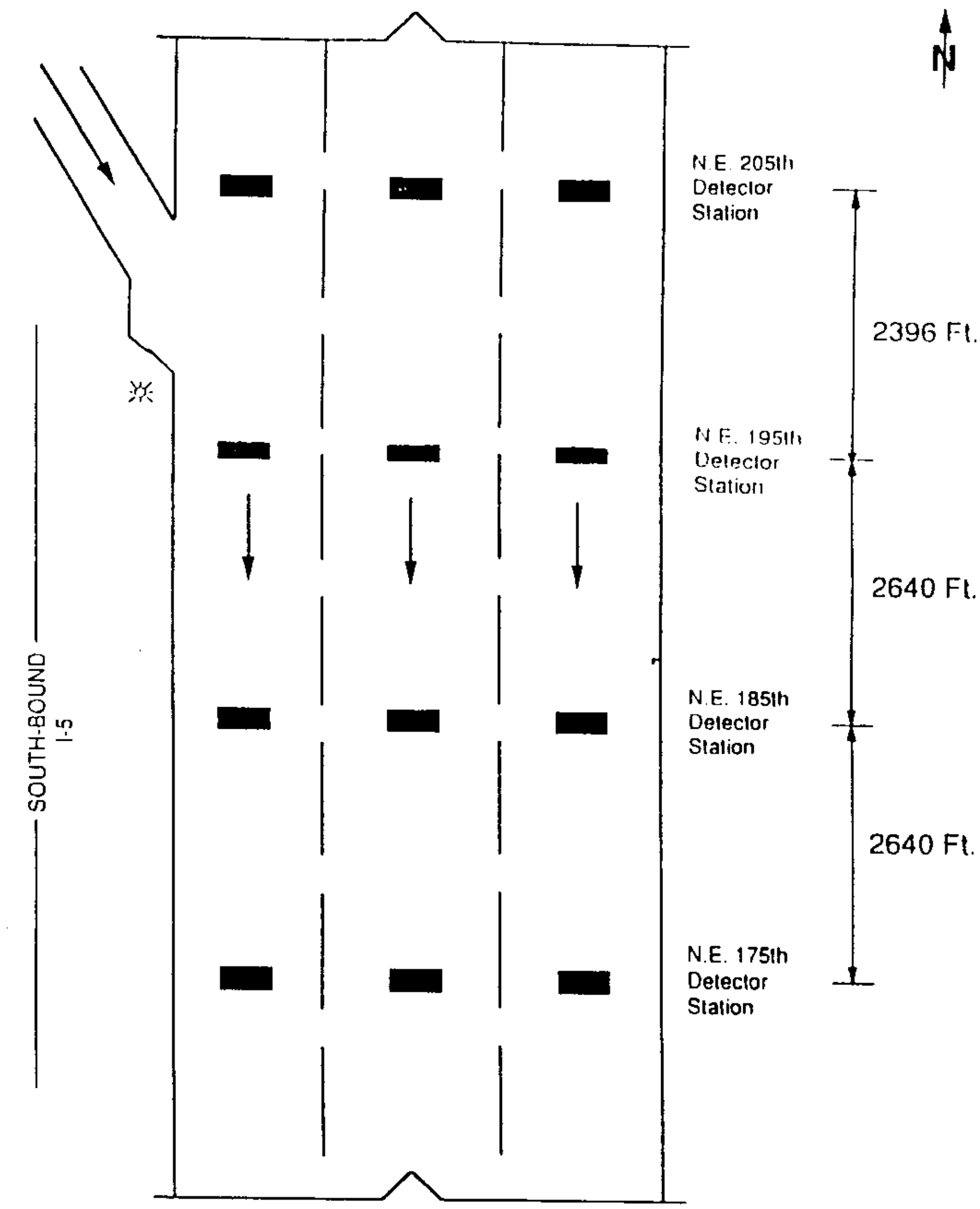

FIGURE 1.2 SECTION OF I-5 USED FOR TESTING AND EVALUATION OF PREDICTING ALGORITHM

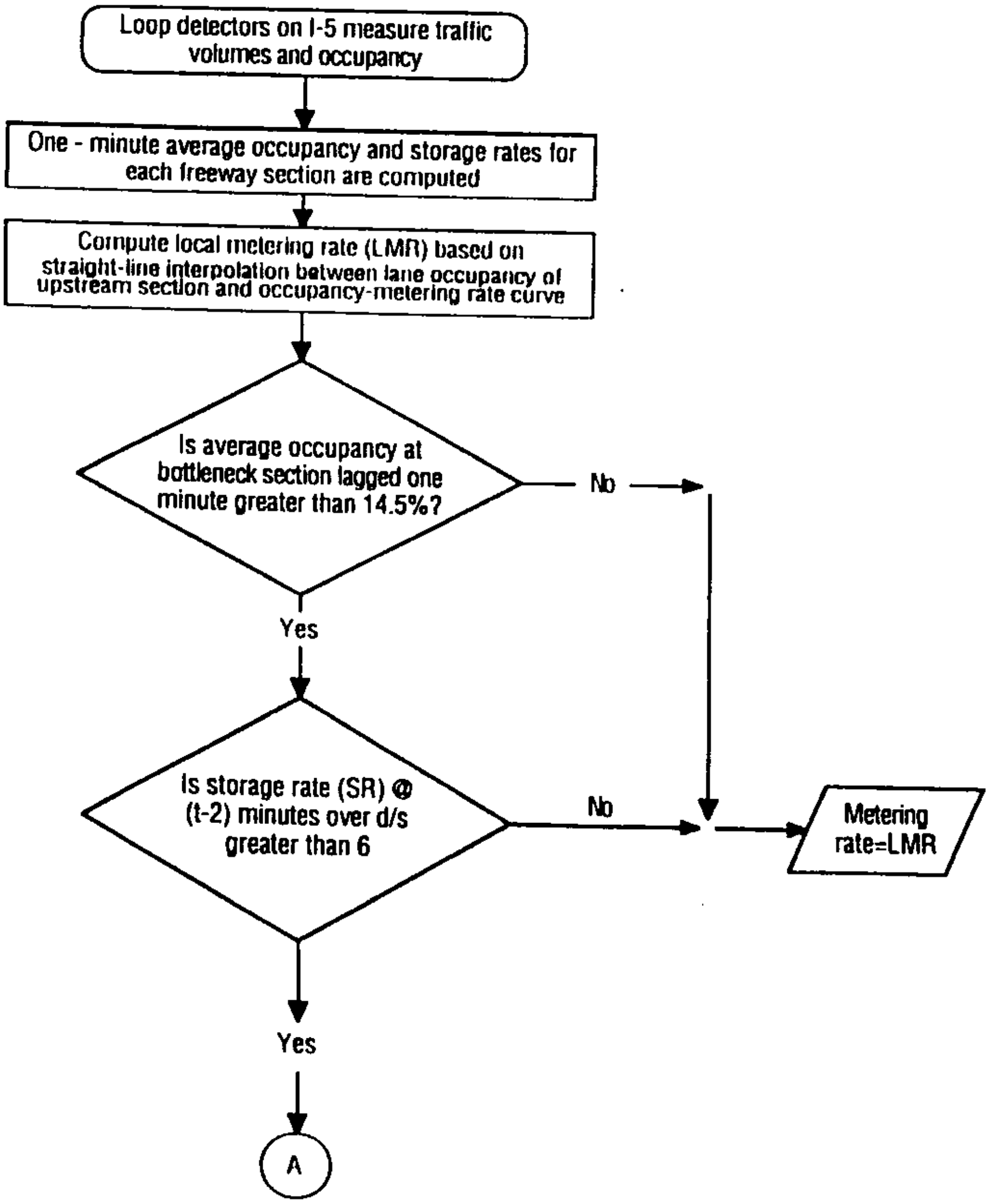

FIGURE 1.3 WSDOT'S TRANSPORTATION SYSTEM MANAGEMENT CENTER IMPLEMENTATION OF PREDICTING ALGORITHM

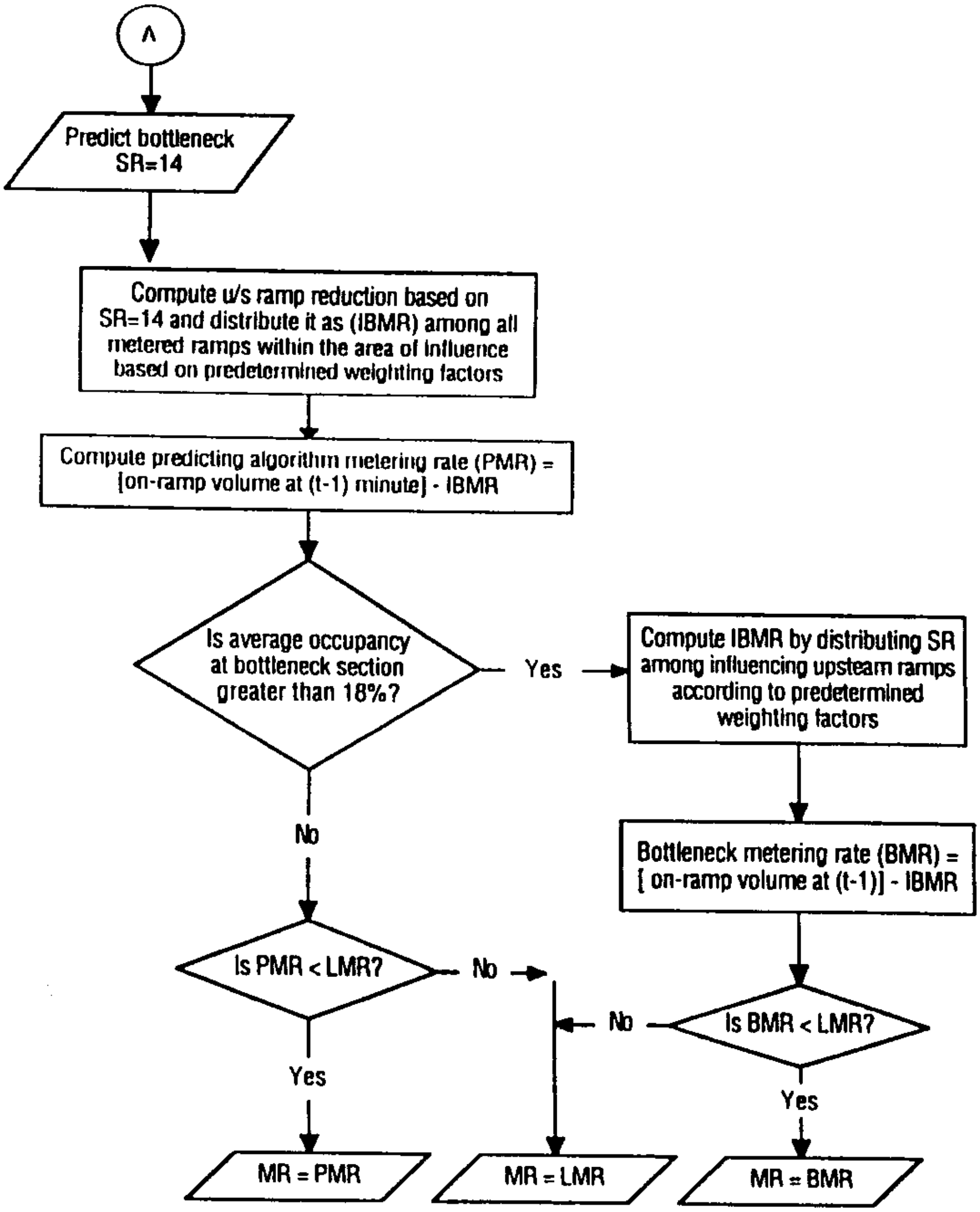

FIGURE 1.3 CONTINUATION: WSDOT'S TRANSPORTATION SYSTEM MANAGEMENT CENTER IMPLEMENTATION OF PREDICTING ALGORITHM

The first stage of the research consisted of on-line testing of the algorithm and data collection. This was implemented by TSMC in Spring 1990. The second stage consisted of evaluation of the impact associated with the algorithm's intervention using the data collected by TSMC. This research report presents the procedure and findings of that second stage.

RESEARCH OBJECTIVE

The main objective of this report was to reevaluate the predictive algorithm's performance. Two aspects of these performances were evaluated:

- the accuracy of the algorithm's predicting ability, and
- the type and significance of the algorithm's impact on the traffic conditions of the study section.

Although each of these analyses was estimated separately, they were analyzed together because of the interdependent relationship of the data. For instance, traffic conditions affect the ability of the algorithm to make predictions. In turn, the algorithm's intervention affects traffic conditions.

In summary, the main objective of this research was to determine how effectively the algorithm anticipated traffic congestion, and what improvements in the traffic conditions were obtained as a result of the adjustments of ramp metering rates. Some expected improved traffic conditions, for instance, could be maximization of capacity (an increase in vehicle volumes), improvement in level of service (LOS), or, simply, the attainment (or maintenance) of stable traffic conditions throughout the freeway section.

BACKGROUND

The urban activity system, that is, the spatial distribution of people and activities within an urban area, is shaped by a variety of social and economic conditions. These conditions can result in population growth and the addition and relocation of businesses. As a result, complex travel patterns are generated. The problem is, that while the urban area steadily evolves, the transportation system that serves it has only been marginally adjusted. For instance, areas that were once bedroom communities scattered throughout metropolitan areas, have become high-density suburban centers that support a variety of economic activities. Existing transportation systems, were designed and built based on the conditions that existed at the time of their construction, that is, they were meant to serve the travel pattern generated between the metropolitan area and the suburbs. The current urban situation generates increased and complex traffic demands. (6) Freeways are forced to accommodate, for example, an increasing number of short trips people make between the suburbs and metropolitan areas, as opposed to a moderate amount of long trips. This imbalance of increased and constant demand and limited supply, results in either complete stoppage of traffic flow or in restriction or interference of normal traffic flow.

Depending on its degree of predictability, freeway traffic congestion has been classified into two types: recurrent and non-recurrent. (7) Recurrent freeway congestion occurs routinely during specific time periods and locations, such as morning and afternoon peak periods; at freeway locations that provide access from or to employment areas; the Central Business District, etc. Recurrent congestion is typical in locations where geometric deficiencies decrease the freeway's operational capacity, causing bottleneck formation during peak periods. Non-recurrent congestion, on the other hand, occurs randomly, with regard to location and time. It is unpredictable; it can happen anywhere, at any time. Frequent causes of non-recurrent congestion are traffic incidents, accidents, and bad weather. The worst traffic congestion is the result of all three conditions happening concurrently, for example, a traffic accident in bad weather occurring during peak hours. Regardless of the type, freeway traffic congestion has serious consequences in terms of economic losses, environmental pollution, accident risks, delay, and driver frustration and discomfort. For freeway users, commuters especially, traffic congestion is a problem that frequently occurs. The amount of traffic congestion commuters are willing to put up with is related to the length of their trip. (8) For instance, commuters making short freeway trips, though not pleased with complete stoppage or stop and go conditions are willing to sacrifice some travel time. On the other hand, the longer the trip, the more impatient drivers become regarding extended travel time. In addition, longer freeway trips made in highly congested freeways, (where density is greater than 42 vehicles per mile) cause increased tension that most drivers are unwilling to tolerate. Therefore, for all the reasons mentioned above, freeway congestion is a problem that must be faced.

The traditional approach to the freeway congestion problem prior to the early 1970s was to increase capacity. As people began to experience the negative side effects of freeway construction in terms of social, economic, and environmental impact, and as governmental budget restraints limited the resources allocated to new freeway construction, a new philosophy began to emerge. Incorporated in the transportation system management's (TSM) approach to the traffic congestion problem, the basic principle of this approach is to maximize the efficiency of the existing transportation system. Within TSM, two broad areas have been developed: demand management and supply management. Demand management is mainly concerned with the reduction of peak-period vehicular demand. This is achieved by redistributing vehicular demand over time so that the concentration of traffic during peak periods is reduced. Examples of demand management techniques are peak-period dispersion, ridesharing, and transit system improvements. Supply management is concerned with effective redistribution of travel demand within the existing facilities. Examples of supply management techniques are:

entrance ramp control,

mainline control,

corridor control, and

priority control. (9)

Both demand and supply management techniques have been applied with varying degrees of success in the United States. In the Seattle metropolitan area, traffic congestion will continue to increase due to a projected population increase of up to 29 percent by the year 2000. (4) WSDOT has developed a TSM program to cope with Seattle's freeway congestion. The Freeway and Arterial Management Effort (FAME), implemented in 1987, is an example of WSDOT's strategy to maximize the operational efficiency of the freeway and arterial system. (10) Since then, a number of procedures for improving and comparing traffic management systems have been planned, designed, and implemented.

Ramp metering is another key element of WSDOT's TSM program. WSDOT's Transportation System Management Center operates an integrated traffic-responsive on-ramp control system in a section of Interstate-5 north of Seattle. This ramp metering system uses real-time volumes and occupancy data measured by loop detectors that are placed along the mainline freeway and at exit and entrance ramps. These data are used by an on-line algorithm at The TSMC's central computer system to estimate on-ramp metering rates. The algorithm's local metering routine determines on-entry rates based on the measurement of lane occupancy at the section immediately upstream of the metered ramp. When the demand for use of a section of freeway exceeds its capacity, bottlenecks form and a "bottleneck" routine is implemented. The "bottleneck" routine first estimates on-entry rates (the bottleneck metering rate, BMR) by distributing the storage rate (the number of vehicles "stored" on that freeway section in the past minute), among all metered ramps within its area of influence according to predetermined weighting factors, and then subtracts this value from the on-ramp volume. This bottleneck metering rate (BMR) is then compared to the local metering rate (LMR), and the most restrictive one is applied during the next control interval. Too restrictive metering rates can cause queuing at on-ramps to spill over onto the arterial system. To prevent this from occurring, when queuing at on-ramps goes beyond the advance queue detector, metering rates are automatically increased. The resulting metering rates, however, can never exceed 24 veh/min or be less than 5 veh/min.

The most significant problem of the WSDOT's on-ramp control system is that it is unable to anticipate or prevent system overloads. That is, once traffic congestion occurs, the only option is to restrict even more access at vehicle on-ramps; however, at that point, the reduction in speed and instability has already affected the mainline traffic system.

One way to optimize the WSDOT's on-ramp control system is to include a forecasting routine that would allow for the anticipation of bottleneck formation. At the University of Washington the application of statistical pattern recognition principles to the development of an algorithm that forecasts bottleneck formation has shown encouraging results. This research evaluates the performance of the predictive algorithm. The implementation of an effective predicting type algorithm at the WSDOT's ramp control system would greatly enhance the ability of this system to cope with recurring freeway traffic congestion.

APPENDIX A

RAMP CONTROL SYSTEMS

During the last twenty years ramp control systems have become an important element of urban freeway management programs throughout the world. The main purpose of such systems is to improve overall freeway operation by limiting the rate at which vehicles enter the freeways. Some of the benefits associated with the implementation of ramp control systems are reduced accident risks, minimization of freeway travel time, reduction in vehicle operating costs, reduced fuel consumption, and less pollution. Ramp control systems include ramp closures, merge controls, priority-entry controls and ramp metering. (9)

Ramp closure has been recommended in cases where there is not enough storage capacity at on-ramps to accommodate vehicles waiting to enter the freeway, or when the freeway section upstream of the on-ramp operates at capacity. Although successfully implemented in Japan, Europe and the United States, ramp closure attracts strong public opposition. Therefore, its application has been somewhat limited. Ramp metering is the most frequently implemented ramp control system. It has been improved by application of automatic control theory and advanced computer technology. This is reflected by the evolution of control modes and control strategies, which have increased in sophistication.

The control mode is used in ramp metering systems to determine ramp signal cycle and metering rates. Ramp metering systems fall into three basic control mode categories: pre-timed, local traffic responsive, and integrated traffic responsive. (11) With the pre-timed control mode, ramp metering rates are only governed by the time-of-day, day-of-week, and occurrence of special events. A metering plan is established based on studies of the historic traffic conditions corresponding to the freeway mainline at the vicinity of the controlled ramp. Payne/Thompson used optimization techniques to establish a fixed ramp metering plan aimed at achieving optimum corridor traffic conditions in their research. (12) The problem with the model developed was the assumption of fixed traffic demand over both the short run and the long run. In real situations, demand is not constant over time, it fluctuates around mean values. Papageorgiou developed a dynamic freeway traffic optimization model to derive a time-of-day control strategy that takes into account not only the evolution of traffic flow over a given time period, but also the time delay associated with changes in volume at on-ramps and their corresponding disturbances at downstream freeway sections. (13)

With the local traffic responsive control mode ramp signal cycle and ramp metering, rates are directly affected by the traffic conditions occurring in the immediate vicinity of the controlled ramp. Because metering rates are based on real-time measurements of traffic flow variables, the system is able to respond to short-term fluctuations in demand. Resulting metering rates are, thus, related to the characteristics of freeway traffic flow.

The integrated traffic responsive control mode controls a series of ramps as a single system. For each control interval, a metering strategy is calculated at a central computer based on real-time system-wide traffic conditions. The results are then used to determine the metering strategy for the next control interval, and the process repeats continuously. In this way, metering rates are adjusted in response to real-time system-wide traffic conditions.

Though guidelines have been developed for the analysis, design, and implementation of ramp metering systems, adequate procedures for the evaluation of their effectiveness have not been proposed. The literature offers relatively few studies of ramp metering systems of which the effectiveness has been thoroughly evaluated. Despite the problem caused by the absence of adequate evaluation procedures that would allow comparison between different ramp metering systems, some projects have been successful in achieving some of the benefits mentioned at the beginning of this chapter. For instance, the ramp metering system implemented at Harbor Freeway in Los Angeles, California achieved considerable operational gains. (14) The comparison between before and after conditions showed a significant reduction in freeway delay, while not affecting the traffic conditions at the parallel street system. Ahmed, in his overview of urban freeway management technology, discussed other successful ramp metering systems implemented throughout the United States, Europe, and Japan. In the Chicago area, impressive operational gains were obtained as a result of ramp metering. A reduction of up to 60 percent of peak-period congestion and a reduction of up to 18 percent of accidents were attained. In the Seattle portion of Interstate-5, an evaluation of ramp metering impacts and traffic volumes conducted using time series analysis techniques showed that decreased traffic volume occurred as a result of ramp metering implementation. (15) Ramp metering kept mainline traffic volumes under capacity.

Successful existing ramp metering systems have addressed a previously severe degree of traffic congestion and included a parallel street system with the ability to absorb traffic diverted by the ramp meters.

SHORT-TERM PREDICTIVE ALGORITHMS FOR IMPROVEMENT OF REAL-TIME CONTROL STRATEGIES

The motivation behind modeling short-term freeway traffic forecasting is that by adding forecasting capability to traffic-responsive ramp metering systems, improvement in freeway traffic conditions is more feasible via optimized surveillance and control methods. Considerable research has been done in the development of short-term traffic forecasting models to enhance the performance of freeway controls. This research has not been entirely successful. Freeway traffic flow is a very complex phenomenon, characterized by non-linearity and non-stationarity, which greatly complicates the freeway traffic modeling process. Payne discussed the discontinuity that characterizes the volume/density curve at the transition from an uncongested to congested traffic flow regimen. (16) Based on the results of that research, Davis and Nihan corroborated the need for an anticipatory, rather than reactive, ramp metering strategy, given the two-regimen nature of freeway traffic flow and the transitional nonequilibrium stage that occurs between the two regimens.(17) Short-term traffic forecasting models generally belong to two broad categories: ad-hoc models and point-process models.

AD-HOC MODELS

Ad-hoc models, also referred to as descriptive or correlative models, are not based on causal analysis, but rather on arbitrary weighing schemes assigned to current or previous observations of traffic flow variables under consideration. Models, such as second and third generation urban traffic control systems (UTCS-2 and UTCS-3), moving average, exponential smoothing, and adaptive exponential smoothing are examples of ad-hoc models. Comparative analysis of the performance of four ad-hoc short-term traffic predicting models, conducted by Stephanedes, showed that UTCS-2 performed consistently better than UTCS-3, but not significantly better than moving average models. (18) Kreer pointed out that one possible reason for an only slight gain in performance was that the vehicles measured by the detectors were not the ones to which resulting changes in control strategy were applied. (19) The most serious criticism of ad-hoc traffic predicting models is that the averaging and aggregating that take place within these models destroy their ability to forecast the short-term fluctuations that are typical of traffic flow processes.

POINT PROCESS TRAFFIC PREDICTING MODELS

The second category of short-term traffic models, point-process models, are categorized on the basis of the properties of the observations and the characteristics of the underlying processes that generate those observations. In other words, these models take into account the stochastic nature of the processes under consideration. The time-series forecasting models, based on Box-Jenkins analysis techniques, Kalman filtering theory, spectral analysis, and cross-spectral analysis are typified in this category.

Box-Jenkins analysis techniques have been successfully applied to freeway traffic data, not only for prediction purposes, but also for incident detection analysis, (20) and estimation of changes in level of service. (21) By using these techniques, Ahmed and Cook developed a short-term freeway forecasting model based on traffic volumes and occupancy time-series data collected at three freeway surveillance system locations in Los Angeles, Minneapolis, and Chicago. (22) By following the general Box-Jenkins procedure, which involves preliminary identification, estimation, and diagnosis checks, an ARIMA model (0,1,3) was fitted to the time-series data. When compared to the performance of moving average, double exponential, and adaptive exponential smoothing models, the performance of this model was considered superior. Levin and Tsao also fitted ARIMA (p,d,q) models to freeway traffic volumes and occupancy data collected at two freeway locations of the Dan Ryan Expressway in Chicago, Illinois.(23)

Among the several ARIMA models investigated, the ARIMA performed up to 50 percent better. In addition, the research concluded that 60 seconds was the optimum interval, and that traffic volumes were more stable predictors than occupancy data.

In general, the benefits associated with ARIMA models included ease of application, flexibility, and accuracy. One significant weakness of these models was their inability to forecast extreme values; that is, the predicted values tended to hover around or follow the mean values. (2)

Spectral analysis is another type of time-series modeling technique that has been applied to the development of short-term traffic forecasting models. This technique is especially suitable for the prediction of time-series processes that exhibit cyclical and long-term trends. It involves the series expansion of a set of model functions (periodic behavior), and previously measured data that takes the form of a covariance matrix. The series expansion represents the broad class of non-stationary random processes. Nicholson and Swann applied this method to traffic volumes of four lanes of the Messey tunnel in England. (24) The quality of the prediction obtained was relatively high, with resulting prediction errors of 8 percent for morning peak data and 11 percent for afternoon peak data. This method was determined to be satisfactory for on-line implementation in traffic control.

The last point-process forecasting model reviewed was the model based on the Kalman filtering theory. Okutani and Stephanedes successfully applied the Kalman filtering approach in predicting 15-minute traffic volumes. (25) A comparison of this model and UTCS-2 showed the Kalman filtering theory to be superior. Additional benefits were its ability to predict traffic volumes based on data from connecting links and its reasonable computation time requirements.

PATTERN RECOGNITION MODELS

In addition to point-process and ad-hoc models, recent approaches to short-term traffic modeling include the application of pattern recognition principles. Statistical and non-parametric pattern recognition models have been developed by Davis and Nihan (2), and Babla and Nihan. (3) Davis and Nihan applied a non-parametric pattern recognition model, the K-nn (or nearest neighbor model), to freeway traffic data measured at a section of Interstate-5 in the state of Washington. (17) The general modeling procedure involved the construction of a learning sample of input and output pairs. From this learning sample, inputs were classified according to their distance to a specific input value x(t), from which an output value y(t) was forecast. The forecast value is the average output corresponding to the nearest neighbor of the input value x(t). The K-nn model did not perform significantly better than the forecasting models based on Box-Jenkins techniques.

The main purpose of applying statistical pattern recognition to the development of short-term freeway prediction models was to develop decision rules for classifying traffic data (input vectors) into those preceding congested traffic conditions and those preceding uncongested traffic conditions. The discriminating or decision function is identified by class of probability densities defined by parameters, such as the mean and covariance, used to derive the decision function.

Nihan and Davis developed a short-term freeway forecasting model for specific application to real-time ramp metering control strategy. (2) One-minute occupancy, and input and output difference (I/O) data measured at a routinely congested section of Interstate-5 north of Seattle, were classified into those meeting bottleneck conditions (I/O>0, and occupancy >18 percent), and those preceding uncongested traffic conditions. The next step was to sort the lagged measurement of the other variables (I/O and occupancy data measured downstream and upstream of the bottleneck section) into those preceding bottleneck formations and those preceding uncongested traffic conditions. The box plot feature of Minitab was used to evaluate the lagged variables' ability to discriminate between bottleneck (congested) and non-bottleneck (uncongested) intervals. The best candidates obtained were the occupancy of the bottleneck section lagged 1-minute and I/O difference of the downstream section lagged 2-minutes. This model has been tested on-line and evaluated, and the results, although satisfactory, warrant additional research. The Babla/Nihan model was developed in order to improve the accuracy level obtained with the Nihan/Davis model. A comparison of these models via simulation testing using INTRAS software showed that although the Babla/Nihan model achieved higher system-wide average speed and lower system-wide total delay, the accuracy of its predicting capability was not better than that of the Davis/Nihan model.

2. RESEARCH DESIGN

INTRODUCTION

During the spring of 1990, a new on-line testing of the predictive algorithm was performed by integrating it into WSDOT's ramp metering system at TSMC. The predictive algorithm was implemented into the existing on-line control strategy according to the procedure shown in Figure 1.3. The predicting process and subsequent ramp metering rates adjustment that occurred during the on-line testing are referred to as the predictive algorithm's intervention. During the study periods, that intervention was in effect at three separate intervals. In between those intervals, the on-line testing was temporarily interrupted to allow conditions to return to normal.

Data on traffic volumes and occupancy, measured by loop detectors placed at the station shown on Figure 1.2., were collected by TSMC, and used to evaluate the impact of the predictive algorithm's intervention on the traffic conditions of the study section. The evaluation was performed by applying multiple linear regression techniques to the traffic volumes and occupancy data aggregated in 5-minute periods from 6:00 am to 8:00 am. Two statistical packages, MINITAB and SST, were used to perform the statistical analysis.

In addition to the statistical analysis, the accuracy of the algorithm's predicting ability was estimated using the prediction messages printed during the on-line testing and during the time intervals the intervention was not in effect.

PREDICTIVE ALGORITHM ON-LINE TESTING AND DATA COLLECTION EFFORTS

Three factors seemed to have clouded the results of a previous evaluation of the predictive algorithm's intervention; the type of intervention design, the time frame of the data collection effort, and the size of the after data set. (4) The data for the evaluation were collected over a time frame that included two seasons, eliminating seasonal effects that could have been confused with intervention effects. In addition, the intervention took place during a single time interval that included only 18 days. The size of the after data set was, thus, relatively small.

At TSMC the new on-line test and data collection effort was then designed and implemented with the purpose of overcoming the above-mentioned problems. The rest of this section describes in detail how these problems were addressed.

The predictive algorithm's intervention took place at three separate periods as opposed to a single intervention period. The first period began on February 28, 1990, and lasted for 13 days. The second intervention period began April 10, 1990, and lasted for 12 days. The last intervention period was from May 17, 1990 to June 11, 1990, a total of 17 days.

Only weekdays were included in the analysis since ramp metering is not used on weekends. The data were collected over a period of 3 months during the spring of 1990. By collecting the data during just one season and alternating between on-line and off-line periods within this 3-month interval, it was expected that the seasonal variation in the time series would be minimized. Of the 69 data samples provided by TSMC, 65 were included in the analysis. Some extraneous factors may have affected traffic conditions on the days some of the samples were collected since their values were either too low or too high. Of the 65 data samples used in the statistical analysis, 42 corresponded to the days the predictive algorithm intervention took place. The remaining 23 data samples were collected on days the predictive algorithm made predictions, but did not alter ramp metering rates. Therefore, for the present evaluation, the size of the after data set was 42 data samples collected during three separate periods. The size of the before data sets was 22 data samples collected at two different intervals during the study period.

The size of the data set for the prediction accuracy's estimates corresponding to the intervention period was 26 data samples. Thirty-two data samples were available to estimate the accuracy of the algorithm's predicting ability when only prediction was allowed. As mentioned at the beginning of this chapter, the data for the accuracy estimation consisted of the prediction messages printed during the on-line and off-line intervals.

TRAFFIC VOLUMES AND LANE OCCUPANCY TIME SERIES

Traffic volumes and occupancy data are collected at TSMC on a continuous basis. Twenty seconds of traffic volumes and lane occupancy averages measured from loop detectors were aggregated in 5-minute intervals from 6:00 am to 8:00 am, which is the time period used for the evaluation of the predictive algorithm's intervention. Thus, for each of the four stations in the study section, two data sets were assembled. The first data set corresponded to the period from 6:00 am to 7:00 am and contained time series of traffic volumes and occupancy for each 5-minute period. The second data set consisted of the same type of data, but was collected from 7:00 am to 8:00 am. The traffic conditions during the period from 6:00 am to 7:00 am can be categorized as lightly congested traffic conditions, while the period from 7:00 am to 8:00 am can be categorized as more congested traffic conditions.

The 5-minute aggregation period was preferred, in this research, to the 15-minute aggregation period used in the past evaluation. In conducting the statistical analysis, the 5-minute aggregation period performed better than the 15-minute aggregation period, at illustrating the impacts of the algorithm's intervention. Five-minute aggregation periods are large enough to smooth out random fluctuations, and yet small enough to show the changes taking place within the AM peak period.

Once the data sets were assembled, the data were screened to account for any unusual observations. Unusual observations, called outliers, are sometimes very useful in providing information about unusual circumstances. In this case, extreme values either too low or too high were considered missing values. Unlike SST, MINITAB has no difficulty dealing with data sets containing missing values.

The time series of traffic volumes and occupancy were plotted prior to the statistical analysis. The time series plots, shown in Appendix B, were analyzed in a preliminary step to determine if the effects of seasonal trends or cyclical variations were present in the time series that could otherwise be confused with the intervention effect. The true characteristics of a given time series can only be confirmed through analysis. Different modeling techniques are used, depending on the type of time series. Past research has shown that traffic volumes and occupancy time series can be characterized as random stationary processes when aggregated in periods greater than 5 minutes. (26) A stationary process, defined from an intuitive point of view, is one that does not experience systematic changes in the mean and variance; that is, there is no long term change in the mean or the variance. In mathematical terms, stationarity is demonstrated if the joint distribution of any consecutive group of points of the time series is constant with respect to displacement in time.

To prove the stationarity and randomness of the time series, which in turn would prove the absence of seasonal or trend effects in the time series, two diagnostic checks were conducted: the run test and autocorrelation function.

The object of the run test is to determine the expected and actual number of runs corresponding to a time series. A run is a set of consecutive data points in the time series either all greater, or smaller, than the mean. For a time series to be considered random, it must have a moderate number of runs with regard to the total number of data points contained in the time series. The expected number of runs as a function of the number of observations was estimated using the following formula: (27)

$$Uk=E(k)=[(2p(n-p)/n)\ +1] \tag{1}$$

where k is the number of runs in the time series, and n is the total number of data points above the mean in the sample. Since the traffic volumes and occupancy time series passed the run test, it was assumed that the condition for randomness was satisfied (see Appendix C).

The condition of stationarity was approved by using the autocorrelation function. The graphic representation of the autocorrelation function, which is called the correlogram, characterizes the structure of the time series (28,29,30). In this case, since the correlograms did not show any long-lasting persistent pattern, and since approximately only one value of the autocorrelation coefficient lay outside the limits of $+/- 2/\sqrt{N}$, the time series was considered random and stationary (see Figure 2.1).

TIME SERIES INTERVENTION ANALYSIS

The purpose of the time series intervention was to determine the effect of the predictive algorithm's intervention on the traffic volumes and occupancy time series collected at the study section. As a result of the predictive algorithm intervention, it was expected that smoother traffic conditions would occur, specifically an increase in traffic volumes and a decrease in occupancy.

Given the characteristics of the time series, multiple linear regression models were fitted. The parameters of the models were estimated using ordinary least square methods. The stationarity and randomness of the time series eliminated the

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8
           +----+----+----+----+----+----+----+----+----+----+-
  1   0.230                         XXXXXXX
  2  -0.029                        XX
  3   0.037                         XX
  4  -0.043                        XX
  5  -0.149                     XXXXX
  6   0.151                         XXXXX
  7   0.124                         XXXX
  8  -0.023                        XX
  9   0.097                         XXX
 10   0.108                         XXXX
 11   0.192                         XXXXXX
 12   0.155                         XXXXX
 13   0.193                         XXXXXX
 14  -0.053                        XX
 15  -0.074                       XXX
 16  -0.078                       XXX
 17  -0.068                       XXX
 18  -0.023                        XX
```

FIGURE 2.1 AUTOCORRELATION PLOT

FIVE-MINUTE OCCUPANCY STATION NE 205

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8
           +----+----+----+----+----+----+----+----+----+----+-
  1  -0.008                         X
  2  -0.017                         X
  3   0.134                         XXXX
  4  -0.089                       XXX
  5   0.133                         XXXX
  6  -0.130                      XXXX
  7  -0.052                        XX
  8   0.050                         XX
  9  -0.110                      XXXX
 10   0.039                         XX
 11   0.114                         XXXX
 12  -0.040                        XX
 13   0.070                         XXX
 14   0.113                         XXXX
 15   0.006                         X
 16  -0.032                        XX
 17  -0.060                       XXX
 18   0.244                         XXXXXXX
```

FIGURE 2.2 AUTOCORRELATION PLOT

FIVE-MINUTE TRAFFIC VOLUMES STATION NE 205 need for using more complicated models, such as spectral analysis or ARIMA models. There was also no need to include covariates as independent variables in the regression equation since the seasonal variation was not significant.

The following multiple regression models were fitted to the time series data to determine the statistical significance of the predictive algorithm's impacts:

$$V_t = a_0 + a_1 I_t + a_2 V_{t-1} + \ldots + a_4 V_{t-3} + a_5 O_t + \ldots + a_6 O_{t-1} + \ldots + a_8 O_{t-3} + e_t \quad (2)$$

$$O_t = b_0 + b_1 I_t + b_2 V_t + \ldots + b_5 V_{t-3} + b_6 O_{t-1} + \ldots + b_8 O_{t-3} + e'_t \quad (3)$$

where:

V_t, O_t : Traffic Volumes and Lane Occupancy for a given 5-minute period, t.

a_0, b_0 : Intercepts of the regression equation.

a_1, b_1: Estimable coefficients of the intervention variable. It represents the expected unit variability of the dependent variable accounted for by the intervention variable; that is, the predictive algorithm's intervention.

I_t : A variable that represents the predictive algorithm's intervention. It is called an indicator or qualitative variable. It took values of either one or zero. (One on days the intervention took place, and zero when it did not).

$a_2, \ldots a_8$

$b_2, \ldots b_8$: Estimable coefficients of the independent variables.

e_t, e'_t: Regression residual.

The regression model was specified mainly to determine the effect of the predictive algorithm's intervention on the traffic flow variables. It expresses the inherent relationship between the level of traffic flow variables corresponding to a specific highway location at consecutive 5-minute periods during the AM peak period. In this sense, the model established a functional relationship based on the continuity of the traffic flow variables within the AM peak period, but, at the same time, it took into account short term fluctuations in traffic flow.

In addition to the coefficient of determination, residual analysis was conducted to check the adequacy of the regression model. Standard residuals were computed and plotted to determine if 95 percent of them fell within the interval between -2 and +2. Since approximately 95 percent of the standardized residuals did fall within this interval range, the assumption regarding the normality of the errors term was validated.

Two problems were encountered in using the regression models specified. One was related to the multicolinearity problem often found when using multiple linear regression. The othere was related to the inclusion of endogenous variables in the regression model.

Multicolinearity is present when the independent or regressor variables are highly correlated; that is, when the absolute value of the coefficient of correlation between the regressor variables equals one. In this situation, the variance and covariance of the regression coefficients become very large, and as a result they are poorly estimated.

In this analysis when multicolinearity was found, some regressor variables were deleted from the model, as recommended in the literature. (31) Given the nature of the data, dropping one or two variables from the basic regression model was the most effective way to deal with this problem.

The inclusion of endogenous variables in the regression model was the second area of concern. Traffic volumes and occupancy for a given time period are interdependent. If both are present in the regression equation, either as the dependent or the independent variable, a method other than the ordinary least square technique should be used to estimate the parameters of the regression equation. (32,33) It is recommended that single equation methods, such as the two-stage least squares method, be used in these cases. However, this requires the creation of instrumental variables, for which no data were available for this study.

The computational method during the model building stage involved a direct search on t. That is, the variable selection procedure started with the full model, which contained eight regressor variables and then, based on each variable's individual contribution to the regression sum of squares, variables were dropped if their t statistics were low. In a significant number of cases, the endogenous variables were dropped from the basic regression model. Therefore, this eliminated the need to use methods other than the ordinary least square technique. The results of the statistical analysis are summarized in Tables D.1 through D.4 in Appendix D. The analysis and interpretation of the results are presented in Chapter 3.

3. ANALYSIS AND INTERPRETATION OF RESULTS

INTRODUCTION

The analysis of the predictive algorithm's intervention involves two aspects:

estimation of the accuracy of the algorithm's predicting ability, and

determination of the statistical significance of the predictive algorithm's impacts.

The results of the statistical analysis are presented in the Tables D.1 through D.4 in Appendix D. Table D.1 contains the results of data collected at the NE 205th St. station, which is the location where traffic congestion usually occurred during the AM peak period. The remaining tables contain the results of data collected at the NE 195th St., NE 185th St., and NE 175th St. stations, all of which are located downstream of the bottleneck section.

The accuracy of the algorithm's predicting ability was estimated based on the prediction message printed during the on-line testing period. Table 3.1 shows the results for the period during which the algorithm was allowed to make predictions without any adjustment of the ramp metering rates. Table 3.2 shows the results obtained during the period when the predictive algorithm's intervention was in effect; that is, when predictions were made and ramp metering rates **were** adjusted. In this case, the prediction indicators were estimated for every 5 minutes from 6:00 a.m. to 8:00 a.m.

PREDICTIVE ALGORITHM'S ACCURACY

In order to determine the accuracy of the predictions made by the algorithms, three indicators were estimated:

percent correct,

false positive rate, and

false negative rate.

Percent correct is an indicator of the overall ability of the predictive algorithm to correctly predict both congested and uncongested intervals. It is a measure of the predictive algorithm's reliability. This indicator was calculated by adding the number of times a congested interval was predicted and occurred, plus the number of times a congested interval was not predicted and, subsequently, did not occur. This total was divided by the number of 20-second intervals contained in the analysis period.

False positive rate is an indicator that represents the probability of having uncongested intervals falsely predicted as congested intervals. The false positive rate was estimated by adding the number of times congested intervals were predicted and did not happen, and dividing this total by the total number of uncongested intervals there were during the analysis period.

The false negative rate is simply the percentage of congested intervals that the algorithm was not able to anticipate. This indicator was obtained by adding the number of times congestion was not predicted but did occur, and dividing this total by the number of congested intervals that occurred during the analysis period.

TABLE 3.1: ACCURACY OF PREDICTIVE ALGORITHM
COMPARISON OF PREDICTION INDICATORS
(Intervention OFF)

	FALSE POSITIVE	FALSE NEGATIVE	% OF CORRECT PREDICTIONS
Cabrera's Evaluation	15.0	41.4	80.8
Berg's Evaluation	7.1	40.8	79.6

The results shown in Table 3.1, which also includes those corresponding to the past evaluation, (4) were based on a combination of lightly- and heavily-congested periods. The only significant difference between the two research groups' results were related to the false positive rates. The false positive rates obtained in this analysis were significantly higher than the ones obtained in the past evaluation, even though the false negative rate and percent correct were similar. One reason for this difference may be attributed to the fact that different data sets have a different proportion of lightly- and highly-congested intervals. The reference here is to highly-congested intervals as those intervals in which traffic congestion actually occurred. In general, from analysis of the prediction messages, one may conclude that a high number of false positive predictions is associated with data sets that contained a relatively high number of lightly-congested intervals. On the other hand, a low number of false positive predictions seemed to be typical of data sets that contained a high number of heavily-congested intervals. In summary, the occurrence of congested and uncongested intervals was correctly predicted 80.8 percent of the time. This is roughly the same percentage obtained in the past evaluation. 41.4 percent of the congested intervals were not anticipated, and 15 percent of the uncongested intervals were incorrectly predicted as congested intervals. The high false positive rate is discouraging; however, it could be an indication of a predominance of lightly-congested intervals, i, that the data set used to estimate these indicators.

Table 3.2 illustrates the prediction indicators obtained for each 5-minute period from 6:00 a.m. to 8:00 a.m., based on the data sets corresponding to the period when the intervention was in effect. Unfortunately, data for only 26 days were available to estimate the prediction indicators. Therefore, it was not possible to obtain a complete picture of the situation.

TABLE 3.2 INTERVENTION ANALYSIS
ACCURACY OF THE PREDICTION INDICATORS
(Intervention ON)

PERIOD	PERCENT FALSE POSITIVE	PERCENT FALSE NEGATIVE	PERCENT CORRECT
6:10-6:15	18.91	43.60	76.1
6:15-6:20	13.22	56.20	77.9
6:20-6;25	10.86	36.76	84.6
6:25-6:30	15.85	45.16	79.5
6:30-6:35	13.43	54.28	78.5
6:35-6:40	14.23	48.86	77.9
6:40-6:45	13.14	64.10	76.7
6:45-6:50	13.08	55.07	79.5
6:50-6:55	15.16	52.07	77.2
6:55-7:00	11.18	41.17	83.6
7:00-7:05	10.80	56.17	81.5
7:05-7:10	16.15	53.22	77.9
7:10-7:15	14.95	44.92	79.7
7:15-7:20	14.95	40.44	78.2
7:20-7;25	15.27	39.21	78.5
7:25-7:30	9.80	41.33	84.1
7:30-7:35	10.43	47.32	78.9
7:35-7:40	11.03	55.00	77.7
7:40-7:45	11.26	50.51	78.9
7:45-7:50	11.98	38.72	82.8
7:50-7:55	9.36	31.86	85.4
7:55-8:00	10.31	35.71	85.1
AVERAGE	**13.10**	**46.90**	**80.10**

The 80.1 average percent correct coincides with the value shown on Table 3.1. The false positive rate (13.1 percent) was not significantly different. It includes the effect of the algorithm's intervention, that is, the number of congested intervals that were anticipated and successfully avoided. The false negative rate (46.8 percent) is somewhat discouraging. One may still contend, however, that the ramp metering system is not worse off than before the predictive algorithm's intervention, since more that 50 percent of the congested intervals were correctly predicted.

The results from Table 3.2 were also useful in explaining or corroborating some of the results of the statistical analysis. In this respect, the most meaningful indicators were the false positive rate and the percentage of congested intervals correctly predicted. Comparing both the false positive rate, shown in Table 3.1 (which was estimated for the entire period of analysis that did not include the effect of the intervention), with the false negative rate for each 5-minute period in Table 3.2 that did include the effect of the intervention, one might assume that the difference represents the actual intended effect of the predictive algorithm, that is, a measure of its ability to avoid traffic congestion. On the other hand, the percentage of congested intervals correctly predicted gives an indication of the number of congested intervals for which the severity was reduced due to the predictive algorithm's intervention. The prediction indicators will be discussed in the next section in the results' analysis.

RESULTS AND INTERPRETATION OF STATISTICAL ANALYSIS

The results of the statistical analysis corresponding to the period from 6:00 a.m. to 6:10 a.m were not included in the analysis and interpretation of results because ramp metering at on-ramps upstream of the bottleneck section usually starts after 6:10 a.m. Therefore, even though predictions were made, ramp metering adjustments did not take place during this period. A summary of the predictive algorithm's significant impacts are shown in Table 3.3. In this table, the numbers in brackets are the coefficients of the intervention variable.

TABLE 3.3 INTERVENTION ANALYSIS
SUMMARY OF SIGNIFICANT STATISTICAL IMPACTS

PERIODS	STATIONS NE 205th St.	NE 195th St.
6:10-6:15	vol $\uparrow$ $p<.10$ [35.49]	vol $\uparrow$ $p<.05$[39.52]
	occ $\downarrow$ ins	occ $\downarrow$ ins
6:30-6:35	vol $\uparrow$ $p<.10$[12.43]	vol ins
	occ $\downarrow$ ins	occ ins
6:40-6:45	vol ins	vol ins
	occ $\downarrow$ $p<.10$[-1.43]	occ ins
6:45-6:50	vol ins	vol $\uparrow$ ins
	occ ins	occ $\downarrow$ $p<.10$[-1.46]
6:55-7:00	vol ins	vol $\uparrow$ $p<.05$[20.03]
	occ $\uparrow$ $p<.05$ [2.33]	occ ins
7:05-7:10	vol ins	vol ins
	occ $\downarrow$ $p<.05$[1.82]	occ ins
7:20-7:25	vol ins	vol $\downarrow$ $p<.01$ [-34.89]
	occ ins	occ ins
7:30-7:35	vol ins	vol ins
	occ $\downarrow$ $p<.10$[-1.65]	occ ins
7:35-7:40	vol ins	vol ins
	occ $\uparrow$ $p<.10$ [3.29]	occ ins

TABLE 3.3 (Continuation)

PERIODS	STATIONS NE 185th St.	NE 175th St.
6:10-6:15	vol ins occ ins	vol ins occ↑ p<.10[.98]
6:15-6:20	vol↓ p<.10[-13.49] occ ins	vol ins occ ins
6:25-6:30	vol ins occ↓ p<.10[-.8361]	vol ins occ ins
6:30-6:35	vol ins occ ins	vol↑ p<.05[12.7] occ ins
6:50-6:55	vol ins occ ins	vol ins occ↑ p<.05[1.63]
6:55-7:00	vol↑ p.<01[24.6] occ ins	vol ins occ ins
7:00-7:05	vol ins occ ins	vol ins occ↑ p.<05[1.63]
7:05-7:10	vol↓ p<.1[-13.3] occ ins	vol ins occ↑ p<.05[1.91]
7:15-7:20	vol ins occ ins	vol ins occ↑ p=.10[1.61]
7:35-7:40	vol ins occ ins	vol ins vol↑ p<.05[-29.9]
7:40-7:45	vol ins occ↑ p<.10 [1.58]	vol↓ p<.05[-20.9] occ↑ p<.05 [2.39]
7:45-7:50	vol ins occ↑ p<.10[15.65]	vol ins vol ins
7:55-8:00	vol↑ p<.10]15.65] occ ins	vol ins occ ins

RESULTS FROM 6:10 A.M. TO 6:15 A.M.

In the following analysis, the researchers refer to the average traffic conditions occurring during each period, illustrated in Figures 3.1 and 3.2.

During the period from 6:10 a.m. to 6:15 a.m., the expected impacts of the predictive algorithms's intervention were clearly noticeable. On the average, traffic flow variables at the bottleneck section corresponded to the level of service D, probably approaching level of service E, with an average traffic volume of 1900 vph and average occupancy of 17.35 percent. These are considered lightly-congested conditions, and are representative of the conditions under which the algorithm was calibrated.

The statistical analysis presented in Table 3.3 shows a significant increase in traffic volumes due to the algorithm's intervention; this was noticeable, not only at the bottleneck section, but also at the downstream station at NE 195th. There were significant increases in the number of vehicles at the bottleneck section, and at the downstream section due to intervention. The impact of the intervention on occupancy was not significant. The average values of occupancy were lower than critical at all sections (with the exception of NE 195th St.). They were lower than 18 percent, which is the threshold value for traffic congestion. The analysis of prediction indicators, shown in Table 3.2, corroborates the results of the statistical analysis with regard to the effectiveness of the predictive algorithm's intervention during this period.

The false positive rate of 18.9 percent was clearly greater than the 13.1 percent average for all of the periods, as seen in Table 3.2. The indicators shown in this table were estimated with the data that included the effects of the algorithm's intervention and the false positive rate of 18.9 percent was also greater than the false positive rates shown in Table 3.1., which was estimated with data that did not include the effect of the prediction algorithm's intervention. Therefore, during this period, there was a significant percentage of contested intervals that were successfully avoided by the prediction algorithm's intervention. By doing this, occupancy at the mainline was maintained under critical values, increasing vehicle throughput at the section. The false negative rate was lower than the average for all periods (see Table 3.2), but still a bit higher than the false negative rate shown in Table 3.1. In summary, lightly-congested traffic conditions that characterized this period facilitated the predictive algorithm's intervention, causing the intervention to be effective.

The NE 175th St. station, which is farthest downstream, was not significantly affected by the intervention during this period. The main reason for this seemed to be the one mile distance between this section and the bottleneck section. It was not possible to evaluate the impact of the intervention at the 236th St. SW station, located upstream of the bottleneck section, due to the lack of data. The inclusion of the traffic flow variables corresponding to this section could have been very useful in illustrating the effect of the avoidance of traffic congestion at the upstream section. When traffic congestion occurs, the traffic stream traversing the upstream station experiences a reduction in speed as it approaches the bottleneck section. The speed of the wave carrying this traffic stream is higher than the wave carrying the traffic at the bottleneck section. Therefore, a shock wave is produced. The effect of this shock wave is mainly a reduction in traffic stream speed, which is subsequently reflected upstream. (34) If traffic congestion is avoided, vehicle speed is maintained throughout the entire section; therefore, traffic flow stability is attained.

During this period, the predictive algorithm successfully achieved its objective, as shown by the significant increases in traffic volumes at the NE 195th St. and NE 185th St. stations. Similar impacts probably occurred at the 236th St. SW station as a result of the intervention; however, there were no data to validate this.

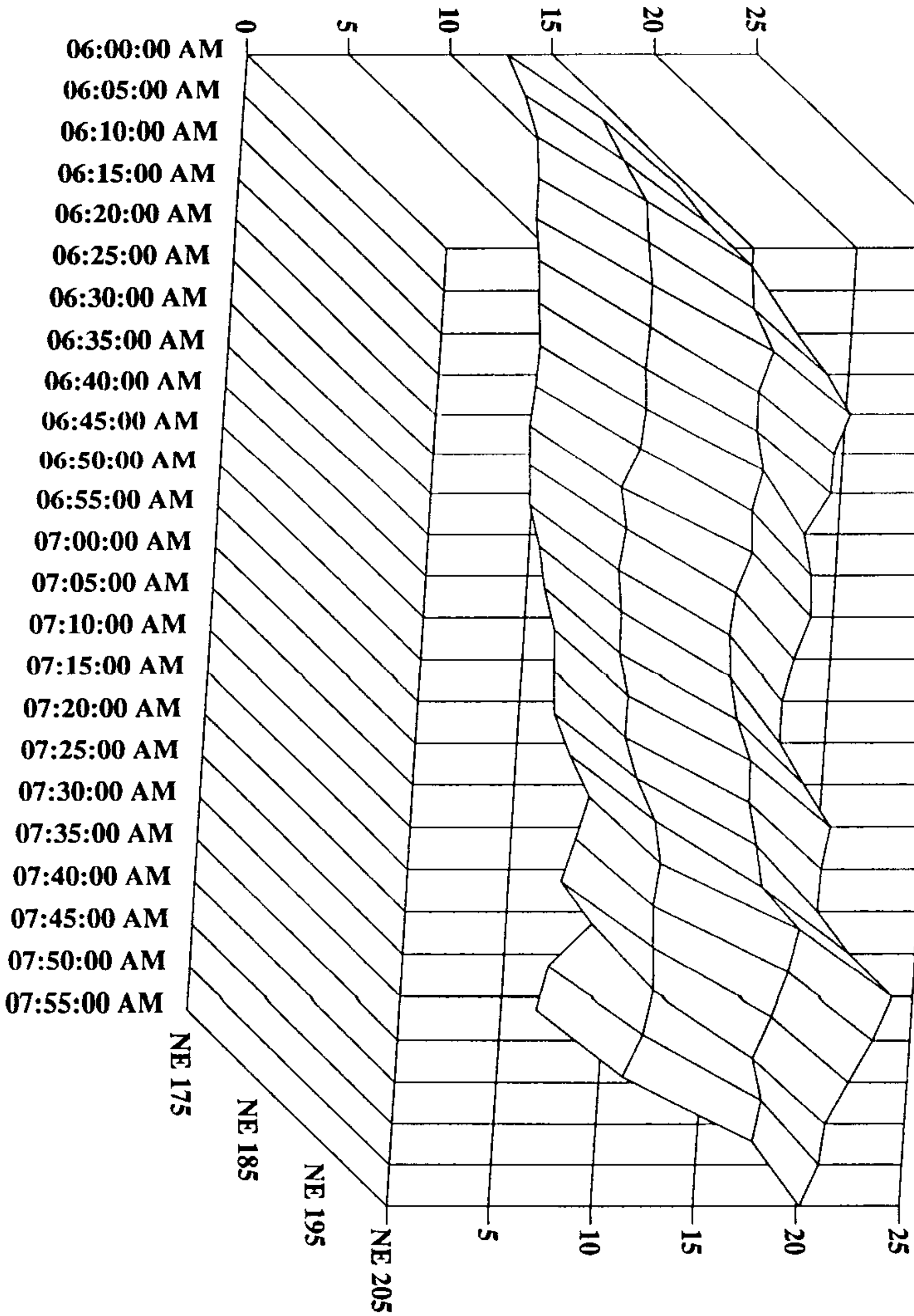

FIGURE 3.1 VEHICLE OCCUPANCY (%)

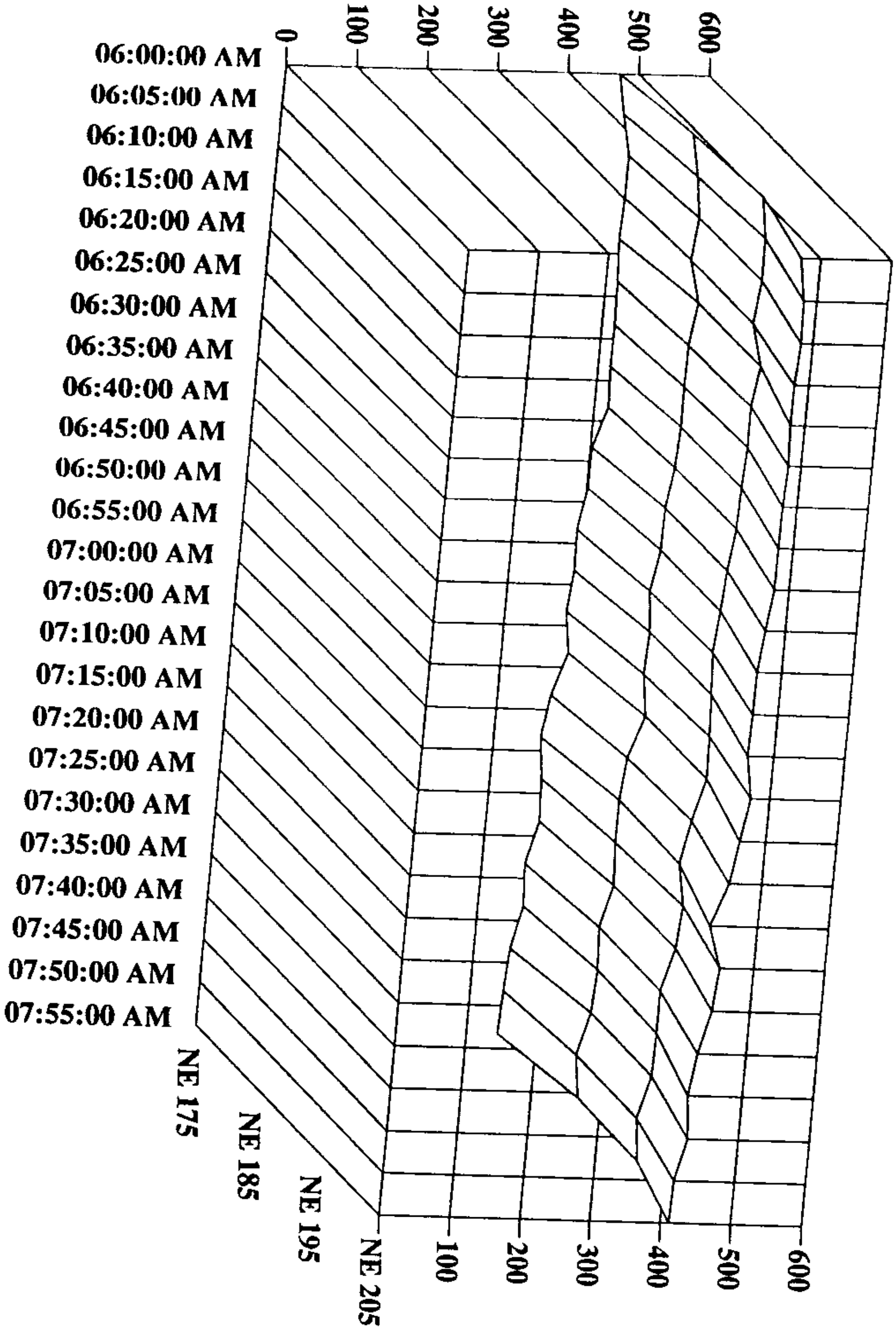

FIGURE 3.2 TRAFFIC VOLUMES

RESULTS FROM 6:15 A.M. to 6:20 A.M. and FROM 6:20 A.M. to 6:25 A.M.

The statistical analysis of these periods shows similar results, which are insignificant for the most part. Analyzing the traffic variables corresponding to the NE 205^{th} St. station , it is seen that, even though traffic volume was maintained at the same level during the previous period, there was a significant increase in the occupancy during the period from 6:15 a.m. to 6:20 a.m. that continued in the next period, reaching a peak occupancy of 20.2 percent. Similar situations occurred at the downstream sections.

At these downstream sections, however, there were increases in traffic volumes up to or exceeding capacity. During these two periods, traffic conditions became more congested along the mainline. In this situation, the predictive algorithm could only have had a marginal effect on occupancy reductions and level of service improvements. One of the most important effects of the predictative algorithm was avoiding breakdown conditions that may have had a negative impact on traffic flow stability.

The analysis of the prediction indicators was inconclusive. The false positive rate corresponding to the 6:15 a.m. to 6:20 a.m. period was similar to the average rate for all periods, whereas the false negative rate was considerably higher than the average rate for all periods (see Table 4.2). They may account for the low significance of the results of the statistical analysis, since more than half of the congested intervals were missed; it is possible that only a very low percentage of the congested intervals were avoided. During the period from 6:20 to 6:25 a.m. the false positive rate was even higher than average, but there was also a very low false negative rate, which may indicate the effectiveness of the algorithm regarding the reduction of the severity of the correctly predicted congested intervals. But, this did not have a very significant impact on the traffic flow. The effectiveness of the predictive algorithm's effort toward reducing the severity of traffic congestion probably does not translate into a significant impact.

In summary, during these two periods, 6:15 a.m. to 6:20 a.m. and 6:20 a.m. to 6:25 a.m., traffic congestion at the study section increased, as shown by increases in the average value of occupancy at all stations. Traffic volumes increased at all stations, with the exception of the NE 205th St. station, where traffic volumes remained at the level of the earlier period (6:15 to 6:20). As traffic conditions approached capacity, the main effect of the predictive algorithm was to avoid breakdown conditions.

RESULTS FROM 6:25 A.M. TO 6:30 A.M. AND FROM 6:30 A.M. TO 6:35 A.M.

Traffic conditions were similar during these two periods. It appears that a trend toward a slight decrease in the average value of occupancy started at the NE 205th St. and NE 195th St. stations, while no changes occurred at the next downstream sections. Again, no changes in the average traffic volumes occurred at the bottleneck section. Traffic kept flowing at the bottleneck section at the same previous levels. A decrease in traffic volume occurred, however, at the NE 195th St. and NE 185th St. stations, and no changes at all were observed at the NE 175th St. station. Although similar traffic conditions occurred during both periods, the results of the statistical analysis were somewhat different; from 6:25 a.m. to 6:30 a.m., traffic volume increased due to the intervention, but not significantly. With regard to occupancy the only significant impact occurred at the NE 185th St. station . At the other stations, the impact was insignificant. From 6:30 a.m. to 6:35 a.m., the statistical analysis results show that a significant increase in traffic volumes occurred at the NE 205th St. and NE 175th St. stations. These increases were accompanied by insignificant decreases in occupancy at all stations, with the exception of the NE 195th St. station, where the impact was negative, but fortunately, insignificant. The analysis of the prediction indicators for these periods was inconclusive. It appears that the period from 6:25 a.m. to 6:30 a.m., given its higher-than-average false positive rate, should have shown more significant changes than the period from 6:30 a.m. to 6:35 a.m. This period had a considerably higher false negative rate, which was expected to affect the significance of the results, but did not. In fact, there were more significant changes during this period than the previous period. One possible explanation of the difference in the significance of the impacts was found by analyzing the histograms of occupancy for these two periods. Even though average values of occupancy were almost the same (see Figure 3.1), the median values were different, and with a higher number of lightly-congested values during the period from 6:30 a.m. to 6:35 a.m. than during the period from 6:25 a.m. to 6:30 a.m. Therefore, one may assume that, even though on the average, traffic conditions were similar during these two periods (as shown in Figures 3.1 and Figure 3.2), light congestion predominated from 6:30 a.m. to 6:35 a.m., thereby facilitating the predictive algorithm's intervention, making it more effective.

In summary, during these periods, a slight decrease in occupancy at the bottleneck section and at the NE 195th St. station probably contributed to improvements in the level of service. No changes in traffic volumes took place at the NE 205th St. and NE 175th St. stations, but a decrease in traffic volumes occurred at the NE 195th St. and NE 185th St. stations. The entire section seemed to have operated at, or near, capacity levels. The prediction algorithm's intervention had a significant impact on traffic volumes during the period from 6:30 a.m. to 6:35 a.m., and a marginal impact on occupancy. It seems that in this situation, even a marginal impact on occupancy at the bottleneck section had a positive effect at maintaining traffic stability throughout the entire section.

RESULTS FROM 6:35 A.M. TO 6:45 A.M.

On average, occupancy continued to decrease at the bottleneck section during this period, while traffic volumes continued to flow at the same levels as during the previous two periods. At the rest of the stations traffic flow variables did not experience significant changes. One may interpret this situation as an improvement in the level of service at the bottleneck section. This improvement, however, did not recur at the next two downstream sections, as no changes were observed at the occupancy level. The intervention of the predictive algorithm had no significant impact from 6:35 a.m. to 6:40 a.m. This was corroborated by the analysis of prediction indicators, which showed close to average values of false positive and false negative rates (see Table 3.2). Similarly, insignificant results were obtained for the period from 6:40 a.m. to 6:45 a.m. with regard to statistical analysis. The only exception was the significant decrease in occupancy obtained at the NE 205th St. station. This decrease in occupancy was accompanied by insignificant decreases in traffic volumes at the NE 195th St. station. The prediction indicators for this period were very discouraging, especially the false negative rate, which was extremely high.

RESULTS FROM 6:45 A.M. TO 7:05 A.M.

During these periods, there was a trend at the bottleneck section toward a decrease in traffic volumes and occupancy. This provided the researchers an opportunity to evaluate the effectiveness of the predictive algorithm in a situation where, due to an existing commuter pattern at the bottleneck section, there was a shift backward in the volume/density curve toward significantly less-congested conditions. These conditions were found at other stations. The changes, however, were less prominent at the NE 195th St. station, where traffic volumes did not change significantly and maintained operating at capacity. The same conditions applied to the NE 185th St. station. One may assume that commuters arriving at their work places at 7:00 a.m. probably traverse the bottleneck section at periods between 6:15

a.m. and 6:35 a.m., while those arriving at about 8:00 a.m. do not usually traverse the section until after 7:10 a.m. This may explain the decrease in occupancy and traffic volumes at most of the stations in the study section. The results of the statistical analysis were varied, with significant impact on traffic volumes at some times, and significant increases in occupancy. In a situation (characterized by a backward shift in the volume/density curve), when a decrease in volume was accompanied by a decrease in occupancy, the predictive algorithm's intervention seemed to decrease the level of service by unnecessarily increasing the occupancy at the NE 175th St. station. These significant increases in occupancy mainly occurred from 6:50 a.m. to 6:55 a.m. and from 7:00 a.m. to 7:05 a.m. During the period from 6:55 a.m. to 7:00 a.m., a significant impact occurred due to the intervention. In general, an increase in traffic volumes occurred along the entire section. The next period, however, did not show evidence of a significant impact due to the intervention. The prediction indicators were not encouraging, either: a false negative rate of 56 percent undoubtedly affected the significance of these results (see Table 3.2). The only period in which the false negative rate was lower than the average for all the periods was the period from 6:55 a.m. to 7:00 a.m. During this period, a significant impact on traffic volumes occurred at the NE 195th St. and NE 185th St. stations.

It is not easy to clarify what could be expected of the predictive algorithm's intervention on a situation like the one characterized by a shift toward less congested conditions, provided this shift was caused by or due to a normal shift in commuter patterns within the A.M. peak period.

RESULTS FROM 7:05 A.M. TO 8:00 A.M.

Beginning at 7:05 a.m., the average occupancy at all stations began to increase until it reached a peak during the period from 7:30 a.m. to 7:35 a.m. These changes in occupancy were accompanied by a decrease in traffic volumes. After 7:35 a.m., occupancy started to decrease again; however, traffic volumes did not increase.

The results of the statistical analysis corresponding to these periods were generally similar to those obtained in the past evaluation of the predictive algorithm's intervention. (4) Even if the predictive algorithm correctly predicted traffic congestion during highly-congested periods, such as those from 7:10 a.m to 7:35 a.m., it was expected that the effect of the intervention would not be significant. The traffic congestion in these circumstances was not caused by vehicles entering the section at on-ramps, but by those coming from the upstream sections of the bottleneck section. Therefore, the intervention of the predictive algorithm alone, did not decrease occupancy at the bottleneck section significantly enough to increase traffic volumes at the downstream sections.

The effectiveness of the predictive algorithm's intervention seemed to decrease as the level of congestion increased, even though during some of the periods, especially from 7:10 a.m. to 7:25 a.m., the prediction indicators were very encouraging.

4. CONCLUSIONS AND RECOMMENDATIONS

SUMMARY

Following recommendations made in past research regarding predictive algorithm intervention, the researchers tested the predictive algorithm on-line by incorporating it into the WSDOT's ramp metering computer system at the Traffic System Management Center. By conducting the on-line testing during a time frame of one season only, (the spring of 1990), and by following the "operant" design time series intervention approach (5), they expected the effect of the predictive algorithm's intervention to be more clear. The algorithm made predictions during the entire study period, but was allowed to intervene, by adjusting ramp metering rates, only at three separate intervals. In between these intervention intervals, conditions were expected to return to normal.

During the study period, data were collected on traffic volumes and occupancy at four stations located in the study section. In addition to data on traffic volumes and occupancy, the computer's prediction messages generated during the on-line testing were saved in order to estimate the accuracy of the algorithm's predicting ability. The time series of traffic volumes and occupancy did not show any significant trends or seasonal effects. Once it was demonstrated that they were random and stationary, multiple linear regression techniques were applied to determine the impact of the predictive algorithm's intervention on the traffic conditions at the study section.

Conclusions

Prediction Accuracy

- The predictive algorithm correctly anticipated traffic conditions 80.8 percent of the time. There were no significant differences between the values estimated with the data that included the intervention effects and the values obtained during the past evaluation.
- The predictive algorithm predicted congestion 58.6 percent of the time. It did not predict congestion 41.4 percent of the time. The ramp metering system was less effective than before the predictive algorithm was used since the percentage of congested intervals predicted was higher than the percentage of missed congested intervals.
- The predictive algorithm falsely predicted congestion 15.0 percent of the time. This rate is higher than the rate obtained during the past evaluation. This may be attributed to the different proportions of lightly- and highly-congested intervals in the data sets that were used to estimate this indicator.
- In summary, the results of the research confirm that the predictive algorithm is able to predict traffic conditions with some degree of accuracy. However, since the percentage of correct predictions is only useful as an overall predictor of the ability of the algorithm to correctly anticipate traffic conditions (congested and uncongested intervals), it is the false positive and false negative rates that are important to consider in assessing the accuracy of the predictions. In this sense, the false positive rates were not very encouraging.

Impact on Traffic Volumes and Occupancy

Some effective results did occur because of the predictive algorithm's intervention. During certain time periods, the intervention seemed to have improved traffic conditions at some locations of the study section. There were more increases in traffic volumes than significant decreases in occupancy. The main effect, however, seemed to be toward achieving or maintaining traffic flow stability during those periods when operation was at capacity.

Some specific observations were:

- Significant changes in traffic volumes occurred, mainly at the bottleneck section and at the next downstream section during periods when the average occupancy at the bottleneck section was under the critical value (18.0 %).
- Decreases in occupancy were achieved in some cases, but significant decreases occurred only in very few cases, and mainly at the bottleneck and at the next downstream section.
- The traffic conditions within the a.m. peak period experienced short-term fluctuations that affected the effectiveness of the algorithm's intervention even if the predicting ability of the algorithm was not significantly affected.
- The predictive algorithm seemed to be more effective in the periods when occupancy along the mainline was under the critical value (18.0 %). During these periods, only by maintaining occupancy under this value, did the intervention have a significant impact on traffic volumes. In the traditional volume/density curve, this corresponds to the left side of the curve, within the region of stable flow, in the area representing level of service D, approaching level of service E.
- As congestion increased and occupancy reached values greater than 18.0%, the effectiveness of the intervention decreased, and its effects became marginal. Increases in traffic volumes and decreases in occupancy were not expected in these circumstances. Only by avoiding breakdown conditions, did the predictive algorithm achieve advantageous results.
- When given the particularity of the traffic pattern at the study section, a shift toward a less-congested condition was observed (occupancy went back to values

closer or lower than 18%), the predictive algorithm's intervention produced some significant increases in vehicle throughput.

- After 7:05 a.m., as highly-congested conditions predominated, the effects of the intervention became insignificant, as was expected. However, accuracy indicators were encouraging at certain periods.

In summary, the predictive algorithm achieved its main objective with regard to the correct anticipation of traffic conditions. The impact of the intervention was noticed during those periods in which lightly-congested conditions predominated. This was especially noted with occupancy lower than 18%. Once the value of occupancy at the bottleneck section reached values higher than 18%, the effect of the intervention became insignificant.

Recommendations

It is obviously more beneficial to be able to anticipate congestion than to contend with the consequences after it has already occurred. Therefore, a predicting type algorithm, one that anticipates traffic congestion and intervenes before it actually occurs, by adjusting ramp metering rates, is clearly needed.

The predictive algorithm evaluated in this report represents a step toward the management of recurrent congestion at specific freeway locations. However, this predictive algorithm still needs improvement so that it is able to anticipate congestion with a higher degree of accuracy and achieve more significant impact in the traffic conditions. That is, a higher degree of predictive accuracy and adjustments to the metering process are necessary to make the predictive algorithm's intervention more effective.

- Additional research is needed to refine the predictive algorithm. The statistical pattern recognition approach has already shown promising results. Therefore, it should continue to be used to test other combinations of variables, such as storage rate and occupancy at the upstream section, using different lags. Two models should be developed, one to be applied during lightly-congested traffic conditions and the other to be used during heavily-congested traffic conditions.

- The "operant" design approach should continue to be followed in future interventions. When possible, however, intervention and non-intervention periods should be allocated the same number of days. In this way, an imbalance that could affect the results would be avoided.

- The predicting messages printed during future on-line testing should be saved for the entire study period. These messages constitute a useful source of information not only to estimate the accuracy of the predictions indictors for both intervention and non-intervention intervals, but also to indicate possible potential improvements that could be made to the predictive algorithm.

- The traffic flow variables corresponding to the location where recurrent bottleneck formation takes place should be analyzed. The more that is known about the behavior of traffic variables at those specific locations, the more apparent the effects of an intervention should be. For instance, analysis of the short-term fluctuations that normally take place at the bottleneck section, and how these fluctuations affect the entire study section could be useful. In addition, it would be possible to identify those periods that, although very short in duration, are stable enough to show specific characteristics such as extremely high volumes, or highly-congested conditions. The identification of these periods within the a.m. peak period would help determine when the predictive algorithm's intervention would be more effective, when only marginal impacts could be expected, and finally, when other options such as ramp closure (for only short periods of time) should be implemented in order to compensate for the deficiencies of the existing system. In order to implement the above-mentioned analysis, the data collection effort presently implemented for driver information system-related projects should be used to obtain the required data. In addition, these data could be used for the simulation testing of predictive algorithms developed in the future.

- One simple way to evaluate the impact of any future or present predictive algorithm could be to estimate the number of bottleneck occurrences that take place during each period (5, 10, 15 minutes) for both intervention and non-intervention situations. Once this has been determined, hypotheses about the mean and variance of both data sets could be tested. One would have to assume, however, that any change in the average number of bottleneck occurrences during a given time interval was due to the intervention.

If multiple linear regression models including endogenous variables are used to estimate the statistical significance of the predictive algorithm's intervention, it is recommended that an additional estimation of the parameters of the model be done using single equation methods. Though these methods require the creation of instrumental variables, for which additional data are needed, this effort could provide more sound results.

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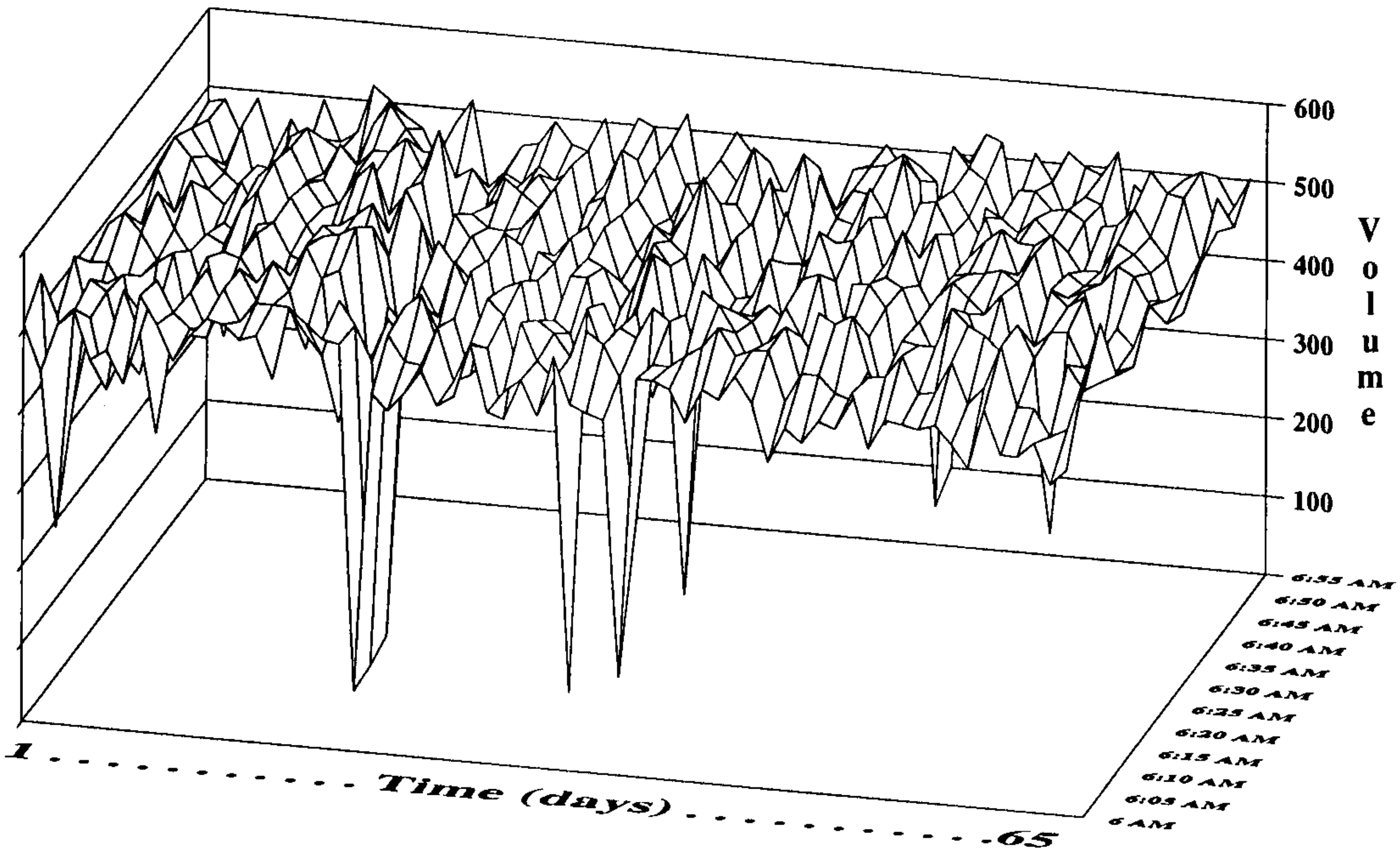

Figure B.1 Station NE 205th

Time Series Plot
Traffic Volumes
Period from 6:00 to 7:00 am

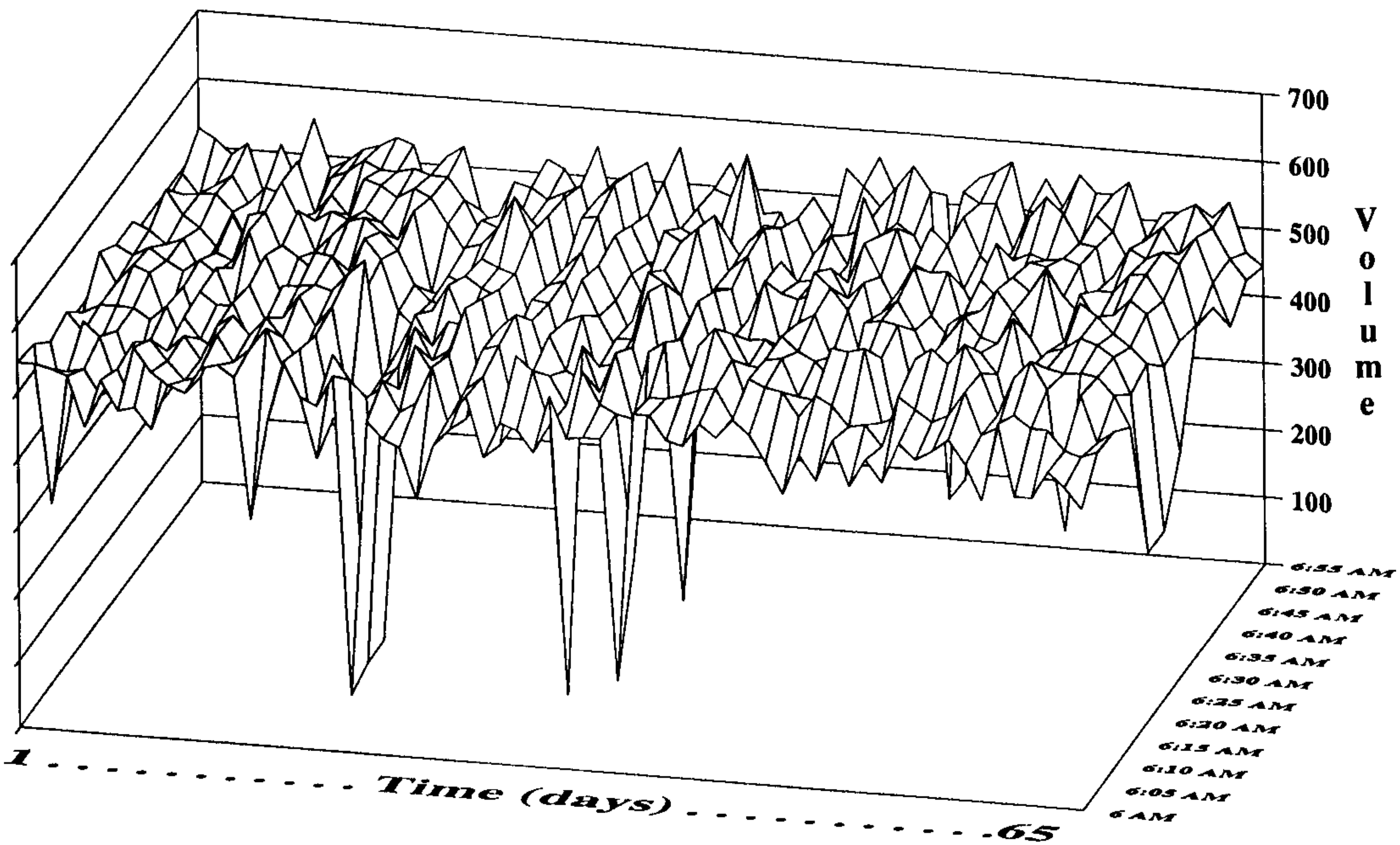

Figure B.2 Station NE 195th
Time Series Plot
Traffic Volumes
Period from 6:00 to 7:00 am

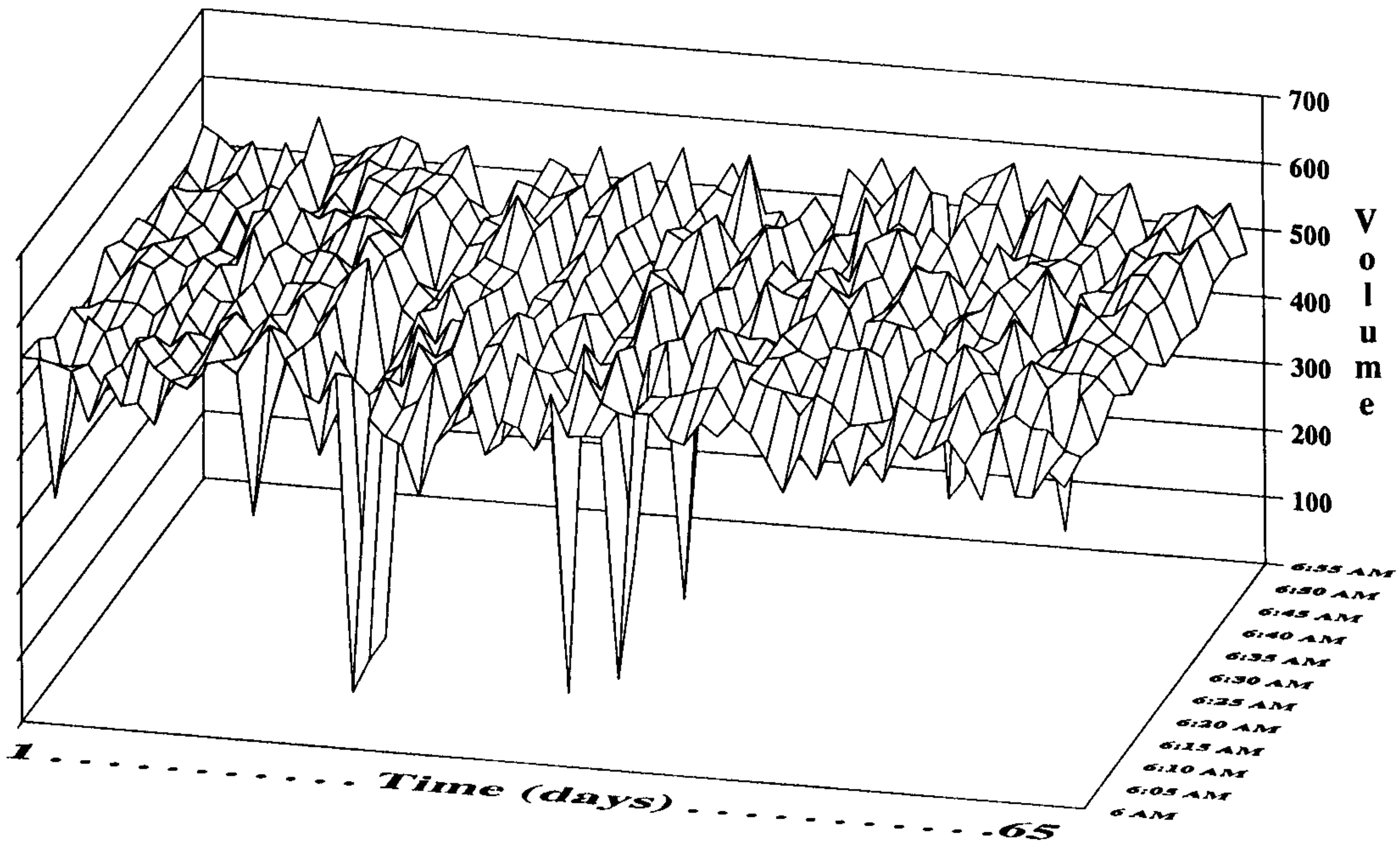

Figure B.3 Station NE 185th
Time Series Plot
Traffic Volumes
Period from 6:00 to 7:00 am

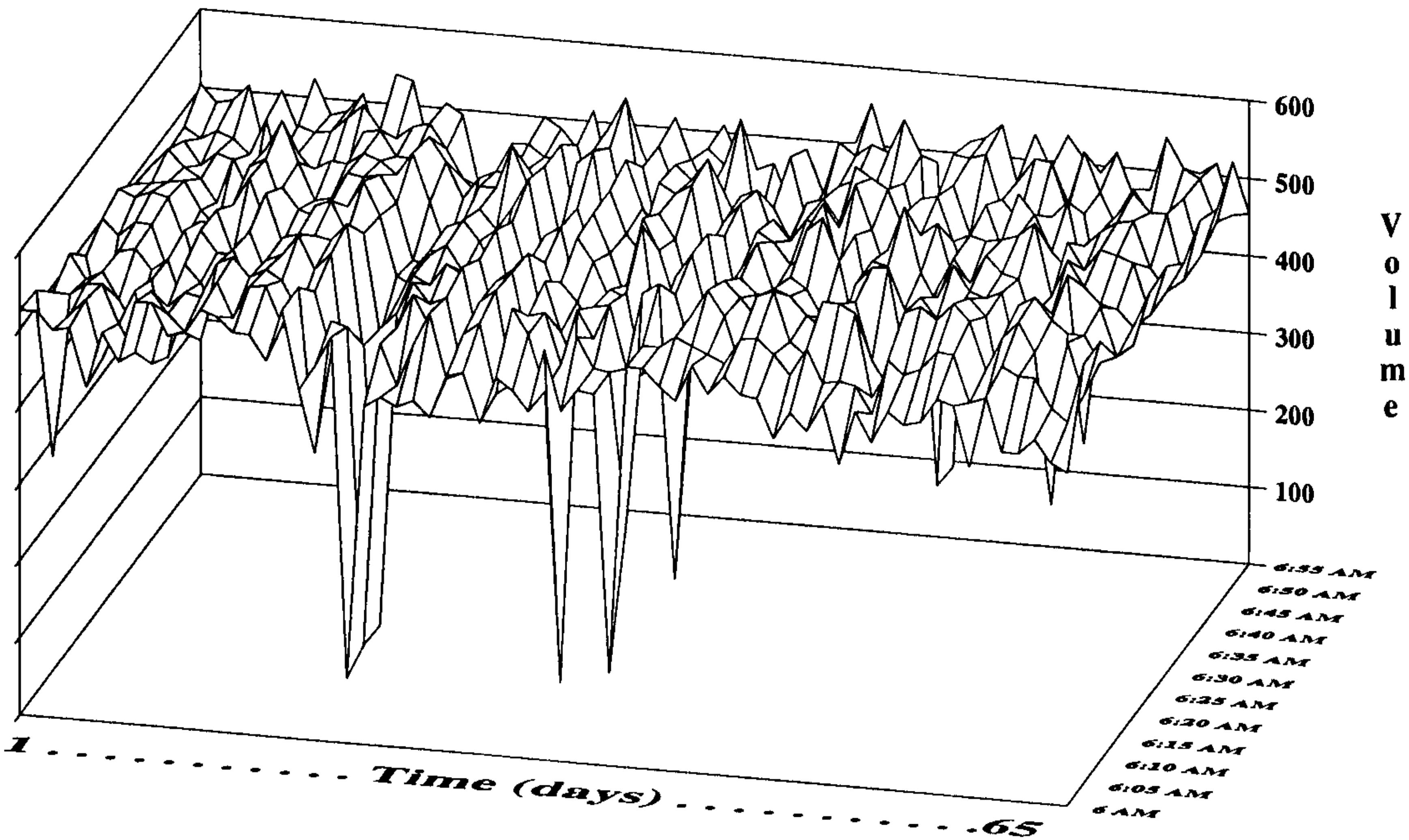

Figure B.4 Station NE 175th
Time Series Plot
Traffic Volumes
Period from 6:00 to 7:00 am

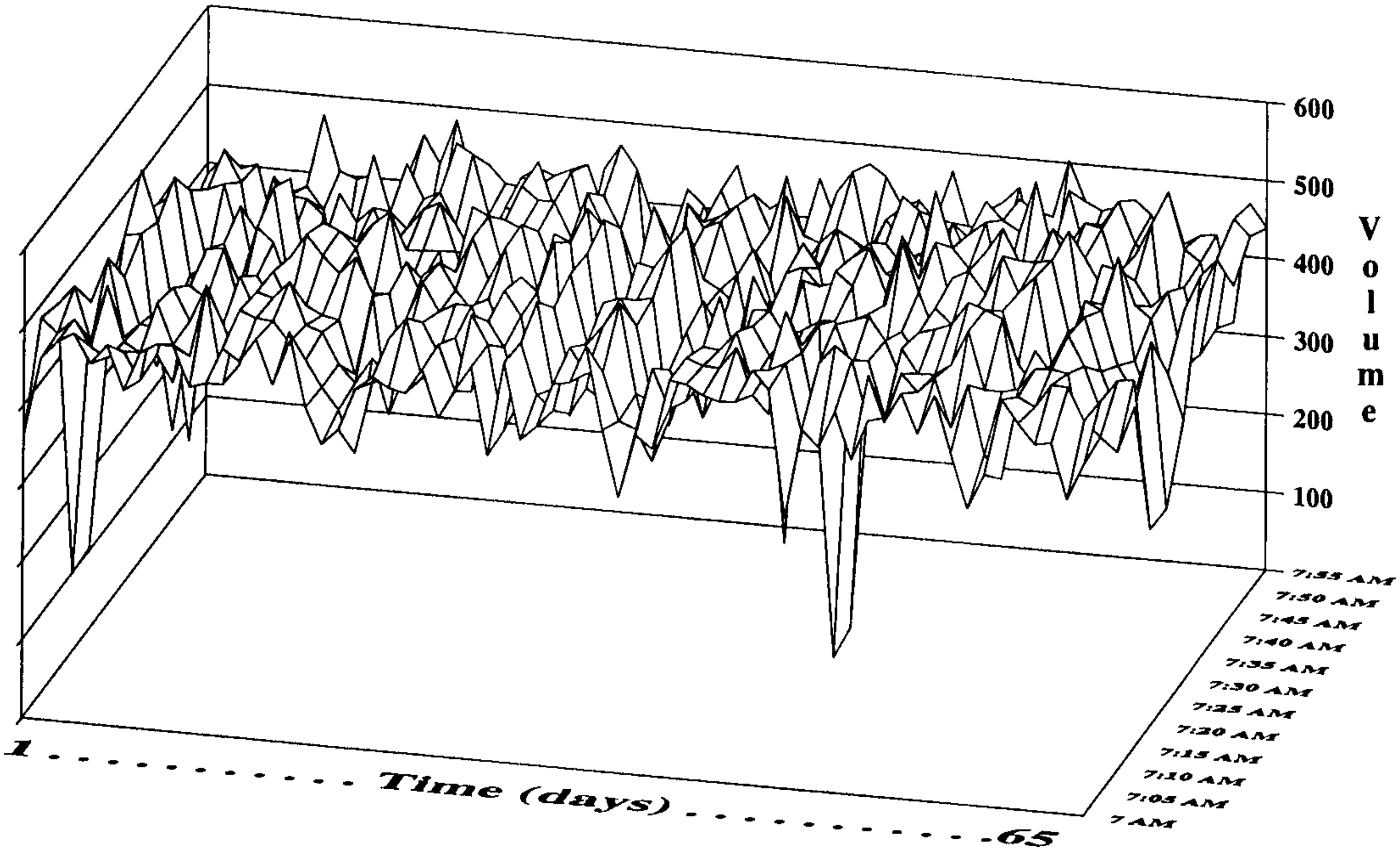

Figure B. 5 Station NE 205th
Time Series Plot
Traffic Volumes
Period from 7:00 to 8:00 am

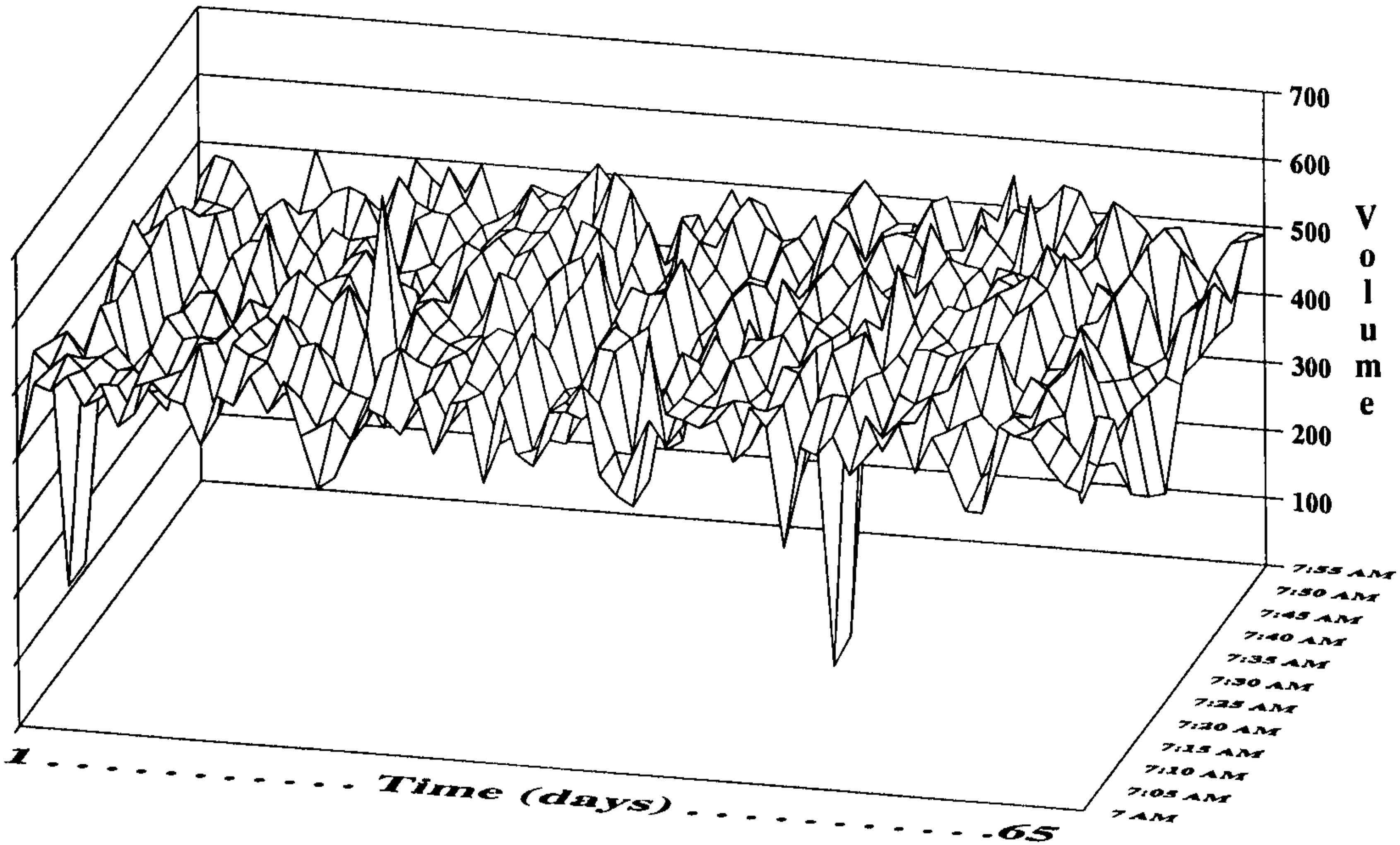

Figure B.6 Station NE 195th
Time Series Plot
Traffic Volumes
Period from 7:00 to 8:00 am

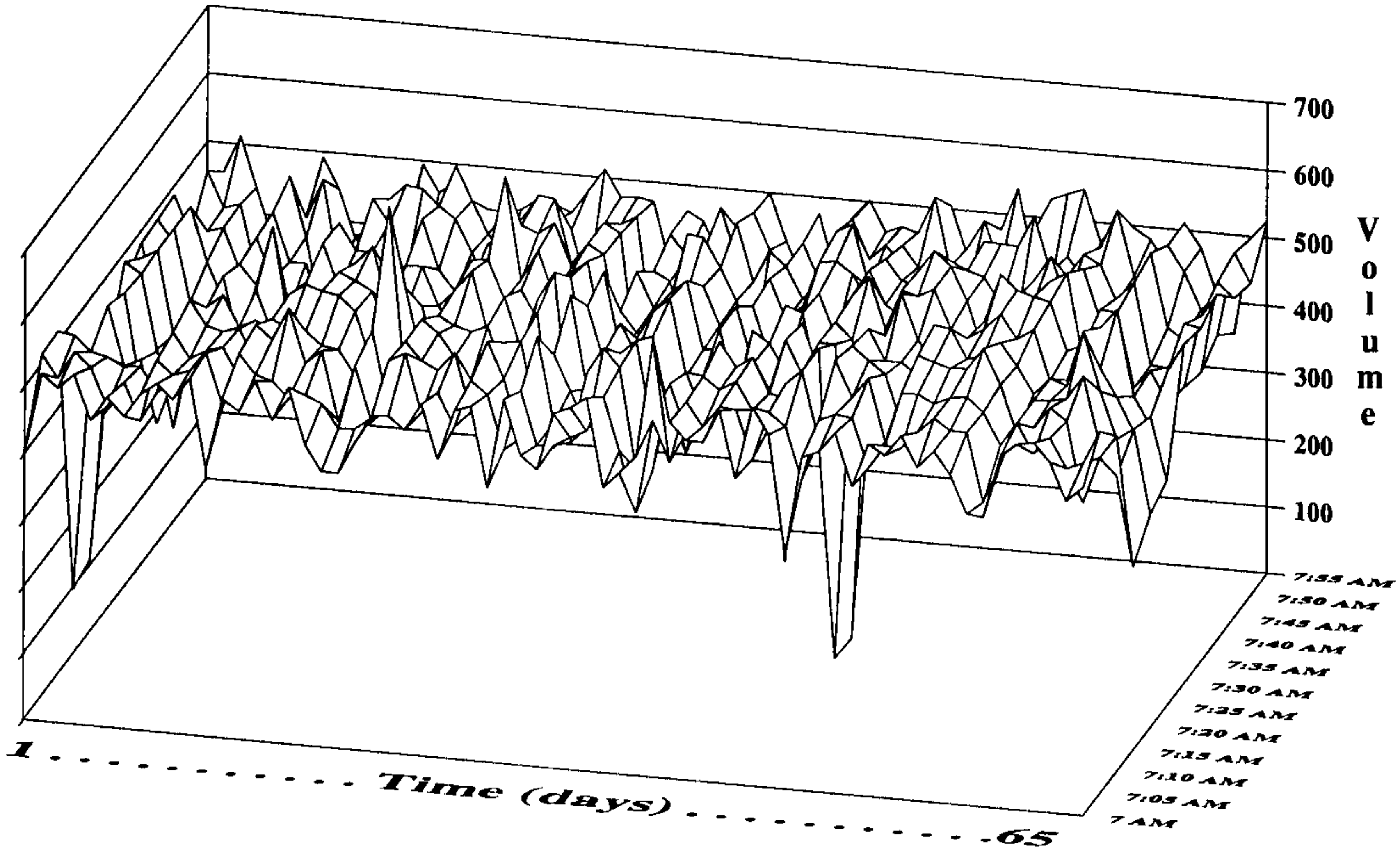

Figure B.7 Station NE 185th
Time Series Plot
Traffic Volumes
Period from 7:00 to 8:00 am

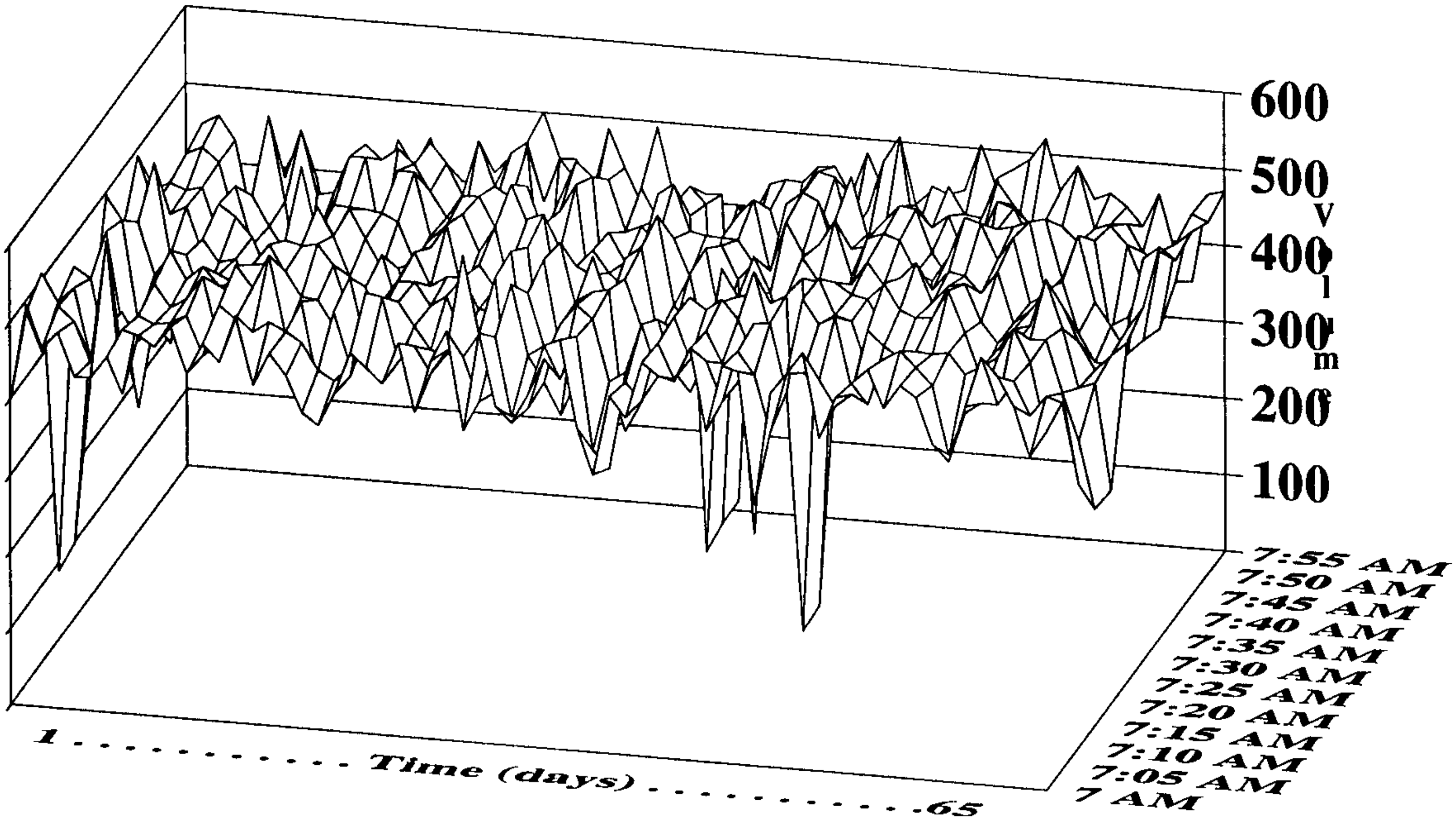

Figure B.8 Station NE 175th

Time Series Plot
Traffic Volumes
Period from 7:00 to 8:00 am

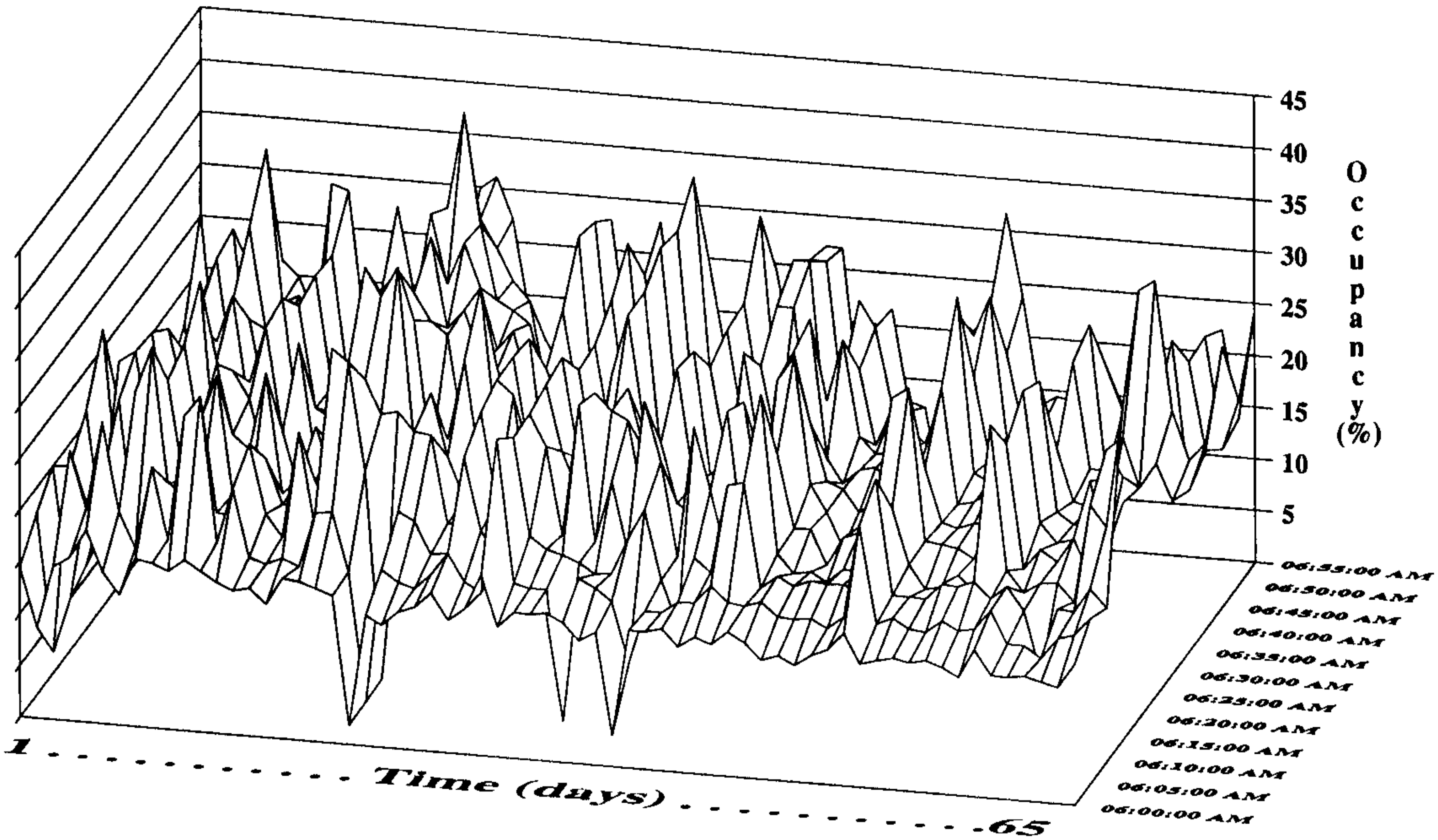

Figure B.9 Station NE 205th
Time Series Plot
Occupancy
Period from 6:00 to 7:00 am

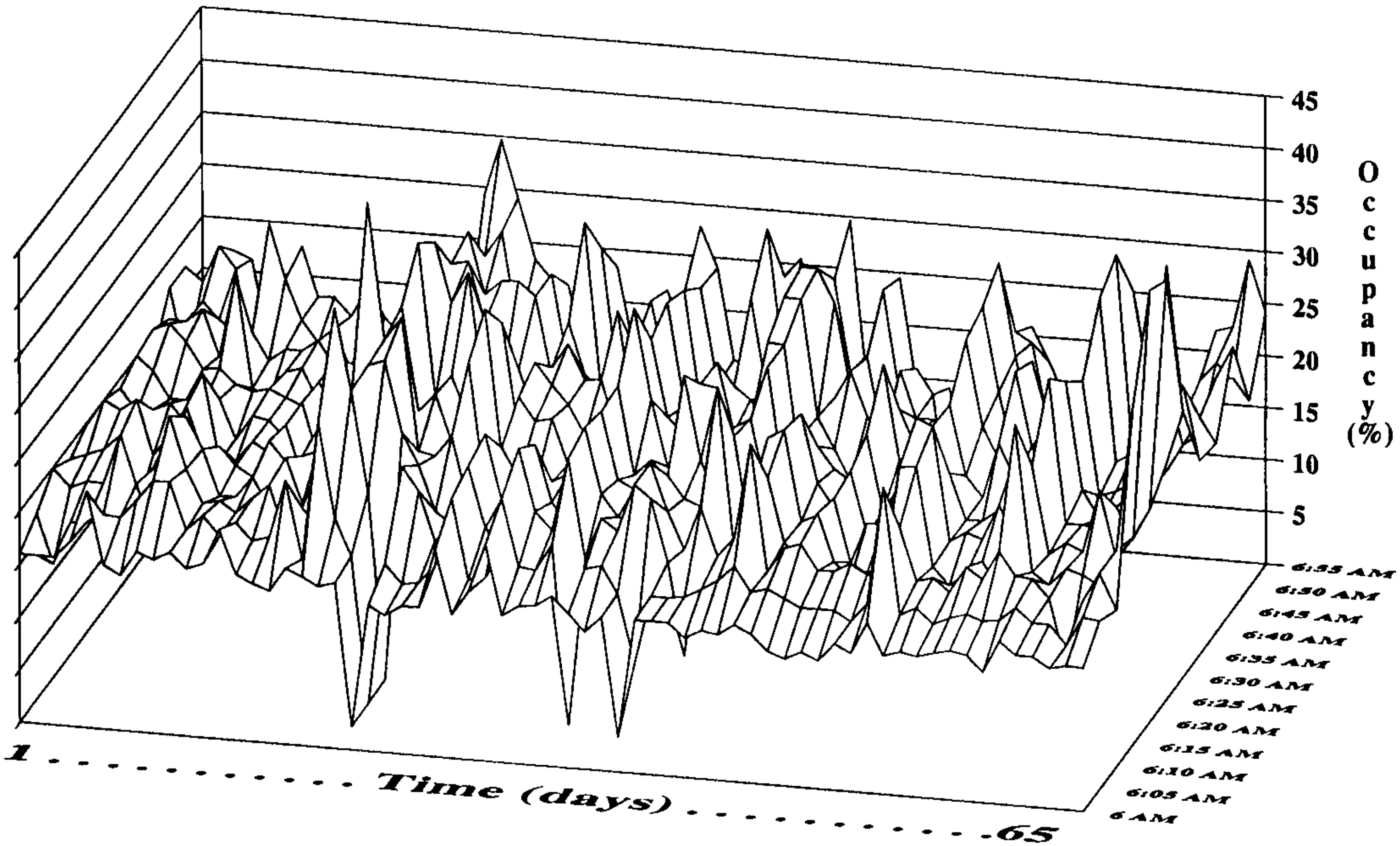

Figure B. 10 Station NE 195th
Time Series Plot
Occupancy
Period from 6:00 to 7:00 am

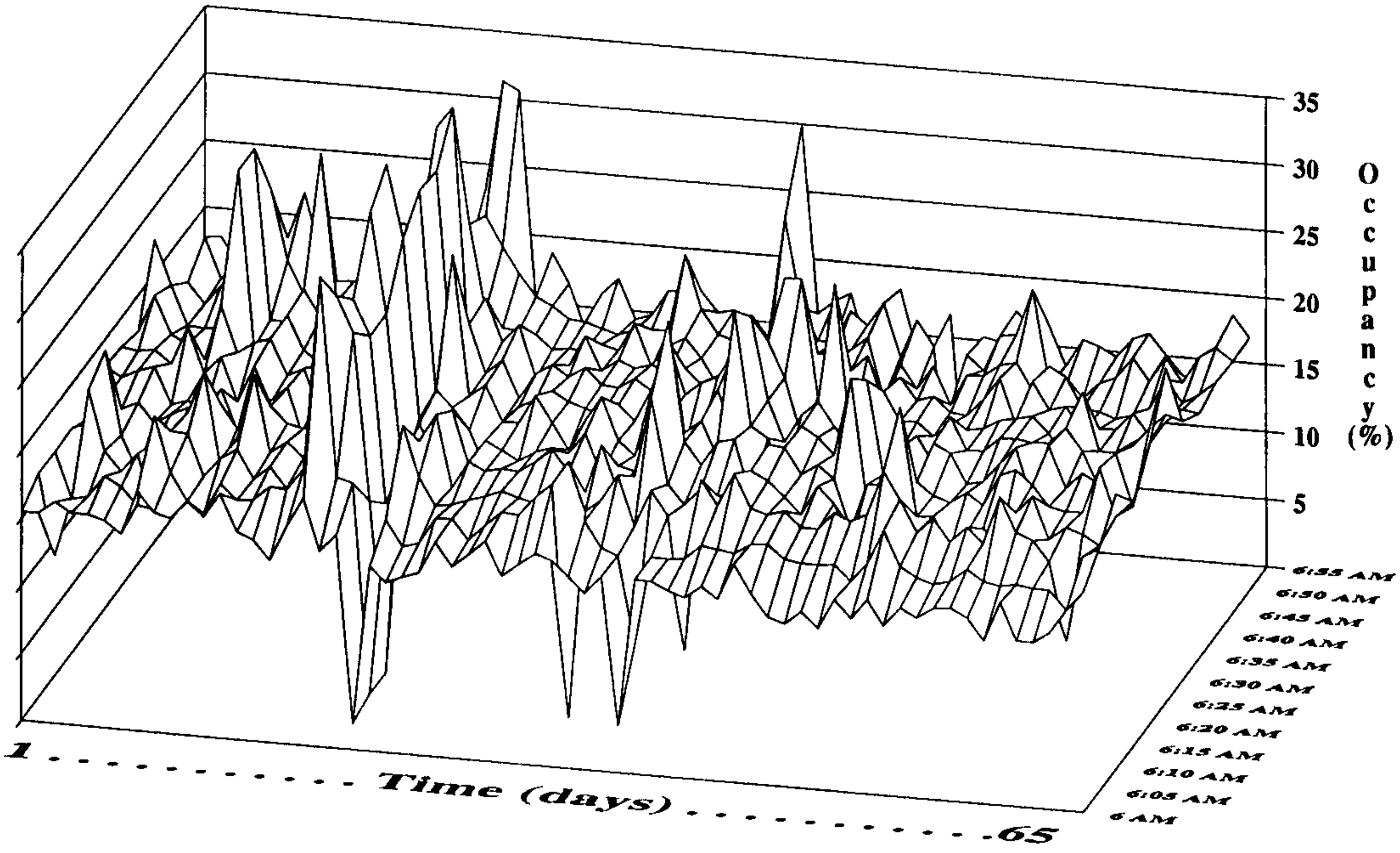

Figure B.11 Station NE 185th
Time Series Plot
Occupancy
Period from 6:00 to 7:00 am

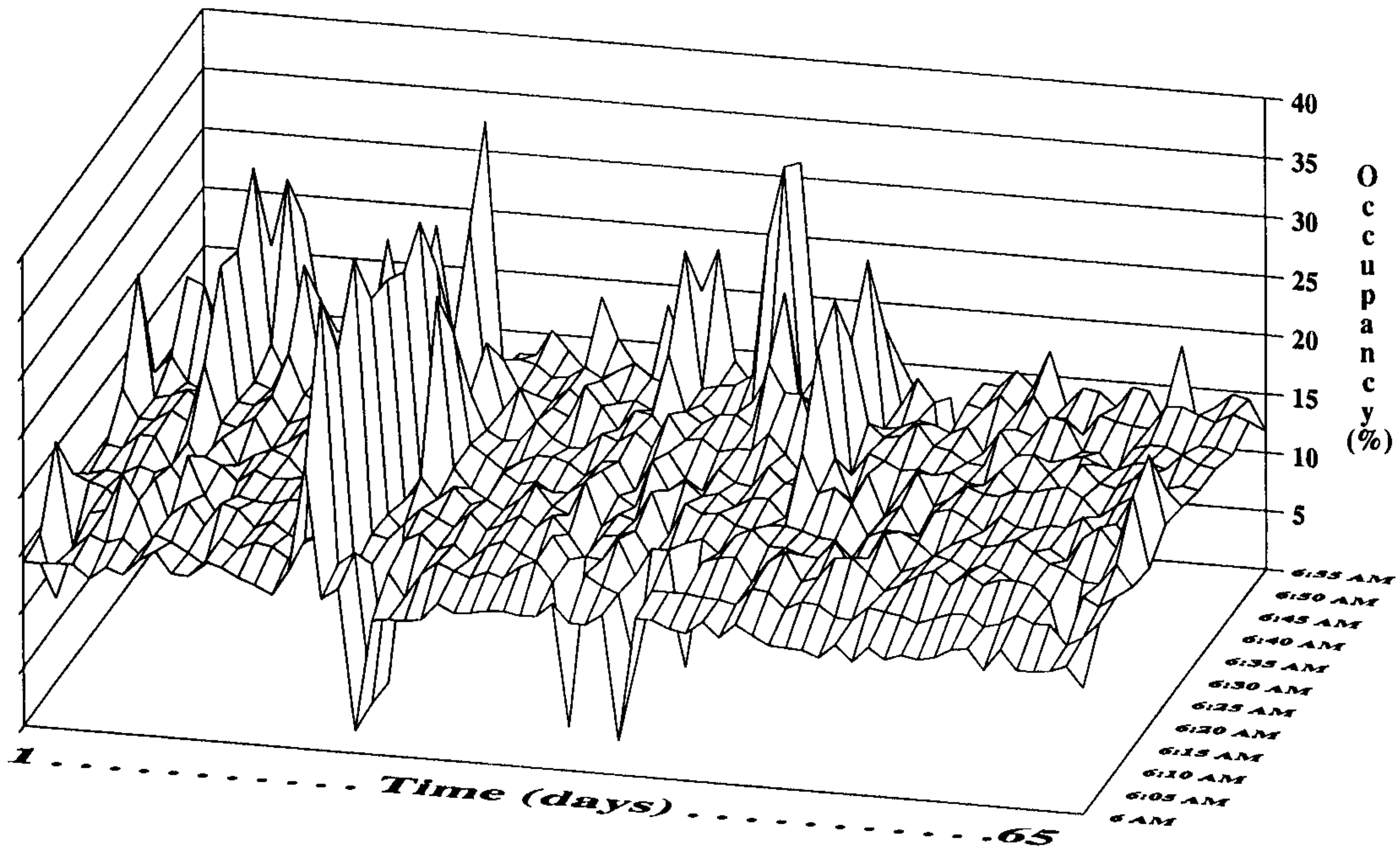

Figure B.12 Station NE 175th

Time Series Plot

Occupancy

Period from 6:00 to 7:00 am

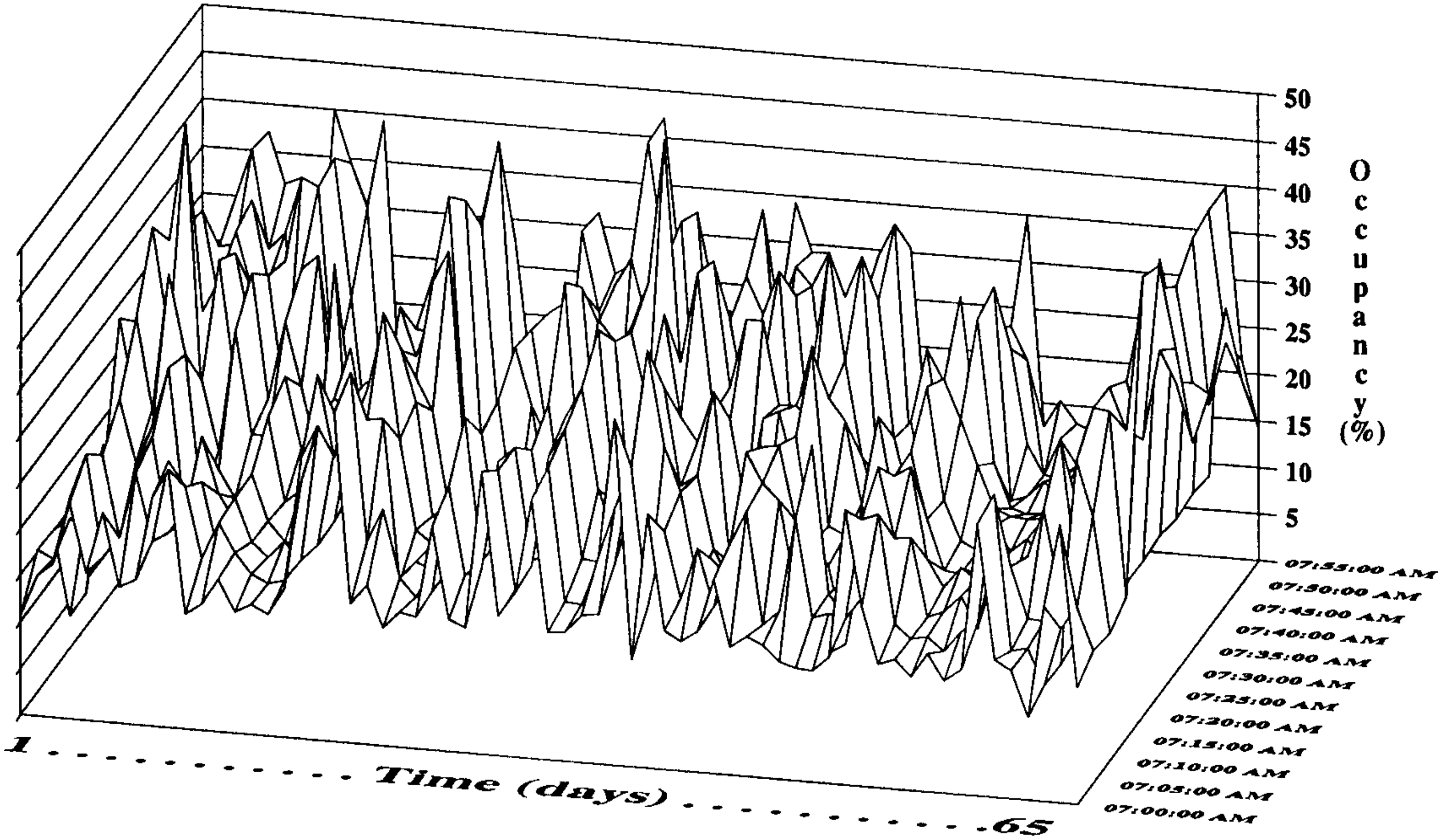

Figure B. 13 Station NE 205th
Time Series Plot
Occupancy
Period from 7:00 to 8:00 am

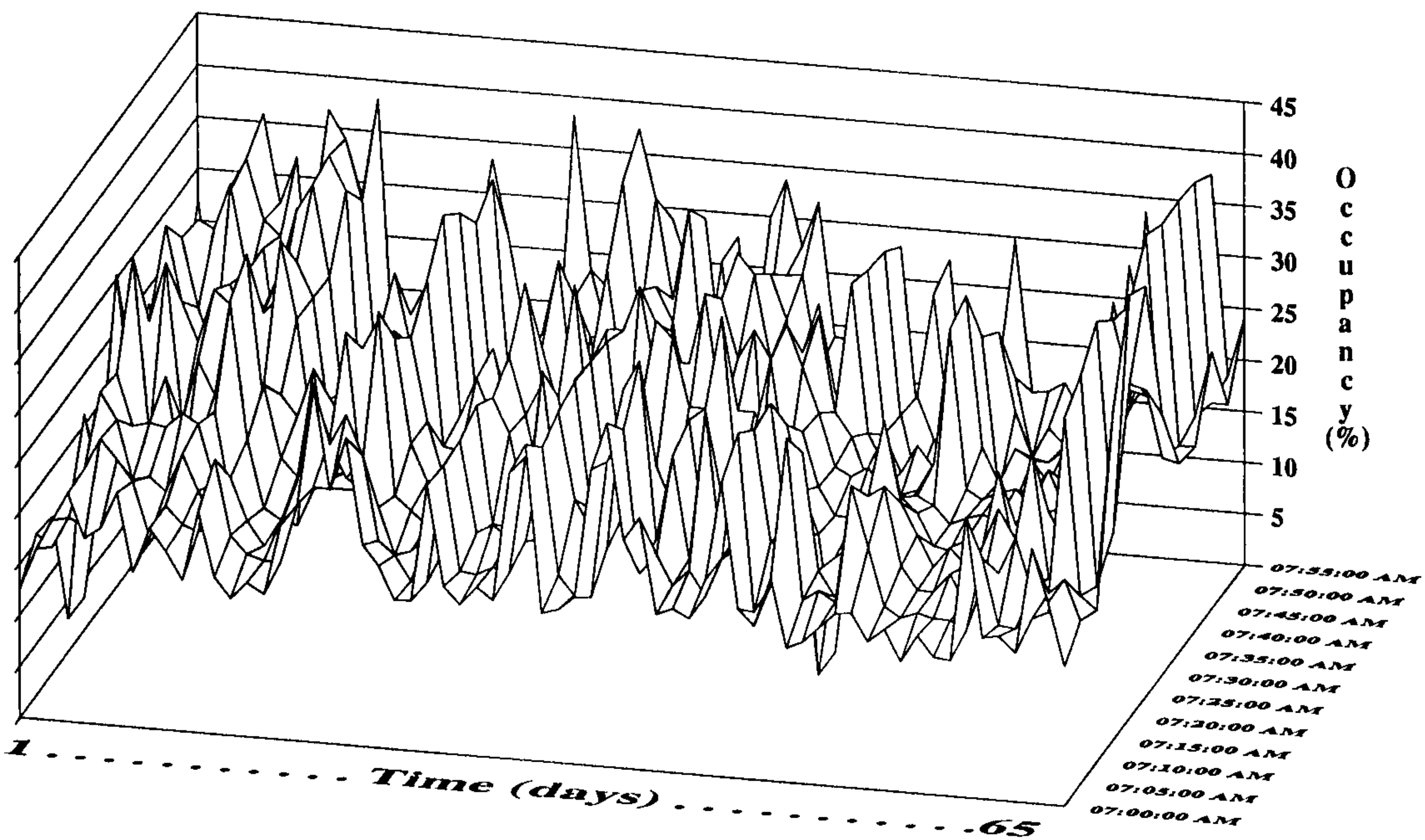

Figure B.14 Station NE 195th
Time Series Plot
Occupancy
Period from 7:00 to 8:00 am

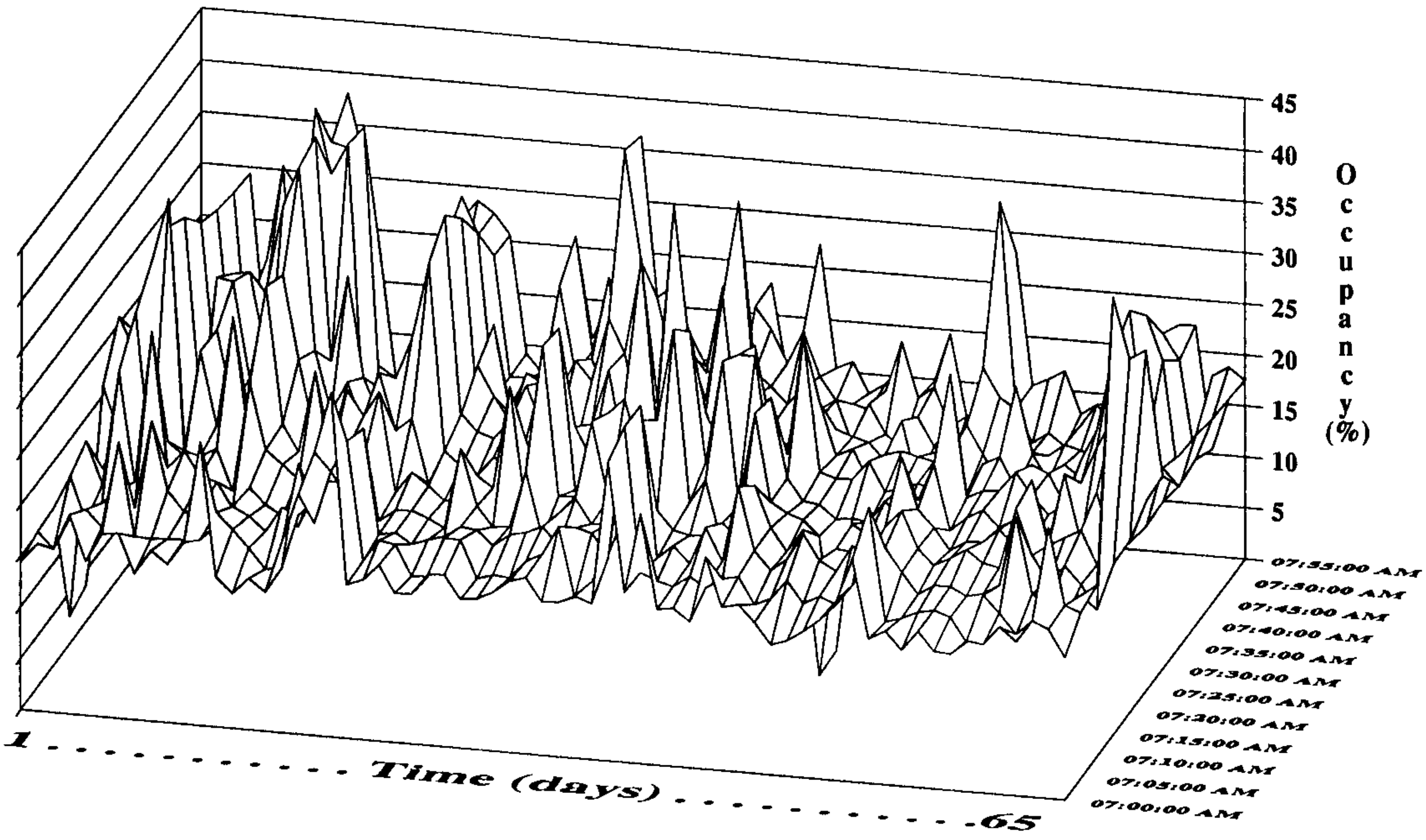

Figure B. 15 Station NE 185th
Time Series Plot
Occupancy
Period from 7:00 to 8:00 am

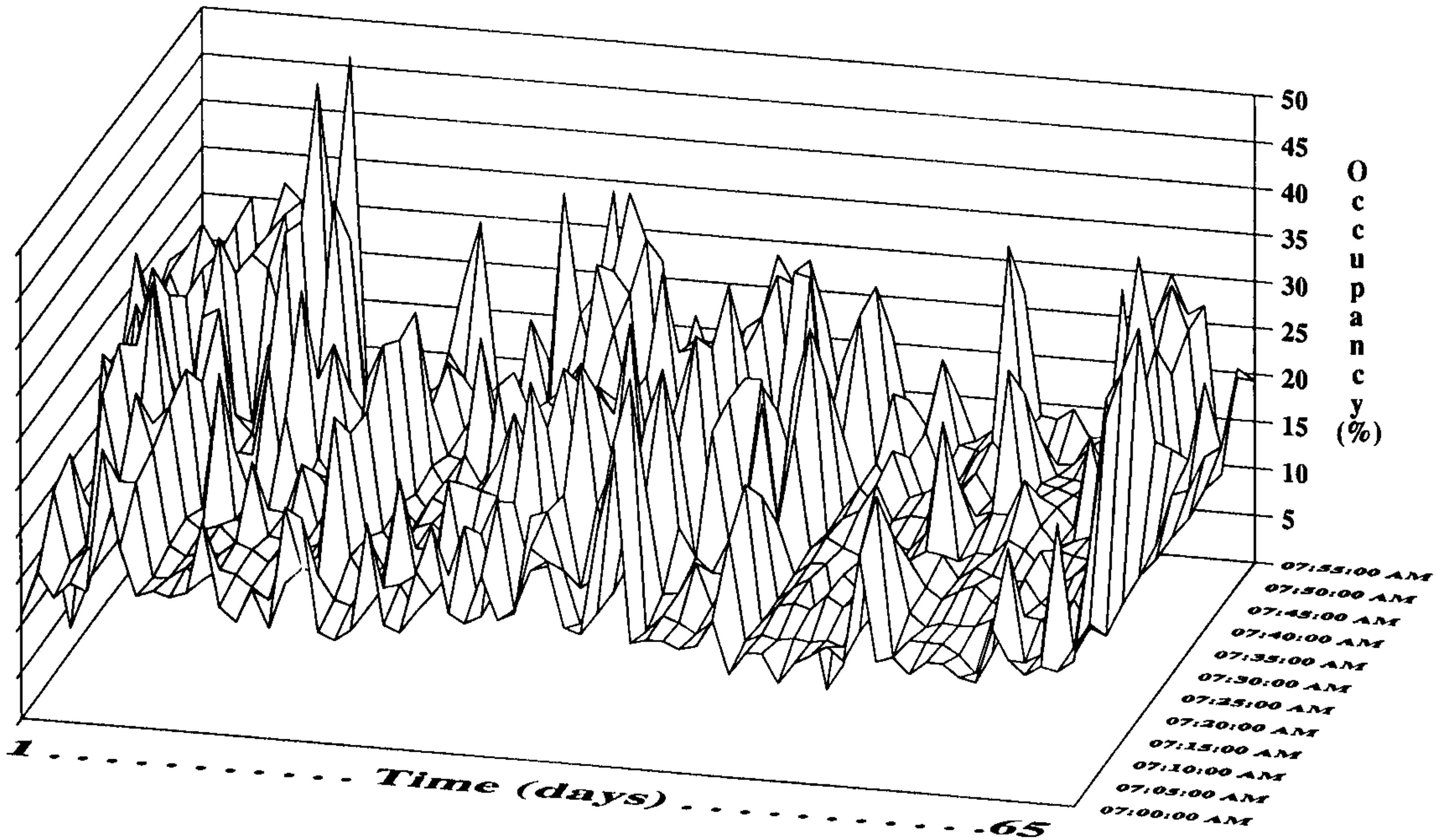

Figure B.16 Station NE 175th

Time Series Plot
Occupancy
Period from 7:00 to 8:00 am

APPENDIX C

TABLE C.1 SUMMARY OF RUN TEST RESULTS

	Station NE 205				Station NE 195			
Period	O	E	O	E	O	E	O	E
1	20	27	27	28	26	32	27	32
2	29	27	29	33	26	31	34	32
3	24	29	31	32	20	32	29	32
4	30	30	35	33	24	23	28	31
5	30	32	25	35	32	32	27	30
6	32	33	29	32	29	31	24	32
7	29	32	25	33	29	31	37	33
8	31	33	32	30	28	32	25	33
9	33	31	24	31	22	29	27	33
10	31	32	23	30	31	33	31	33
11	30	31	26	32	25	31	23	31
12	31	33	33	33	30	32	24	33
13	27	31	29	33	26	29	29	32
14	35	33	29	32	30	32	22	33
15	27	31	24	33	28	31	30	33
16	29	31	27	31	31	32	21	33
17	27	31	23	33	25	31	30	33
18	30	33	23	32	27	31	25	33
19	27	32	30	33	27	33	28	33
20	33	31	28	23	25	31	-	-
21	28	30	26	33	35	32	-	-
22	33	23	30	33	25	30	-	-
23	33	31	25	32	31	32	-	-

O: Observed number of runs in the time series.

E: Expected number of runs in the time series.

APPENDIX D

RESULTS OF STATISTICAL ANALYSIS

TABLE D.1 INTERVENTION ANALYSIS RESULTS

STATION: NE 205TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:00 - 6:05	Occupancy	.63	.94	INS	IV
	Volume	-15.49	-1.50	INS	IV,O_c (t)
6:05 - 6:10	Occupancy	.48	.70	INS	IV,O_c (t-1),V(t-1),V(t)
	Volume	-16.45	-.95	INS	IV,O_c (t-1),V(t-1),O(t)
6:10 - 6:15	Occupancy	-1.58	-1.22	INS	IV,O_c (t-1)
	Volume	35.49	1.71	P<.10	IV,O(t-1),V(t-1)
6:15 - 6:20	Occupancy	-.47	-.42	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-9.93	-1.13	INS	IV,V(t-1),O_c (t)
6:20 - 6:25	Occupancy	1.35	1.28	INS	IV,O_c (t-1),V(t-2)
	Volume	-7.016	-.90	INS	IV,V(t-3),O(t-2),V(t-1),O(t)
6:25 - 6:30	Occupancy	-.99	-1.19	INS	IV,O(t-1),O(t-2),V(t)
	Volume	9.52	1.31	INS	IV,V(t-1),V(t-2)
6:30 - 6:35	Occupancy	-.31	-.35	INS	IV,O_c (t-1),V(t)
	Volume	12.43	1.84	P<.10	IV,V(t-3),O(t-1),O(t)
6:35 - 6:40	Occupancy	-.11	-.14	INS	IV,O(t-1),O(t-2)
	Volume	-4.04	-.55	INS	IV,V(t-2),V(t-1),O(t)
6:40 - 6:45	Occupancy	-1.43	-1.84	P<.10	IV,O(t-3),O(t-1),V(t)
	Volume	-9.60	-1.78	INS	IV,V(t-3),V(t-2)
6:45 - 6:50	Occupancy	.70	0.93	INS	IV,O(t-2),O(t-1),V(t)
	Volume	9.54	1.16	INS	IV,V(t-1),O(t)

TABLE D.1 (Continued)

STATION: NE 205TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:50 - 6:55	Occupancy	1.22	1.44	INS	IV,O(t-2),O(t-1),V(t)
	Volume	12.37	0.91	INS	IV,V(t-2),O(t)
6:55 - 7:00	Occupancy	2.33	2.29	P<.05	IV,O(t-3),O(t-1),V(t-2),V(t-1)
	Volume	12.22	1.62	INS	IV,V(t-2),O(t-1),V(t-1),O(t)
7:00 - 7:05	Occupancy	-.007	-.01	INS	IV,O(t-2),O(t-1),V(t-2),V(t)
	Volume	-.33	-.43	INS	IV,V(t-2),O(t-2),V(t-1),O(t)
7:05 - 7:10	Occupancy	-1.82	-2.15	P<.05	IV,O(t-1),V(t)
	Volume	-11.27	-1.56	INS	IV,V(t-2),V(t-1),O(t-1),O(t)
7:10 - 7:15	Occupancy	-1.00	-.89	INS	IV,O(t-1),V(t)
	Volume	-6.94	-.99	INS	IV,V(t-2),O(t)
7:15 - 7:20	Occupancy	1.17	1.10	INS	IV,O(t-3),V(t-3),O(t-1),V(t-1),VO(t)
	Volume	-9.10	-.57	INS	IV,O(t-3),V(t-3),O(t-2),O(t-1)
7:20 - 7:25	Occupancy	.11	.09	INS	IV,O(t-2),V(t-2),V(t)
	Volume	-16.73	-1.61	INS	O(t-2),V(t-2),O(t), IV
7:25 - 7:30	Occupancy	0.56	.62	INS	IV,O(t-2),O(t-1),V(t-1),V(t)
	Volume	6.45	0.78	INS	IV,V(t-3),V(t-1),O(t-2),O(t)
7:30 - 7:35	Occupancy	-1.65	-1.71	P<.101	IV,V(t-3),V(t-1),O(t-1),V(t)
	Volume	-14.00	-1.52	INS	IV,V(t-3),V(t-1),O(t-2),O(t)
7:35 - 7:40	Occupancy	3.29	1.79	P<.10	IV,O(t-2),O(t-1),V(t-1),V(t)
	Volume	-.57	-.03	INS	IV,O(t-2),V(t-2),O(t-1),O(t)

TABLE D.1 (Continued)

STATION: NE 205TH

Period	Dependent Variable	Coefficient of Intervention Variables	T-Ratio	Sig.	Independent Variables
7:40 - 7:45	Occupancy	.81	.68	INS	IV,O(t-2),V(t-2),O(t-1),V(t-1),V(t)
	Volume	1.63	.18	INS	IV,O(t-2),V(t-2),O(t-1),V(t-1),O(t)
7:45 - 7:50	Occupancy	1.34	1.24	INS	IV,O(t-3),V(t-3),O(t-1),V(t)
	Volume	-1.26	-.16	INS	IV,O(t-3),V(t-3),V(t-1),O(t)
7:50 - 7:55	Occupancy	1.34	1.13	INS	IV,O(t-2),O(t-1),V(t)
	Volume	-2.63	-.23	INS	IV,O(t-2),V(t-2),O(t)
7:55 - 8:00	Occupancy	-.64	.51	INS	IV,O(t-3),O(t-1),V(t-1),V(t)
	Volume	-13.18	1.47	INS	IV, O(t-3),V(t-2),O(t-1),V(t-1)

TABLE D. 2 INTERVENTION ANALYSIS RESULTS

STATION: NE 195TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:00 - 6:05	Occupancy	1.39	1.87	P<.10	IV
	Volume	-24.65	-1.76	P<.10	IV, O(t)
6:05 - 6:10	Occupancy	-.51	-.67	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-2.22	-.12	INS	IV,O(t-1),V(t-1),O(t)
6:10 - 6:15	Occupancy	-1.16	-1.24	INS	IV,O(t-1),V(t-1)
	Volume	39.52	2.03	P<.05	IV,O(t-1),V(t-1),O(t)
6:15 - 6:20	Occupancy	-.942	-1.07	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-12.00	-1.41	INS	IV,O(t-1),V(t-1),O(t)
6:20 - 6:25	Occupancy	-.63	-.88	INS	IV,O(t-2),O(t-1),V(t-2),V(t)
	Volume	-14.02	-1.35	INS	IV,O(t-1),O(t)
6:25 - 6:30	Occupancy	.19	0.28	INS	IV,O(t-2),O(t-1),V(t)
	Volume	11.38	1.48	INS	IV,V(t-2),V(t-1),O(t)
6:30 - 6:35	Occupancy	.31	.54	INS	IV,O(t-1),O(t-2)
	Volume	-1.17	-.15	INS	IV,O(t-1),V(t-2),O(t-2)
6:35 - 6:40	Occupancy	.19	-.28	INS	IV,O(t-1),V(t)
	Volume	-.10	-.02	INS	IV,V(t-2),O(t)
6:40 - 6:45	Occupancy	-.74	-1.10	INS	IV,O(t-1),V(t)
	Volume	-10.41	-1.44	INS	IV,V(t-1),O(t)
6:45 - 6:50	Occupancy	-1.46	-1.79	P<.10	IV,V(t-1),O(t)
	Volume	13.68	1.75	P<.10	IV,V(t-1),V(t-2),O(t)

TABLE D. 2 (Continued)

STATION: NE 195TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:50 - 6:55	Occupancy	.92	1.14	INS	IV,O(t-1),O(t-2),V(t)
	Volume	10.27	0.75	INS	IV,V(t-2),O(t)
6:55 - 7:00	Occupancy	1.14	1.11	INS	IV,O(t-1),V(t-1),V(t)
	Volume	20.03	2.03	P<.05	IV,V(t-2),O(t-2),V(t-1),O(t-1)
7:00 - 7:05	Occupancy	-1.20	-.83	INS	IV,V(t-1),O(t-1),V(t)
	Volume	-6.01	-.50	INS	IV,V(t-1),O(t-1),O(t)
7:05 - 7:10	Occupancy	-.64	-.87	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-7.77	-1.09	INS	IV,V(t-1),O(t-1),O(t)
7:10 - 7:15	Occupancy	0.69	.83	INS	IV,V(t-2),O(t-1),V(t)
	Volume	-9.21	-1.25	INS	IV,V(t-2),V(t-1),O(t)
7:15 - 7:20	Occupancy	0.56	0.42	INS	IV,O(t-1),V(t)
	Volume	6.65	0.34	INS	IV,V(t-1),O(t)
7:20 - 7:25	Occupancy	0.91	0.70	INS	IV,V(t-1),O(t-1)
	Volume	-34.89	-3.07	P<.01	IV,V(t-1),V(t-2)
7:25 - 7:30	Occupancy	-.24	-.26	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-.055	-.01	INS	IV,V(t-2),V(t-1),O(t)
7:30 - 7:35	Occupancy	1.42	1.52	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-.55	-.06	INS	IV,O(t-1),V(t-1),O(t)
7:35 - 7:40	Occupancy	-.06	-.05	INS	IV,O(t-1),V(t)
	Volume	22.38	1.40	INS	IV,O(t-2),V(t-1)

TABLE D. 2 (Continued)

STATION: NE 195TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
7:40 - 7:45	Occupancy	-.07	-.06	INS	IV,O(t-2),O(t-1),V(t)
	Volume	-2.44	-.24	INS	IV,V(t-1),O(t)
7:45 - 7:50	Occupancy	1.54	1.51	INS	IV,O(t-1),O(t-2),V(t)
	Volume	-17.75	-1.58	INS	IV,V(t-2),O(t)
7:50 - 7:55	Occupancy	1.11	0.86	INS	IV,O(t-1),V(t)
	Volume	1.04	0.08	INS	IV,V(t-2),O(t)
7:55 - 8:00	Occupancy	0.25	0.22	INS	IV,O(t-1),O(t-2),V(t)
	Volume	6.47	0.72	INS	IV,V(t-2),O(t)

TABLE D. 3 INTERVENTION ANALYSIS RESULTS

STATION: NE 185TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:00 - 6:05	Occupancy	.80	1.27	INS	IV
	Volume	-9.36	-.83	INS	IV,O(t)
6:05 - 6:10	Occupancy	-1.27	-1.99	.05	IV,V(t-1),O(t-1),V(t)
	Volume	1.71	.09	INS	IV,O(t-1),V(t-1),O(t)
6:10 - 6:15	Occupancy	-.21	-.37	INS	IV,O(t-1),V(t-1),V(t)
	Volume	19.72	1.28	INS	IV,O(t-1),V(t-1),O(t)
6:15 - 6:20	Occupancy	.40	.75	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-13.49	-1.75	INS	IV,V(t-1),O(t-1),O(t)
6:20 - 6:25	Occupancy	-.41	-.90	INS	IV,O(t-1),V(t-1),V(t-2),V(t)
	Volume	-.02	-.06	INS	IV,V(t-3),V(t-1),O(t)
6:25 - 6:30	Occupancy	-.83	-1.78	P<.10	IV,O(t-3),V(t-3),O(t-1)
	Volume	9.86	.70	INS	IV,V(t-3),V(t-2),V(t-1)
6:30 - 6:35	Occupancy	-.57	-.99	INS	IV,V(t-2),V(t-1),O(t-1)
	Volume	4.23	.65	INS	IV,V(t-1),V(t-2),V(t-3),O(t-1)
6:35 - 6:40	Occupancy	-.48	-1.05	INS	IV,O(t-2),O(t-1),V(t-1),V(t)
	Volume	4.46	0.88	INS	IV,V(t-2),O(t-2),V(t-1),O(t)
6:40 - 6:45	Occupancy	-.64	-.93	INS	O(t-2),V(t-2),O(t-1),V(t-1),O(t),IV
	Volume	-13.48	-1.60	INS	IV,O(t-3),V(t-1)
6:45 - 6:50	Occupancy	.22	.53	INS	IV,O(t-3),V(t-2),O(t-1),V(t)
	Volume	7.63	1.01	INS	IV,O(t-3),O(t-1),V(t-1)

TABLE D.3 (Continued)

STATION: NE 185TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:50 - 6:55	Occupancy	.77	1.25	INS	IV,O(t-3),V(t-3),O(t-1),V(t)
	Volume	-10.65	-.88	INS	IV,V(t-3),O(t-3),V(t-1),O(t-1),O(t)
6:55 - 7:00	Occupancy	-.58	-.77	INS	IV,V(t-3),O_c (t-1)
	Volume	24.68	2.67	P<.01	IV,O(t-2),V(t-1)
7:00 - 7:05	Occupancy	-1.21	-1.37	INS	IV,O(t-2)
	Volume	-11.43	-.58	INS	IV,O(t-2),V(t-1)
7:05 - 7:10	Occupancy	.52	.81	INS	IV,O(t-1)
	Volume	-13.30	-1.73	P<.10	IV,V(t-1),V(t-2),O(t-1)
7:10 - 7:15	Occupancy	-.25	-.37	INS	IV,O(t-2),V(t-1)
	Volume	-6.57	-.80	INS	IV,V(t-2),V(t-1)
7:15 - 7:20	Occupancy	1.55	1.16	INS	IV,V(t-1),V(t-2)
	Volume	-1.92	-.10	INS	IV,V(t-1)
7:20 - 7:25	Occupancy	.29	.29	INS	IV,O(t-1),V(t-1),V(t)
	Volume	-5.31	-.50	INS	IV,O(t-1),V(t-1),O(t)
7:25 - 7:30	Occupancy	.06	.07	INS	IV,V(t-3),O(t-1),V(t)
	Volume	-4.93	-.54	INS	IV,V(t-2),O(t)
7:30 - 7:35	Occupancy	-.51	-.53	INS	IV,V(t-3),V(t-2),V(t),O(t-1)
	Volume	-.16	-.02	INS	IV,V(t-3),O(t)
7:35 - 7:40	Occupancy	0.56	0.42	INS	IV,V(t-3),V(t-2),O(t-2),V(t-1)
	Volume	1.08	0.07	INS	IV,O(t-1),O(t-2),V(t-2),V(t-1)

TABLE D.3 (Continued)

STATION: NE 185TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
7:40 - 7:45	Occupancy	1.58	1.76	P<.10	IV,O(t-3),O(t-1),V(t-1),V(t-2)
	Volume	-11.97	-1.37	INS	IV,O(t-2),V(t-2),O(t-1),V(t-1)
7:45 - 7:50	Occupancy	2.48	1.84	P<.10	IV,O(t-3),O(t-2),V(t)
	Volume	-17.83	-1.55	INS	IV,V(t-1),V(t-2)
7:50 - 7:55	Occupancy	1.27	1.15	INS	IV,O(t-3),O(t-1)
	Volume	-5.31	-.44	INS	IV,O(t-2),V(t-2),O(t-1)
7:55 - 8:00	Occupancy	-1.05	-.97	INS	IV,O(t-1),O(t-3)
	Volume	15.71	1.98	P<.10	IV,V(t-1),V(t-2),V(t-3),O(t-3),O(t)

TABLE D. 4 INTERVENTION ANALYSIS RESULTS

STATION: NE 175TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
6:00 - 6:05	Occupancy	-.02	-.04	INS	IV
	Volume	2.65	0.21	INS	IV,O(t-1)
6:05 - 6:10	Occupancy	-9.37	-1.72	P<.10	IV,V(t-1),O(t-1)
	Volume	-11.18	-.60	INS	IV,V(t-1),O(t-1)
6:10 - 6:15	Occupancy	0.98	1.70	INS	IV,V(t-2),V(t-1),O(t-1)
	Volume	22.68	1.43	INS	IV,V(t-1),V(t-2),O(t)
6:15 - 6:20	Occupancy	.08	.35	INS	IV,O(t-2),V(t-2),V(t-1),O(t-1),V(t)
	Volume	-7.50	-1.11	INS	IV,V(t-2),O(t-2),V(t-1),O(t-1),O(t)
6:20 - 6:25	Occupancy	0.31	1.02	INS	IV,V(t-3),O(t-1)
	Volume	-7.24	-.90	INS	IV,O(t-3),V(t-2),V(t-1),O(t)
6:25 - 6:30	Occupancy	-.78	-1.50	INS	IV,O(t-3),O(t-1)
	Volume	4.65	.76	INS	IV,V(t-2)
6:30 - 6:35	Occupancy	-.47	-1.30	INS	IV,O(t-1),V(t-1),V(t)
	Volume	12.66	1.98	P<.10	IV,V(t-3),V(t-1)
6:35 - 6:40	Occupancy	.22	.48	INS	IV,O(t-3),O(t-2),O(t-1)
	Volume	3.22	0.54	INS	IV,V(t-1),V(t-2)
6:40 - 6:45	Occupancy	-.51	-1.43	INS	IV,O(t-1),O(t-2),V(t-2),V(t)
	Volume	-3.34	-.56	INS	IV,O(t-2),V(t-2),V(t-1),V(t)
6:45 - 6:50	Occupancy	+.94	1.69	INS	IV,O(t-2),O(t-1)
	Volume	-3.75	-.57	INS	IV,O(t-3),O(t-1),V(t-1)

TABLE D. 4 (Continued)

STATION: NE 175TH

Period	**Dependent Variable**	**Coefficient of Intervention Variable**	**T-Ratio**	**Sig.**	**Independent Variables**
6:50 - 6:55	Occupancy	2.26	2.27	P<.05	IV,O(t-1),O(t-3)
	Volume	11.83	0.87	INS	IV,V(t-1),V(t-2)
6:55 - 7:00	Occupancy	.33	0.46	INS	IV,O(t-1),O(t-2),O(t-3)
	Volume	10.94	1.12	INS	IV,O(t-1),V(t-1)
7:00 - 7:05	Occupancy	1.63	2.05	P<.05	IV,O(t-1),O(t-3)
	Volume	1.20	0.14	INS	IV,V(t-2),V(t-3)
7:05 - 7:10	Occupancy	1.91	1.99	P=0.05	IV,O(t-2),O(t-1),V(t)
	Volume	-10.41	-1.15	INS	IV,O(t-3),O(t-2),O(t-1),V(t-2), V(t-1)
7:10 - 7:15	Occupancy	-.70	-.64	INS	IV,V(t-2),V(t-1),V(t),O(t-1)
	Volume	-4.67	-.55	INS	IV,V(t-2),O(t)
7:15 - 7:20	Occupancy	1.61	1.66	P=0.10	IV,V(t-2),O(t-1),V(t-1),V(t)
	Volume	-22.92	-1.40	INS	IV,V(t-3),V(t-1)
7:20 - 7:25	Occupancy	0.80	0.73	INS	IV,O(t-1),V(t-1),V(t)
	Volume	15.49	1.52	INS	IV,V(t-1),β_0
7:25 - 7:30	Occupancy	0.91	0.74	INS	IV,O(t-3),V(t-2),O(t-1)
	Volume	-4.66	-.55	INS	IV,O(t-3),V(t-3),V(t-2),O(t)
7:30 - 7:35	Occupancy	-.19	-.15	INS	IV,O(t-3),O(t-1)
	Volume	13.98	1.45	INS	IV,O(t-3),V(t-3),O(t-2),v(t-1),O(t)
7:35 - 7:40	Occupancy	2.59	1.74	P<.10	IV,O(t-3),V(t-3),O(t-1),V(t-1)
	Volume	-1.62	-.110	INS	IV,V(t-1)

TABLE D. 4 (Continued)

STATION: NE 175TH

Period	Dependent Variable	Coefficient of Intervention Variable	T-Ratio	Sig.	Independent Variables
7:40 - 7:45	Occupancy	2.39	2.00	P=0.05	IV,O(t-2),O(t-1),V(t)
	Volume	-29.92	-2.94	P<.01	IV,O(t-3),V(t-2),V(t-1)
7:45 - 7:50	Occupancy	.33	0.22	INS	IV,O(t-3),O(t-1),V(t-1),V(t)
	Volume	-13.96	-.74	INS	IV,V(t-1)
7:50 - 7:55	Occupancy	1.64	1.11	INS	IV,O(t-3),O(t-1),V(t-1)
	Volume	-5.12	-.47	INS	IV,V(t-2),O(t-3)
7:55 - 8:00	Occupancy	1.29	0.13	INS	IV,V(t-1),V(t-2)
	Volume	-3.04	-.33	INS	IV,O(t-2),V(t-2),V(t-1)