FINAL REPORT

TRAFFIC FLOW FORECASTING FOR INTELLIGENT TRANSPORTATION SYSTEMS

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16. Abstract

The capability to forecast traffic volume in an operational setting has been identified as a critical need for intelligent transportation systems (ITS). In particular, traffic volume forecasts will directly support proactive traffic control and accurate travel time estimation. However, previous attempts to develop traffic volume forecasting models have met with limited success.

This research focused on developing such models for two sites on the Capital Beltway in Northern Virginia. Four models were developed and tested for the single-interval forecasting problem, which is defined as estimating traffic flow 15 minutes into the future. The four models were the historical average, time series, neural network, and nonparametric regression models. The nonparametric regression model significantly outperformed the others.

Based on its success on the single-interval forecasting problem, the nonparametric regression approach was used to develop and test a model for the multiple-interval forecasting problem. This problem is defined as estimating traffic flow for a series of time periods into the future in 15-minute intervals. The model performed well in this application. In general, the model was portable, accurate, and easy to deploy in a field environment.

Finally, an ITS system architecture was developed to take full advantage of the forecasting capability. The architecture illustrates the potential for significantly improved ITS services with enhanced analysis components, such as traffic volume forecasting.

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(The opinions, findings, and conclusions expressed in this
report are those of the authors and not necessarily
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Traffic Research Advisory Committee

ABSTRACT

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This research focused on developing such models for two sites on the Capital Beltway in Northern Virginia. Four models were developed and tested for the single-interval forecasting problem, which is defined as estimating traffic flow 15 min into the future. The four models were the historical average, time series, neural network, and nonparametric regression models. The nonparametric regression model significantly outperformed the others.

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INTRODUCTION

Virginia and the nation are facing transportation challenges of increasing magnitude and complexity. Because of financial and environmental constraints, the traditional solutions of constructing new facilities and enlarging existing ones are becoming less attractive. There is a need to improve the efficiency and safety of the extensive, existing transportation system. Intelligent transportation systems (ITS) will play an important role in accomplishing these improvements.

ITS can be defined as the application of information technology to the surface transportation system. Information technology, which has been developed primarily in the defense, computer, and telecommunication industries, facilitates the collection, analysis, and dissemination of information describing the status of the transportation system. The fundamental objective of ITS is to provide an environment that allows for improved transportation decision making. For example, transportation agencies can use ITS to control traffic signals more efficiently and clear congestion-causing accidents more rapidly. Travelers can use ITS to make more informed decisions about when to travel, what mode of travel to use, and what route to take. In short, ITS will allow society to use the surface transportation system more intelligently, resulting in safer, more efficient travel.

Although ITS holds much promise, it is associated with significant risk. ITS hardware is developing at a rapid rate. For example, a wide variety of sensors and communication media that can support extensive data collection and transmission applications is currently on the market. However, software support systems, which process and analyze these data, are less advanced. Such systems are critical in that they provide the true "intelligence" in ITS. A traffic control specialist cannot be expected to select optimal signal timings based on "raw" vehicle counts. Likewise, a traveler cannot be expected to identify the optimal route to a destination based on such counts. It is clear that advanced analysis tools, which include artificial intelligence, simulation, and optimization, are required to derive usable information from raw data.

Traffic flow prediction, the ability to estimate future traffic volume (measured in units of vehicles/hour), plays a particularly important role in transforming raw data into usable

information. Without a predictive capability, ITS will provide services in a *reactive* manner. For example, there will be a lag between the collection of data and the implementation of a traffic control strategy, resulting in the transportation system being controlled based on old information. In order to control the system in a *proactive* manner, ITS must have a predictive capability; that is, it must be able to make and continuously update predictions of traffic flows and link times for several minutes into the future using real-time data (Cheslow et al., 1992).

Traffic flow prediction also plays a key role in providing travelers with high-quality route guidance information. Travelers must be able to base their decisions on expected traffic conditions (Kaysi et al., 1993). Clearly, the success of ITS depends on the development of a traffic flow prediction capability. This leads to the conclusion that "special attention should be given to the ability to make short-term traffic predictions with real-time sensor data" (Cheslow et al., 1992).

PURPOSE AND SCOPE

The purpose of this project was to investigate the feasibility of forecasting freeway traffic flow and develop a framework in which to use a forecasting capability in ITS traffic management and traveler information services.

All data used to develop and evaluate candidate forecasting models were collected at the Virginia Department of Transportation's (VDOT's) Northern Virginia Traffic Management System (TMS). This ensured that any model that was developed would be compatible with existing and future freeway traffic management systems.

METHODS

Five tasks were undertaken to accomplish the study's objectives:

1. review of the literature

2. collection of data

3. development and evaluation of a single-interval model

4. development and evaluation of a multiple-interval model

5. development of ITS software support system architecture.

Literature Review

The literature on research in traffic flow forecasting was reviewed, and desirable characteristics of traffic flow forecasting models were identified. These characteristics were then used to select advanced or emerging models to apply in this study.

Data Collection

Data were collected for the development and evaluation of traffic flow forecasting models at two sites monitored by the Northern Virginia TMS. The sites are both on Virginia's Capital Beltway, as shown in Figure 1. This section of the Beltway is heavily traveled, with an average annual daily traffic volume of 149,000 vehicles (VDOT, 1993). As shown in the figure, the Telegraph Road site is westbound (or the inner loop), and the Woodrow Wilson Bridge site is eastbound (or the outer loop).
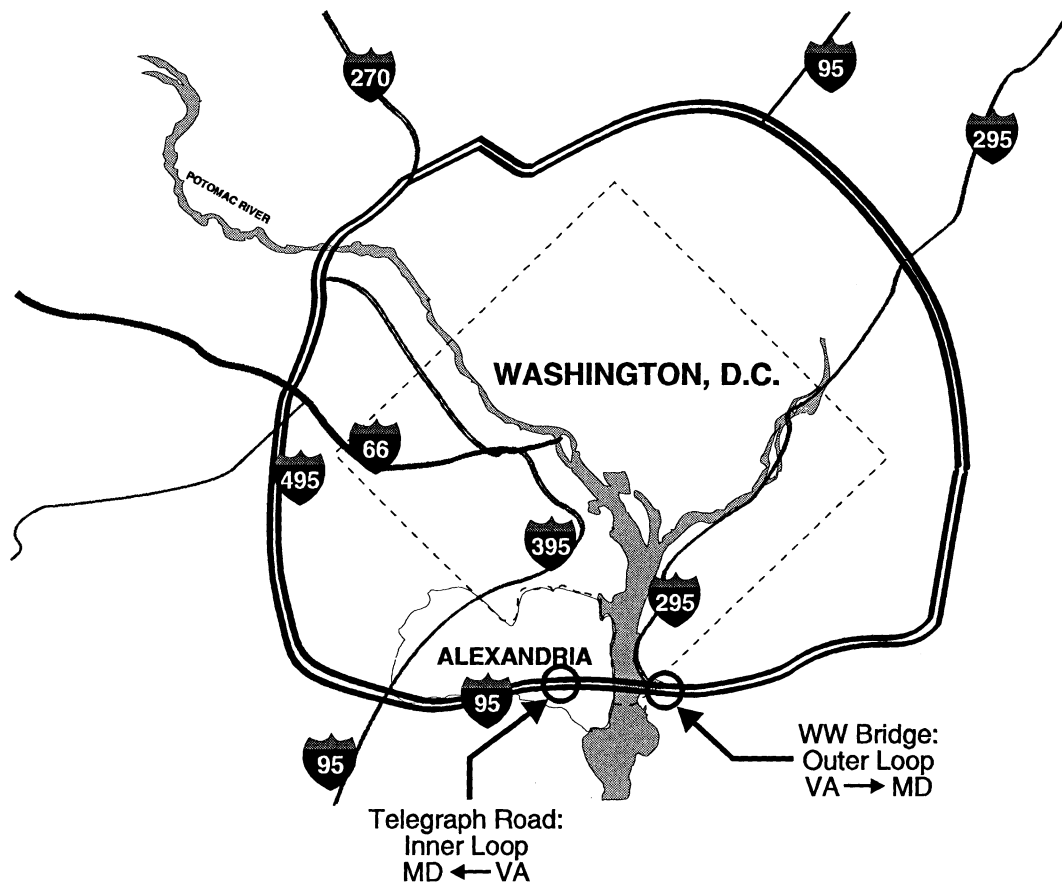

Figure 1. Test Sites

Average traffic volumes for 15-min intervals were collected at each site using the TMS's loop detectors over the period from June 3, 1993, to October 29, 1993. In order to allow for model development and evaluation, the data were split into two independent samples: the development data set and the evaluation data set. The development data set was composed of data collected from June through August, representing roughly 60% of the data, and the evaluation data set included data collected in September and October, roughly 40% of the data.

Development and Evaluation of a Single-Interval Model

Single-interval traffic flow forecasting models (models that at time t estimate traffic volume at time $t + 15$ min) were developed for each test site. The process varied based on the modeling technique used. However, in general, the development data set was used to define model parameters or "fit" the model to the site.

The models were then evaluated to select the most promising model for application to multiple-interval traffic flow forecasting. The evaluation was based on the following performance indices:

1. ability of the model to produce accurate forecasts, on average

2. ability of the model to avoid significant overestimation or underestimation of future traffic volume

3. consistency of the model's results at the two sites (this serves as an indication of the model's portability)

4. ease of model calibration in a field environment.

Development and Evaluation of a Multiple-Interval Model

Using the single-interval model selected, a multiple-interval traffic flow forecasting model (a model that at time t estimates traffic volumes at time $t + 15$ min, $t + 30$ min, $t + 45$ min, ..., 24:00) was developed for each test site. This process used the development data set.

The model was then evaluated based on the following performance indices:

1. ability of the model to produce accurate forecasts, on average

2. ability of the model to produce forecasts of comparable quality in the near term (periods within 1 hr of the forecast time) and the extended term (periods 3 to 4 hr after the forecast time)

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3. consistency of the model's results at the two sites (this serves as an indication of the model's portability)

4. ease of model calibration in a field environment.

Development of ITS Support System Architecture

A software architecture defines the functional components of a software system and details the relationships between the components. An ITS software support system architecture that fully utilized the capabilities of the multiple-interval traffic flow forecasting model was developed. This was accomplished by identifying the information needs of ITS decision makers and the sources of data in a "generic" ITS system. Then, analysis functions were identified to extract the information from the data. Finally, the functions were organized to achieve an efficient means of transforming ITS data into usable information for decision makers.

RESULTS AND DISCUSSION

Literature Review

Previous Efforts at Traffic Flow Forecasting

"The short-term forecasting of traffic conditions has had an active but somewhat unsatisfying research history" (Davis & Nihan, 1991). Most attempts at developing forecasting models have been applied to signal control systems, such as the Urban Traffic Control System (UTCS). The number of freeway traffic flow prediction applications is limited. The approaches used for traffic prediction are largely dictated by the fact that traffic conditions are time-dependent and follow fairly well-defined patterns. Previous traffic flow prediction approaches can best be classified in two categories: historical data-based algorithms, and time series models.

Historical Data-Based Algorithms

The premise underlying these algorithms is that traffic patterns are cyclical. In other words, knowledge of "typical" traffic conditions on Tuesday at 5:30 P.M. will allow one to predict the conditions on any particular Tuesday at 5:30 P.M. AUTOGUIDE, a demonstration project in London, used the most simple historical data-based algorithm possible: a traffic database to predict travel times based on time of day (Jeffrey et al., 1987).

UTCS uses traffic condition prediction in an attempt to control signals in a proactive manner. In general, it relies on historical data for prediction. A weakness of this system is that it requires an extensive set of historical data, making it difficult to install in a new setting (Stephanedes et al., 1981). The prediction capabilities of UTCS were enhanced in a second generation, UTCS-2, which uses "current traffic measures to correct for the traffic deviation from the average historical pattern" (Okutani & Stephanedes, 1984). In other words, if current traffic volumes are observed to be lower than normal, the historical average for the upcoming period is scaled down to reflect "current" conditions.

It is interesting to note that the third generation, UTCS-3, abandoned the historical data-based algorithm and attempted to make predictions based only on current traffic measurements. However, experience has shown that UTCS-3 is incapable of performing at a level comparable to that of UTCS-2 (Stephanedes et al., 1981).

Time Series Models

Traffic management systems use detectors to measure traffic flow at time t, defined as $x(t)$. A series of these measurements can be stored for use in predicting traffic flow at time $t + D$ where D is the prediction interval. Therefore, the prediction problem can be formulated as estimate $x(t + D)$, given $x(t)$, $x(t - D)$, $x(t - 2D)$, etc. This formulation describes a time series. Many statistical techniques have been developed to model time series, and transportation researchers have applied many of them to traffic flow prediction.

The Box and Jenkins technique is a widely used approach to specifying a variety of time series models (Nihan & Holmesland, 1980). The most well-developed Box and Jenkins technique is the auto regressive integrated moving average (ARIMA) method. ARIMA models require very little computational time for execution, an attractive quality for application in real-time traffic management. However, they have not shown much promise in traffic applications. Attempts to apply ARIMA models to UTCS "resulted in unsatisfactory goodness of fit and high errors; in certain cases they have not been more accurate than a simple moving average" (Okutani & Stephanedes, 1984).

Advanced Modeling Techniques

Based on the review of traffic flow forecasting research, one can conclude that three characteristics are desirable for models applied to the traffic prediction problem. First, the model must be able to represent complex relationships. Second, given the lack of traffic flow forecasting theory, the model must not require any prior knowledge of the functional form of the relationship. Third, as seen in the evolution of UTCS, the model should rely strongly on historical data.

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Two advanced modeling techniques, nonparametric regression and neural networks, possess these characteristics. The basic concepts underlying these models are described here. For more detail on nonparametric regression, the reader is referred to Eubank (1988). For more detail on neural networks, the reader is referred to Hecht-Nielsen (1990).

Nonparametric Regression

Most modeling techniques can be classified as parametric. A parametric model assumes that the functional form of the relationship between the dependent and independent variables is known (Eubank, 1988). For example, a linear regression model assumes a linear relationship between the dependent and independent variables. Given the functional form, a set of parameters can be defined to fit the function to the relationship in question. In the case of a linear regression model, the parameters are the slope and the y intercept. Using a parametric approach, therefore, results in two primary challenges: (1) identifying the functional form in question, and (2) defining parameters.

In many cases, these challenges are difficult, if not impossible, to overcome. For example, there may be no supporting theory to justify the selection of a linear function to represent a particular relationship. In order to address these challenges, a new approach, nonparametric regression, has been developing rapidly over the last 20 years (Eubank, 1988). Nonparametric regression relies heavily on the data describing the relationship between dependent and independent variables. In essence, the approach locates the state of the system (defined by the independent variables) in a "neighborhood" of past, similar states. Once this neighborhood is established, the past cases in the neighborhood can be used to estimate the value of the dependent variable.

Figure 2 depicts an example where a nonparametric model is used to estimate a single dependent variable, y, based on a single independent variable, x, given a data set of previously observed x,y pairs. The 13 previously observed x,y pairs are plotted. In order to estimate y when $x = 4$, a neighborhood in the area of $x = 4$ is established. The size of the neighborhood, described as k, the number of past observations to use in estimating y, is defined to be 3. Figure 2 shows the 3 previously observed x,y pairs selected from the data set to serve as the neighborhood. The nonparametric regression model generates the estimate for y by averaging the y values of the previously observed cases in the neighborhood. In this example, the model forecasts $y = 5.5$ given an x value of 4.

The challenge to applying nonparametric regression effectively lies in choosing a set of independent variables that adequately describe the dynamics of the system being modeled. For example, if time served as the independent variable, the dependent variable estimate would simply be an average of past conditions at that time. In effect, this describes a historical data-based algorithm. On the other hand, the use of other independent variables may allow the model to be more selective in defining a neighborhood. This would likely result in a more responsive model.
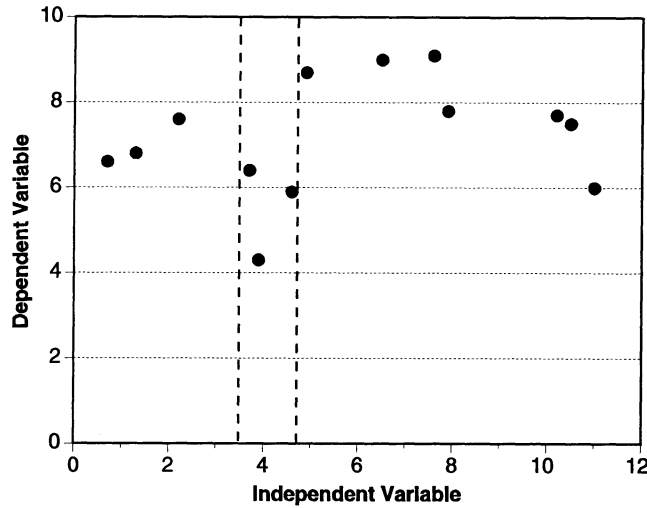
Figure 2. Nonparametric Regression Neighborhood *(x = 4)*

Neural Networks

Algorithmic approaches require that one fully understand the details of the problem at hand, e.g., how each independent variable affects the system as a whole. If one is addressing a problem with a long history of research and theory, such an approach is reasonable. However, if this is not the case, such an approach may be quite time-intensive, and possibly unsuccessful. The use of a neural network allows one to learn the system's behavior *automatically* from a database of past observations. This substantially reduces the time required for problem solving.

A neural network learns a system's behavior using a rigorous mathematical procedure. The various neural network parameters, which can be thought of as being similar to regression coefficients, are iteratively modified to reduce the model's error when applied to the database. In fact, the neural network learning procedure is similar to the method of least squares used for developing regression models.

Neural networks have been successfully applied to problems such as classification, forecasting, process control, and signal processing (Klimasauskas, 1991). One of their key advantages is the ability to perform highly nonlinear mappings. In addition, their structure is well suited for implementation on parallel computers. Finally, a neural network developer need not make any assumptions about the functional form of the underlying distribution of the data.

A significant weakness of neural networks is the complexity of the learning process. A modeler must make many decisions with very little guidance. In addition, although the model captures the behavior of a system, it is difficult for one to understand exactly how it represents the behavior. In other words, one can learn very little about the underlying process modeled by a neural network.

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Data Collection

A preliminary examination of the data collected revealed unique characteristics at each test site. The typical daily traffic pattern at Telegraph Road is displayed in Figure 3. Traffic peaked as expected during the morning and evening commute periods. However, given the high demands on the Beltway, the volumes were somewhat lower than expected. Assuming that the maximum capacity of each of the four lanes is 2,300 vehicles per hour, as defined in the *Highway Capacity Manual* (TRB, 1994), one would expect to see maximum volumes in the range of 8,000 to 9,000 vehicles per hour, as opposed to 4,200 vehicles per hour as seen in Figure 3. This discrepancy can be attributed to the fact that the Woodrow Wilson Bridge, which has only three westbound lanes, is actually metering traffic as it comes into Virginia.
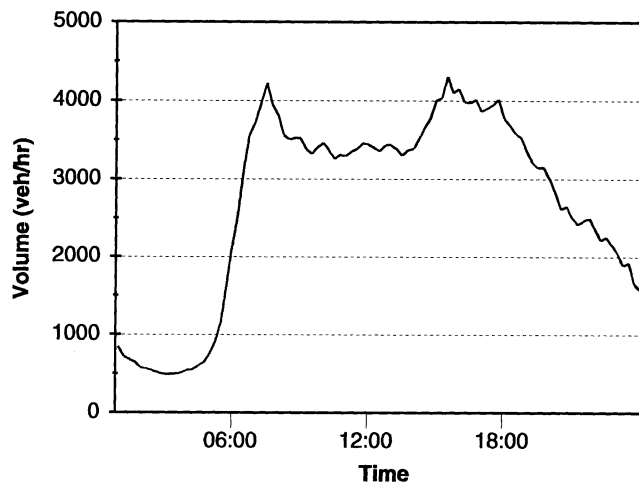

Figure 3. Daily Traffic Pattern at Telegraph Road Site

The typical daily traffic pattern at Wilson Bridge is displayed in Figure 4. This site has significantly higher volumes than Telegraph Road. In addition, the peaks for the morning and evening commutes are more pronounced. In fact, during both peak periods, the three lanes operate near capacity, assuming a per lane capacity of 2,300 vehicles per hour as defined in the *Highway Capacity Manual* (TRB, 1994).

On many occasions over the 5-month data collection period, malfunctions of the Northern Virginia TMS resulted in errors in volume measurements. For example, the loop detectors, central computer, and communications system failed on numerous occasions. As a result, the traffic volume measurements for roughly 20% of the time intervals over the data collection period were logged as missing values.

Finally, based on discussions with personnel at the Northern Virginia TMS, it can be concluded that the data collected over the 5-month period reflected a wide variety of conditions, including incidents of varying magnitude, special events, and holiday travel. Although it would have been desirable to collect data in the winter and spring to examine seasonal effects, this was
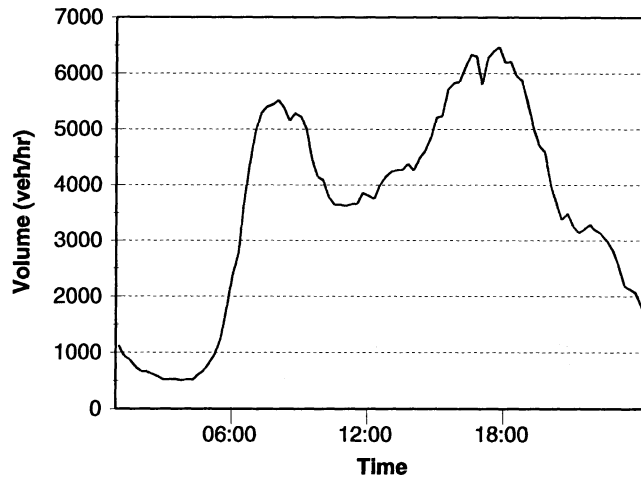
Figure 4. Daily Traffic Pattern at Woodrow Wilson Bridge Site

not possible due to the schedule and budget of the project. However, the database does reflect a wide enough set of conditions to serve as a solid basis in examining the feasibility of developing effective traffic flow forecasting models.

Development and Evaluation of a Single-Interval Model

Model Development

The historical average, time series, neural network, and nonparametric regression traffic flow forecasting models were developed using the development data sets.

Historical Average Model

This model was simply formulated by computing the average volume for each time interval at each site. In this case, the average was computed using the development data set only. This model is easily developed at any loop detector site.

Time Series Model

The development of this model was challenging because of the large number of missing values in the database. In time series analysis, missing values distort the evenly spaced time series of data, which precludes the use of a time series model (SPSS, 1993). A suggested method to deal with missing values is to "fill in" the data using a method such as linear interpolation. However, a traffic volume time series often undergoes rapid, erratic changes between time intervals. Therefore, the use of a fill technique for missing values is likely to produce unacceptable results.

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However, given that time series models have been used in previous traffic flow forecasting research efforts, a simplified model was developed for comparison purposes. In order to achieve a continuous, complete set of data for development, the average volumes for each time interval on each weekday were computed. This provided 5 consecutive days of development data with no missing values. The statistical software package SPSS was used to calibrate the model based on this set of data.

Neural Network Model

The objective of developing the model was to use sound network development principles without using an exhaustive iterative approach that looked at all possible combinations of parameters. Such an approach is normally used for one-of-a-kind neural network applications, such as stock market forecasting. However, to meet the needs of ITS, traffic flow prediction models must be capable of implementation on a "production" basis. In other words, the development, or calibration, process must be simple. There are not personnel available in the field to devote a significant amount of knowledge and time to neural network calibration at multiple sites.

Only one network was developed to predict single-interval traffic volumes at the Beltway location. This network was calibrated using the development data set for Telegraph Road. Again, because expertise and time are scarce in the field, the network was developed at only one site in order to assess its portability. The neural network development software package *NeuralWorks Professional II/Plus* was used to define the neural network parameters. Although the package provides the modeler with significant assistance, it cannot be used effectively by someone unfamiliar with neural network theory.

Nonparametric Regression Model

The nonparametric regression modeling technique was coded in the programming language *C* for this application. The algorithm searches for k cases in the development data set that are the most similar to the case at hand. It then simply uses the average volume from the similar cases to forecast the future volume. This code was straightforward to develop and had the advantage of being very portable. To install the model, one simply "plugs in" a database from any site.

The number of samples to use, k, was selected by applying the model using different values of k to a subset of the evaluation database at Telegraph Road, comprising 2 days worth of data. After the accuracy of the model was compared using the different k values, a k value of 10 was selected for the single-interval traffic volume prediction model.

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Model Evaluation

The four models were applied and evaluated using the independent evaluation data sets collected at the Telegraph Road and Wilson Bridge test sites.

Telegraph Road Site

Table 1 shows the measures of error. Since the time series model cannot function in an environment with missing data, the evaluation data set would allow for testing it on only 2 consecutive days. Table 2 shows the measures of the tendency to grossly over- or underestimate future traffic volume. Of particular note is the distribution of these measures. Performance during an evening peak period was considered to illustrate particular characteristics of the models.

Table 1
Error Measures at Telegraph Road Site

Model	Average Absolute Error (vehicles/hour)	Average Percentage Error
Historical average	214.6	9.57%
Neural network	182.5	8.93%
Nonparametric regression	167.3	7.54%
Time series[a]	195.0	9.03%

[a]Includes only 2 days of evaluation data.

Table 2
Bad Miss Measures at Telegraph Road Site

Model	% Cases Over 10% Error		% Cases Over 20% Error	
	Underestimate	Overestimate	Underestimate	Overestimate
Historical average	14.02%	19.30%	3.95%	6.95%
Neural network	24.08%	7.28%	10.02%	1.75%
Nonparametric regression	13.31%	10.98%	1.87%	4.08%
Time series[a]	16.67%	16.15%	5.21%	5.21%

[a]Includes only 2 days of evaluation data.

Historical Average Model. This model had the highest average level of error among the four models, averaging 9.57% error per estimate. However, as can be seen, it did not grossly over- or underestimate future traffic volumes when compared to the other models. These results indicate that although the model cannot be expected to produce the most accurate forecasts, the forecasts should be within a reasonable range of the true value.

Table 2 shows that the model tended to overestimate future traffic flow. This can most likely be attributed to the fact that the model has no way of reacting to external changes in the system, such as incidents. When incidents occur, reducing roadway capacity and effectively metering traffic, the model forecasts based on "normal," nonmetered conditions.

Figure 5 illustrates the model's difficulty adjusting to external changes. From 3 P.M. until 6 P.M. , the model consistently forecast volumes higher than the actual volumes.
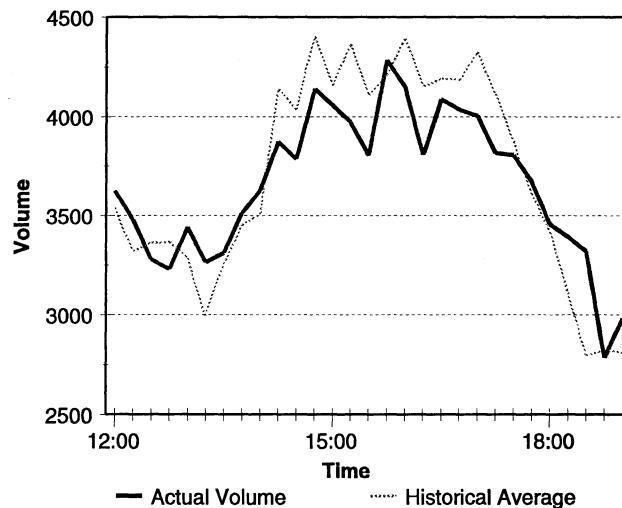

Figure 5. Historical Average Model Performance at Evening Peak Period

Time Series Model. As seen in Tables 1 and 2, this model performed slightly better than the historical average model. It was associated with roughly the same number of bad misses as the other models (with the exception of the nonparametric regression model), but the misses were well distributed. For both the 10% and 20% levels, the model was equally likely to over- or underestimate the future volume.

Figure 6 illustrates the model's performance during the evening peak period and indicates its weakness. The forecasts lagged one time period behind actual volumes. However, the most telling evidence of the model's poor potential for effective field application is that, due to missing values, it could be applied to only 2 days of the evaluation data set. It is clear that the time series model is poorly suited for application to the traffic flow prediction problem and, therefore, was dropped from consideration and not evaluated at Wilson Bridge.
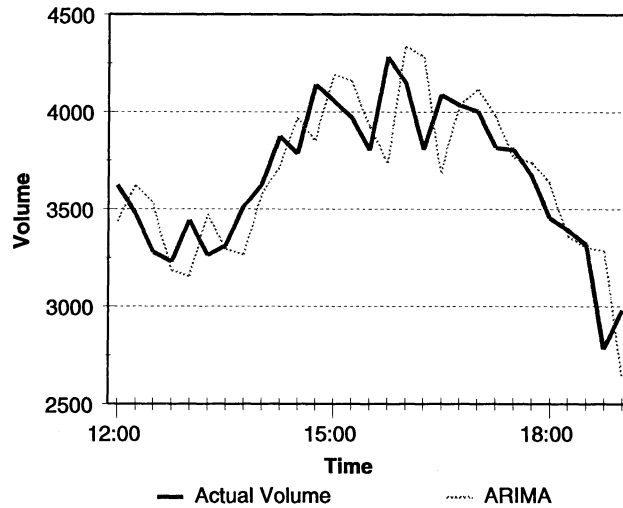
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Figure 6. Time Series Model Performance at Evening Peak Period

Neural Network Model. As seen in Table 1, this model was the second most effective model among the four, with an average error of 8.93% per estimate. The most troubling aspect of its performance was the distribution of over- and underestimates, as shown in Table 2. For example, in nearly a quarter of the cases, it underestimated future traffic flow by at least 10%. Overestimates of 10% or more comprised only 7.3% of the cases.

The cause of the model's tendency to underestimate future traffic volume is most likely the neural network development process. It is possible that cases in the development data that described incident conditions resulted in extreme modifications of the model's parameters. In other words, a few incident conditions in the development data may have caused the network to reduce flow estimates across the board. This illustrates that a careful selection of development data is necessary to calibrate a neural network properly, another significant challenge in the already demanding neural network development process.

The model performed extremely well during the evening peak period, as shown in Figure 7. In general, it did an excellent job of tracking fluctuation in actual traffic volume. However, in this case, the model benefited from a lower than normal traffic flow. As seen in Figure 5, the historical average volume was higher than the volumes on this particular day between 3 P.M. and 6 P.M. In this example, the neural network model may have performed well because of its tendency to underestimate flow.
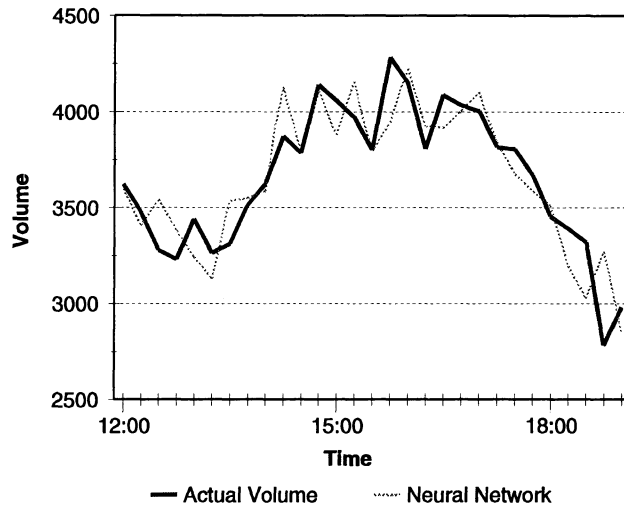
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Figure 7. Neural Network Model Performance at Evening Peak Period

Nonparametric Regression Model. This model significantly outperformed the other models at Telegraph Road. With an average error per estimate of 167 vehicles/hour, the model was the most accurate of the four considered. However, the area in which the model particularly shines is shown in Table 2. Whereas each of the other three models had errors of 10% or greater in more than 30% of the evaluation data set test cases, the nonparametric regression model had such errors in only 24% of the cases. Further, only 6% of the cases had an error of more than 20%, roughly half that of the other models. Finally, the distribution of the bad misses was fairly even between over- and underestimates.

Figure 8 illustrates the model's performance during the evening peak period. It reacted well to fluctuations in traffic volume and adjusted to the lower than normal traffic flow between 3 P.M. and 6 P.M.
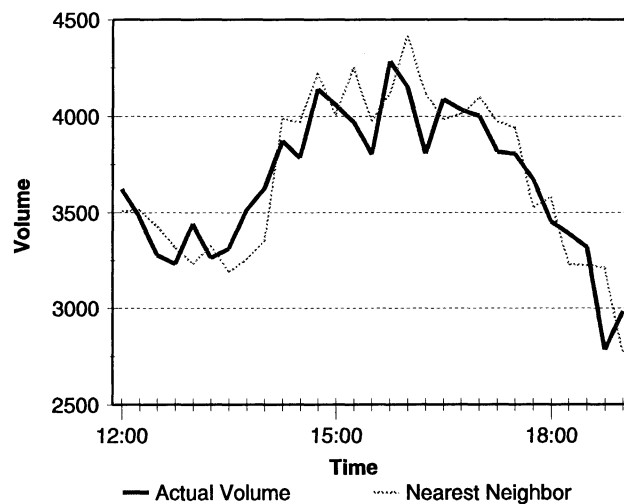

Figure 8. Nonparametric Regression Model Performance at Evening Peak Period

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Table 3 shows the measures of error. (The time series model was dropped from consideration.) Table 4 shows the measures of the tendency to grossly over- or underestimate future traffic volume.

Table 3
Error Measures at Woodrow Wilson Bridge Site

Model	Average Absolute Error (vehicles/hour)	Average Percentage Error
Historical average	300.4	9.86%
Neural network	450.3	11.00%
Nonparametric regression	229.3	8.07%

Table 4
Bad Miss Measures at Woodrow Wilson Bridge Site

Model	% Cases Over 10% Error Underestimate	Overestimate	% Cases Over 20% Error Underestimate	Overestimate
Historical average	13.99%	19.85%	4.60%	6.33%
Neural network	32.86%	12.11%	14.47%	5.58%
Nonparametric regression	11.01%	14.58%	1.53%	4.68%

Historical Average Model. Tables 1 through 4 make clear that the historical average model had an equivalent performance at both sites. These results illustrate that the model is portable in that consistent performance can be expected from it at any location where it is applied. Of course, this conclusion is intuitive, given that it is based on past observations at the site. However, the model's overall inaccuracy remains a serious drawback. As shown at Telegraph Road, and reflected in the relatively high error measures at Wilson Bridge, the model's inability to react to current conditions often results in inaccurate forecasts.

Neural Network Model. As shown in Tables 3 and 4, this model had a significantly higher error rate at Wilson Bridge. The average error per estimate was 11.0%, as compared to 8.9% at Telegraph Road. The most problematic indication of the model's poor performance is the fact that nearly half (45.0%) of the cases in the evaluation data set had errors of 10% or more,

and 20.1% of the cases had errors greater than 20%. In addition, the model was much more likely to underestimate future volume than overestimate it.

The results at Wilson Bridge show that the model is not portable. The model was developed at Telegraph Road, where it did a reasonable job of estimating future volume, but it did not capture a "universal" underlying relationship between the transportation system's current status and the future volume. Rather, it is clear that for the model to be effective, it must be re-calibrated with data at each site where it will be deployed.

Nonparametric Regression Model. This model was the most effective model at Wilson Bridge. In addition, its performance was comparable at both sites. The model was associated with an average of 8.0% error per estimate at Wilson Bridge, as compared to 7.5% at Telegraph Road. Further, only 6.2% of the cases in the evaluation data set had errors of more than 20%.

Based on the performance indices described in the methodology, this model was judged to be most promising for application to multiple-interval traffic flow forecasting. It produced the most accurate average forecasts, produced the fewest bad misses, proved to be portable, and was demonstrated to be easily calibrated in the field.

Development and Evaluation of a Multiple-Interval Model

Model Development

The nonparametric regression algorithm was modified slightly to meet the requirements of the multiple-interval traffic flow forecasting problem. The most significant modifications were necessary to allow for a series of volumes to be predicted, rather than a single forecasted volume. In addition, modifications were needed to allow the model to function with missing values. The C programming language was used to automate the execution of the algorithm. The k value was defined using the same process described for the single-interval model. In this case, a k value of 3 was selected.

Model Evaluation

The model was applied for each day in the evaluation data set from 5 A.M. through 7 P.M., at intervals of 15 min. The resulting estimate was a time series of volumes for the remainder of the day, with intervals of 15 min. For example, at 1 P.M. , the model would forecast volumes at 1:15 P.M., 1:30 P.M., and so on, until midnight. For each forecast, the error measures were averaged over four time periods, referred to as error intervals, as shown in Table 5.

Table 5
Multiple-Interval Forecasting Model Error Intervals

Error Interval	Forecast Times Included in Error Interval Average
1 hr	$t + 15, t + 30, t + 45, t + 60$
2 hr	$t + 75, t + 90, t + 105, t + 120$
3 hr	$t + 135, t + 150, t + 165, t + 180$
4 hr	$t + 195, t + 210, t + 225, t + 240$

Telegraph Road Site

Table 6 shows the average percentage error over the four error intervals. The error averages were calculated for three time periods and for the overall daily period. The periods roughly corresponded to times of prediction during the morning peak period, the mid-day period, and the evening peak period.

Table 6
Average Percentage Error at Telegraph Road Site

| Time Period | Average Percentage Error Per Interval | | | |
	1 Hr	2 Hr	3 Hr	4 Hr
5:00-8:45	9.97%	10.77%	11.31%	11.51%
9:00-14:00	10.84%	10.87%	10.74%	10.49%
14:00-19:00	9.21%	10.16%	11.08%	12.19%
Overall Average	9.99%	10.58%	11.03%	11.40%

As discussed previously, the average percentage error for the single-interval nonparametric regression model at Telegraph Road was 7.5%. Table 6 shows that the multiple-interval model did not deliver this level of performance. However, it is important to note that the single-interval error measure was for 15-min forecasts, whereas the 1-hr error interval takes into account forecasts over a 1-hr period. Given this fact, a 9.21% average error over the 1-hr error interval during the evening peak period represents a fairly good performance.

Overall, forecasts in the nearer term are more accurate than in the longer term. Particularly, this is true for the 1-hr error interval as compared to the 2-, 3-, and 4-hr intervals, especially during the peak periods. During the mid-day period, forecasts over all intervals were

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of nearly constant accuracy. Given that mid-day is not a rush period, it is logical that volumes would be less predictable during this time.

Although nearer-term forecasts are generally the more accurate, the performance of the model did not drop off significantly with the 2- to 4-hr error intervals. An average percentage error of 11.4% in the 4-hr error interval is quite respectable. Figure 9 illustrates the performance of a 6 A.M. forecast over an entire day. The model was able to predict the general trends in the volumes, keeping within roughly 350 vehicles/hour of the true volume.
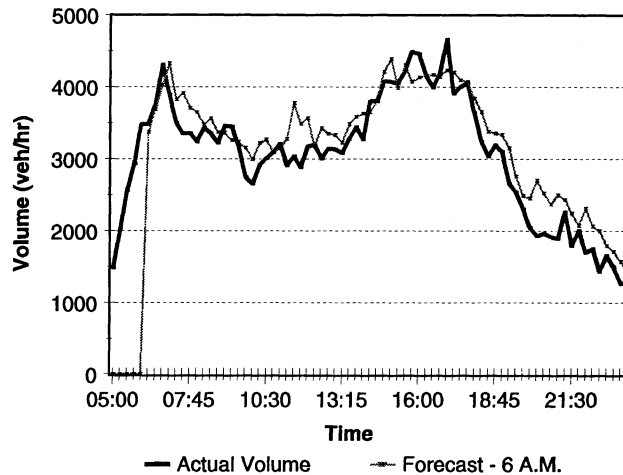

Figure 9. 6 A.M. Forecast Series

However, the forecast began to lose its effectiveness around 6 P.M. Figure 10 compares this forecast with one using more recent information, the 3 P.M. forecast. Clearly, the 3 P.M. forecast performed more effectively during the evening hours. This illustrates the need to continually re-forecast future traffic volume in an ITS application.
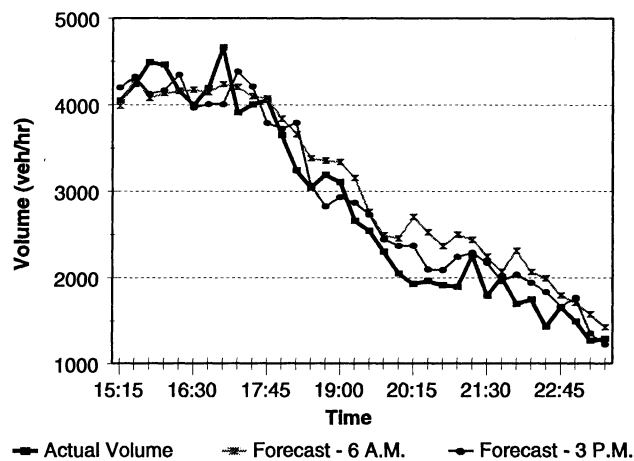

Figure 10. 3 P.M. Forecast Series

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Table 7 shows the measures of error over the four error intervals. The error averages were calculated for three periods, morning and evening peak periods and mid-day, as well as for the overall daily period.

Table 7
Average Percentage Error at Woodrow Wilson Bridge Site

| Time Period | Average Percentage Error per Interval | | | |
	1 Hr	2 Hr	3 Hr	4 Hr
5:00-8:45	5.83%	7.04%	8.07%	8.82%
9:00-14:00	10.95%	10.88%	10.62%	10.33%
14:00-19:00	8.13%	8.99%	9.86%	10.86%
Overall average	8.48%	9.10%	9.62%	10.10%

The most striking aspect of the results at Wilson Bridge was that the multiple-interval model performed almost as well as the single-interval model. Over the 1-hr error interval, the average percentage error of the single-interval model was 8.1%, as compared to 8.5% for the multiple-interval model. This demonstrates that although the model was modified to allow for multiple-interval forecasting, its short-term performance suffered no significant deterioration.

It is also important to note that the model performed noticeably better at Wilson Bridge than at Telegraph Road. In general, error levels were 1.5% less per corresponding error interval. It is difficult to attribute this difference to one factor. It is possible that the development data set at Wilson Bridge was more representative of a variety of conditions than at Telegraph Road. Therefore, it could better match patterns and develop more accurate forecasts. In real-world applications, such a difference could be overcome by more extensive data collection at all sites.

Another possible reason for the difference could be the fact that Wilson Bridge operates near capacity during peak periods. This may reduce variability in volumes and allow for more accurate forecasting. Regardless of the difference, the model performed more than adequately at both locations, showing that such a model is portable and can be fielded successfully at multiple locations.

Development of ITS Software Support System Architecture

The development of an accurate, portable, multiple-interval traffic flow forecasting model was shown to be feasible and practical. However, taken alone, such a model is of limited use to the transportation community. Individual travelers, and even traffic management system operators, will be hard pressed to use raw forecasts of a time series of volumes to improve their daily decisions. There is a need to identify a framework that will allow for the full utilization of the information contained in the forecasts.

Figure 11 illustrates an example of an ITS software support system architecture that defines the framework for the utilization of a traffic flow forecasting capability and supports two key ITS services: freeway traffic management and traveler information. The traffic volume forecast module is central to this system architecture. Its output serves as the necessary input to additional modules, which combine to provide high-quality information to an operator for use in devising traffic control strategies and to a traveler for use in developing travel plans. The architecture has four main components: (1) a data layer, (2) an analysis layer, (3) an information layer, and (4) a decision layer.
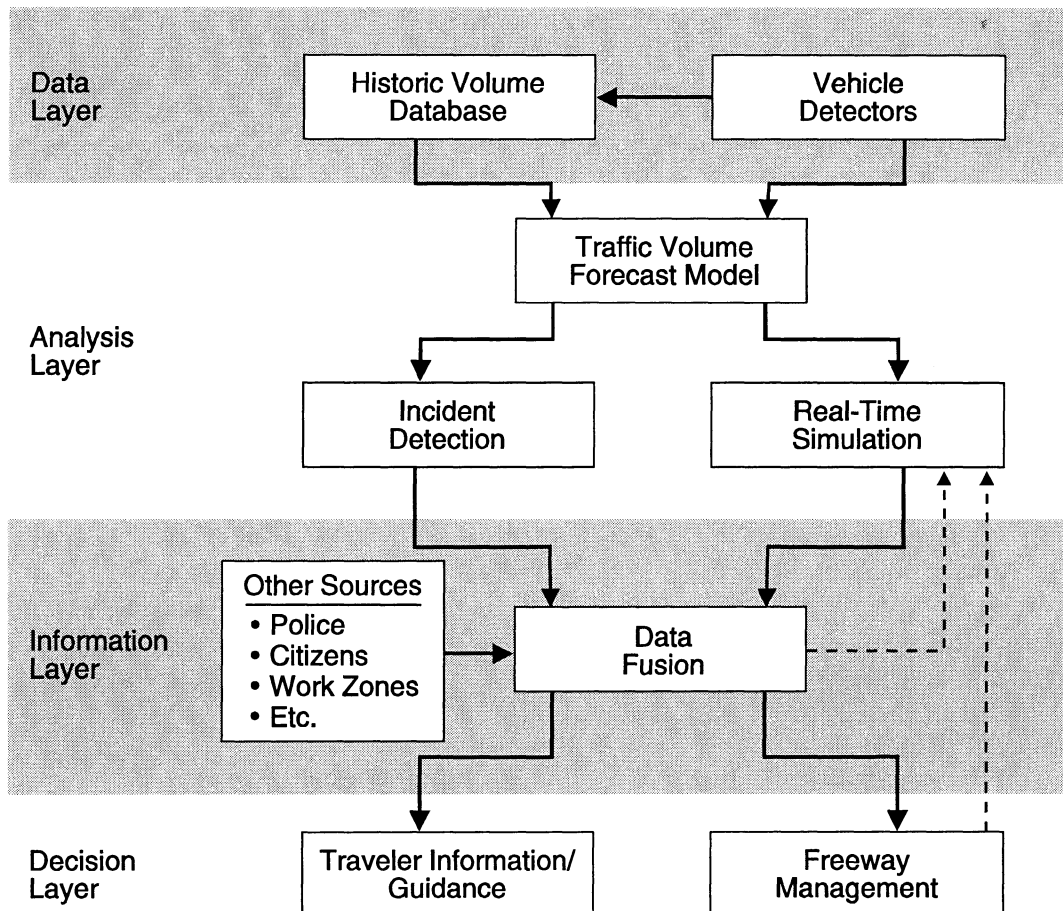

Figure 11. ITS Software Support System Architecture

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Data Layer

The data layer consists of the raw traffic volume data collected and stored by the surveillance infrastructure of the freeway management system. Specifically, this layer consists of the vehicle detectors themselves, communications, and a database that stores past volume levels reported by detectors.

Analysis Layer

The analysis layer extracts information from the raw data collected in the data layer. As one will immediately see in Figure 11, the traffic volume forecast module is central to this layer. The module serves to provide valuable input to other analysis modules.

The incident detection module looks for unexpected changes in traffic conditions that would signify a disturbance in the flow of traffic. By quickly identifying incidents, decision makers can take actions to minimize the impact on the transportation system. In most cases, incident detection algorithms simply compare current conditions with historical conditions to see if the facility is operating within "normal" parameters. The availability of forecast conditions may provide a better estimate of normal parameters than purely historical data, thereby improving the performance of this module.

The traffic volume forecast module predicts the demand for travel; it does not provide any operational forecasting capability. The real-time simulation module provides this function. It provides information as to how the transportation system is expected to react to different levels of demand for travel. Currently, no simulation program is available that can operate within the tight time constraints of a traffic control system. Once such a program is developed, the traffic forecasting model developed in this research effort will allow the module to be implemented quickly and effectively.

Information Layer

The information layer is where the results of the analysis layer are merged with other "outside" information sources, such as police reports and motorist cellular telephone calls. A complete description of the status of the transportation system results from this merging operation. The objective of the information layer is to provide the most supportive environment for transportation decision making. Examples of information that are consolidated in this layer are the location and expected duration of disruptions to normal traffic flow, expected speeds on portions of the freeway system, operational problem locations, and areas operating below capacity.

Another important point to make about this layer is that the resulting status information will be "fed back" to the appropriate analysis modules, as seen in Figure 11. For example, the real-time simulation module needs to be updated with incident locations so that available capacity may be adjusted accordingly.

Decision Layer

Decisions are made and actions are taken at this layer of the architecture. The strength of the architecture lies in the fact that both modules in the layer, freeway management and traveler information/guidance, have access to high-quality information to support decision making. These two modules represent two of the primary ITS services.

The objective of the freeway management module is to take action to ensure the most efficient possible flow of traffic over the freeway system. Decisions made in this module include alternate route determination, incident response, ramp metering, and perhaps even dynamic road pricing. The module relies on human operators for final decision making. However, it is likely that decision support tools will be required to take some of the load off the operators. For example, expert systems may be used to "screen" the information layer for specific problem locations and then present operators with suggested strategies to address the problems.

The traveler information/guidance module is intended to assist a traveler in making effective travel decisions. These decisions include when to travel and what route to use. In effect, the module "packages" the information developed by the architecture in a form that is usable by the general public. For example, although the general public will not be able to use volume information effectively, they will be able to use average speed information or travel time estimates in making efficient travel decisions.

CONCLUSIONS AND RECOMMENDATIONS

The nonparametric regression modeling technique is well suited for application to traffic flow forecasting. Nonparametric regression models developed for sites on the Capital Beltway were accurate, responsive, and easy to implement at multiple locations. Based on this conclusion, the following recommendations are offered:

1. Freeway traffic management software purchased by VDOT in the future should possess the capability to archive traffic volume data at strategic locations for a minimum of 12 months. This will allow for the future incorporation of a nonparametric regression traffic flow forecasting model.

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2. VDOT should implement the multiple-interval traffic flow forecasting model developed in this effort at the Suffolk TMS for further evaluation. The Virginia Transportation Research Council would work with Suffolk TMS staff to monitor the model's effectiveness over the long term.

3. Language should be included in future requests for proposals for freeway management software that VDOT expects a product that meets or exceeds the functional capabilities of the ITS software support system architecture described in this report. Although the software may not include all of the components described, it must be capable of evolving to such an architecture.

4. VDOT should consider investigating the application of the nonparametric regression modeling approach to arterial traffic volume forecasting. This forecasting model would directly support the real-time, adaptive control of signal systems. Such a study could be conducted by the Research Council or a state university, or it could take the form of a submission to the National Cooperative Highway Research Program (NCHRP).

ACKNOWLEDGMENTS

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