Comparative Evaluation of Adaptive and Neural-Network Exit Demand Prediction for Freeway Control

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Reliable on-line predictors that can accurately predict freeway demand in real time are of critical importance in developing optimal control systems for freeway corridors. New freeway exit demand predictors have been developed using two prediction approaches: model-based adaptive-parameter and backpropagation neural network-based prediction. The adaptive-parameter predictor requires prespecified models with parameters determined on line using the Kalman filter. Two such models are formulated. The first model is developed for normal weekdays and requires both historical and current-day measurements. The second model is designed for situations in which no historical information is available. Neural network-based prediction does not require a prespecified functional form that relates traffic measurements to predicted flow. However, an appropriate network structure and training method need to be determined before the network is trained. A three-layer backpropagation neural network was trained with the same data that are used to determine the historical pattern for the adaptive-parameter predictor. The new predictors were tested with real data from the I-35W freeway during a 2-week period and their performance was compared with that of the urban traffic control system (UTCS)-2 predictor. The error indexes from the two new predictors are very close and substantially better than those from UTCS-2 under the same conditions.

The most advanced concept for optimal freeway control that has been proposed in the literature employs a hierarchical structure. In such a structure, the overall control problem is decomposed into components, such as demand prediction, network optimization, and direct control (*1,2*). The main principle is that, on the basis of predicted demand, optimization determines optimal control strategies over a short period. Because of the discrepancies between predicted demand and actual traffic volume, these strategies are further adjusted by direct control in real time. However, the lack of reliable algorithms that can predict freeway demand in real time has forced traffic engineers to adopt reactive control strategies. To be sure, most traffic-responsive ramp metering systems currently in operation employ automatic rate selection procedures that are based on past freeway data. Ramp metering rates are selected from a predetermined library using previously collected data, generally 1 min old, from detectors on the main freeway, thereby reacting to freeway conditions rather than acting to prevent congestion. Similarly, in urban network traffic control, the inaccuracy of existing on-line predictors, such as the third-generation urban traffic control system (UTCS), has led to the development of purely reactive control systems (*3*).

Addressing the need for reliable real-time prediction, earlier work by the authors developed a method for adaptive prediction of demand diversion at freeway entrance ramp areas. This method determines the parameters in the prediction models on line using the extended Kalman filter (*4,5*). This paper assesses the effectiveness of two approaches for on-line prediction of freeway exit demand. To accomplish this, it develops an extension of the model-based adaptive-parameter prediction method previously developed by the authors and neural network-based prediction. Two models are formulated for adaptive-parameter prediction, depending on the availability of historical information. Further, a three-layer backpropagation neural network is trained with the same data used for extracting the historical demand pattern for the adaptive-parameter predictor.

The resulting predictors were tested with real data from the I-35W freeway exit ramps in Minneapolis, Minnesota. The test data were collected during two periods, a normal weekday period and a Thanksgiving holiday period. The performance of each predictor was compared with that of the UTCS-2 predictor.

BACKGROUND

Most traffic prediction algorithms developed to date use a functional form that relates the traffic measurements to the predicted flow with a set of parameters. Such model-based algorithms can be categorized into four classes, depending on the method used for determining the model parameters, such as, off or on line, and the type of data used, that is, historical and current-day data versus current-day data only (Table 1). The most common predictors use constant parameters determined off line with historical data. For example, the parameters in the demand predictor of the second generation of UTCS-2 are determined off line using a representative data set collected from the location in question. The UTCS-2 predictor employs both historical and current-day measurements. Using current-day traffic measurements, the UTCS-2 predictor tries to correct for the traffic deviations from the average historical pattern. In contrast, the UTCS-3 predictor, employing only current-day measurements, uses the interpolation between the most recent smoothed and unsmoothed measurements as the predicted value. Off-line determination of parameters and use of only current-day measurements for prediction are also featured by later research that focuses on freeway mainline volume and occupancy prediction (*6–8*). These models, mostly ARIMA-type Box-Jenkins time series models, assume that demand prediction is a point process and use purely statistical techniques to identify the stochastic nature in the observed data.

The above constant-parameter algorithms treat demand prediction as an open-loop process and employ historical demand pat-

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TABLE 1 Traffic Demand Prediction Algorithms

	CURRENT-DAY & HISTORICAL DATA	CURRENT-DAY DATA ONLY
OFF-LINE CALIBRATION (CONSTANT PARAMETERS)	UTCS-2 (FHWA, 1973)	UTCS-3 (Lieberman, 1974) Time-Series Models - Ahmed (1979,1983) - Moorthy (1988)
ON-LINE CALIBRATION (VARIABLE PARAMETERS)	Okutani & Stephanedes (1984) Stephanedes & Kwon (1989,1992)	

terns to predict the current-day trend. Therefore, the accuracy of these algorithms depends on the similarity between the trend of the historical data used for the determination of the parameters and that of the actual measurements. Although the algorithms that use only current-day measurements are more responsive to current traffic variations, inherent time lags characterize prediction with those algorithms (*9*). Further, under normal traffic conditions, the algorithms employing historical information as reference provide better prediction than those that use only current-day measurements (*9*).

Updating the prediction parameters in real time with filtering was first introduced by Okutani and Stephanedes (*10*), who applied the Kalman filtering algorithm to 15-min volume prediction in urban networks. Recent research by the authors combines behavioral modeling and the extended Kalman filter. In this approach, the prediction model parameters represent the behavioral state of traffic flow. The nonstationary random walk process describes the time-dependent state evolution of the model parameters, and the extended Kalman filter updates the model parameters. This approach employs both historical data and current-day measurements and was applied to predict the traffic diversion in freeway entrance ramp areas (*5*).

Recent developments in the area of neural networks provide a new dimension in traffic prediction. Unlike the above model-based predictors, the neural network-based approach does not require a prespecified functional form for prediction. A large data set is needed to identify a set of parameters associated with each link of the neural network. The neural network learns by adjusting the parameters of each link in the direction of desired output (*11*). Although the neural network-based prediction approach, using mostly the backpropagation network, has been studied by researchers in other areas, only limited research has been conducted in predicting traffic demand in real time.

In this research, an adaptive-parameter predictor that predicts freeway exit demand at 5-min intervals is developed first. The predictor consists of two prediction models. The first, developed for normal traffic conditions, uses both historical data and current-day measurements. The second model employs only current-day measurements and is designed for applications in which substantial discrepancies exist between historical demand patterns and actual measurements as a result of unexpected events or holidays. In both models, the parameters are estimated on line using the most recent prediction error. Second, a neural network-based predictor is developed by training a three-layer backpropagation neural network with the same data used in developing the adaptive predictor. The trained network uses both current- and previous-day measurements to predict freeway exit demand at 5-min intervals. The resulting predictors were tested with real data collected from the I-35W freeway section and their performance was compared with that of the UTCS-2 predictor. The model formulation, training method, and test results are described in this paper.

DEVELOPMENT OF ADAPTIVE-PARAMETER PREDICTOR

A model-based freeway-exit demand predictor is developed by extending the adaptive prediction approach previously developed by the authors for freeway-entrance demand. This approach determines the parameters in the prediction model in real time using the Kalman filtering algorithm and thus requires a prediction model that relates the traffic measurements to the predicted flow. Two models are formulated to predict the exit demand by using the data collected from the ramp in question. The first model is developed for normal traffic conditions, such as normal weekdays without incidents or unexpected events, and uses both historical data and current-day measurements collected from the exit ramp in question; for example,

$$V_t = \sum_{i=1}^{t} V_i^H - \theta_{1,t} V_{t-1} - \theta_{2,t} \sum_{i=1}^{t-2} V_i \tag{1}$$

where

V_t = predicted exit demand for tth time interval;
V_t^H = historical average exit volume for tth time interval;
V_t = current-day measurements at tth time interval; and
$\theta_{1,t}$, $\theta_{2,t}$ = parameters to be updated in real time.

The model is based on the findings from an extensive analysis of the Twin Cities freeway data, indicating that cumulative exit ramp volume exhibits limited daily variations during weekdays in normal traffic conditions (*5*). Prediction reflects the current traffic trend by applying time-variant weights on the current-day exit volume measurements in the previous interval and on the cumulative exit volume before that interval. The weights are updated on line by a Kalman filter and the most recent prediction error.

The second model is designed for situations in which substantial discrepancy between historical demand pattern and actual traffic volume exists, such as during incidents or holidays, so that the historical data are no longer meaningful for prediction. The model updates the moving average of current-day exit volume measurements with a time-variant parameter determined on line with a Kalman filter; that is,

$$V_t = \theta_t\left(\sum_{i=1}^{N} V_{t-i}\right)/N \tag{2}$$

where

V_t = predicted exit volume for tth interval;
V_t = current-day exit volume for tth interval;
N = number of periods considered (here, $N = 4$); and
θ_t = parameter to be updated in real time.

This model adjusts the moving average of current-day measurements to reflect the current traffic pattern. Because the model does not require historical data and the parameter is estimated on line, no prior knowledge of exit demand trends is necessary for prediction.

The adaptive prediction approach considers the model parameters as status variables representing the behavioral status of traffic flow at a given interval, and the Kalman filter algorithm identifies the optimal unbiased estimates of the behavioral status in real time using the most recent prediction error. The status evolution of the model parameters, θ, is assumed to follow the nonstationary random walk process; that is,

$$\theta_{t+1} = \theta_t + w_t \tag{3}$$

where w denotes noise. The random walk process has been successfully applied to model physical systems that are subject to rapid variation (*12*). Using the prediction models as observation equations, the Kalman filter continuously updates the model parameters by recursively determining the minimum variance estimates of the prediction parameters. The Kalman filter is based on the theory developed by Kalman (*13*) and was intended for the status identification of a linear dynamic system. The procedure for updating the model parameters via the Kalman filter is summarized as follows:

1. Initialize algorithm ($k = 0$) with any prior knowledge of model parameters for each ramp:

$$\theta_{t/t} = \theta_0 \qquad \Sigma_{t/t} = \Sigma_0$$

where $\Sigma_{t/t} = E[(\theta_t - \theta_{t/t})(\theta_t - \theta_{t/t})^T]$.

2. Set the model parameters $\theta_{t+1/t} = \theta_{t/t}$.
3. Predict the exit ramp demand V_t using prediction Model 1 or 2 with the parameters $\theta_{t+l/t}$
4. Measure actual exit ramp volume V_t and obtain prediction error e_t, where e_t = [measured value]$_t$ − [predicted value]$_t$.
5. Update model parameters $\theta_{t+l/t}$ using gain and error;

$$\theta_{t+1/t+1} = \theta_{t+1/t} + K_{t+1}e_t \tag{4}$$

where

$K_{t+1} = \Sigma_{t+1/t}S_{t+1}^T[S_{t+1}\ \Sigma_{t+1/t}S_{t+1}^T + s_t]^{-1}$ is the gain vector,
$\Sigma_{t+1/t} = \Sigma_t + q_t$, the covariance matrix;
$S_{t+1} = [\partial V/\partial\theta]^T$ with $\theta = \theta_{t+1/t}$;
V = prediction Model 1 or 2;
$\Sigma_{t+1/t+1} = (I - K_{t+1}S_{t+i})\ \Sigma_{t+1/t}$, the updated covariance matrix;
$E[w_t w_j^T] = q_{tj}$, the covariance of state noise vector;
$E[v_t v_j^T] = s_{tj}$, the covariance of observation noise vector; and
w, v = zero-mean Gaussian white noise sequences for state Equation 3 and prediction Model 1 or 2, respectively.

6. Let $t = t + 1$ and return to Step 2.

DEVELOPMENT OF NEURAL NETWORK-BASED PREDICTOR

An artificial neural network is an abstract simulation of a real nerve system. It is determined by the connection between neurodes, the transfer function used by the neurodes and the weight change law that controls training of the network (*11*). Owing to their self-organizing and adaptive features without a prespecified functional form representing a physical system, neural networks have become a popular alternative to the traditional model-based approaches in various areas of science and engineering. In this research, a three-layer backpropagation neural network (BNN) is designed and trained to predict freeway exit demand at 5-min intervals. The three-layer backpropagation network, the most widely used network in the area of prediction, has one hidden layer linking input and output layers. The following weight change law, also called the generalized delta rule, is used to adjust the weight associated with each connection link between neurodes:

$$\Delta w_{i,j,k} = \beta E_i X_i + \alpha \Delta w_{i,j,k-1}$$

where

$\Delta w_{i,j,k}$ = change in the weight for link ij for kth iteration;
E_i = error for neurode i; for example, the difference between desired and actual outputs;
X_i = input for neurode i;
α = momentum constant; and
β = learning rate.

As noted in the weight change law, the backpropagation training algorithm requires two parameters—learning rate and momentum constant—whose values need to be specified before training. Further, the number of neurodes in the hidden layer should be determined before training starts. The values of these training parameters and the input-output structure substantially affect the performance of the neural network.

First, the input-output structure of the backpropagation neural network is determined. Although a neural network does not require a prespecified functional form for prediction, the type of output, that is, the value to be predicted, and the input to the network need to be specified before the network is trained. The neural network, trained with real data, is expected to have learned the inherent pattern that may exist between the inputs and the output. In this research, it is assumed that the freeway exit demand is affected by both upstream and downstream traffic conditions from the ramp in question. Table 2 summarizes the input-output structure used in the BNN predictor developed in this research. As indicated in Table 2, the BNN predictor uses both current- and previous-day measurements upstream, downstream, and at the ramp in question. A total of 80 input and one output data are identified for the proposed BNN predictor.

Second, the training method for the proposed BNN predictor is determined to achieve the best prediction performance. As dis-

TABLE 2 Input-Output Specifications for BNN Predictor

		Ramp in question	Upstream 3 entr. ramps 3 exit ramps	Upstream 3 mainline locations	Downstream 2 mainline locations
INPUT	Current day	Volume at t-1, Cumulative volume at t-1, t-2	Volume at t-1, Cumulative volume at t-1, t-2	Volume at t-1	Volume at t-1
	Previous Day	Volume at t, t-1, Cumulative volume at t, t-1, t-2	Volume at t, k-1, Cumulative volume at t, t-1, t-2	Volume at t, t-1, Cumulative volume at t	Volume at t, t-1, Cumulative volume at t
OUTPUT	Currenttday	Volume at t			

cussed earlier, the performance of the BNN predictor substantially depends on the training method, that is, values of the training parameters, such as learning rate, momentum, and the number of neurodes in the hidden layer. However, no theory is available that can determine the best set of these values for any given problem. In this research, a sensitivity analysis is conducted on these parameters with real data collected from the test section. An example ramp that shows a typical exit demand pattern in the test section is selected and the sensitivity of the BNN-based prediction with respect to various values of the training parameters is analyzed for the selected ramp. Finally, a set of training parameters with the best prediction performance is selected. The resulting training parameters are used to train the BNN predictor for all other ramps in the test section.

TESTING AND COMPARISON WITH UTCS-2 PREDICTION

The performance of the new predictors was tested with the real data collected from the I-35W northbound freeway in Minneapolis, Minnesota. Further, the results were compared with those of the UTCS-2 predictor using the same data. The test freeway section and the location of the loop detector stations operated by the Traffic Management Center, Minnesota Department of Transportation, are illustrated in Figure 1. As a result of the detection system configuration, only 5-min exit ramp–mainline volume data were available from each detector station. Four exit ramps of the test section were selected and their 5-min exit volume was collected during a 2-week period, November 12 through 23, 1989. The data from the first week, November 12 through 16, were used to determine the historical demand pattern for the adaptive-parameter predictor. Data from the first week also were used to train the BNN predictor. The resulting predictors were applied to predict the exit demand of the selected ramps in the second week, November 19 through 23.

The exit ramps selected for testing are also indicated in Figure 1, in which ramp notation indicates the traffic movement and cross street; for example, 94NX represents the northbound exit ramp at 94th Street. In particular, 94NX and 66NX ramps are typical low-volume ramps in the test section. Demand at the 82NX ramp is high relative to the other ramps, and the 78NX2 ramp is the busiest, serving as the exit to westbound I-494 freeway. For evaluating the performance of the predictor, the mean absolute error (MAE) and the mean square error (MSE) are calculated for each prediction. These are defined as

$$\mathrm{MAE} = \frac{\sum_{t=1}^{N} |(\mathrm{Measured})_t - (\mathrm{Predicted})_t|}{N}$$

$$\mathrm{MSE} = \frac{\sum_{t=1}^{V} |(\mathrm{Measured})_t - (\mathrm{Predicted})_t|^2}{N}$$

where N denotes the number of predictions.

Prediction with On-Line Adaptive-Parameter Predictor

First, the adaptive-parameter predictor was tested with the data collected from the four exit ramps in the test section. For each ramp, the exit volume of three normal weekdays, November 19 through 21, was predicted with the first prediction model using both current-day measurements and the historical data for every 5-min interval from 6:00 to 9:00 a.m. each day. For each day's prediction, the average exit volume of the previous week, that is, November 12–16, at the same interval was used as historical data. The following set of the initial parameter values was used for all exit ramps in the test section:

$$\theta_{1,0} = 1.0, \qquad \theta_{2,0} = 1.0, \qquad s_0 = 5.0,$$

$$\Sigma_0 = \begin{pmatrix} 10 & 5 \\ 3 & 15 \end{pmatrix} \qquad q_0 = \begin{pmatrix} 30 & 5 \\ 10 & 25 \end{pmatrix}.$$

The remaining two days, November 22 and 23, were Thanksgiving holidays, and prediction was performed with the second prediction model without historical data because a substantial discrepancy exists between holiday traffic demand and normal weekday traffic patterns. The following initial parameter values were used:

$$\theta_0 = 1.0, \Sigma_0 = 5.0, s_0 = 7.0, q_0 = 10.0.$$

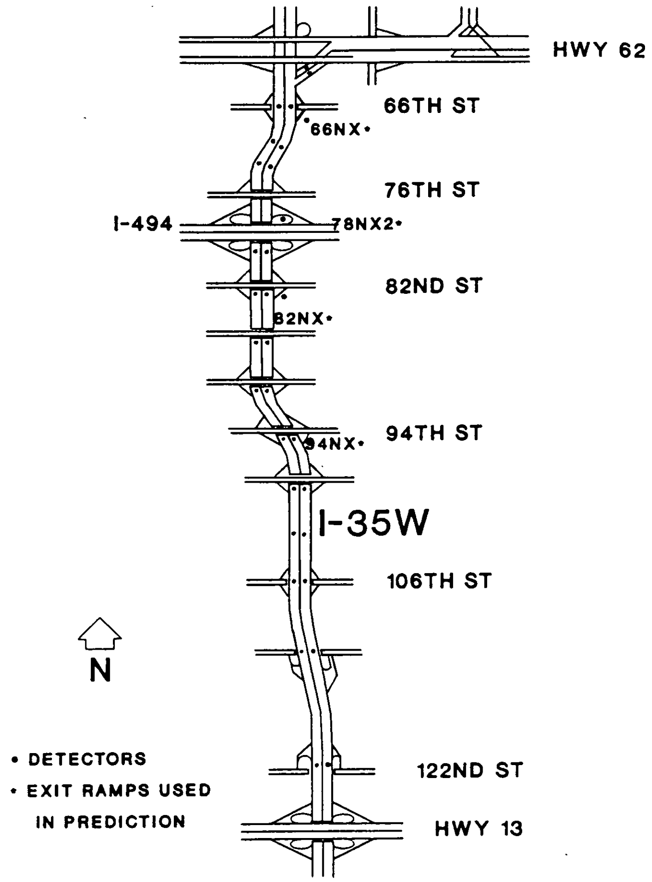

FIGURE 1 Location of test freeway section (I-35W, northbound, Minneapolis, Minnesota).

The initial parameter values for both models were determined by conducting limited sensitivity analysis with real data for each model. The prediction results from the two models are summarized in Table 3.

Prediction with BNN Predictor

Determination of the appropriate values for the training parameters, that is, learning rate, momentum, and the number of the hidden neurodes, is of critical importance in developing neural network-based predictors. In this research, the values of training parameters were determined by conducting a sensitivity analysis on those parameters with the real data collected from the test section. The 82NX exit ramp, located in the middle of the test freeway section, is the example ramp for this analysis. For each parameter, three values were selected:

1. Number of hidden neurodes: 50, 30, 10;
2. Learning rate: 0.05, 0.03, 0.01; and
3. Momentum: 0.7, 0.5, 0.3.

The proposed BNN predictor was trained for the example ramp with the above parameters using the real data collected from the test section. A total of 136 patterns, each with 80 inputs and one output, were developed using the data from the first week (November 12–16) for this training. The training of the BNN was performed using the NeuroShell 2 software, developed by Ward Systems Group. The training was stopped when no error improvement was made after 10,000 iterations.

First, the proposed BNN was trained with varying numbers of the hidden neurodes while the other two parameters remained same. The trained networks were applied to predict the exit demand of the example ramp for three days in the second week (November 19–21). Table 4 summarizes the prediction results of the proposed BNN predictor trained with different numbers of hidden neurodes. In particular, the network trained with 30 hidden neurodes was consistently the best performer in terms of MAE and MSE, but the differences are not substantial. Because the time necessary for training the network increases with the number of hidden neurodes, 30 neurodes were considered adequate. Following the same procedure, three values of learning rate and momentum constant were tested and evaluated, and the results are summarized in Tables 5 and 6. On the basis of these results, the structure of the proposed BNN predictor is determined to be 80-30-1 with a learning rate of 0.05 and a momentum of 0.5.

The proposed BNN with the above structure was trained for each exit ramp in the test freeway section with the data from the first week (November 12–16). After the training, the trained network was applied to predict the exit demand of the first three days of the second week (November 19–21). The last two days of the second week (November 22–23) were the Thanksgiving holidays and were not included in this prediction. Table 3 includes the prediction results with the BNN predictor for each ramp during the 3-day period.

Prediction with UTCS-2

The second-generation UTCS predicts the next-control-interval (5–15 min) traffic volume at each detector location in real time on the basis of the measurements from the same location only. The UTCS-2 demand prediction equation of UTCS-2 is as follows (*9,13*):

$$V_t = m_t + \gamma(m_t - \gamma f_{t-1}) + (1 - \alpha) \sum_{s=0}^{t-1} \alpha^s (f_{t-s-1} - m_{t-s-1})$$

$$+ \gamma(1 - \alpha) \sum_{s=0}^{t-2} (f_{t-s-2} - m_{t-s-2})$$

where

V_t = predicted volume at time t,
m_t = Fourier series approximation of historical volume at time t for each measurement location,
f_t = measured volume at time t, and
α, γ = constants computed off line using representative volume data from the location in question.

For each ramp, to determine the best set of UTCS-2 parameter values, α and γ, a sensitivity analysis was conducted on those parameters with the real data collected from that ramp. The parameter values that result in the best prediction are summarized in Table 7. Table 3 includes the UTCS-2 prediction results for each ramp in the test section. For purposes of comparison, the

TABLE 3 Prediction Error Comparisons

Prediction Error Comparison, 94NX

	Day 1		Day 2		Day 3	
	MAE	MSE	MAE	MSE	MAE	MSE
UTCS-2	5.0	45.9	4.2	29.2	5.3	45.8
MODEL 1	4.2	30.9	3.6	19.3	4.0	28.9
BNN	4.5	37.0	4.0	25.5	3.7	22.9

Prediction Error Comparison, 78NX2

	Day 1		Day 2		Day 3	
	MAE	MSE	MAE	MSE	MAE	MSE
UTCS-2	10.9	175.9	16.6	372.8	12.1	197.8
MODEL 1	6.5	77.8	11.4	178.6	8.1	105.4
BNN	7.6	94.3	9.1	122.3	8.3	97.8

Prediction Error Comparison, 82NX

	Day 1		Day 2		Day 3	
	MAE	MSE	MAE	MSE	MAE	MSE
UTCS -2	6.4	60.2	8.9	121.2	6.4	60.2
MODEL 1	5.9	26.9	6.3	57.2	4.5	26.9
BNN	5.2	42.3	5.2	41.6	4.8	33.5

Prediction Error Comparison, 66NX

	Day 1		Day 2		Day 3	
	MAE	MSE	MAE	MSE	MAE	MSE
UTCS-2	3.6	22.8	3.6	21.0	3.7	23.5
MODEL 1	3.0	11.7	3.6	12.5	3.7	22.5
BNN	3.1	14.9	3.0	14.2	3.6	18.3

TABLE 4 BNN Prediction Results with Different Numbers of Hidden Neurodes for 82NX

Learning rate = 0.05		Number of neurodes in hidden layer		
Momentum = 0.5		52	30	10
Nov. 19	MSE	46.89	42.3	45.4
	MAE	5.49	5.18	5.36
Nov. 20	MSE	43.04	41.55	38.41
	MAE	5.41	5.2	5.01
Nov. 21	MSE	35.28	34.83	37.49
	MAE	4.79	4.93	4.85

TABLE 5 BNN Prediction Results with Different Learning Rates for 82NX

Hidden Neurodes = 30		Learning rate		
Momentum = 0.5		0.05	0.03	0.01
Nov. 19	MSE	42.3	44.49	44.91
	MAE	5.18	5.42	5.43
Nov. 20	MSE	41.55	41.78	41.99
	MAE	5.2	5.27	5.32
Nov. 21	MSE	34.83	33.09	33.46
	MAE	4.93	4.83	4.84

TABLE 6 BNN Prediction Results with Different Momentum Values for 82NX

Hidden neurodes = 30		Momentum		
Learning rate = 0.05		0.7	0.5	0.3
Nov. 19	MSE	43	42.3	43.56
	MAE	5.25	5.18	5.32
Nov. 20	MSE	42.17	41.55	41.77
	MAE	5.27	5.2	5.26
Nov. 21	MSE	33.46	34.83	34.09
	MAE	4.82	4.93	4.89

same historical volume used in the adaptive-parameter predictor was also used as the historical volume for the UTCS-2 predictor, that is, as the value for m_t in the above model.

Test Results

As indicated in Table 3, the new predictors, that is, the adaptive-parameter (Model 1) and the BNN predictors, resulted in almost the same level of accuracy in terms of MAE and MSE. The MAE from the adaptive-parameter predictor (Model 1) for three normal weekdays ranges from 3.0 to 11.4 vehicles per 5 min, whereas the MAE from the BNN predictor is between 3.7 and 9.1. The adaptive-parameter predictor uses only the data collected from the ramp in question, whereas the BNN predictor uses the upstream and downstream measurements in addition to the ramp data. Both predictors performed consistently better than the UTCS-2 predictor; this improvement was larger in the case of MSE and is probably the result of the higher proportion of large errors in the UTCS-2 prediction. Figures 2 and 3 show typical prediction examples resulting from Model 1 and the BNN predictor for the 78NX2 ramp on November 19 and for the 82NX ramp on November 20, 1989. As indicated, the UTCS-2 predictor tends to fluctuate, depending on the prediction results of the previous interval, whereas Model 1 tries to capture the trend in the current-day exit volume without a substantial time lag. The prediction with the BNN does not exhibit substantial time lag but tends to

TABLE 7 Parameter Values in UTCS-2 Prediction

Exit Ramp	alpha	gamma
66NX	0.001	0.89
78NX2	0.001	0.97
82NX	0.001	0.94
94NX	0.001	0.92

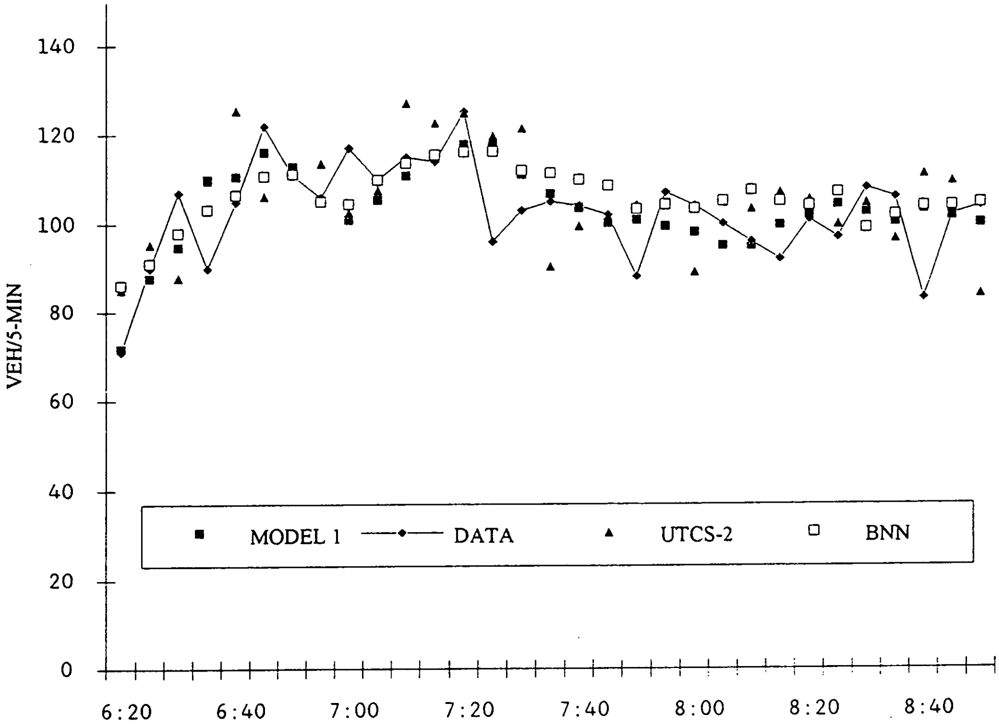

FIGURE 2 **Prediction results at 78NX2 ramp on November 19, 1989.**

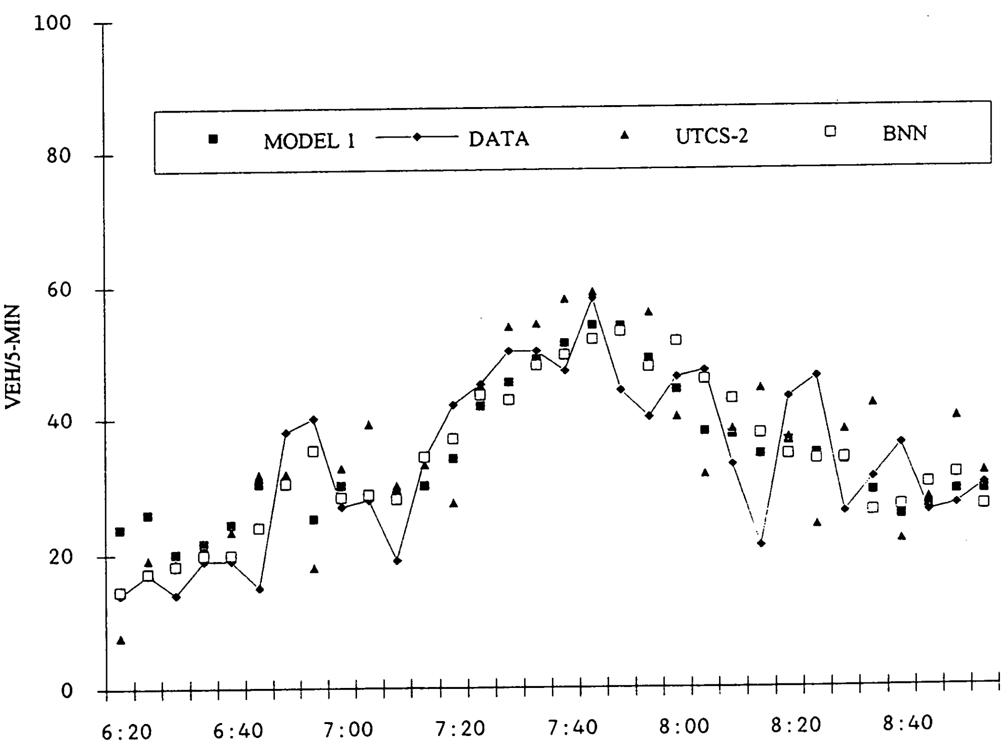

FIGURE 3 **Prediction results at 82NX ramp on November 20, 1989.**

TABLE 8 Predictor Error for Holidays with Model 2

	Day 4		Day 5	
	MAE	MSE	MAE	MSE
78NX2	3.9	24.3	6.1	75.6
82NX	n/a	n/a	5.1	28.2
66NX	n/a	n/a	6.0	48.0

without historical data

be less adaptive to the demand fluctuation compared with the adaptive-parameter predictor.

The prediction results from 2 days over the Thanksgiving holiday with the second model of the adaptive-parameter predictor using only current-day measurements are summarized in Table 8; the table indicates an MAE range between 3.9 and 6.1 vehicles per 5 min. Figure 4 shows the prediction results with Model 2 for the 78NX2 ramp on November 23, 1989, a Thanksgiving holiday. In addition, Figure 5 shows the performance comparison between Models 1 and 2 for the 78NX2 ramp on November 19. As indicated, prediction with Model 2, without using historical data, tends to follow the measurements at the previous interval. This can cause a large amount of error when substantial fluctuations exist in traffic demand, as indicated in Figure 5. The prediction error for Models 1 and 2 of the adaptive-parameter predictor do not propagate through time, and this indicates the adaptability of prediction.

DISCUSSION OF RESULTS

New freeway exit demand predictors are developed using two different prediction approaches: model-based adaptive-parameter and backpropagation neural network-based prediction. The adaptive-parameter predictor uses the data collected from only the exit ramp in question; the neural network-based predictor also uses the traffic measurements collected from other locations, including those upstream and downstream from the ramp. Prediction Model 1 and the BNN predictor use historical and current-day measurements, but the second adaptive prediction model is developed for the case in which no historical information is available. The new predictors are tested with real data from the I-35W freeway section, and their performance is compared with that of the UTCS-2 predictor. The error indexes from the two new predictors are very close and consistently better than those from the UTCS-2 predictor under the same conditions.

The adaptive-parameter prediction approach determines the parameters in the prediction models in real time using a Kalman filter with the most recent prediction error. In this approach, an appropriate functional form of the prediction model must be determined to relate the traffic measurements to the predicted traffic volume. Although the on-line parameter adaptation tries to minimize the prediction error, the accuracy of the prediction largely depends on how closely the selected model represents the actual traffic demand process. The models formulated in this research use only the volume data collected from the ramp in question,

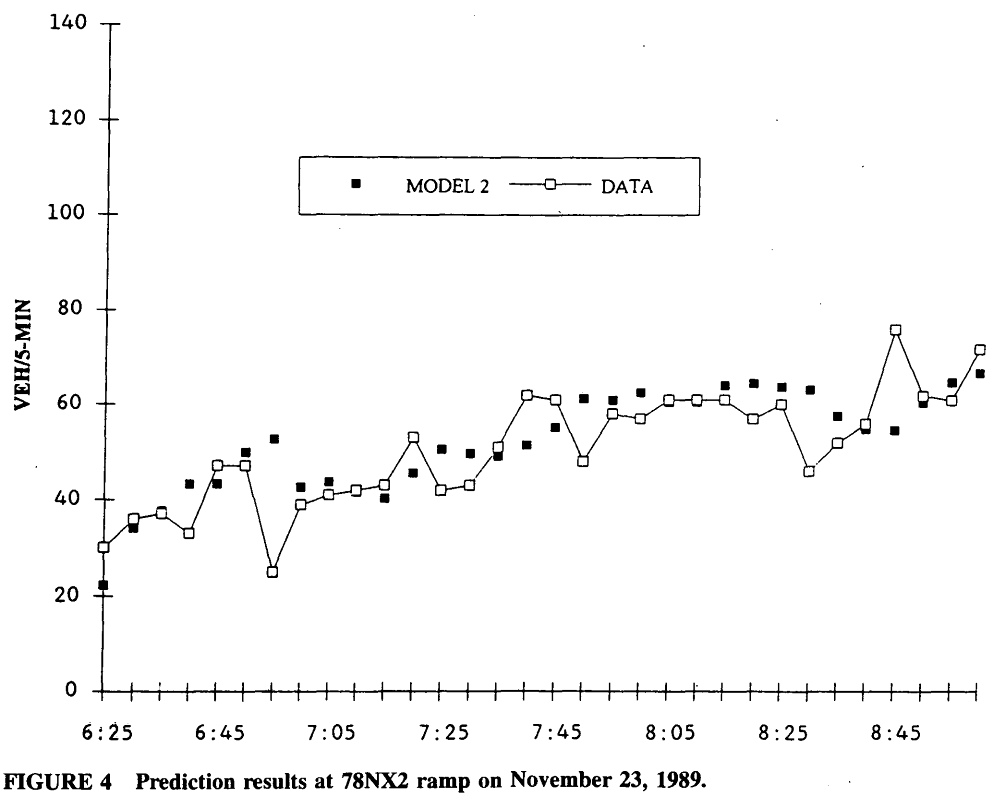

FIGURE 4 Prediction results at 78NX2 ramp on November 23, 1989.

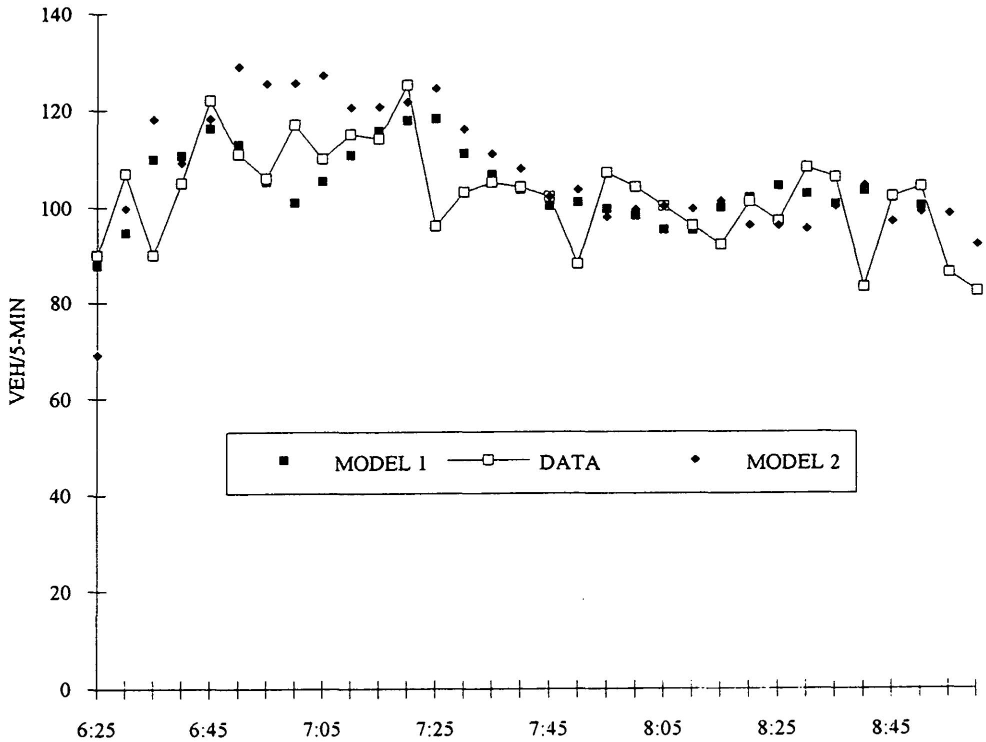

FIGURE 5 Prediction results at 78NX2 ramp on November 19, 1989.

and efforts to include additional information, such as upstream and downstream volume data, have not improved the prediction results significantly.

Unlike the model-based approach, the backpropagation neural network-based prediction does not require a predefined functional form for the given traffic demand process. However, the performance of the BNN predictor substantially depends on the network structure including the input-output specifications and the training method, that is, the values of the training parameters, such as learning rate and momentum. Although the selection of input and output values for a given network may be less difficult than the determination of an appropriate functional form for the adaptive-parameter approach, no robust theory is available that can determine the best training procedure for a given problem. The comparison of results from the limited testing conducted in this research indicate that, with the same amount of historical data, the BNN predictor requires less time and effort than the adaptive-parameter predictor and produces almost the same level of performance. However, prediction with the BNN tends to be less adaptive to demand fluctuations than prediction with the adaptive prediction approach because the BNN prediction error is not reflected in the prediction at the next interval unless the network is retrained with new data.

Current research seeks to combine the two approaches and to develop a comprehensive, hierarchical prediction algorithm that is more reliable and adaptive to the underlying traffic demand. In addition, research to develop new metering thresholds for ramp control reflecting the predicted exit demand volume is also ongoing. Finally, future phases of this research will address the need for developing optimal control algorithms that can determine metering rates on the basis of predicted demand.

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