CHAPTER 5
FORECASTING TRAVEL TIME WITH NEURAL NETWORKS

5.1 - Introduction
The estimation and predication of link travel times in a road traffic network are critical for many intelligent transportation system (ITS) applications such as route guidance system (RGS), advanced traveler information systems (ATISs) and freeway traffic management systems. The common objective of these systems is to provide information necessary to help individual drivers identify optimal routes based on real-time information on current traffic conditions. To identify these optimal routes, the selection algorithms should base their link travel times on when the driver actually arrives at a given link rather than the current link travel time. This would be particularly important for trips where the travel time is relatively long (e.g., greater than 30 minutes) and where it is unlikely that the current travel time will remain stable. In reality, most drivers base their routes on the estimated travel time when they arrive at a particular link; the ATIS projects also should have the same capabilities. The current travel time information can obtain from a number of sources including loop detectors, prove vehicles, AVI system and GPS system etc. This chapter examines how the AVI Tag data gathered in San Antonio can be used to predict link travel times for the near future.

The focus of this study is on examining artificial neural networks (ANNs) for forecasting multiple-periods link travel times. ANN models were these modals have the ability to take into account spatial and temporal travel time information simultaneously (Park, 1999). For example, it might be expected that travel time information on the link for proceeding times could be used to predict what will happen in the near future. Additionally, an increase in congestion on an upstream link may be a useful indicator of an increase in travel time in the near future on the target link. The data used as input are actual link travel time from San Antonio, Texas, collected as part of the automatic vehicle identification (AVI) system of Texas TransGuide system.

5.2 – Literature Review: Previous Traffic Prediction Efforts
“The short-term forecasting of traffic conditions has had an active but somewhat unsatisfying research history” (Davis and Nihan, 1991). In the past years, transportation engineers have tended to focus on short-term traffic flow prediction that is used in surface control systems, such as the Urban Traffic control System (UTSC). With the advent of route guidance system (RGSs), the prediction of short-term link travel times has become increasingly important. In order for RGSs to be successful, the calculated route should be based on anticipatory link travel time information which forecasted from the historical or current travel time information. Most of the link travel time research has focused on link travel time estimation rather than on link travel time forecasting, and the input data from loop detectors, probe vehicles, and simulation programs. There have been a limited number of freeway traffic prediction applications. The approaches used for traffic prediction are largely dictated by the fact that traffic conditions are time dependent and often follow fairly well-defined patterns. Previous traffic prediction efforts can be classified as historical, data-base algorithms; time-series and Kalman filtering models; simulation models and neural network models.

5.2.1 – Historical, Data-Based Algorithms
The Basic premise behind historical, data-based algorithms is that traffic patterns are cyclical. In other words, a knowledge of typical traffic conditions on Monday at 9:00 a.m. will allow one to predict the conditions on any particular Monday at 9:00 a.m. AUTOGUIDE, an ATIS demonstration project in London, simply uses a historical traffic data base to predict travel times on the basis of time of day. Such an algorithm is attractive in that it requires no real-time data.

The UTCS traffic control system utilizes predictions of traffic conditions in an attempt to control signals in a proactive manner. In general, UTCS relies on historical data as support for predictions. A weakness of this method is that UTSC is difficult to apply to a new setting since it requires an extensive set of historical data. An enhancement of UTCS (UTCS-2) uses “current traffic measures to correct for the traffic deviation from the average historical” (Stephanedes, 1981). Recently, The new generation UTCS does not utilize historical data; it predicts conditions on the basis of current measurements only.
LISB, which is a European traveler information experiment, uses a simple methodology to predict future traffic condition. LISB used both historical data and real-time data. A projection ratio of the "historical travel time on a specific link to the current travel time as reported by equipped vehicles" is used to predict travel times on the link for future intervals. A major weakness of this methodology is that it implicitly assumes that the projection ration will remain constant (Kaysi, 1993).

Hoffman and Janko (1988) developed a link travel-time estimation and prediction method that has been used in the ALL_SCOUT system in Berlin, which is a centralized RGS that the best route is identified by a central computer and then sent to the vehicles through roadside beacons located at major intersections. In their approach the link travel time is predicted by scaling the historical travel time on the basis of current detected link travel time.

The method for travel time forecasting assumes that the ratio of the current travel time to the mean travel time from the historical data remains unchanged over the future time period. This ratio is called the Deviation coefficient ($\rho_{ij,k}$) and is shown in Equation (5.1):

$$\rho_{ij,k} = \frac{\bar{tt}_{ij,k}}{k_{ij}}$$  \hspace{1cm} (5.1)

Where

$\rho_{ij,k}$ = deviation coefficient on link (i,j) for time period k

$\bar{tt}_{ij,k}$ = historical profile (mean travel time) on link (i,j) for the time period k

$k_{ij}$ = current travel time on link (i,j) for time period k

If there is no current travel time available, then $\rho_{ij,k}$ is set to 1. The predicted travel time on link (i,j) at a future time interval m, $tt^*_{ij,m}$, is calculated using Equation (5.2):

$$tt^*_{ij,m} = \frac{\bar{tt}_{ij,m}}{\rho_{ij,k}}$$  \hspace{1cm} (5.2)

Where
\[ t^{*}_{ij,m} = \text{predicted travel time on link (i,j) for time period m} \]

\[ t_{ij,m} = \text{historical profile (mean travel time) on link (i,j) for time period m} \]

Koutsopoulos and Xu (1991) presented an approach based on information-discounting theory as an attempt to improve on Hoffman’s approach. In the ADVANCE project, two types of link travel time profiles were used. The first type is a historical profile and is used for route calculation when the road traffic is assumed to be operating under stable and historical conditions. The second type is a real-time profile and is used by the Traffic Information Center (TIC) to estimate the link travel time when the real-time link travel time deviates significantly from the historical value. Based on Equation (5.2), the future link travel time can be forecasted, and the differences between the predicted link travel time and the historical link travel time are sent to each equipped vehicle for the route calculation.

### 5.2.2 – Time-Series and Kalman Filtering Models

The basis idea of time-Series analysis techniques are to forecast the condition \( X(t+d) \), given \( X(t) \), \( X(t-d) \), \( X(t-2d) \), and so on while \( d \) is the prediction time interval. There have been a number of techniques developed in the field of statistics to model time series. Transportation researchers have applied many of these time series analysis techniques to traffic prediction.

The Box and Jenkins technique is a widely used approach to specifying a variety of time-series models. It has been shown to yield accurate forecasting results in a number of application areas. The most developed Box and Jenkins techniques is the auto-regressive integrated moving average (ARIMA) method. Van Arem et al. used a linear input-input-output ARIMA model to forecast freeway travel time using travel time from inductive loop detectors. In 1993, Anderson et al. examined these ARIMA techniques to predict the link travel times based on the approaching traffic flow. They used the travel time observations of the last 11 vehicles and the traffic flow in the preceding minute to predict the one-time-step-ahead (5 minutes) link travel time. Takahashi used the filtering model to forecast travel time based on the travel time from AVI and the time-occupancy rate obtained from vehicle detectors. However, these studies are limited with respect to RGS in that they are concerned only with one-time-period-ahead
prediction. The comparison study of filtering model with neural network model made by Park also supports this assessment.

5.2.3 – Simulation Models
Simulation models provide predictive capability because they demonstrate how the system is likely to react to varying conditions and control strategies. Given the importance of predictive capabilities in ATMS, it is nature to consider the application of simulation in a real-time environment: "An effective on-line simulation model would enable the ATMS control center to project promptly future traffic patterns considering any previously implemented strategies in a real-time operating environment"(Junchaya, 1992). Unfortunately, at this time, the real-time application of traffic simulation is not feasible because existing mode/algorithm constructs can not support real time application. A need exists for new approaches to the simulation of transportation system. The recent research effort in parallel computing attempted to develop an architecture for a parallel traffic simulation application. However, the effort is still in preliminary stage and the wide-scale deployment of parallel traffic simulation appears to be far from realization.

5.2.4 – Neural Network Models
Over the past several years, both in research and in practical applications, neural networks have proven to be a very powerful method of mathematical modeling. In particular, neural networks are well suited for pattern recognition, offer efficient execution, and model nonlinear relationships effectively. Clearly, neural networks are well worth exploring as a tool for the short-term prediction of traffic.

Neural networks may be defined as “an information processing technology inspired by studies of the brain and nervous system”(Klimasauskas, 1991). This inspiration obviously led to the use of the word neural. However, neural networks in no way attempt to produce biological clones; rather, they are simply models with a rigorous mathematical basis. Although neural networks are typically associated with the field of artificial intelligence, they function as a sophisticated from of regression. The use of neural networks has been proven successful in a number of applications for the following reasons:
1. Neural networks can perform highly nonlinear mappings between input and output spaces;
2. The parallel structure of neural networks lends them to implementation on parallel computers, which offers the potential for extremely fast processing; and
3. The neural network approach is nonparametric; therefore, one need not make any assumptions about the functional form of the underlying distribution of the data.

These characteristics have attracted the attention of transportation researchers. In the past decade, a large number of research projects have been done with neural network technology in the area of incident detection; incident delay; signal control system; short-term traffic flow prediction and freeway travel time forecasting.

The ANN approach proposed by Wei and Schonfeld has been shown fairly economic and accurate for predicting system total travel time of multiple periods. Through several designed experiments, it is confirmable that the training time and prediction error are critical factors associated with the ANN approach (Wei, 1996).

Lapedes and Farber reported that simple neural networks can outperform conventional methods. Sharda and Patil concluded from their work on 75 different time series that the simple neural network could forecast about as well as the Box-Jenkins forecasting technique. Tang et al. in their comparative study of the performance of ANNs and conventional statistical techniques concluded that for short-term memory series, ANNs appear to be superior to the Box-Jenkins model. Kalaputapu and Demetsky investigated the application of artificial neural network for developing bus schedule behavior models. The results from this case study indicate the suitability of the schedule behavior modeling methodology using ANNs.

Ritchie and Ruey investigated the capability of Multilayer, feed-forward neural networks (MLF) to recognize spatial and temporal traffic patterns using data simulated with INTRAS. The author showed that MLF outperformed the California 8, McMaster, and Minnesota algorithms. Using real life data, Dia and Rose applied the MLF to freeway incident detection and showed improvement in performance over the existing ARRB-VicRoads models. Sherif and Haithan
applied the Fuzzy ART neural networks to incident detection on freeways. The Fuzzy ART model produced better performance compared to California algorithms 7 and 8.

Florio and Mussone applied a neural network model to simultaneously predict three traffic variables: density, flow, and speed on freeways at instant $t + d$ $(d=10$ minutes$)$, which was referred as one-time-step-ahead prediction by Park and Laurence. Park developed a neural network model for forecasting arterial travel times for one time step ahead $(d=3$ minutes$)$. The average link travel time forecasting errors from these two neural network applications were found to be 15.0 and 6.4%, respectively.

Some studies have applied neural network models for link travel time estimation rather than for link travel time forecasting. Hua and Faghri applied neural network models to estimate that link travel time using the traffic flow of the target link. Nelson and Palacharla employed a counterpropagation neural network model to classify the traffic flow patterns on neighboring links and to estimate the link travel time of the target link. However, they did not provide quantitative results. Both studies were based on traffic-related data using simulation models such as NETSIM and INTRAS.

Brain Smith and Demetsky examined a backpropagation neural network for predicting short-term traffic conditions in real time. The results showed that such neural network prediction models hold considerable potential for use in real time ITS applications.

5.3 – Data Source and Preliminary Analysis

The proposed neural network models in this study were tested on travel time collected by the TransGuide AVI system in San Antonio. The 53 AVI antenna sites provide coverage of a total of 94 links in San Antonio. In the mean time, travel times for each link are updated every five minutes by a rolling average algorithm to provide the travel time information to travelers.

The rolling average algorithm calculates link travel times by matching unique tag reads recorded by the AVI readers at the start and at the end of defined AVI links. The origin AVI data file recorded the site ID, vehicle ID, record time of the day and date (Table 5.1). For each link, the
algorithm sums and averages the travel times of the trips completed by AVI-equipped vehicles during five-minute time windows. It then reports the resulting averaged travel times. Trips are filtered so that excessively high travel times are eliminated prior to calculating any link travel time average. This filtering step effectively eliminates vehicles which have exited and re-entered the link, or which have taken an indirect route to proceed between link-bounding readers. Such an instance might arise on AVI-equipped freeways if a vehicle passes an AVI reader, and then proceeds to the nearest freeway exit to purchase gasoline or food, prior to arriving at the next AVI reader site. If the vehicle were to then return to the freeway and traverse the remainder of the AVI link, its time would be significantly higher than vehicles that did not exit the freeway. Such a travel time would inappropriately inflate the rolling average value calculated for the five-minute window during which that vehicle finished traversing the AVI link. Similar scenarios can be easily visualized on arterials for travelers who are shopping or eating at restaurants located between AVI readers.

<table>
<thead>
<tr>
<th>Site #</th>
<th>Tag ID # (encrypted for privacy)</th>
<th>Time of Day</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>HEa4HwS9NdsgBoK37VstAEq6WYN437.o2</td>
<td>00:01.8</td>
<td>6/17/98</td>
</tr>
<tr>
<td>40</td>
<td>q1o8yL1zY67JlGansl6YznMtIcX06bY</td>
<td>00:06.1</td>
<td>6/17/98</td>
</tr>
<tr>
<td>29</td>
<td>9AJBA5t.e4lfchfxE/8VNMo6WYN437.o2</td>
<td>00:18.5</td>
<td>6/17/98</td>
</tr>
<tr>
<td>4</td>
<td>HBPOTnSC5wMpBYSxuK4PBM8.A/UDe2/.</td>
<td>00:26.6</td>
<td>6/17/98</td>
</tr>
<tr>
<td>24</td>
<td>8Bv4JnG0VFsD5ixpKGRs4sZnMtIcX06bY</td>
<td>00:31.6</td>
<td>6/17/98</td>
</tr>
<tr>
<td>47</td>
<td>HEa4HwS9NdjsJSB1t85Dy2wq6WYN437.o2</td>
<td>00:40.8</td>
<td>6/17/98</td>
</tr>
<tr>
<td>29</td>
<td>1o9fGHXn/MMVp3DhAlfHbkq6WYN437.o2</td>
<td>01:04.0</td>
<td>6/17/98</td>
</tr>
<tr>
<td>52</td>
<td>lKaH0W9PT.o.lrhgDjoM5gZnMtIcX06By</td>
<td>00:48.5</td>
<td>6/17/98</td>
</tr>
</tbody>
</table>

Table 5.1 - AVI Tag Data

In the previous study of San Antonio AVI system, John Reily found that the aggregated travel times, which were obtained using a Visual Basic program which processes AVI tag read archives to calculate average link travel time, was closely correlated to test vehicle’s freeway and arterial link travel times (GPS data). The following Figure 5.1 and Figure 5.2 illustrate how the test vehicle’s travel times compared to aggregate travel time of 2, 5 and 15 minutes for link AVI site 43-44 on I-35 North and 45-44 on I-35 South on June 11, 1998. Figure 5.1 shows a moderate level of congestion during both morning and evening peak hours while Figure 5.2 shows significant AM – Peak congestion.
Figure 5.1 – Individual Test Vehicle’s Travel Time vs. 2-, 5-, & 15-min Averages
(AVI Site 43 → 44 On I-35 North)

Figure 5.2 – Individual Test Vehicle’s Travel Time vs. 2-, 5-, & 15-min Averages
(AVI Site 45 → 44 On I-35 South)
The AVI study by John Reily also suggested that 5-min aggregate travel time were preferable to 2-min and 15 min averages in achieving the most accurate link travel time estimation according to Root Mean Square Error (RMSE) method analysis (Figure 5.3) and correlation analysis.

Equation 5.3 describes the correlation coefficient between two random variables X and Y:

\[
\rho_{xy} = \frac{\text{cov}(X,Y)}{\sqrt{\text{var}(X)\text{var}(Y)}} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sqrt{\text{var}(X)\text{var}(Y)}}
\] (5.3)

Based on this equation, the freeway GPS/aggregate AVI correlation coefficients was calculated in 4 links (Site 42 → 43, 43 → 44, 44 → 45, 45 → 44, 44 → 43, 43 → 42) and shown by Table 5.2.

<table>
<thead>
<tr>
<th>Link</th>
<th>2-Min AVG vs. GPS</th>
<th>5-Min AVG vs. GPS</th>
<th>15-Min AVG vs. GPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>42 → 43</td>
<td>0.8918</td>
<td>0.9917</td>
<td>0.9871</td>
</tr>
<tr>
<td>43 → 44</td>
<td>0.9770</td>
<td>0.9807</td>
<td>0.9550</td>
</tr>
<tr>
<td>44 → 45</td>
<td>0.9409</td>
<td>0.9389</td>
<td>0.9254</td>
</tr>
<tr>
<td>45 → 44</td>
<td>0.9995</td>
<td>0.9992</td>
<td>0.9982</td>
</tr>
<tr>
<td>44 → 43</td>
<td>0.8962</td>
<td>0.5734</td>
<td>0.8121</td>
</tr>
<tr>
<td>43 → 42</td>
<td>0.9904</td>
<td>0.9908</td>
<td>0.9921</td>
</tr>
</tbody>
</table>

Table 5.2 – Freeway GPS/Aggregate AVI Correlation Coefficients by Link
The correlation analysis generally revealed that single-vehicle link travel times show a high correlation to aggregate link travel times of 2-, 5-, 15-min aggregation levels, among which the 5-min aggregation level is the best.

These results support the use of the 5-minute rolling average algorithm currently used by TransGuide system to calculate travel time on AVI links. Hence 5-min aggregate travel time on I-35 south between AVI site 47 and 45; 45 and 44; 44 and 43; 43 and 42 (Figure 5.4) will be used to forecast the freeway link travel time in next time interval as input data.

![Figure 5.4 – The Location of AVI Site 42, 43, 44 and 45](http://www.mapquest.com)

5.4 – Neural Network Model Design
A fully connected multilayer feedforward neural network combined with a backpropagation algorithm was selected for forecasting link travel times in this study. The backpropagation algorithm is an extension of the least mean square (LMS) algorithm and was developed for training multilayer neural networks with the objective of minimizing the errors between the actual and desired output. A detailed discussion was introduced in chapter 2. The backpropagation algorithm neural network was coded in Matlab and run on a 133-Mhz Pentium desktop computer.

5.4.1 – Input/output Design
AVI site Link 45 to 44 was chosen as a target link because it experiences significant AM – Peak congestion. The input variables of a neural network model should be chosen based on a
preliminary analysis or by empirically comparing the results from different models having
different input variables. Since the impact of the increase in volume and travel time on
neighboring links may effect the travel time in study link, this study will also design the models
to test it and thus use the neighboring link (link 43-44 and 45-47) travel time as input data. From
the point of view of traffic-flow theory, when a forward-moving shock wave exists, a backward-
moving shock wave occurs some time later, and vice versa (May. A. D., 1990).

Two neural network models were designed and tested in this study, and the principal differences
among them were the type and input variables. Neural network model 1 (NNM1) used the
preceding travel time data of link 44-45 as input without considering neighboring links’ travel
time patterns. Neural network model 2 (NNM2) used the travel time data of study link and two
immediate upstream and downstream links as input. Both models forecasted the link travel time
5 steps ahead. Figure 5.5 illustrates the input-output structure of NNM1. From past experiences,
NNM1 performed best when travel time data from seven preceding time periods were employed
for input. It was also found that NNM2 performed best when travel time data from five
preceding time periods were used for input. The designs of data input-output were summarized
in Table 5.3.

![Figure 5.5 – Input-output Structure of Neural Network Model 1 (NNM1)
5.4.2 – Structural Design of Models

It is commonly accepted that multilayer feedforward neural networks can be used to approximate almost any function if there are enough neurons in the hidden layers. The appropriate number of hidden neurons and layers of neural network depends on the pattern and complexity of the approximated function and the transfer function of the layers. According to previous study in travel flow prediction and preliminary analysis, one hidden layer was proven to perform well and used here. The best number of hidden neurons for NNM1 and NNM2 were found as 4 and 5, respectively.

5.4.3 – Neural Network Training

The travel time data of link 45→44 on whole June, 11,1998, a typical weekday, was used as the data for training and testing the proposed neural networks. The forecasted travel time data $K(i+1)$, $K(i+2)$, $K(i+3)$, $K(i+4)$, $K(i+5)$ was obtained from neural networks as output. The Table 5.4 illustrated that how the training works. $I_1$, $I_2$, $I_3$, $I_4$, $I_5$, $I_6$ and $I_7$ are the input data for each training, while $O_1$, $O_2$, $O_3$, $O_4$ and $O_5$ are the output for each training. $X_i$ is the observed travel time recorded by AVI system. $Y_i$ is the forecasted travel time. The subscript i means the i-th time intervals (5- min averages). The forecasted travel time in (i+8)-th time interval $Y_i$ in the column $O_1$ (shadowed in red) was compared with observed travel time in (i+8)-th time interval $X_{i+8}$ obtained from AVI system in the column $I_7$ (shadowed in green) to perform the performance analysis. The result will be better if more observed travel time information would be available. For some time intervals, the travel time obtained from AVI system is zero since it did not have vehicle pass the study link in those time intervals. In this case, it is assumed that the travel time in this time interval would be the same as the travel time in the preceding time interval.

<table>
<thead>
<tr>
<th>Model Number</th>
<th>Input Link</th>
<th>Input Data</th>
<th>Number of Input Data</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>NNM1</td>
<td>45→44</td>
<td>$K(i-6), K(i-5),…,k$</td>
<td>7</td>
<td>$K(i+1),…, K(i+5)$ of Link 45→44</td>
</tr>
<tr>
<td>NNM2</td>
<td>47→45,45→44,44→43</td>
<td>$K(i-4), K(i-3),…,k$</td>
<td>15</td>
<td>$K(i+1),…, K(i+5)$ of Link 45→44</td>
</tr>
</tbody>
</table>

Table 5.3 – Input-output Designs for the Proposed Neural Network Models
Table 5.4 – Training and Testing Design for Proposed Neural Network Models

The Figure 5.6 illustrate how the forecasted travel time compared to the observed travel time recorded by AVI system in 5-min average on the link 45→44.
5.5 – Performance Analysis

The mean absolute percentage error (MAPE), described in Equation 5.4, was used to measure model performance. It may be seen that the performance of the proposed ANN models for each time period (i.e., \( \delta = 1, 2, \ldots, 5 \)) is based on the average error taken over \( n \) testing samples. The best model was chosen based on the average prediction error for all five time periods.

\[
\text{MAPE}_\delta = \frac{\sum_{i=1}^{n} \left| \frac{K(i + \delta)_p - K(i + \delta)_o}{K(i + \delta)_o} \right| \times 100}{n}
\]

(5.4)

Where

- \( K(i+\delta)_p = \) predicted link travel time for \( \delta \) time period(s) ahead at the i-th time interval (seconds)
- \( K(i+\delta)_o = \) observed link travel time for \( \delta \) time period(s) ahead at the i-th time interval (seconds)
- \( i = \) time interval of the i-th sample (24*60/5-7 for one time step ahead)
- \( n = \) number of testing samples (24*60/5-7 = 281 for one time step ahead)
- MAPE\(_\delta = \) mean absolute percentage error for \( \delta \) time period(s) ahead of forecasting (%)

5.5.1 – MAPE Analysis of Proposed Models

According to equation 5.4, the forecasted results from the two proposed neural network models were shown in Figure 5.7. The MAPE for one time step ahead ranged from 6.9 to 8.1%. It was found that as the time periods increases, the forecasting error also increases in a linear fashion. For five time steps ahead forecasted travel time, the MAPE ranged from 15.9 to 17.2%, and this represents an approximate 100% increase in error compare to one-time-step-ahead forecasting. From the Figure 5.7, it was also found that predicting one or two times step ahead, the NNM1 model gave the best result, while for three, four and five times ahead, the reverse was true. This result indicated that the NNM1 could be used as the model to forecasting the freeway travel time with one-time-step-ahead and will produce better result than another neural network model.
5.5.2 – Comparisons of NNM1 with Other Models

While it is important to identify the best neural network configuration, it is equally worthwhile to compare the best neural network model (NNM1) with other standard prediction to Kalman filtering model, the ALL_Scout method, a historical travel time profile, the real-time travel time profile, and an exponential smoothing model. The results are shown in Table 5.5.

The neural network models gave the best results for predicting three through five time periods ahead into the future, while the Kalman filtering model gave superior results for predicting one and two time periods ahead into the future. The real-time profile, Kalman filtering model, ALL_SCOUT model, and exponential smoothing showed similar prediction MAPEs for three through five time periods ahead into the future. Note that while Kalman filtering minimizes the error for one-time-period-ahead forecasting, the ANN models minimize the overall errors (i.e. one through five time periods). It should be noted that if NNM1 was developed for forecasting...
one time period ahead only, the MAPE would be 5.9%, which is better than that of the Kalman filtering model.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAPE(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K(i+1)</td>
</tr>
<tr>
<td>Historical Profile</td>
<td>17.3</td>
</tr>
<tr>
<td>Real-time Profile</td>
<td>8.3</td>
</tr>
<tr>
<td>Kalman Filtering</td>
<td>6.3</td>
</tr>
<tr>
<td>ALL_SCOUT</td>
<td>7.8</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>8.0</td>
</tr>
<tr>
<td>NNM1</td>
<td>6.9</td>
</tr>
</tbody>
</table>

Table 5.5 – Prediction Result of different Models

5.6 – Summary
This chapter proposed two ANN link travel time forecasting models for freeway in San Antonio, Texas, based on data obtained from San Antonio TransGuide AVI system. The ANN models were used to forecast one through five time periods ahead into the future, and the best model for a given situation was determined by the lowest mean absolute percentage error. It was found that when forecasting one and two time periods into the future the ANN model that used only the preceding travel times from the observed link was best. However, when forecasting three, four and five time periods into the future the ANN models that employed link travel times on links immediately upstream and downstream from observed link gave the better result.

While the results demonstrated in this study are promising, a number of issue still need to be resolved before ANN models can be implemented. This study used the data based on 5-min aggregation level which supported by John Reily’s previous study in AVI travel time data collecting. Obviously, a sensitively analysis is required to examine the optimal level of aggregation. It also would be interesting to find a more basic issue: Should the data be aggregated or not? This topic is one of the important directions for future research. Lastly, other
ANN model structures, such as feedforward ANN with backpropagation, which was successfully used in many studies, may lead to better performance and definitely also is an important direction for future research.