



1752-8

1. Report No. FHWA/TX-01/1752-8	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle DYNAMIC ROUTING ON FREEWAY SYSTEMS USING AUTOMATIC VEHICLE IDENTIFICATION (AVI) DATA		5. Report Date January 2001	
		6. Performing Organization Code	
7. Author(s) Laurence R. Rilett, Associate Research Scientist		8. Performing Organization Report No. Report 1752-8	
9. Performing Organization Name and Address Texas Transportation Institute The Texas A&M University System College Station, Texas 77843-3135		10. Work Unit No. (TRAIS)	
		11. Contract or Grant No. Project No. 0-1752	
12. Sponsoring Agency Name and Address Texas Department of Transportation Construction Division Research and Technology Transfer Section P. O. Box 5080 Austin, Texas 78763-5080		13. Type of Report and Period Covered Letter Report: September 1998 - August 2000	
		14. Sponsoring Agency Code	
15. Supplementary Notes Research performed in cooperation with the Texas Department of Transportation Research Project Title: TransLink(r) Research Program			
16. Abstract This report examines issues related to identifying the potential routes and their associated attributes for an individual wishing to travel along the Houston freeway network. A dynamic approach is taken whereby the link travel time that is used in calculating the route travel time is based on the time the drivers arrive at a given link rather than the time when they began their journeys. The link travel times were calculated using Automatic Vehicle Identification (AVI) data from a test bed on U.S. 290. It was found that real-time link travel times are relevant, as compared to historical link travel times, for approximately 20 minutes into the future. In contrast, forecast link travel times are relevant, as compared to historical link travel times, for approximately 30 to 35 minutes on average. A prototype computer model has been developed for examining dynamic routing issues and tested on the Houston network. It was demonstrated that in certain situations, particularly those for longer distance trips, a driver has a choice of routes in the Houston network and that often the different route travel times are not statistically different. In this situation it may be best to allow an option whereby the routes and their attributes are provided to the driver rather than a recommendation of the best or fastest route.			
17. Key Words Dynamic Routing, Multiple Routes, Automatic Vehicle Identification Data		18. Distribution Statement No Restrictions. This document is available to the public through NTIS: National Technical Information Service 5285 Port Royal Road Springfield, Virginia 22161	
19. Security Classif.(of this report) Unclassified	20. Security Classif.(of this page) Unclassified	21. No. of Pages [18]	22. Price

Report 1752-8

Dynamic Routing on Freeway Systems Using
Automatic Vehicle Identification (AVI) Data

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The problem addressed in this project is to identify routes and their associated attributes for an individual wishing to travel along the Houston freeway network. An important attribute is the route travel time, which is calculated by summing the individual link travel times along each link of the route. The route travel time is calculated using link travel times based on the time the driver arrives at a given link rather than the time when they began their journey. This dynamic approach is particularly important when traffic conditions are changing rapidly, such as during the morning and afternoon peak periods, because it provides more accurate and reliable information to drivers.

Choice Set Determination

The first step in this dynamic routing approach is to determine the choice set or the list of potential routes the driver can take. To be included in the choice set, the alternatives must be feasible and known to the driver. For example, each route in the choice set must be available for use by the driver, and the driver must have the resources required to use the route. These resources may be defined in terms of money, time, etc. or in terms of vehicular equipment such as electronic toll tag readers. This project assumes that all freeway routes are viable options. When the Intelligent Transportation System

(ITS) implementation becomes more widely used the choice set identification will require more sophisticated methods because of the large number of potential routes. For the Houston freeway system the routes can be enumerated directly. A prototype computer program has been developed that can read in network information, display the network on a computer screen, calculate the set of feasible routes, and display these routes on the computer screen.

Identify Attributes of Alternatives

A number of additional studies conducted during the last 30 years have investigated the attributes that influence route choice (1-7). Rather than describe the specific findings of each study, a summary of the identified attributes that influence route choice behavior was developed and is shown in Table 1. Note that while it may be easy to define the important attributes, quantifying these attributes for a given route may not be straightforward. For example, a route is usually defined as a series of links from the origin to the destination. Typically, it is assumed that the route attribute is the summation of the individual link attributes. However, many of the attributes listed in Table 1 are not commonly available. Of particular interest in dynamic routing are the link and route travel time and the associated reliability.

To study some of the above issues this project used travel time data collected through the AVI system in Houston, Texas. Data from a 27.6 km stretch of U.S. 290 during the time period from 6:00 A.M. to 10:00 A.M. were collected for 12 months in 1996. This yielded data for 231 weekdays. The travel time data from the AVI vehicles were subsequently aggregated at five-minute periods for each link. Only the eastbound

A.M. peak travel time data were used because these links experienced more severe congestion than the westbound links. During this study period, an average of approximately 15 to 30 AVI equipped vehicles per five minute period traveled the corridor.

Consider the problem of providing forecast link travel time information to drivers using the corridor. The mean absolute percent error (MAPE), which is shown in Equation 1, was used as a measure of reliability of the different techniques. Figure 1 shows a graph of the mean absolute percent error versus the forecast time for three different forecasting techniques for a link on U.S. 290.

$$\text{MAPE} = \frac{\sum_{i=1}^n \frac{|l_{tt_p} - l_{tt_o}|}{l_{tt_o}} \times 100}{n} \quad (1)$$

Where:

l_{tt_p}	Predicted link travel time
l_{tt_o}	Observed link travel time
n	Number of samples
MAPE	Mean absolute percent error

The first technique provides drivers with information based on the historical link travel time from previous days for that time period. It may be seen that the average MAPE for this approach is approximately 24 percent.

The second technique involves providing drivers with real-time information under the assumption that the current link travel time will also be accurate into the near future. When the real-time data are used the percent error ranges from 9 percent when looking at

five minutes into the future to approximately 28 percent when looking 25 minutes into the future. As would be expected, the forecasting error increases as the forecast time increases. For this link the real-time information is “relevant”, as compared to the historical travel time, for approximately 20 minutes into the future. After this point the historical travel time is more accurate than the real-time travel time.

The third technique involves forecasting the link travel time directly using a spectral-basis neural network (SNN). SNN is a statistical technique that uses current real-time information and historical trends to forecast link travel times. This approach has markedly better results in terms of both overall accuracy and the rate at which the percent error increases with travel time. By using a SNN to forecast link travel time the relevance of the AVI data extends longer into the future and can result in more accurate forecasts. Note that while Figure 1 is for a specific link on U.S. 290, similar findings were identified for the other links on the roadway.

From the perspective of dynamic routing the prediction of the route (or corridor) travel time is more important than the individual link travel time. Figure 2 shows the MAPE versus the forecasting period for the U.S. 290 corridor for the A.M. peak period. The corridor travel times are dynamic and are calculated by summing the forecast link travel times. The particular forecast link travel time used in the corridor travel time estimate is based on the estimated time of arrival at the upstream end of the link. Results show a similar pattern to that of Figure 1. Basically the historical approach has a percent error of approximately 27 percent while the real-time percent error ranges from 10 to 28 percent. As before, the SNN gave the best results, indicating that forecasting corridor travel times can result in superior performance. Interestingly, the average link

forecasting error when predicting five minutes ahead was approximately 10 percent. However, the average corridor forecast error when predicting five minutes ahead was 8 percent. This means that the errors in link travel time are 1) not additive and that 2) the errors may tend to cancel each other out such that the error on a corridor estimate can be less than the relative error of the link travel time estimates.

The prototype routing program can read in dynamic link travel times that are then used in identifying potential routes. These dynamic link travel times can be obtained from historical records, real-time sources or forecasting programs.

Decision Making Process

The last step is to identify the best route from the choice set based on the relevant attributes. In the situation where there is only one route, then it is relatively straightforward. However, if there are multiple routes a decision-making process must be used. Note that in most of the ATIS that have been implemented the fastest route is assumed to be the best route.

To illustrate the difficulties associated with using the fastest route approach consider a traveler on the Houston network shown in Figure 3. Note that Figure 3 is a screen shot of the prototype route selection software that uses AVI information as input. If the traveler wishes to travel from an origin at Station 27 on U.S. 290 (point A on Figure 3) to a destination at Station 114 on Interstate Highway (IH) 45 (Point B on Figure 3) along the Houston freeway network during the A.M. peak period, it may be seen that there are four reasonable routes to choose as shown in Figure 3 and Table 2.

The historical travel times and their associated variances for the A.M. peak period are shown in Figure 4. This information was calculated from Automatic Vehicle Identification data from the TranStar system in Houston, Texas, in October and November of 1996. The travel time means and variances were calculated for 54 five-minute time periods within the A.M. peak period. It may be seen that Route 3 is the fastest route in the early morning while route 2 is the fastest route from approximately 7 A.M. until 9 A.M.

The first step in identifying the best route is to find the set of potential routes. For a route to be included in the choice set it must not be dominated by any other route. A route A is dominated by route B if the attributes of route B are less than or equal to the attributes of route A and if at least one attribute of route B is less than the same attribute value of route A. As an example consider two routes A and B. Route A has a travel time of 10 minutes and a standard deviation of 5 minutes and route B has a travel time of 10 minutes and a standard deviation of 3 minutes. Because no rational user would choose route A then it can be stated that route A is dominated by route B and should not be considered.

In order to do identify the dominated routes the important attributes need to be known. For this example the driver uses four criteria when choosing a route: 1) mean route travel time, 2) variance of route travel time, 3) distance, and 4) number of interchanges along a route. The non-dominated routes are shown in Table 3 as a function of time of day. For example, if the driver was traveling between 6:40 A.M. and 9:10 A.M. he or she would have to choose among routes 2, 3 and 4. No single route will dominate the other routes in terms of all attributes. Note that the dynamic travel time

attribute values are known and deterministic although this is clearly not the case in a real-time situation.

Note as well that the importance of travel time may be relative. For example, at 7:40 A.M. the importance of travel time may be very high because there is clearly a large difference in travel times. However, at 6:40 A.M. it is not clear that a commuter would consider travel time important because the routes have similar travel times. In short the valuation by the driver of specific attributes will be dependent on the decision context. The variation in attribute values can be even more important on a real-time basis as shown in Figure 5 which illustrates the route travel times for October 9, 1996 as a function of time of day. It may be seen that from 6:30 to 9:30 A.M. three of the routes have approximately the same travel time and standard deviation. In this situation, other attributes may predominate, including some not originally considered by the decision-maker.

There are essentially two approaches one could use to provide information to drivers in the multiple route scenario. The first is to simply identify the routes and provide the attributes. The decision maker could then select the most appropriate route. Given the small number of routes in Houston this may be the best approach. Alternatively, the best route can be identified based on pre-selected criteria and weights if the user is able to provide input on the relative importance of each attribute. As shown in Figure 3 the former approach was adopted in the prototype program.

Concluding Remarks

The following paragraphs give the primary research findings on dynamic routing.

The test bed was a section of the Automatic Vehicle Identification network in Houston, Texas.

Travel Times

For the test bed examined real-time link travel times are relevant as compared to historical link travel times, for approximately 20 minutes into the future.

For the test bed examined forecast link travel times are relevant, as compared to historical link travel times, for approximately thirty to thirty-five minutes into the future.

While the confidence intervals on individual links can be high (i.e. on the order of 10 percent) the errors on corridor travel times based on the individual link travel times can be 25 percent lower. That is, the errors tend to cancel out leading to a higher reliability of corridor travel time.

Multiple Routes

Drivers use many criteria when deciding which route to use. These criteria include travel time, reliability, distance, etc.

In many instances, particularly for long trips, a driver has a choice of routes in the Houston network. In this situation it is often the case that the route travel times are not statistically different and therefore it may be best to allow an option whereby the routes and their attributes are provided rather than a recommendation of the best or fastest route.

Prototype Routing Program

A prototype computer model has been developed for examining dynamic routing. The test bed is in Houston, Texas although any network can be used. The program can read in dynamic link travel times from historical data, real-time systems and/or forecasting models. Based on the chosen attributes the choice set of potential routes and their associated routes are calculated and displayed to the user.

The next step in this project is to implement the dynamic routing algorithms. The Houston AVI network will be the test bed. The route selection program will be developed for use on the Internet. Users will select their origins and destinations and the program will present the potential routes and associated attributes. The program will first be implemented with real-time data from the AVI system. Subsequently, capabilities for using historical and forecast data will be added. The program will be fully tested off-line.

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Table 1: Important Route Attributes

Minimize:	travel time distance travel time variability number of traffic control devices congestion number of turns monetary costs at-grade railroad crossings
Maximize:	safety
Choose route according to:	road hierarchy scenery commute enjoyment personal habits

Table 2: Route Choice Set

Route	Sections	Distance (km)	Number of Interchanges
1	Eastbound on U.S.290 Counter-clockwise on IH 610 Southbound on IH 45	21.1	2
2	Eastbound on U.S. 290 Clockwise on IH 610 Southbound on IH 45	19.3	2
3	Eastbound on U.S. 290 Counter-clockwise on IH 610 Eastbound on IH 10 Southbound on IH 45	17.2	3
4	Eastbound on U.S. 290 Clockwise on IH 610 Southbound on IH 45	18.3	2

Table 3: Nondominated Routes by Time of Day

Route	Time of Day		
	5:30~6:40	6:40~9:10	9:10~9:30
1	D	D	D
2	D	N	N
3	N	N	N
4	N	N	N

D Dominated
N Nondominated

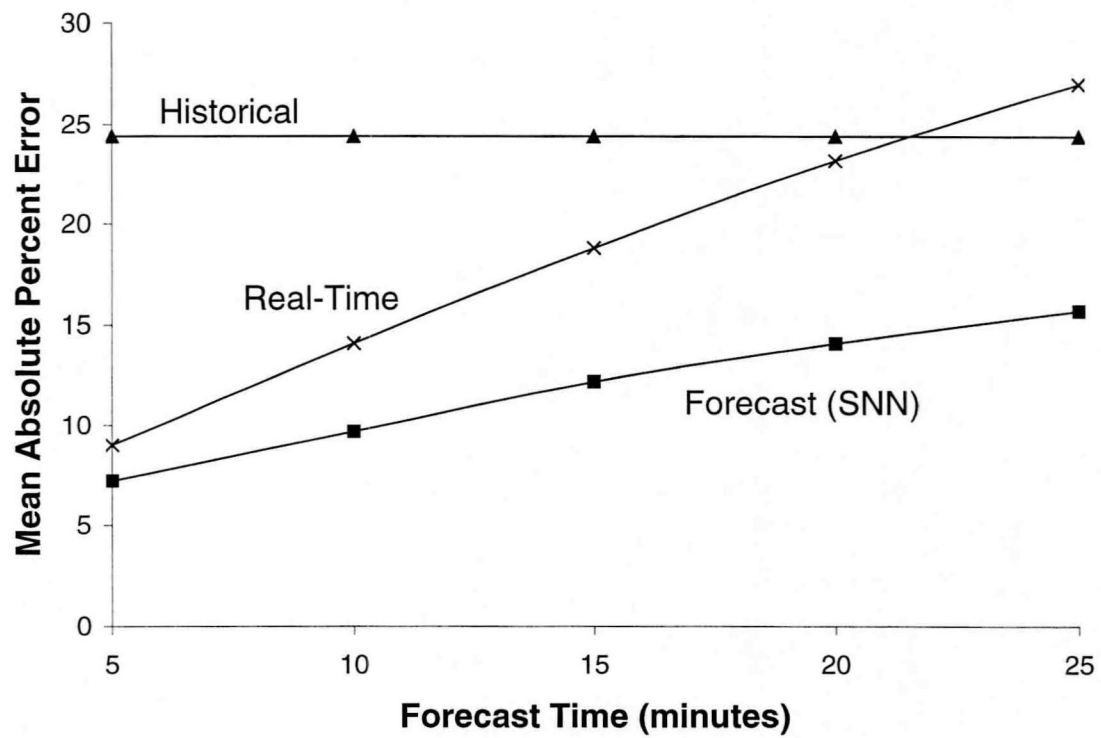


Figure 1: MAPE versus Forecast Travel Time for U.S. 290 Link during the AM Peak Period

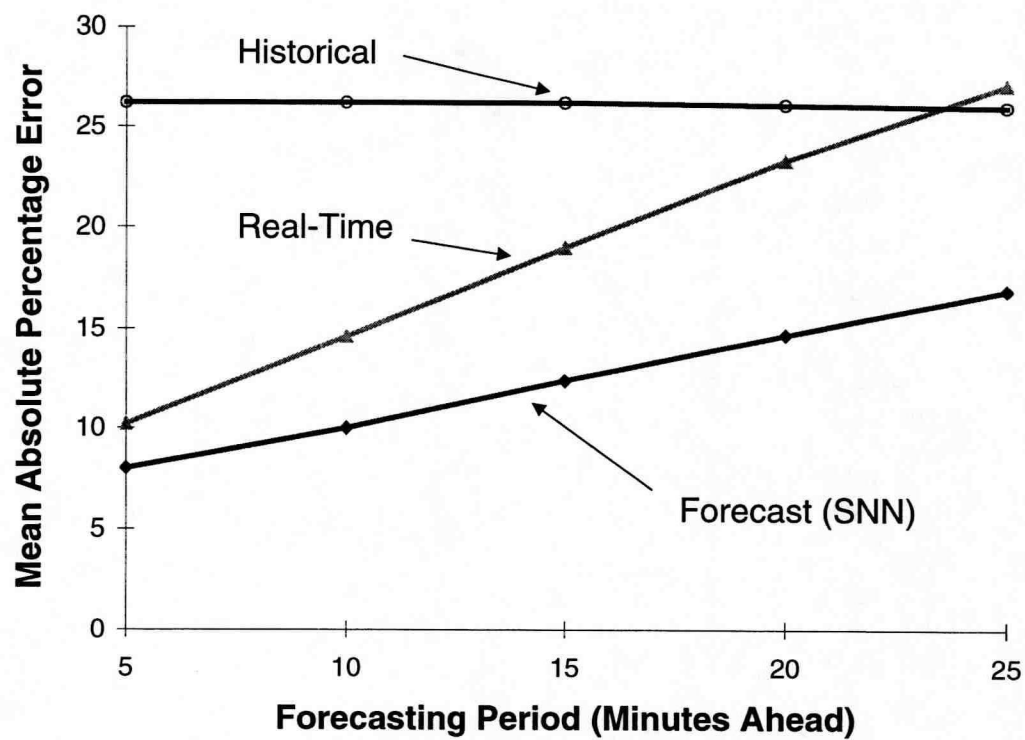


Figure 2: MAPE versus Forecasting Period for U.S. 290 Corridor Travel Time

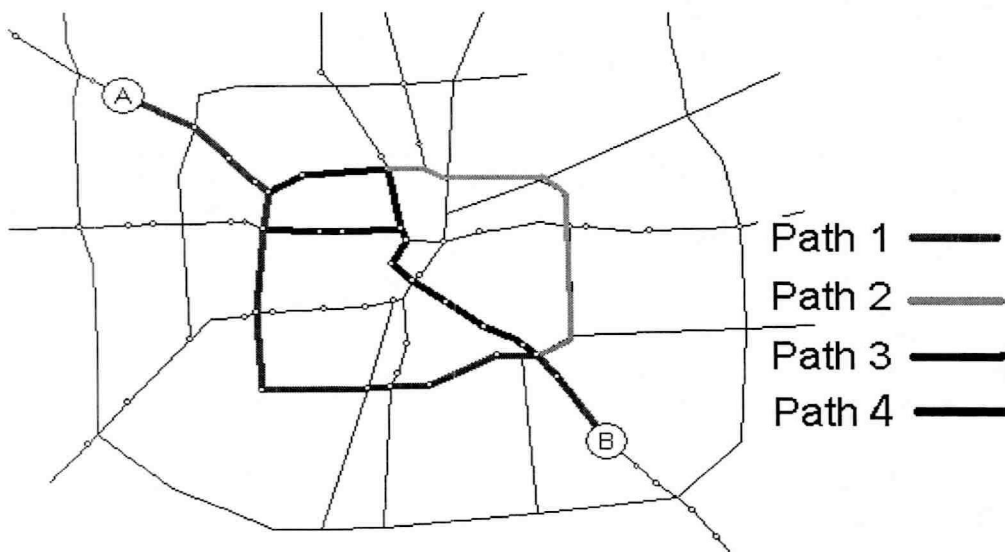
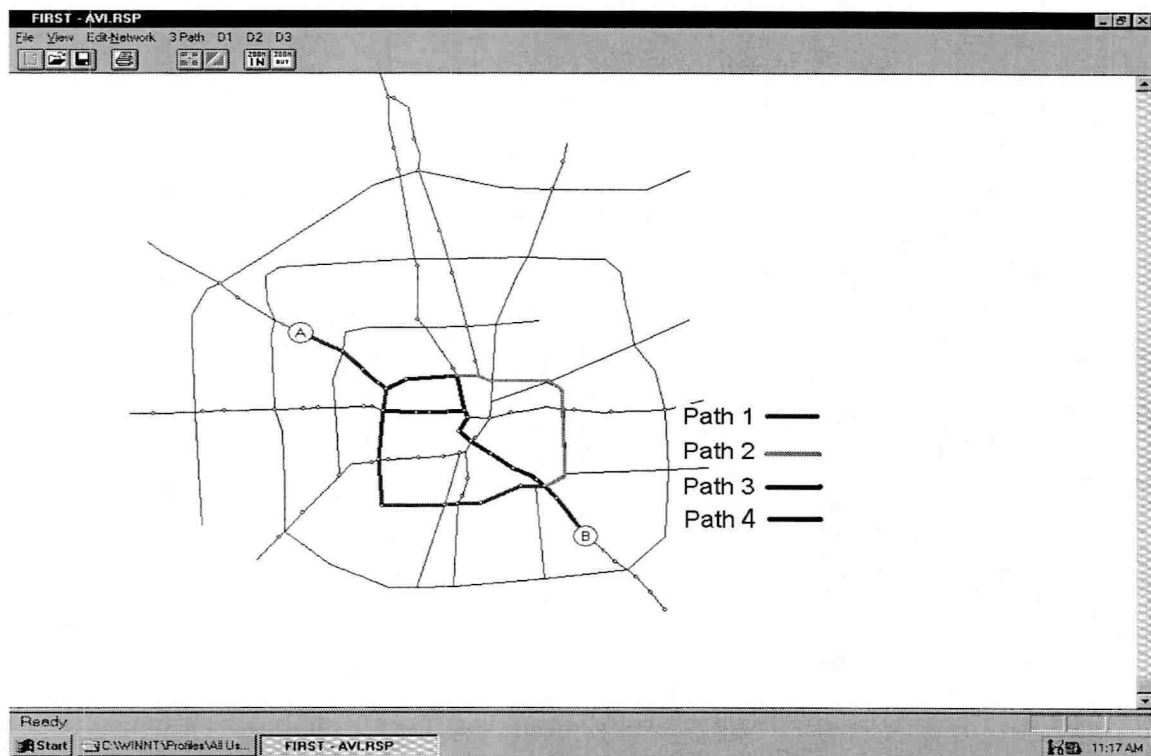


Figure 3: Multiple Routes in Houston, Texas

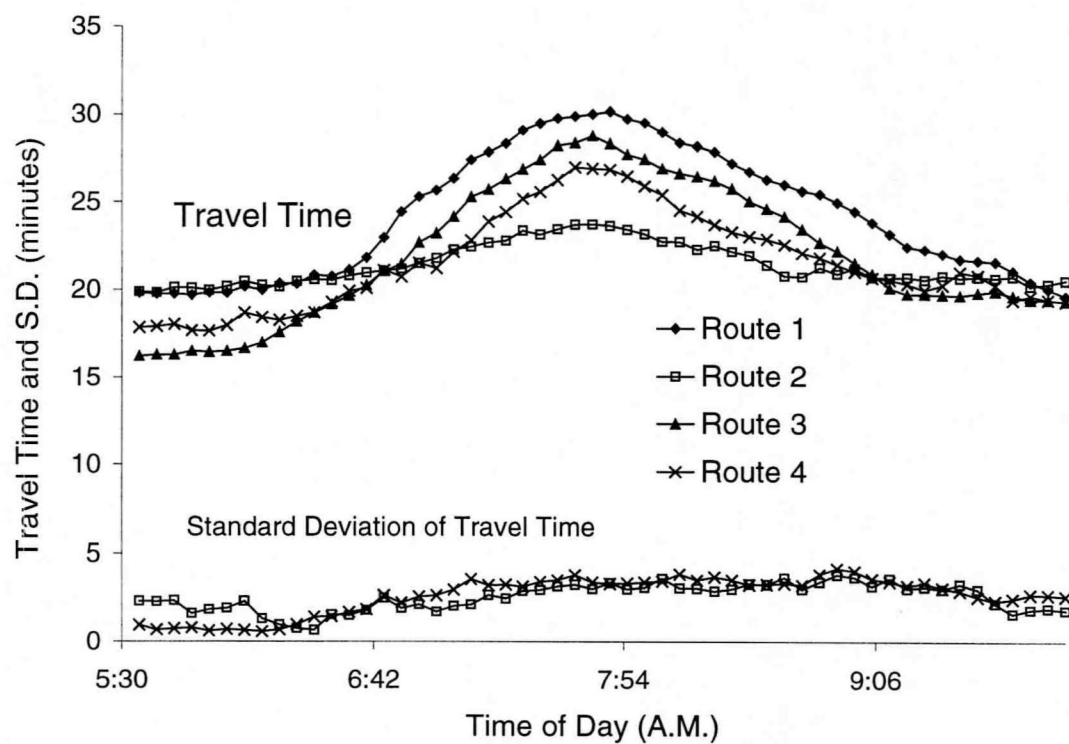


Figure 4: Historical Mean and Standard Deviation of Travel Times

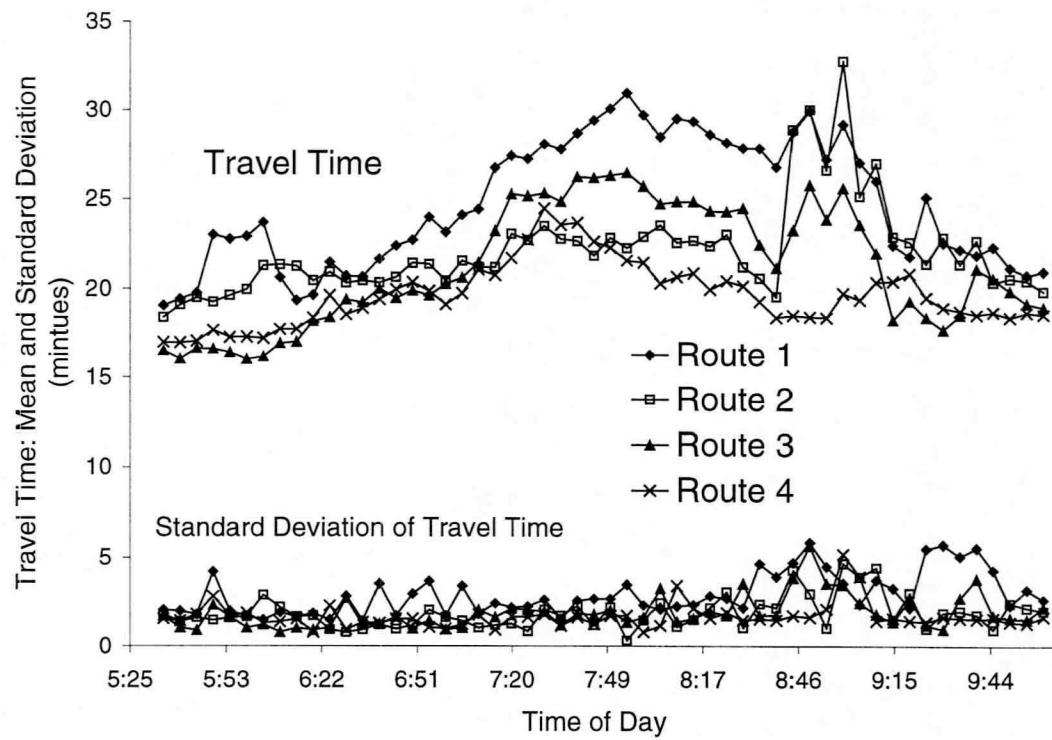


Figure 5: Real-Time Mean and Standard Deviation of Travel Times