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USE OF NEURAL NETWORK/DYNAMIC ALGORITHMS TO PREDICT BUS TRAVEL TIMES UNDER CONGESTED CONDITIONS

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16. Abstract

Automatic Passenger Counter (APC) systems have been implemented in various public transit systems to obtain various types of real-time information such as vehicle locations, travel times, and occupancies. Such information has great potential as input data for a variety of applications including performance evaluation, operations management, and service planning. In this study, a dynamic model for predicting bus arrival times is developed using data collected by a real-world APC system. The model consists of two major elements. The first one is an artificial neural network model for predicting bus travel time between time points for a trip occurring at given time-of-day, day-of-week, and weather condition. The second one is a Kalman filter based dynamic algorithm to adjust the arrival time prediction using up-to-the-minute bus location (operational) information. Test runs show that the developed model is quite powerful in dealing with variations in bus arrival times along the service route.

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TABLE OF CONTENTS

INTRODUCTION
Overview 1
Background 1
Objective 3
Scope of Work and Organization 4

LITERATURE REVIEW
Introduction 5
State of the Practice APTS 6
Applications 12
Prediction Algorithms 24
Media for Information Dissemination 27

DATA COLLECTION
APC Data 33
GIS Data 33
Weather Data 37
Field Data 40

SELECTION OF STUDIED PATTERNS AND SOFTWARE
Selection of the Study Patterns 42
Selection of Software 46

DATA PROCESSING
Data Screening 47
Data Calculation 47
Data Interpolation 48
Summary 50

MODEL DEVELOPMENT
Introduction 51
Artificial Neural Networks (ANNs) 51
Kalman Filtering Algorithm 65

PREDICTION EVALUATION AND ANALYSIS
Performance of Artificial Neural Networks (ANNs) 68
Performance of the Neural/Dynamic (N/D) Model 74

CONCLUSIONS 87
REFERENCES 89

LIST OF FIGURES

Figure 1	Configuration of the Studied Route and Its Adjacent Streets	35
Figure 2	Potential Stops on the Studied Route	36
Figure 3	Alignment of Bus Route 62 in GIS	36
Figure 4	NCDC Weather Observation Stations	37
Figure 5	Newark International Airport Station	38
Figure 6	Weather Information of the Selected Station	38
Figure 7	Time Period Selection for Querying Weather Information	39
Figure 8	Example of Collected Weather Information	39
Figure 9	Configuration of Bus Route 62	42
Figure 10	The Studied Patterns in GIS	45
Figure 11	MLP with One Hidden Layer	53
Figure 12	BPN Training Procedure	54
Figure 13	Sample Data File	57
Figure 14	Network Architecture of Model I	59
Figure 15	Learning Curves of Model I	60
Figure 16	Learning Curves of Model II	65
Figure 17	Learning Curves of Model III	63
Figure 18	Learning Curves of Model IV	65
Figure 19	Predicted (Model I vs. Scheduled Errors for TP-to-TP Travel Times	70
Figure 20	Predicted (Model I) vs. Scheduled Errors for Travel Times In Different Periods	70
Figure 21	Predicted (Model II) vs. Scheduled Errors for TP-to-TP Travel Times	71
Figure 22	Predicted (Model II) vs. Scheduled Errors for Travel Times In Different Periods	71
Figure 23	Predicted (Model III) vs. Scheduled Errors for TP-to-TP Travel Times	72
Figure 24	Predicted (Model III) vs. Scheduled Errors for Travel Times In Different Periods	72
Figure 25	Predicted (Model IV) vs. Scheduled Errors for TP-to-TP Travel Times	73
Figure 26	Predicted (Model IV) vs. Scheduled Errors for Travel Times In Different Periods	73
Figure 27	Prediction Errors from TP 1 to All Time Points (Model I)	78
Figure 28	Prediction Errors from TP 1 to All Time Points (Model III)	79
Figure 29	Difference between Predicted and Actual Arrival Times (Pattern PAIWM)	80
Figure 30	Difference between Scheduled and Actual Arrival Times (Pattern PAIWM)	80
Figure 31	Difference between Predicted and Actual Arrival Times (Pattern WMIAP)	81
Figure 32	Difference between Scheduled and Actual Arrival Times (Pattern WMIAP)	81

Figure 33	Difference between Predicted and Actual Arrival Times (Pattern WM-AP)	82
Figure 34	Difference between Scheduled and Actual Arrival Times (Pattern WM-AP)	82
Figure 35	Difference between Predicted and Actual Arrival Times (Pattern PAWM)	83
Figure 36	Difference between Scheduled and Actual Arrival Times (Pattern PAWM)	83
Figure 37	Performance Comparison (Pattern WM-AP)	84
Figure 38	Performance Comparison (Pattern PA-WM)	85
Figure 39	Performance Comparison (Pattern WMIAP)	85
Figure 40	Performance Comparison (Pattern PAIWM)	86

LIST OF TABLES

Table 1	Media for Information Dissemination	28
Table 2	APC Data	34
Table 3	Weather Data Provided by NCDC	40
Table 4	Time Points Description on the Timetable	40
Table 5	Field Data for Pattern PAIWM	41
Table 6	Field Data for Pattern WMIAP	41
Table 7	Time Points for Pattern WMIAP (inbound)	43
Table 8	Time Points for Pattern PAIWM (outbound)	44
Table 9	Time Points for Pattern WM-AP (inbound)	44
Table 10	Time Points for Pattern PA-WM (outbound)	45
Table 11	Developed ANN models	59
Table 12	Values of Parameters in Model I	61
Table 13	Values of Parameters in Model II	62
Table 14	Values of Parameters in Model III	64
Table 15	Values of Parameters in Model IV	65
Table 16	Performance Measure for ANN Models	68
Table 17	Travel Time Prediction (N/D Model) for One Trip (seconds)	76
Table 18	Predicted Vs. Actual Bus Travel Times (seconds)	77

LIST OF ABBREVIATIONS AND SYMBOLS

APTS	Advanced Public Transportation Systems
ITS	Intelligent Transportation Systems
FTA	Federal Transit Administration
GPS	Global Positioning Systems
AVLS	Automatic Vehicle Location Systems
APCS	Automatic Passenger Counter Systems
TIS	Traveler Information System
ATIS	Advanced Traveler Information Systems
APC	Automatic Passenger Counter
AVL	Automotive Vehicle Location
APC	Automatic Passenger Counter
APTS	Advanced Public Transportation Systems
FHWA	Federal Highway Administration
CAD	Computer Aided Dispatch
RTD	Regional Transportation District
AOS	Advanced Operating System
AATA	Ann Arbor Transit Authority
NJT	New Jersey Transit
CTA	Chicago Transit Authority
MTA	Mass Transit Administration
BCTA	Beaver County Transit Authority
COTA	Central Ohio Transit Authority
MARTA	Metropolitan Atlanta Rapid Transit Authority
TIMS	Transit Integrated Monitoring System
ANN	Artificial Neural Network
IVR	Interactive Voice Response
WAP	Wireless Application Protocol
CCTV	Closed-circuit Television
MMDI	Metropolitan Model Deployment Initiative
PDA	Personal Digital Assistants
TP	Time Point
PE	Processing Element
MLP	Multilayer Perceptron
BPN	Back-propagation Network
MSE	Mean Square Error
PA	Penn Station
WM	Woodbridge Mall
KF	Kalman filter
RMSE	Root Mean Squared Error

D_a	Distance of time-point ‘A’ from the origin
D_b	Distance of time-point ‘B’ from the origin
D_c	Distance of time-point ‘C’ from the origin
T_a	Leg time of ‘A’ from the preceding time point (=0 for the first stop)
T_{ab}	Leg time of ‘B’ from ‘A’
T_{ac}	Leg time of ‘C’ from ‘A’
P	Number of output neurons
N	Number of samples in the data set
d_{ij}	Desired output for sample i at neuron j
y_{ij}	Network output for sample i at neuron j
t_k	Travel time from time point k to the given destination
$T_{k,k+1}$	Travel time from time point k to time point $k+1$
s_k	Travel time from origin to time point k
z_k	Observed travel time from origin to time point k
e_{ANN}	Prediction error from the ANN
t_{ANN}	Predicted travel time from the ANN
e_S	Prediction error of scheduled travel time
t_S	Scheduled travel time from the timetable
t_a	Actual travel time
e_{ND}	Prediction error of the N/D model
t_{ND}	Predicted travel time from the N/D model
t_a	Actual travel time
y_i	Actual travel time of sample i
$\hat{y}_i$	ANN estimated travel time of sample i

INTRODUCTION

Overview

This report summarizes the results of the work performed under the project title "Use of Neural Network/Dynamic Algorithms to Predict Bus Travel Times under Congested Conditions". The objective of the project is to develop a Neural/Dynamic (N/D) model to predict bus travel times at all major stops (time points). The APC data collected from Bus Route 62 of NJ Transit was applied for developing the proposed bus travel time prediction model. The travel times between consecutive time points were predicted considering stochastic traffic congestion, weather condition and ridership distribution. The predicted travel time and actual bus travel time collected from APCs were then combined and fed into the developed Kalman filtering algorithm, which enabled the predicted travel times to be adjusted dynamically based on real time information (e.g., most recent bus travel times, ridership, weather, and time of the day, etc.).

Background

The Advanced Public Transportation Systems (APTS) program, one of the major components in Intelligent Transportation Systems (ITS), was initiated by the Federal Transit Administration (FTA) to encourage the applications of emerging technologies in computers, communication, and navigation for promoting the efficiency, effectiveness and safety of public transportation system. The APTS technologies, such as Global Positioning Systems (GPS), Automatic Vehicle Location Systems (AVLS) and Automatic Passenger Counter Systems (APCS), have been implemented in various public transit systems to obtain real-time information, including vehicle locations, speeds and occupancies. Such information can enhance the capability of transit passenger information systems assist proactive transit planning and management, and improve overall service quality.

With the application of AVLS real-time information, such as vehicle locations and speeds, can be estimated dynamically. However, only a reliable information system embedded in a realistic prediction model can attract passengers to access transit systems and use the predicted information (e.g., travel time) for decisions of trip-making. Such information can be disseminated through Traveler Information System (TIS) accessed by travelers at homes, work places, terminal centers, wayside stops or on board through a variety of media (e.g., TRAVELLINK in Minneapolis, MN; PA.CIS in New York City, NY; AZTech in Phoenix, Arizona, and SMARTBUS in Atlanta, GA).

NJ Transit faces increasing demand and the challenge to know ahead of time, whether or not their buses are running on schedule. It is necessary to know when buses will arrive at the designated onboard and destination stops. Bus travel times are prone to a high degree of variability mainly due to traffic congestion, ridership distribution, and weather condition. There is a need to develop a model for predicting bus arrival times and improve the quality of information provided to customers. Providing timely up-to-date transit information may reduce the negative impact of schedule/headway irregularities on transit service. There is also a need to examine the variability of bus travel times to prepare more accurate schedules and assist transit agencies to restore service disturbances.

The bus travel time deviations between stops are usually caused by several stochastic factors. Transit vehicle (e.g., buses) operations are frequently disturbed by right of way competence with other vehicles, congestion on the service route at different times of the day, intersection delays, variation in demands, and dwell times at stops. The resulting impact of these factors on the transit system comprises of bunching between pairs of operating vehicles, increasing passenger waiting times (and hence risk of passenger safety), deterioration of schedule/ headway adherence, uneven transition of inter-modal transfers, increasing cost of operation and traffic delays. All these factors may reduce the level of service and discourage riders to use the transit system. One way to mitigate the impact is to provide accurate information of vehicle arrival/departure times and expected delays at major stops. This will then enable users either to present at the stop before the bus arrives or (if at all they are already arrived at the stop) to effectively utilize their wait times (e.g., shopping, making phone calls etc.).

The deployment of travel time prediction models in Advanced Traveler Information Systems (ATIS) can benefit both transit providers and users. With accurate vehicle arrival information, transit users may efficiently schedule their departure time from work places/homes and/ or make successful transfers by reducing waiting times at stops. Transit providers can manage and operate their systems in a more flexible manner such as real-time dispatching and scheduling. Therefore, proper control action (e.g., increase or decrease operating speed, dwell longer times at some stops, etc.) can be determined, to maintain a desirable level of service by dynamically restoring the disruptions in scheduled headway.

The automatic passenger counter (APC) has been applied in NJ Transit buses. The primary benefit of APC is the increase in both quantity and quality of information collected. APC can link the time and location of a door open/close event. This technology has provided a good platform to obtain reliable information for predicting bus travel times between pairs of stops as well as arrival times at stops.

Objective

This research applied time and location dependent data automatically collected by APC units installed in buses, including passenger counts and average travel time between major bus stops. The objective of this study is to develop a dynamic model (e.g., the integration of artificial neural networks and Kalman filtering algorithm) that can predict bus arrival information with the use of real-time and historical data. The following tasks have been conducted while achieving the objective:

- Conduct extensive literature review in travel time prediction models.
- Identify geometric factors that affect bus travel times.
- Collect APC data to examine the bus travel times.
- Develop dynamic models that can adequately predict bus arrival times at major bus stops, and
- Evaluate the accuracy of the developed predictive models.

Scope of Work and Organization

In order to achieve the objective, extensive work has been performed and divided into three phases: literature review, model development and model evaluation. In Phase I, a comprehensive review of the current APTS applications was conducted, while the potential prediction models that can be used for predicting transit vehicle arrival/travel times were thoroughly investigated and discussed in chapter 2. In Phase II, several tasks were conducted including preliminary research of the studied patterns, collection of necessary data for developing neural/dynamic (N/D) model. Chapter 3 discussed all the collected data including APC data and GIS data provided by NJ Transit, weather data from National Climatic Data Center (at Asheville in North Carolina and Boulder in Colorado) and geometric data from the studied route. Chapter 4 was to identify the studied patterns and select the appropriate prediction model software. Chapter 5 illustrated the procedure of data processing from data screening, calculation to interpolation. Chapter 6 demonstrated the (N/D) prediction model development and its refine procedures. In Phase III, the evaluation and analysis of the developed prediction model was conducted. Chapter 7 provided statistical index to evaluate the developed prediction models and analyzed the prediction results. Chapter 8 concluded the research endeavor and proposed future research direction.

LITERATURE REVIEW

Introduction

The application of automotive vehicle location (AVL) and automatic passenger counter (APC) systems in transit is becoming more widespread in the United States. The current practices, benefits, and technology associated with the real time locations of buses, as well as, other associated technological components of the advanced public transportation systems (APTS) are examined in this report. Review of literature related to this issue has shown an increase in the usage of the systems, particularly AVL and APC, in transit agencies across the United States. This emergence has also led to an increase in the technology and the quality of technology required for accurate information. Another major step forward for the AVL systems is the increased and more accurate use of GPS data to determine bus locations. The majority of the literature review listed several perceived benefits as common reasons for installing this type of technology on their buses. The most common benefits of AVL systems include increased passenger safety, passenger satisfaction due to improved efficiency, and improved efficiency for the transit-controlled systems. Difficulties or problems experienced by those agencies that have implemented the system will be examined. Similarly, a number of technological problems involving hardware, software, and implementation are also discussed.

A number of studies and publications related to specific transit agencies are also incorporated into this review, in order to determine the effectiveness of the systems from a transportation standpoint. The primary focus will be on particular agencies in order to determine how they are using and benefiting from the implementation of different types of systems. Those agencies found to be using AVL and/or APC systems range from small to large with varying degrees of use. The cost of these systems also varies dependent upon the number of buses as well as the different components utilized by each.

State of the Practice APTS

Use and Options

It was reported by the Federal Transit Administration (FTA) that in 1999 there were 61 agencies utilizing AVL systems. [(1)] At this time there were also 93 more agencies in the planning or implementation phase. The use of AVL is being integrated with other systems to help improve the transit system for the passengers. Some of these systems include: automatic vehicle monitoring/control, emergency location, data collection, customer information, fare collection, and traffic signal priority. Even though the technology is fairly new it is already beginning to change. Earlier systems utilized the signpost method for location; however, most systems today, nearly 70 percent, are GPS (Global Positioning System) operated. The Federal Highway Administration (FHWA) reported that GPS is the most widely used method and that the accuracy has increased significantly [(2)] – it has improved from 100 meters to between 10 to 20 meters in 2000. This increase is explained by the removal of intentional degradation to the signal by the military. The improvement has led to most agencies using GPS, however, for the sake of completeness the four types that can be used are discussed below emphasizing the primary advantages and disadvantages of each: [(1)]

- Signpost and Odometer (active and passive) – The vehicle reads a unique signal from signposts in order to relay their position to dispatch. The primary advantage is that the technology and use has been proven and well established. The primary disadvantages are: (1) the need for signpost, and (2) the system does not work if the bus is off route.

- Global Positioning System – Special receivers on the buses read information from orbiting satellites. The main advantages revolve around the accuracy and the fact that no wayside materials need to be purchased. The only expressed disadvantage is that large buildings or tunnels can block the signals. However, the use of the differential GPS would somewhat correct this problem.

- Ground Based Radio – Receivers read information from a network of radio towers in order to triangulate their position. Again the signals can be obtained from anywhere without the need to purchase any wayside equipment.

- Dead Reckoning –The use of the bus odometer and a compass are used to determine the location. This system is often used in conjunction with one of the other methods. Consequently, this system is rather inexpensive, but is less precise.

Benefits

A number of benefits, along with some problems are examined in order to evaluate the effectiveness of AVL systems. The most common objectives of AVL installation were to improve customer service, through improved safety, reliability, and use of bus status information. A study conducted by the FTA [(1)] surveyed numerous sites where ATPS was deployed and the usefulness of AVL systems that are being used was evaluated. The sites surveyed were: Milwaukee County Transit System (Milwaukee, Wisconsin); Ann Arbor Transportation Authority (Ann Arbor, Michigan); New Jersey Transit (Essex County, New Jersey), King County Department of Transportation, Metro Transit Division (Seattle, Washington); Tri-County Metropolitan Transportation District (Portland, Oregon); the Regional Transportation District (Denver, Colorado); and the Montgomery County Transportation Authority (Rockville, Maryland). The transit agencies surveyed stated the following as benefits of AVL and other system components:

- Improved schedule adherence and transfer coordination.
- Improved ability of dispatchers to control bus operations.

- Increased accuracy in schedule adherence monitoring and reporting.
- Assisted operations during snowstorms and detours caused by accidents or roadway closings.
- Effectively tracked off-route buses.
- Reduced manual data entry.
- Monitored driver performance.
- Reduced voice radio traffic.
- Established priority of operator calls.
- Improved communications between supervisors, dispatchers, and operators.
- Provided capability to inform passengers of predicted bus arrival times.
- Helped meet Americans with Disability Act requirements by using AVL data to provide stop annunciation.
- Used playback function in investigating customer complaints.
- Used AVL data to substantiate agency's liability position.
- Provided more complete and more accurate data for scheduling and planning.
- Aided in effective bus stop placement.
- Used AVL-recorded events to solve fare evasion and security problems.
- Provided more accurate location information for faster response.
- Foiled several criminal acts on buses with quick response.

In order to apply the benefits to other agencies the following characteristics of the survey sites should also be noted:

- AVL use ranged from 82 buses (Ann Arbor) to 1343 buses (King County).
- All utilized computer aided dispatching.
- All but King County used GPS or DGPS systems, King County used signpost & odometer.
- All used mobile data terminals.

- APC were used or planned to be used on all but on Rockville, Maryland and Denver, Colorado systems.

A number of particular agencies and programs also have detailed many benefits from AVL and APTS use. The state of fleet control in the United States and other countries was evaluated by the US DOT Operations Timesaver project [(3)] in which a number of benefits were revealed from collected data. The following were cited as examples of APTS benefits: fleet reduction (2-5 percent) due to increased efficiency, improved travel time (Kansas City reduced scheduled travel time by 10 percent), schedule adherence (Baltimore reported a 23 percent improvement with AVL equipped buses), and improved safety due to less time spent at bus stops. AVL also provided data for analysis that reduces the need for staff to maintain schedules, estimating savings of $40,000 per travel time survey to $1.5 million annually. Particularly, the schedule adherence improvement was cited as: [(4)]

- Milwaukee County Transit System, Milwaukee, Wisconsin, reported an increase of 4.4 percent, from 90 to 94 percent.
- Kansas City Area Transit Authority, Kansas City, Missouri, reported a 12.5 percent increase, from 80 to 90 percent.
- Regional Transportation District, Denver, Colorado, reported an increase of between 12 and 21 percent on various routes. [(4)]

Aside from these, a number of smaller transit agencies also reported the effects of AVL systems. A number of small and medium sized transit agencies were surveyed for the Transportation Research Board to determine the benefits that AVL systems and their components offered. [(5)] Most of the agencies surveyed gained funding from “State and local Governments along with FTA.” The cost for these smaller systems ranged from 50 to 750 thousand dollars. The number of buses served ranged from 14 to 32. The analysis led to the conclusion that the benefit of AVL systems is directly related to the annual ridership of the system.

In addition, most cost differentials are likely to occur with systems that have "problems maintaining schedules and service reliability." It is recommended that AVL systems should be implemented to decrease passenger-waiting times to attain the maximum benefit of the system.

Problems

The primary problems or difficulties experienced by most agencies dealt with integration or implementation problems of the hardware and software. Another problem, reported by the TCRP, from a survey of agencies found that funding was the primary problem with procuring the system [(6)]. Additional problems include the need for more specialized staff to handle the updating, maintaining, and controlling of the system. The process of implementing an AVL system usually took more than a few years from design to full use. Most agencies had not established a method to quantify the efficiency of their systems. Due to this and the lack of comparable price comparisons it is hard to define the benefits of the system quantitatively.

A number of issues needed to be addressed before APTS, particularly AVL, were a beneficial investment. The primary issues revolve around integration of the system, and are outlined below: [(3)]

- Institutional barriers – labor contracts, governmental rules, and political directives can create barriers that prohibit cost effect introduction of such systems.
- Infrastructure problems – Transit agencies are sometimes lacking sophisticated technology, which makes integration of new systems difficult. Installation of APTS is labor intensive, but is getting cheaper.
- Architecture/protocol – There is a technology compatibility problem and integration with other transit technologies has been difficult.

- Integration issues – APTS devices alone are of limited value to management decision-making, but when used in combination with broader information systems they are very powerful.

Most of the issues mentioned are beginning to diminish. As more widespread use of the systems evolve, the process of implementation is becoming easier. Many of the agencies that have or are expecting AVL systems are purchasing new buses with wiring for the system included.

Effects on the Workforce

While the reported benefits of AVL systems are great, there is a certain degree of training that is required for proper control of the system. Most research has shown that after proper training, most workers find the systems beneficial. The workers are able to complete their work more efficiently and accurately.

These human factors are very important and were the focus of a United States Department of Transportation Report in 1999. (7) The effects of real time vehicle location systems on the employees of the transit agency were examined. The study was based on the new Computer Aided Dispatch/Automatic Vehicle Locator (CAD/AVL) system at Denver's Regional Transportation District (RTD). The data collected in 1996 and 1997 were compared with that collected before installation of the system. The collected data include frequency of communications, number of personnel per unit of service, procedures and communication, the attitudes of the dispatchers, street supervisors and bus operators. The employees had to learn how to use and integrate the new technology into their jobs. The analysis found that this new knowledge provided additional information to the personnel, but did not change their responsibilities. The report also found that dispatchers had to make fewer requests for information and could make their decisions more accurately and easily. Operators had more "accountability" in controlling the buses and their schedules, but the dispatchers' workload increased due to an increased number of received calls. It was also stated that street supervisors have more duties than before; however, their need to observe traffic conditions in the field became non-existent. Overall, almost everyone found that the newly provided real-time information led him or her to more accurate information and decisions.

A study that looked at the same transit system in Denver, Colorado offers information about the impacts of an AVL system on the transit employees. [8] The report analyzes the effectiveness of an AVL system installed in Denver, Colorado by the RTD. The system was installed in 1993; however, it was not used until 1996 due to a number of difficulties. After most of the installation was complete and the system was being used, a number of employees were surveyed to determine their feelings about the system. Operators, dispatchers, and field supervisors were all surveyed. Most of those surveyed found the system to be easy to use, helpful in emergencies, and accurate and reliable.

Applications

In order to thoroughly examine the effect APTS systems, specific examples need to be examined. The following sections detail the use of specific systems, programs, or technology to explore the scope and benefit of AVL and/or APC technologies.

<u>Nextbus</u>

The Nextbus System provides services to a number of different agencies. Nextbus Information Systems provides arrival information that is updated at regular intervals. [9] GPS satellites are used to relay the location and other information to the AVL on the buses. Using typical traffic patterns and normal bus stops, Nextbus is able to predict arrival times for the buses at each stop. These arrival times are updated regularly to ensure comfort and security of the riders. Predictions are made available to the web, signs at bus stops, Internet capable cell phones, and Palm Pilots. Nextbus projects include MUNI-Metro Light Rail Vehicles, AC Transit-Alameda County Transit in California, Fairfax, Virginia, METRO Transit-Oklahoma City, Vail Transit, Massachusetts Bay Transportation Authority, MTD-Santa Barbara, and many others. The following descriptions are from the websites of the individual agencies and include relevant information concerning the use of Nextbus systems:

Arlington *(10)* On September 11, 2001 an 18-month, $100,000 pilot program in Arlington County, Virginia will install the Nextbus technology in the eight buses that run the 38B line. Real time information messages will be relayed on 9 new electronic signboards.

AC Transit *(11)* The AC Transit in Almeda County in California is using the Nextbus technology as pilot project. The system is being used on the heavily traveled San Pablo corridor (72, 72L, and 73 lines). Their project enables riders to get bus information over the Internet.

Fairfax CUE *(12)* The City-University-Energysaver (CUE) Bus System that serves the city of Fairfax and George Mason University in Virginia is equipped with Nextbus equipment that uses computer modeling to predict bus arrival times. Each vehicle is equipped with a satellite-tracking device that allows bus arrivals to be estimated within a minute, with 95 percent accuracy. CUE bus system provides information that can be relayed to the web, signs at bus stops, Internet capable cell phones, and Palm Pilots, to provide real time information to patrons.

Vail Bus Service *(13)* Beginning on June 23, 2001 the Town of Vail, Colorado started using the Nextbus System. The following areas are using the systems: Vail Village, LionsHead and Golden Peak corridor. Location information is transmitted every 90 seconds to the AVL system at the central dispatch center. The town is currently evaluating options that would add the Nextbus system to outlying areas of Vail.

San Francisco Municipal Railway (MUNI) *[14]* A 9.6 million-dollar contract was awarded to Nextbus to install their technology on all of their transportation equipment. The equipment was tested on light rail lines and also on one bus line, 22 Filmore, that serves 20,000 passengers a day. The system will provide GPS equipment on all buses and trains. Cable cars and streetcars in San Francisco would also use the technology. Part of the project also includes installing 430 electronic informational signs. GPS "information is sent to a centralized server and compared with historical information and the bus or train arrival is then projected and available via wireless devices such as phones and handhelds." The project is expected to take nearly five years to fully complete on all lines.

Tri-Met – Portland, OR

The Tri-Met Transit Tracker system provides real time transit vehicle arrival time information to patrons on stations of selected routes. [15] The total cost of the project (Transit Tracker) is estimated to be $ 4.5 million with the City of Portland paying $ 3 million and Tri-Met paying $1.5 million. The Transit Tracker system will work with a dispatching system that is already in place, which utilizes AVL and APC technologies. The initial system has led to many improvements:

- Overall improvement of on-time 69 percent to 83 percent.
- Early arrivals declined from 15 percent to 5 percent.
- Schedules have improved using information provided by the Bus Dispatching System.

The Transit Tracker system was expected to be used to relay real time information at 50 rail stations and 250 bus shops initially. This will be followed by deployments of approximately 50 stations per year. The system will also provide the information to the Internet. The following improvements will also be implemented in the near future for use with the existing AVL and APC: Transit Signal Priority, LIFT Scheduling System Upgrade/Electronic Data Transmission, Automated Stop Announcements, Bus Dispatch System Upgrade, Scheduling System Software Procurement, Radio and Microwave Replacement Project (with Motorola Gold), DISPATCH Operations Utilities Program, LIFT Program Integrated Voice Response, and Automated Yard Mapping and Vehicle Assignment.

AOS – Ann Arbor, MI

In Ann Arbor Michigan a fully automated Advanced Operating System (AOS) began to use in 1998. [16] It was expected to offer a "fully integrated public transit communication, operation, and maintenance system." The Ann Arbor Transit Authority (AATA) serves over 4 million riders a year, with 27 bus routes that are offered 7 days a week, 24 hours a day. Each bus utilizes the following equipment:

Advanced Communications: Each bus has an 800 MHZ radio and onboard computer that minimizes "voice transmissions by providing data messages that summarize vehicle status, operating condition, and location." The driver can also switch to a voice system. The system is responsible for relaying all information and for onboard announcements.

AVL: Each bus uses GPS to determine their own location, accuracy is within one to two meters. An insertable memory card stores the bus routes and compares them to the accurate time given by the GPS system. If this comparison determines the bus will not be on time the onboard computer notifies the Operation Center and the AVL relays the announcement to the internal next-stop signs and announcement. The AVL also integrates location data with fare collection, passenger counters, and engine data that are controlled electronically. Dispatchers are able to manage the system and assist drivers by inserting overload vehicles in the system or offering route suggestions.

Emergency System: An onboard emergency system allows drivers to alert dispatchers of an emergency, who in turn can note the bus positions and notify the proper authorities.

En Route Information: Onboard the bus stop announcements, date, time and route are relayed to patrons. The driver can also activate timed and periodic announcements.

Geographic Information System: The Rockwell MapMaster is also a part of the AOS on AATA buses. It allows you to enter locations of bus stops and routes. The data can be “imported to the route generator GIS system.” The GIS system then creates schedules time points, announcement points, transfer points and bus stops by route.

Computer-Assisted Transfer Management: This system, TransitMaster, allows drivers to request transfers that are then calculated by the dispatch computer that advises the drivers whether a transfer is possible or not.

Other benefits provided by AOS include fare collection, ability to relay real time information to patrons, APCs, video surveillance (3 cameras on each bus), and vehicle component monitoring. The video surveillance has lead to improved cleanliness on AATA buses. Rider information is provided through the use of public access cable, monitors at the transit center, and the web. Reviews of the system have found improved departure time accuracy, potential long term cost savings, and an online survey of users found the system very favorable. The study also found that its AVL system has a median positional error of 85 meters, ranging as high as 580 meters and as little as 3.25 meters. The inaccuracy was believed to arise from “differential GPS correction deterioration in outlying areas”.

<u>MyBus – Seattle, WA</u>

The Transit Watch system is an ITS Research Program at the University of Washington [(17)] for the King County Metro Transit. It is part of the Federal Highway Department Smart Trek: Intelligent Transportation Infrastructures, Model Deployment Initiative. Computers have been installed at the Northgate and Bellevue Transit Centers where Transit Watch has been available to bus riders since July 1998. The Transit Watch program includes 4 primary parts: (1) the prediction server (Predictor), (2) data distribution server, (3) the client display applet (Transit Watch), and (4) a database. The entire system utilizes an object-oriented Java Language. The Predictor predicts the arrival times. A Predictor is available at each location that the Transit Watch provides an arrival prediction. The Predictor receives data from an AVL and reads the active trips, trips that are scheduled to depart the prediction site in a particular time window. A trip tracker “uses a tracking algorithm to combine the current position of the bus with historical data about the trip to predict the arrival time.” When new data is received, the predicted time is updated. Information is collected and can be displayed on the Internet or web-capable phones, which is the function of the second component. The third and fourth components backup and save information for subsequent uses.

Dailey and Maclean (18) described the ability of the MyBus system to forecast arrival and departure times, focusing on the system and how it works to predict the necessary information. The algorithm used by the predictor will be discussed in a later section.

<u>RTD – Denver, CO</u>

RTD is an agency that was previously mentioned in this report in regard to the workforce. The Department of Transportation [(8)] further analyzes the effectiveness of an AVL system installed in Denver, Colorado by the Regional Transportation District (RTD). The system was installed in 1993; however, it was not used until 1996 due to a number of difficulties. After most of the installation was complete and the system was being used a number of employees were surveyed to determine their feelings about the system. Operators, dispatchers, and field supervisors were all surveyed. Most of those surveyed found the system to be easy to use, helpful in emergencies, and accurate and reliable. Several did mention that the system was not working properly at all times. This was explained by the difficulties of installation. A survey of patrons was also conducted, finding that 90 percent of passengers thought the bus service was good or better.

Along with the surveys, a cost analysis was also conducted. The final cost of the completed system was 10.4 million dollars, with in-vehicle hardware accounting for half of that cost. The overall results of the system were found to be successful; however, there were a number of problems. The system has helped workers, patrons and improved accuracy, but the RTD did not use the improved data to improve schedules. This fact was used to explain a minimal increase in efficiency. The system was not used to its fullest ability due to the functional problems experienced in the beginning of installation.

Other Practices

The FTA [(1)] documents the use and deployment of all types of intelligent transportation systems, including that used for transit agencies. The report states that the benefits of using an AVL system are improved dispatching and operational efficiency, improved reliability of service, quicker response to disruptions in service, quicker response to criminal disruption, and extensive information at a lower cost that can be used for future planning. In addition a number of cities and agencies were used to evaluate the use of AVL systems. The cities are listed below:

Essex County, New Jersey – The New Jersey Transit (NJT) AVL system has been in place and working since early 1998. NJT purchased a signpost and odometer system as well as a statewide 23-tower radio system from Motorola. Two thousand buses on 26 lines in Essex County are operated fully with the AVL system. It was also reported that there were only about 100 of the original 600 signpost remaining due to weather problems. Due to this fact AVL is not available Statewide, but radio communication is.

Chicago, Illinois – An AVL system utilizing dead reckoning with DGPS correction is used by the Chicago Transit Authority (CTA) on 1210 of the agencies 1872 buses. At the time of the report emergency location and text messaging were available, while new radios were needed for further capability. It was reported that the CTA has 12,900 stops and coding of the first 1,000 took 3 months. Once this is completed 254 buses will operate with both the AVL and new radio systems. CTA expects to provide the equipment on the rest of the fleet as new buses are acquired. At the time of the report they had a contract with NOVA for 150 buses furnished with wiring compatible for the installation of AVL equipment.

Baltimore, Maryland – A phased implementation plan is being utilized by the Maryland Mass Transit Administration (MTA) for acquiring their AVL system. Fifty buses were initially tested using the Loran-C AVL system. Additionally MTA has purchased a DGPS system at an estimated cost of $15,000 per bus. This includes a new radio system consisting of the radio and base station equipment. The project included AVL equipment for 380 of the 868 vehicles, while the rest of the fleet will be equipped as new vehicles are purchased – sixty-five new buses equipped with AVL were expected in late 1999 at a cost of 8 million dollars. The plan includes passenger information being available by phone, along with limited information available by sign. MTA expects to save 2-3 million dollars annually by the fourth to sixth year of operation via purchasing, operating, and maintaining fewer vehicles.

Rochester, Pennsylvania – The Beaver County Transit Authority (BCTA) are upgrading their Loran- C system to a DGPS system. They hope to upgrade the system that has been in existence since 1991 to the DGPS system by 2000. All 20 of BCTA's buses will be equipped with the AVL system, and all new buses will be equipped with the appropriate wiring to install the system. Along with the usual benefits of timesaving, the BCTA hopes to monitor contractors that operate the system and use it to investigate customer complaints.

Of other interest, the report also offers discussion of the Operations Software for Fixed-Route Bus Operations, focusing on the most commonly used system- Computer-Aided Dispatch (CAD). The CAD system is used for bus service, as well as operations planning. Customers are able to use it for itinerary planning and transfer connections. The report discusses implementation challenges and noted that most of the agencies surveyed were still learning how to use the system effectively. Most problems dealt with compatibility issues involving missing information and oversensitive location algorithms.

Automated Passenger Counters (APC) system is also discussed in detail in this report. The primary benefits of the APC's are the reduced cost to collect information and an increase in the amount and quality of the information collected. APC make it possible to reduce or eliminate the need for manual checkers. Several cities using APC's are examined in the report and some are discussed here briefly:

Columbus, Ohio – The Central Ohio Transit Authority (COTA) began using APCs in 1984, when it acquired 37 units. The units purchased from Urban Transportation Associates for $171,000, was enough to equip about 10 percent of their fleet. COTA reported a 95 percent accuracy of the counts, and found the system very useful. COTA planned to upgrade their system with APCs that use vertically pointed infrared beams mounted in the roof of the vehicle to count passengers. The data will be transmitted in real time, and combined with AVL data to be used for planning and to improve schedules.

Atlanta, Georgia – The Metropolitan Atlanta Rapid Transit Authority (MARTA) has installed 74 APCs on AVL-equipped buses. MARTA reported that their data is between 80-85 percent accurate. They use the counters to generate a great deal of information but feel that the systems should not replace manual checkers. As a result, they have not reduced the number of manual checkers that they used previously. They also reported that APCs are the most difficult piece of APTS technology to upkeep, and that only about 40 of the 74 counters provide good information on any given day. Despite such maintenance problems they estimated a savings of 1.5 million dollars in operating expense per year.

Baltimore, Maryland – The Maryland Mass Transit Administration (MTA) has used APCs on 25 buses since 1997. The units count passengers using horizontal infrared beams and were acquired from Urban Transportation Associates. The MTA plans to purchase 75 more APCs in order to equip over 10 percent of their fleet.

Newark, New Jersey – New Jersey Transit plans to purchase 170 APC units for its buses. The units will be considered as part of their AVL system. Data transmission is planned to utilize wireless download after the bus returns to the garage. The report states that the APCs will help NJT generate a greater volume of information and more accurate data to help them better understand ridership and to improve market research.

Developed Applications

Benefits and uses of the AVL system are also reviewed in relation to some of the cities where its use is being proposed. [19] These cities include Albany, NY, Eugene, OR, Los Angeles, CA, and Pittsburgh, PA. Each of the city's projects incorporates the use of AVL and serves thousands of people a day on their transit system. The projects are all in the design or implementation phase. In Albany [20], the Capital District Transit Authority's primary bus route, with 20 percent of the system's passengers, runs 16 miles from Albany to Schenectady. The project for Albany includes signal coordination to optimize bus signal priority. They hope the program will lead to shorter bus route times, improved service to three major routes and higher frequency service. In Los Angeles, Metro Rapid began on June 24, 2000 with the start of service of two routes, Whittier-Wilshire Boulevard (line 720) and Ventura Boulevard (line 750). The Metro Rapid is expected to expand into as many as 15 to 20 new express lines. The Metro Rapid is using ITS including AVL to increase the efficiency of the transit system. Similarly, many of the other cities are beginning with smaller testing areas, with plans of widespread expansion.

Other Technologies

During the course of implementation for the AVL and APC systems a number of other technologies have emerged, some of which were previously mentioned. Another product gaining attention is the Transit Integrated Monitoring System (TIMS). [21] This technology revolves around the use of Passenger Tags. The tags are actually radio frequency identification cards, which “act as bus passes.” The cards are devised to integrate AVL and APC technologies. The tags are used to uniquely identify passengers, and then keep track of their position using GPS satellites that monitor the bus. The card is swiped as the passenger boards the bus and again activated as the passenger leaves the bus. From this the arrival and departure times to be recorded, leading to improved information regarding “origin destination pairs, passenger transit times, and schedule adherence.” Along with this valuable information, the cards can be used as a fare card, acting as a debit card or other billing techniques. The three primary goals of the project as outlined by the author are:

- Advanced systems for transit vehicle location, identification, and management.
- Improved methods of data collection about or from transit users.
- Advanced systems for fare collection and control systems.

Costs and Communication

The John A. Volpe National Transportation Systems Center studied several agencies that utilize AVL systems. [(4)] The study focused on a number of variables including cost. They found the median cost per system was reported to be $8,000, with a range from $1,200 to $23,000. The wide range of cost was explained by varying functions performed by each system. The study found that only operations software and pre-trip automated passenger information had widespread use. It is believed, however, that many other related technologies will reach widespread or moderate levels of use in the near future. This is based on the number of agencies that have plans to implement the technology.

A TCRP synthesis also comments on the cost of implementing advanced technology systems. [(6)] Based on this information gathered it was concluded that the technology is increasing as agencies begin using GPS type information, rather than the older signpost method. As a result, the performance of the infrastructure and onboard equipment has increased. Consequently, GPS systems, which allow for complete coverage, are now being used in most new installations. A major cost of the system, one to two-thirds, involves integration of a communication system. One particular agency, MTD, which provides real-time information to the public, reported a two percent increase in ridership with increased customer satisfaction. At the time of the report many agencies did not provide real time information to their passengers. Also at the time of this report an average cost of $13,700 per bus was reported, with some smaller agencies paying more due to fewer units purchased.

As mentioned previously, the influx of information is insignificant without increased communication abilities. Communication of real time information through wireless phones, electronic message boards, websites, and personal digital assistants are becoming popular. The Metro King County MyBus site, for example, has had a significant increase in the number of hits since providing real time information. Other sites offer real time maps and bus information to keep their patrons informed.

Prediction Algorithms

Many forecasting methodologies have been applied to transportation research, such as prediction of traffic volume, travel time, etc. Particularly, various bus arrival time prediction models have been developed using different methodologies, such as time series, artificial neural network, and Kalman filtering algorithm.

<u>MyBus Application</u>

The predictor for MyBus utilizes three pieces of information including that collected from the posted schedule, a set of previous trips, and the AVL stream. The AVL system supplies information every one to three minutes per vehicle, while the previous trips provide statistics to the systems algorithm used for prediction. The prediction algorithm uses the Kalman filtering technology. Specifically, vehicle location, time, and time until arrival were considered as state variables. The reported position and its time measurement were observables. The predictor in Seattle is capable of making 25,000 predictions every 10 seconds. [(18)] The time and distance to the destination, the bus stop, are calculated for each prediction. The deviations were modeled as a probability surface to show the accuracy of the system. [(22)] The analysis made by the authors found the system to reduce errors by 50 percent to 75 percent, as compared to the schedule alone.

Since the observations of vehicle location can only be recorded at irregular intervals. Typically, linear interpolation was applied to obtain estimated arrival times. Using the latest bus location and time data, the Kalman filter continuously predicts the arrival time.

<u>Blacksburg Transit Application</u>

Algorithms were developed for a transit traveler information system in Blacksburg, Virginia to predict bus arrival time at rural setting (23) GPS data was gathered at variable time intervals, including location and time label. However, because of its inherent constraints (no fixed sample period, erroneous reports), the accuracy of the prediction is compromised.

Four algorithms were developed in the study based on various data sources as input:

- GPS bus location data only
  Arrival time at the downstream time point is estimated based on the arrival time at the upstream time point and historical travel time between them.
- GPS bus location data and bus schedule table
  Bus arrival times at nearby downstream time points are based on GPS data while assuming current delay has little impact on the arrival time at downstream stops that are far away.
- GPS bus location data, bus schedule table, and delay
  This algorithm takes into account the fact that bus drivers tend to adjust their speeds (within speed limits) in order to arrive on time. So the current delay of the bus is taken as an input.
- GPS bus location data, bus schedule table, delay, and time check point
  This algorithm is based on the 3rd algorithm with an added input as dwell time at time check point since it is usually much longer than that at other stops.

Performance of these algorithms was compared based on criteria including overall precision, robustness, and stability. The 4th Algorithm outperformed all other ones. However, it was also concluded that the algorithm performance was also location dependent.

Texas A&M University TransLink Lab

Two algorithms, time-based and distance-based, for predicting travel time of campus buses were developed at the TransLink Lab of the Texas Transportation Institute at the Texas A&M University. [(24)]

In the time-based model, bus route between two stops was divided into a series of one minute zones, and estimated arrival time can be obtained by locating the bus on the route to see how many one-minute zones it needs to traverse to reach the stop. This method is based on historical travel time data and therefore cannot capture real time traffic variations.

The distance-based algorithm uses the distance to a bus stop and time of the day as independent variables. Particularly, the algorithm takes into account the variations in running speeds and dwell times of a bus both during class and during the pedestrian congestion of class breaks.

Comparisons of the prediction results with actual arrival time showed that the distance-based algorithm had a better performance, i.e., with relatively small deviation. However, it was more complex and cost more to calibrate.

NJ Transit Bus Route 39

Chien et al. [(25)] developed a bus arrival time prediction model that combined the forecasting capabilities of artificial neural network (ANN) and dynamic filtering techniques. ANN was chosen because it was proved to be a powerful tool to simulate complicated systems, especially those with large number of variables and complex correlations among these variables that are difficult to be explicitly modeled. Dynamic filtering technique was applied to adjust the ANN prediction output using most recent readings from the bus location as well as traffic information.

This model was established based upon simulation data generated from a model that was calibrated and validated on New Jersey Transit Bus Route 39. The simulation model was able to provide various traffic data such as volume, passenger demand, speed, delay, etc. as the input to the prediction model. Various combinations of these variables were experimented in the ANN training process, and the most relevant ones were identified.

Two algorithms, link-based and stop-based, were developed. The former assumes additive link travel time/cost, and generally defines the segment of the route that is between two adjacent intersections as a link. The latter is established based on aggregated data at each bus stop including demand and volume, speed between to adjacent stops.

Performance evaluation showed that link-based algorithm outperformed the stop-based one when the number of intersections between a pair of stops is relatively small, while the latter one accommodated the stochastic conditions at further downstream stops better.

Media for Information Dissemination

This section will discuss the media for information dissemination from Federal Transit Administration (FTA). [(26)] The types of media that are of interest in the literature include those listed below in Table 1. These media have been designated either interactive or non-interactive.

Table 1Media for Information Dissemination

Interactive Media	Non-Interactive Media
Internet	DMS’s
Interactive voice response (IVR) via telephone	Video monitors
Interactive kiosks	Fax
PDAs	Non-interactive kiosk
Wireless Application Protocol (WAP)-enabled	Telephones (voice information)
Mobile Phones	Cable television

Different from Non-interactive media, interactive devices (such as kiosks and the Internet) allow users to timely get the information they are seeking. Within the two types of media, DMS and the Internet, respectively, were referred with the most in the literature. Hence, more extensive evaluations of the other types of media may be required in the future to arrive at a better understanding of these systems.

Peng and Jan [27] evaluated dissemination media for real-time transit information (e.g., pagers, the Internet, and PDAs). For each media type, they provided a general description, including its advantages and limitations. all the studied media were evaluated based on their accessibility, versatility and interactivity, information-carrying capacity, user friendliness, cost to install, cost to use, and ease of implementation. The Internet and kiosks were found to be the best media overall. DMS and closed-circuit television (CCTV) were considered good dissemination media because of their modest cost and flexibility in the variety of provided information. PDAs and automated voice annunciators were promising technologies for real-time transit information systems, but were not ready for implementation when the paper was published. Reviews on interactive media are discussed below:

Internet

As part of the Smart Trek Metropolitan Model Deployment Initiative (MMDI) in the Seattle, Washington area, two new applications were created to provide real-time transit information. [28] Two types of media were used to relay the information to the transit passengers: (1) on the Internet and (2) at the transit center. Busview displays the real-time location of all the transit vehicles operated by King County Metro. Transit Watch is a real-time arrival prediction system suitable for deployment in transit centers. Busview and Transit Watch are designed to operate over the Internet.

The Transit Watch project deployed an Advanced Public Transportation System APTS /ATIS that predicts the arrival status of transit vehicles. This prediction results in one of four states: (1) On Time, (2) Delayed "n" Minutes, (3) Departed, and (4) No Information. The goal of the project was to develop an interface that promotes the use of transit by reducing the stress inherent in transfers. This project leverages the ITS Backbone component of the SmartTrek MMDI project. This project was originally designed to be deployed at three transit centers, but it has since been made available on the Internet as well.

Stuart Maclean and Daniel Dailey [29,30] discussed the dissemination of real-time transit information to a WAP cellular phone. The use of WAP phones was an extension of the ongoing Internet-based MyBus program in Seattle, Washington. In that study, challenges such as limited display area and capability of using WAP phones for real-time information were discussed. To compensate for the phone's physical restrictions, MyBus maximized its use of the screen by combining information, such as scheduled arrival time and departure status, into one data field. Future work for this project includes formatting bus arrival data for PDAs.

Dynamic Message Signs (DMS)

DMSs at bus stops are used mainly to provide arrival or departure information to reassure the customer that s/he is waiting for the right vehicle in the right place and to inform him/her the vehicle arrive times. In many cases, bus stop displays also are used to provide static information about the transit service and to display advertisements. The sample systems using DMSS include VIA system (Visualizzazione Informazioni Arrivi) in Turin, Italy, COUNTDOWN system in London, and Los Angeles Metropolitan Transportation Authority (MTA).

Interactive Voice Response (IVR)

IVR telephone information systems allow customers to call a single phone number and navigate a menu for needed information. Previously, transit customer service operations relied on agents to provide various types of information over the telephone. For many years, automated telephone information systems assisted agents in answering routine questions. The new systems eliminate the need for agent involvement in many information requests.[31] One problem with IVR systems is that they do not always have good voice recognition. However, speech recognition technology has improved recently. Another difficulty noted in the literature is that some systems incorporate automated distribution features for information that would be too time-consuming to provide over the telephone. In these cases, information can be sent via fax or e-mail. [31] One of the real-world systems applying IVR is the Bay Area's TravInfo® project.

Interactive Kiosks

Kiosks can be located in a variety of places, including near public transit, in stations, at stops, or in other high foot-traffic locations (e.g., in shopping malls). They can also be located at places with high concentrations of people, such as public buildings and tourist locations. The literature suggests that information available via kiosks usually includes: Travel information, (e.g., optimum route, itineraries, and arrival times at specific locations) and general information (e.g., scheduled activities in the city or metropolitan area).

Several functional characteristics of kiosks should be taken into account when a kiosk is being considered. These characteristics include:

- Simplicity of the user interface.
- Provision of useful and understandable answers to the user request.
- Effective location.
- Appropriate housing.
- Efficient maintenance.
- Use of standards.

According to the literature, kiosk users mainly have problems with the touch keys and/or the touch screen, as well as with the time required to wait until they get the system response. However, the general level of satisfaction is rather good.

Video Monitors

According to Advanced Public Transportation Systems: The State of the Art Update 2000, [31] video monitors are often used when a large amount of information needs to be displayed and where flexibility in using graphics, fonts, and color is needed. A video monitor providing real-time arrival updates would be less suited to a central display near a group of bus berths, since transit users might be uncomfortable moving away from the berth and losing their places in line to get close enough to read the display.

Personal Digital Assistants (PDA)

Hand-held PDAs recently appeared as information media in the transit field. The traveler can consult them at any moment anywhere. PDAs can be used to obtain pre-trip and en route information. Advanced Public Transportation Systems: The

State of the Art Update 2000 [31] claimed that one issue with PDAs is the reluctance of customers to pay for traveler information via pagers or handheld computers. However, private sector companies are devising ways to provide more "value added information," such as personalizing information on a traveler's commute by informing him/her when transit delays are occurring.

DATA COLLECTION

APC Data

The collected APC data of Year 2002 consisted of January Pick (from January to June, 2002), June Pick (from June to September, 2002), and September Pick (from September to December, 2002), which were retrieved from the APC database at NJ Transit. The OD pair on Route 62 between Woodbridge Center Mall and Newark Penn Station was selected as the studied route, in which bus service was provided by different patterns. Bus running on different patterns will be assigned a unique pattern abbreviation. For example, there are a total of 10 patterns recorded on both in and out-bound trips for this specific OD in each pick data. All attributes in each APC record that might be related to this project are summarized in Table 2:

GIS Data

With the collected APC data, GIS could efficiently capture, store, retrieve, update and display all these information. In addition, GIS could perform advanced analysis on segment and route level using APC data and enhance demonstration function. Such applications can improve the quality of bus operational data and strengthen the database validation for travel time prediction and planning. Thus, it has proved to be an efficient and a powerful tool for analysis data in public transit.

Table 2 APC Data

Variable	Description
Sched Run Time	Scheduled run time of the bus in the entire trip
Actual Run Time	Actual run time of the bus trip
Sched Start	Scheduled start time of the trip
Sched End	Scheduled end time of the trip
Actual Start	Actual start time of the trip
Actual End	Scheduled end time of the trip
Time Of Day	Starting time of the trip
Transit Day	Date of the service
Open Time	Recorded bus door opening time
Close Time	Recorded bus door closing time
Stop Description	Stop description
Stop Sequence	A unique number attached to all intended stops along the route. It has a value of 10 at the origin and increases in increments of 10 for subsequent stops.
Time Point ID	Time Point indicator number
Direction	Service direction (Inbound or Outbound)
Trip Status	Trip status (Start or End)
Lat	Latitude
Lon	Longitude
On	Number of boarding passengers at a stop
Off	Number of alighting passengers at a stop
Stop Distance	Travel distance between two consecutive stops
Dwell Time	The bus door open time at any particular time-point. They are derived from the original data as, the cumulative time that the vehicle halted at all intermediate stops.
Leave Psgr Load	Number of onboard passengers when the bus leaves a stop
Arrive Psgr Load	Number of onboard passengers when the bus arrives a stop
Leg Time	Inter-stop travel time. The difference of door open time at a subject stop and door close time at previous stop.
Origin	Origin of the trip
Destination	Destination of the trip
Pattern ID	4-digit number associated with each pattern in each pick data file.
Trip Index	Unique index associated with a trip

The GIS data related to the studied route were provided by NJ Transit, including all traversed streets by all patterns running on Route 62 and the locations of all potential stops. The traversed streets are stored into a GIS file, which can be compiled by a GIS software (e.g., Arcview, MapInfo). All locations for the potential stops are stored in a MS-Excel file, which could also be retrieved by the GIS software. The configuration of the studied route and its adjacent streets is shown in Figure 1. All potential stops on the studied route and the GIS diagram of Bus Route 62 alignment are shown in Figures 2 and 3, respectively.

Figure 1 Configuration of the Studied Route and Its Adjacent Streets

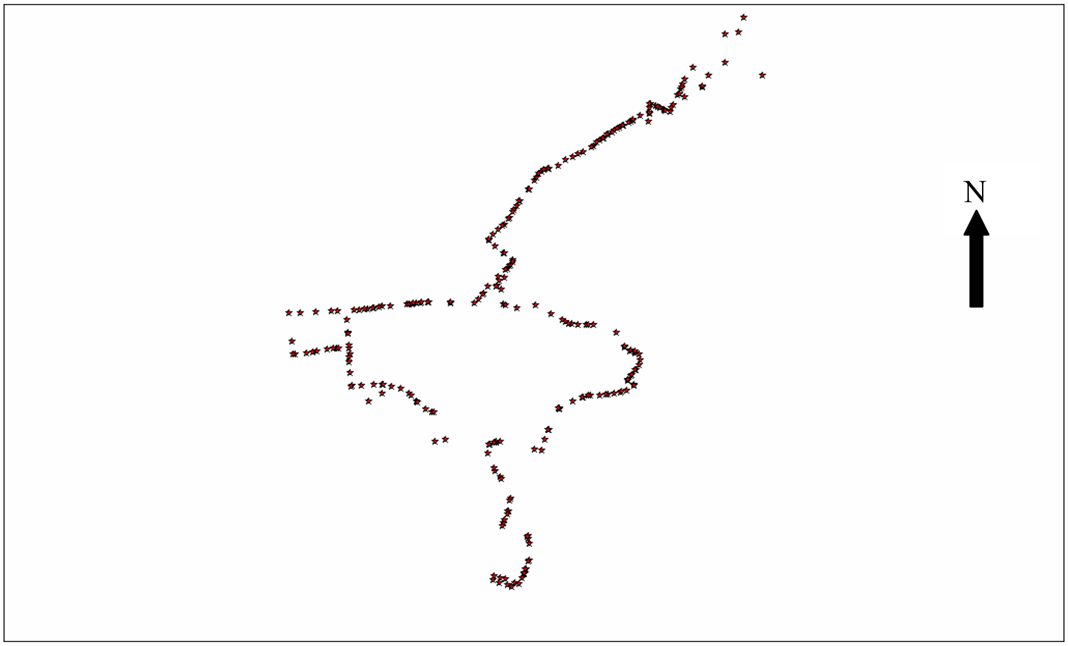


Figure 2 Potential Stops on the Studied Route

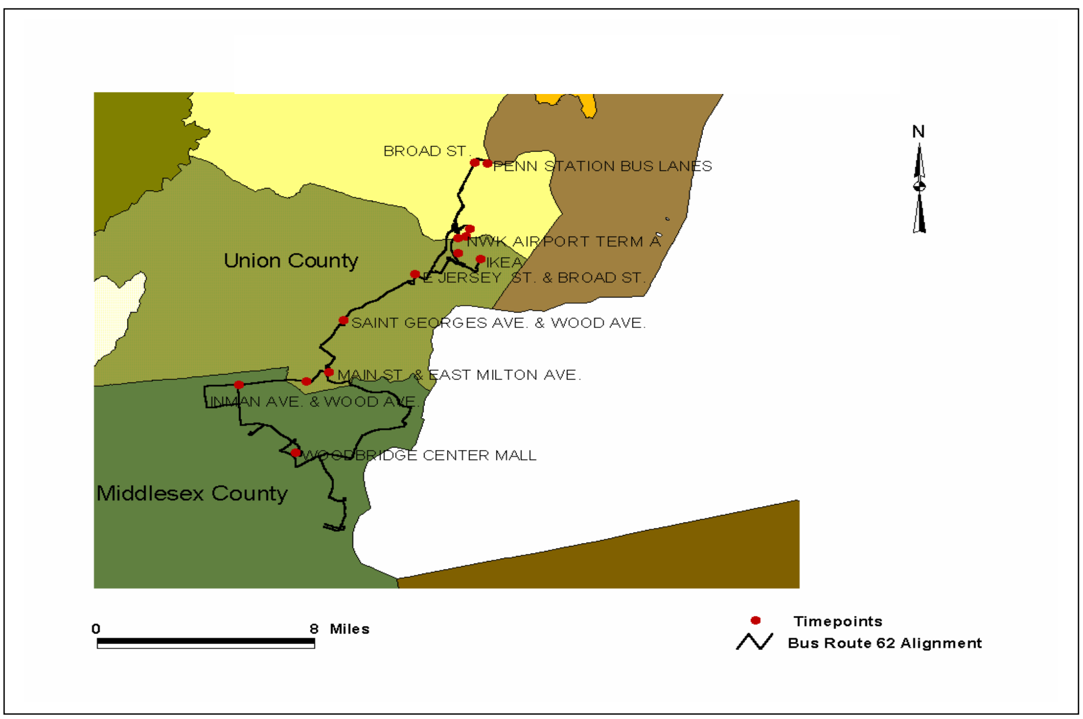


Figure 3 Alignment of Bus Route 62 in GIS

Weather Data

The weather information was obtained from the National Climatic Data Center (at Asheville in North Carolina and Boulder in Colorado). Newark International Airport Station in NJ is selected as the observation station because it is the only station that collected weather data covering the studied route. The weather information includes hourly temperature (e.g., dry bulb temperature), precipitation (e.g., rainfall and snowfall), and sky conditions (e.g., visibility and wind speed)

To access the hourly weather information, a step-by-step procedure is listed below:

Step 1: Log in National Climatic Data Center (NCDC) website at: http://lwf.ncdc.noaa.gov/oa/climate/stationlocator.html. The webpage of the site is shown in Figure 4.

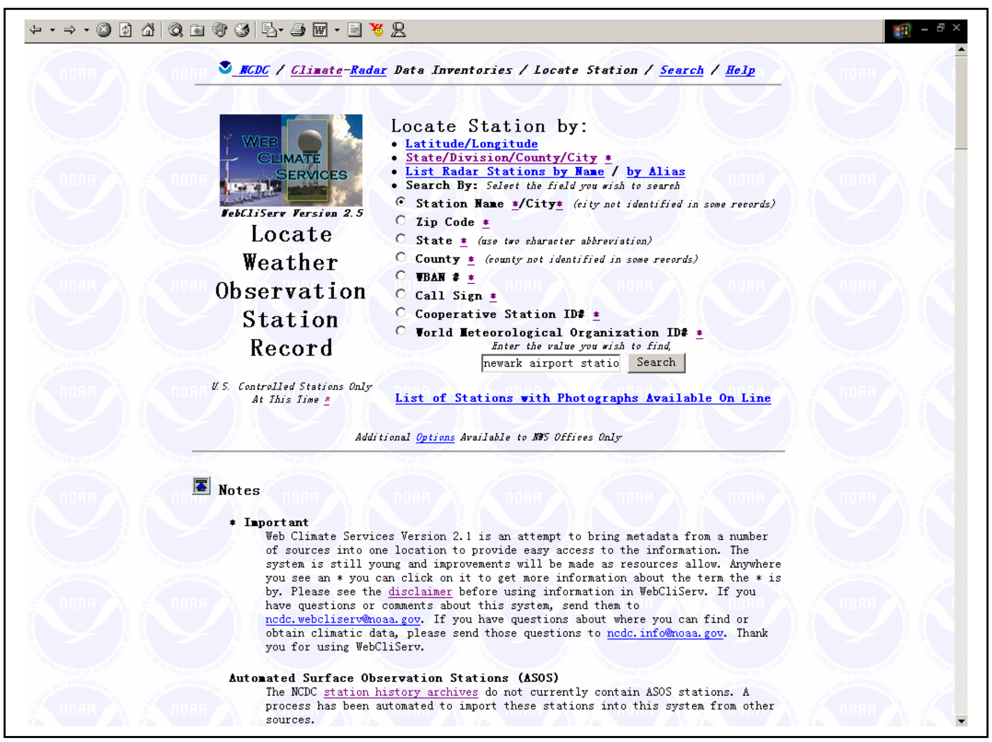


Figure 4 NCDC Weather Observation Stations

Step 2. Input station name “Newark Airport Station” and hit "Search". A new page is shown in Figure 5.

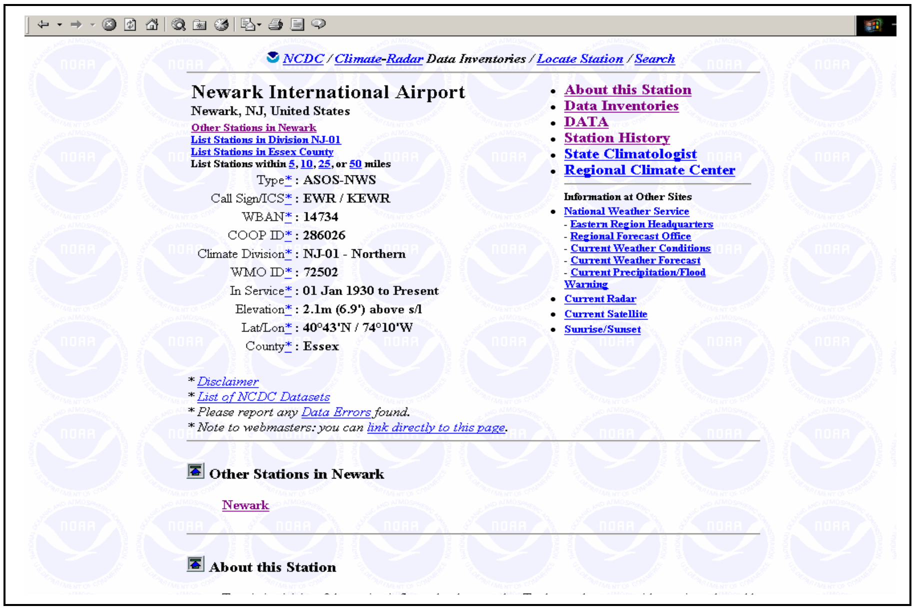


Figure 5 Newark International Airport Station

Step 3. Click "DATA" in the upper right portion of the page in figure 5. A new page is shown in Figure 6

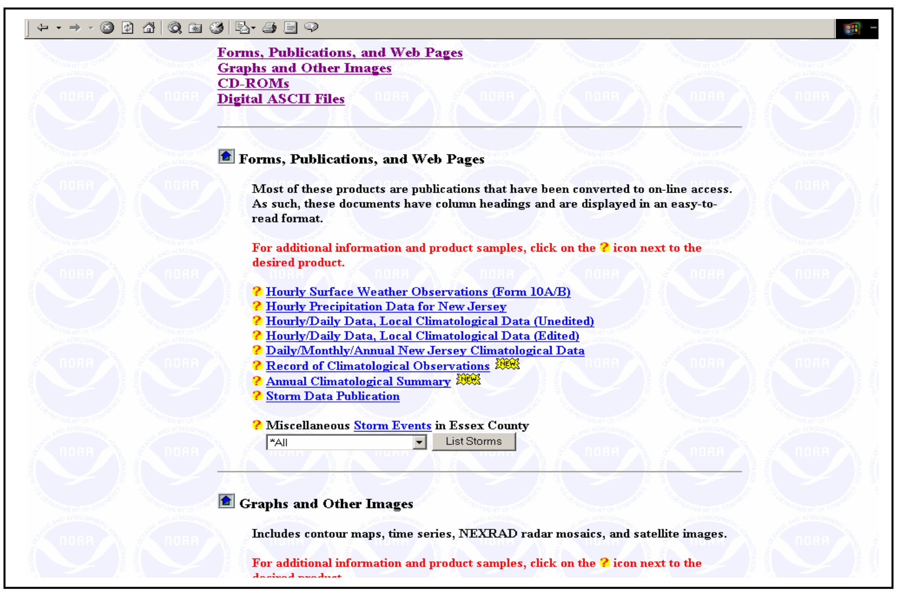


Figure 6 Weather Information of the Selected Station

Step 4. Click "Hourly/Daily Data, Local Climatological Data (Unedited)". A new page is shown in Figure 7.

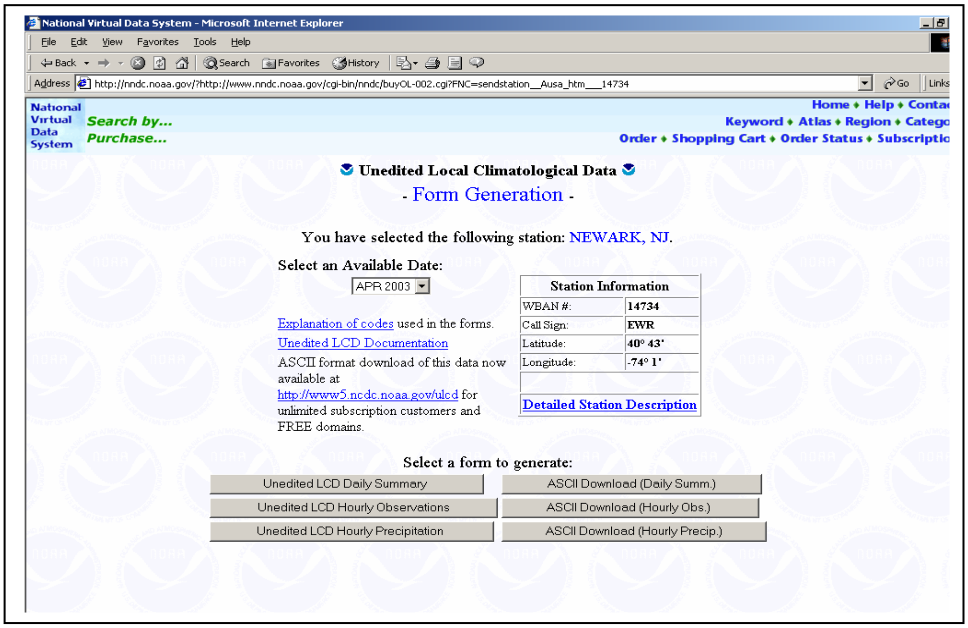


Figure 7 Time Period Selection for Querying Weather Information

Step 5. The hourly weather information for the selected month can be obtained. A new page is shown in Figure 8.

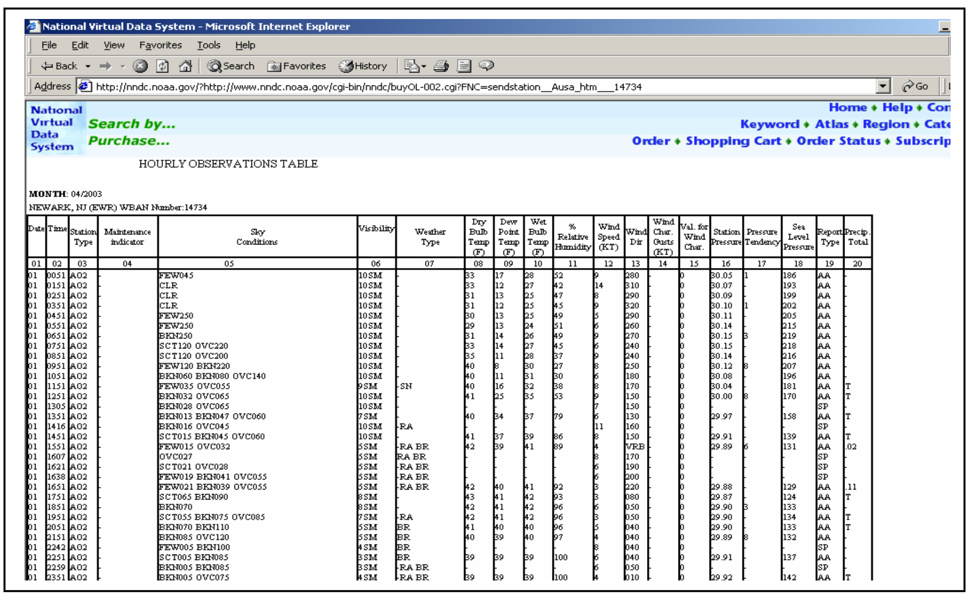


Figure 8 Example of Collected Weather Information

After applying this procedures, the historic weather information at selected locations could be retrieved from the website. The attributes of the data available from NCDC are listed in Table 3, in which the precipitation data variable is used to develop prediction model in this study.

Table 3 Weather Data Provided by NCDC

Date	Time	Station Type	Maintenance indicator	Sky Condition
Precip.Total	Visibility	Weather Type	Dry Bulb Temp (F)	Dew Point Temp (F)
Wet Bulb Temp(F)	% Relative Humidity	Wind Speed(KT)	Wind Dir	Wind Char.Gusts(KT)
Val. For Wind Char.	Station Pressure	Pressure Tendency	Sea Level Pressure	Report Type

Field Data

Since the geometric characteristics of the studied route may affect bus travel times, it is necessary to collect related information along the route. While visiting the studied site, the research team rode the bus to record the number of left/right turns, the numbers of intersections with and without signals, and the bus exclusive lane on each segment between consecutive time points, which might affect the bus travel time. There were no bus exclusive bus lanes on the studied route, and all collected geometric information is shown in Tables 4, 5 and 6.

Table 4 Time Points Description on the Timetable

Number	Time Point Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	FEDERAL EXPRESS - NEWARK AIRPORT
5	IKEA
6	BROAD ST & W JERSEY ST
7	SAINT GEORGES AVE & WOOD AVE
8	IRVING ST & BROAD ST
9	W INMAN AVE & ST GEORGES AVE
10	INMAN AVE & WOOD AVE
11	NJT METROPARK STATION
12	WOODBRIDGE CENTER MALL

Table 5 Field Data for Pattern PAIWM

	Number of Intersections		Number Of Turns	
Outbound	**Signalized**	**Non-signalized**	**Right-turn**	**Left-turn**
1-2	6	0	1	4
2-3	12	13	10	2
3-4	1	1	0	1
4-5	2	0	1	4
5-6	9	3	4	3
6-7	15	0	1	1
7-8	12	5	1	2
8-9	2	6	2	1
9-10	5	8	0	1
10-11	10	3	3	2
11-12	10	4	4	2

Table 6 Field Data for Pattern WMIAP

	Number of Intersections		Number Of Turns	
Inbound	**Signalized**	**Non-signalized**	**Right-turn**	**Left-turn**
12-11	8	5	4	4
11-10	10	1	2	3
10-9	5	7	0	0
9-8	2	5	1	1
8-7	12	5	2	2
7-6	16	0	1	1
6-5	9	3	3	4
5-4	2	0	4	1
4-3	1	1	1	0
3-2	12	7	8	2
2-1	8	0	1	0

SELECTION OF STUDIED PATTERNS AND SOFTWARE

Selection of Study Patterns

The Bus Route 62 of NJ Transit operating on Essex, Union and Middlesex counties in New Jersey was selected as the studied route of this project. APC devices were installed on buses running along this route to monitor bus operation. The whole Bus Route 62 starts from Newark Penn Station and ends at Perth Amboy with a total distance of 29.5 miles on the outbound. There is a total 17 time points located along the bus route as shown in Figure 9, for which the NJ Transit provides the scheduled arrival times on the timetable.

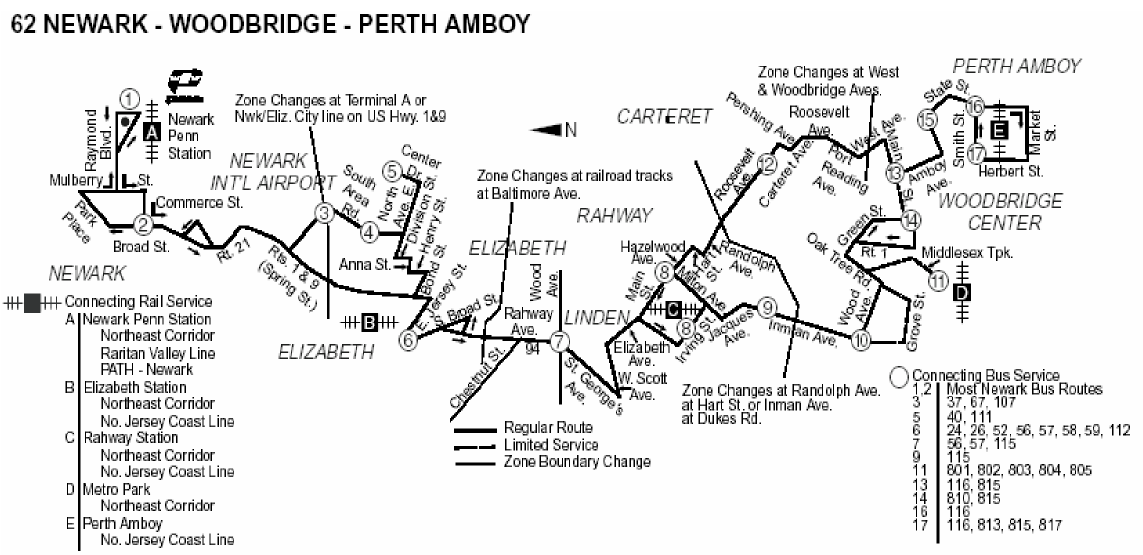


Figure 9 Configuration of Bus Route 62

In the collected APC data (e.g., January pick, June pick or September pick in 2002), 10 patterns were found for the studied OD pair (between Newark Penn Station and Woodbridge Center Mall), which can be classified into inbound and outbound patterns. The sample size was an important criteria for selecting studied patterns. The inbound patterns of WMIAP and WM-AP and outbound patterns of PAIWM and PA-WM were finally identified for developing prediction models. Buses attributed to the same pattern would serve the same number and sequence of time points. The time point sequence for studied patterns are listed in Tables 7, 8, 9, and 10. The GIS diagram of the studied patterns is shown in Figure 10.

Table 7 Time Points for Pattern WMIAP (inbound)

Time Point Description	Distance to Start Point (mi)
WOODBRIDGE CENTER MALL	0.00
NJT METROPARK STATION	3.77
INMAN AVE & WOOD AVE	7.14
W INMAN AVE & ST GEORGES AVE	9.67
MAIN ST & E MILTON AVE	10.81
SAINT GEORGES AVE & WOOD AVE	13.74
E JERSEY ST & BROAD ST	17.30
IKEA	21.06
FEDERAL EXPRESS - NEWARK AIRPORT	23.16
NWK AIRPORT TERM A	24.05
NWK AIRPORT TERM B	24.65
NWK AIRPORT TERM C	25.15
BROAD ST & EDISON PL	28.97
PENN STATION BUS LANES	29.63

Table 8 Sequence of Time Points for Pattern PAIWM (outbound)

Time Point Description	Distance to Start Point (mi)
PENN STATION BUS LANES	0
BROAD ST & BRANFORD PL	0.76
NWK AIRPORT TERM A	4.56
NWK AIRPORT TERM B	5.01
NWK AIRPORT TERM C	5.52
FEDERAL EXPRESS - NEWARK AIRPORT	7.70
IKEA	9.78
BROAD ST & W JERSEY ST	13.74
SAINT GEORGES AVE & WOOD AVE	17.16
IRVING ST & BROAD ST	19.94
W INMAN AVE & ST GEORGES AVE	21.13
INMAN AVE & WOOD AVE	23.66
NJT METROPARK STATION	26.86
WOODBRIDGE CENTER MALL	30.03

Table 9 Time Points for Pattern WM-AP (inbound)

Time Point Description	Distance to Start Point (mi)
WOODBRIDGE CENTER MALL	0.00
NJT METROPARK STATION	3.77
INMAN AVE & WOOD AVE	7.14
W INMAN AVE & ST GEORGES AVE	9.67
MAIN ST & E MILTON AVE	10.81
SAINT GEORGES AVE & WOOD AVE	13.74
E JERSEY ST & BROAD ST	17.30
NWK AIRPORT TERM A	20.86
NWK AIRPORT TERM B	21.30
NWK AIRPORT TERM C	21.81
BROAD ST & EDISON PL	25.70
PENN STATION BUS LANES	26.37

Table 10 Time Points for Pattern PA-WM (outbound)

Time Point Description	Distance to Start Point (mi)
PENN STATION BUS LANES	0.00
BROAD ST & BRANFORD PL	3.77
NWK AIRPORT TERM A	7.14
NWK AIRPORT TERM B	9.67
NWK AIRPORT TERM C	10.81
BROAD ST & W JERSEY ST	13.74
SAINT GEORGES AVE & WOOD AVE	17.30
IRVING ST & BROAD ST	20.86
W INMAN AVE & ST GEORGES AVE	21.30
INMAN AVE & WOOD AVE	21.81
NJT METROPARK STATION	25.70
WOODBRIDGE CENTER MALL	26.37

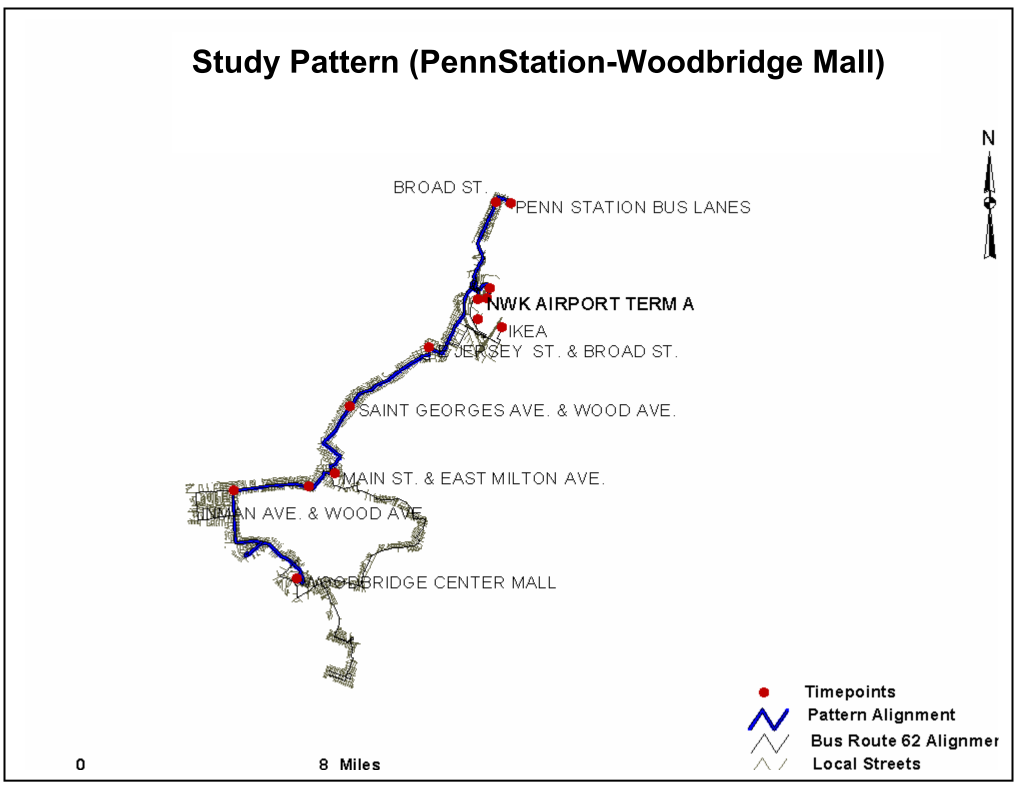


Figure 10 The Studied Patterns in GIS

Selection of Software

As mentioned earlier, the objective of this study is to develop a neural dynamic model for bus travel time prediction. The research team applied a well-developed commercial software to form the proposed model.

Among various software packages, NeuroSolutions was selected because it is at the leading edge of neural network simulation technology. Using an object-oriented approach, NeuroSolutions allows user to create an artificial neural network (ANN) that is composed of individually simple components. The network can be built through an icon-based design interface, which provides much more flexibility than a typical "black box" simulator. NeuroSolutions is capable of generating powerful ANNs to solve complicated problems. A unique feature of the software is that it contains a comprehensive collection of probes that allows the user/designer to monitor every aspect of the ANN during training and testing.

NeuroSolutions is one of the few products on the market that is able to handle all four types of problems: (1) classification, (2) function approximation, (3) prediction, and (4) clustering. There are six different levels of the software: (1) educator, (2) users, (3) consultants, (4) professional, (5) developers lite, and (6) developers. The level used in this study is "users-level".

NeuroSolutions has two separated wizards, NeuralExpert and NeuralBuilder, that one can use to automatically build an ANN to the design specification. The NeuralExpert centers the design specification around the type of problem one wish to solve. Based on this and the size of the data, it can intelligently select the size and architecture of the ANN that will produce a good solution. The NeuralBuilder centers the design around the specific ANN architecture that one wish to build. The network parameters such as the number of hidden layers, the number of processing elements, and the learning algorithm can be customized. In addition, genetic algorithm is available to optimize these parameter settings at the user/designer's choice.

DATA PROCESSING

Data Screening

There were many indices recorded in the APC dataset for each bus trip. Records that were missing or incorrect in the raw data file were identified and removed from the database. Different problems experienced while processing the APC data were itemized below as well as the corresponding solutions.

The problems experienced in APC data:

- Duplicated records.
- Wrong start or end position.
- Unreasonable arrival time along stops.
- Missing data.
- Inconsistent data (e.g., open vs. close time, scheduled vs. actual running time).
- Times are recorded in different format (e.g., hour/minute/second, minutes).

The corresponding solutions to the above problem:

- Delete duplicated records.
- Adjust start or end position.
- Use actually arrival time at time points to interpolate the appropriate arrival.
- Use speed and distance information to derive travel time.
- Correct the wrong information.
- Unify the format of all time indices.

Data Calculation

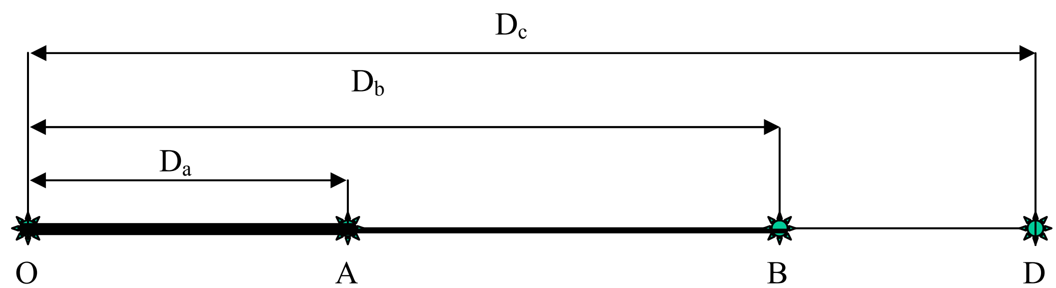
APC devices installed in buses can record the numbers of boarding and alighting passengers when bus doors were opened to serve passengers. Therefore, there was no record for the skipped time points. The cumulative numbers of boarding and alighting passengers and dwell times at stops were calculated for those missing time points. In order to provide sufficient data to develop proposed prediction models, the completed cumulative numbers of boarding and alighting passengers and dwell times at all time points are also generated.

Data Interpolation

The ideal data structure for observing bus operations is a set of successive time point records. Thus, the actual bus travel times between time points can be compared with that posted on the timetable. However, in the APC dataset, some records were missing because buses skipped the time points where there was no demand at that time. In order to generate a completed time point to time point (TP-to-TP) information, the missing data at some TPs were approximated based on the available information at adjacent TP.

An interpolation algorithm is developed to derive arrival time for the skipped time points based on the previous and next time point records. Though the bus arrival times of the skipped time points can be obtained by assuming the bus operated with a constant speed between two several time points, other information such as dwell time and number of boarding passengers are still unavailable. Thus, the actual dwell times and number of boarding passenger information at the skipped TPs were obtained similarly.

The ideal data structure should include all the time points in sequence for each trip. As mentioned earlier, in the APC data, records at skipped time points were unavailable and then an interpolation is needed to approximate bus arrival information. The interpolation was illustrated as follows:



Let A, B, and C be assumed time points, where time point 'B' was skipped. Arrival time at time point 'B' can be computed by adding door close time at stop 'A' and the interpolated travel time of link AB based on arrival times at time points 'A' and 'C'.

Let

$\boldsymbol{D}_a$ = Distance of time-point 'A' from the origin

$\boldsymbol{D}_b$ = Distance of time-point 'B' from the origin

$\boldsymbol{D}_c$ = Distance of time-point 'C' from the origin

All the distances between time points are provided from NJ Transit. In addition, the following information can be obtained from APC data.

$\boldsymbol{T}_a$ = Leg time of 'A' from the preceding time point (=0 for the first stop)

$\boldsymbol{T}_{ab}$ = Leg time of 'B' from 'A'

$\boldsymbol{T}_{ac}$ = Leg time of 'C' from 'A'

Thus, the average speed from A to D can be obtained from Equation (1).

$$s = (D_c - D_a)/ T_{ac} \qquad (1)$$

where $(D_c - D_a)$ represent the travel distance from A to D. Therefore, the interpolated travel time can be estimated by applying Equation (2).

$$T_{ab} = (D_b - D_a)/ s \qquad (2)$$

Finally, the bus arrival time at 'B' would be door close time at 'A' plus $\boldsymbol{T}_{ab}$

Summary

After processing the original APC dataset, the calculated data and interpolated data need to be merged with the weather data as one dataset for developing prediction models. The unique index was chosen between two different datasets. For example, “month/date/hour” could be used to merge weather data with the APC data, and “month/date/pattern/tripID” could be used as the unique index to merge calculated data (e.g., cumulative boarding and alighting passenger at each stop) with the original APC data. After merging the collected data including bus arrival times and numbers of boarding and alighting passengers at all time points, weather information, and accumulated dwell times between pairs of time points were processed and ready for developing the proposed predictive models.

MODEL DEVELOPMENT

Introduction

As the primary form of public transit, bus service operates on urban streets with shared right-of-way with automobiles and commercial vehicles and trucks. As a result, the service reliability of bus transit could be greatly compromised by various unexpected incidents along its route. This also leads to inaccurate or unreliable arrival times, which incur a long and unpredictable wait time experienced by transit users.

Advanced sensing, positioning, and communication technologies have provided a good platform to obtain reliable information on transit vehicle trip information. The Advanced Passenger Counter (APC) system deployed by New Jersey Transit on its partial fleet has been generating such information everyday. This includes bus trip activities such as stop, door open/close, number of passengers boarding/alighting at each stop, and the associated temporal (e.g., time) and spatial (e.g., latitude) information. In addition, the ridership information that is usually expensive to obtain with traditional methods and is extremely valuable in estimating bus arrival times at downstream stops can be collected.

In this chapter, a methodology that has been developed to predict transit vehicle arrival times using data generated by APC devices installed on buses operated by New Jersey Transit is presented next.

Artificial Neural Networks (ANNs)

ANN modeling techniques have been of great interest to many researchers. The advantage of this technique is that it is unnecessary to assume a functional form between the dependent and independent variables. This is extremely useful when the data display non-linear relationship.

Using ANNs in forecasting has become more popular in transportation research. Related studies include Hua and Faghri [32], Chin et al. [33], Dougherty [34], Kalaputatu and Demetsky [35], Smith and Demetsky [36], Zhang et al. [37], Chang and Su [38], Wei and Yang [39], and Ding and Chien [40] Designed with versatile parallel distributed structures and adaptive learning processes, the ANN is considered as a promising approach to describe complex systems such as transit operation that is affected by various inter-correlated and time varying factors.

Unlike other prediction models, the ANN does not require a specific form of function. This eliminates the need of function development and parameter estimation for nonlinear and time varying systems. A well-trained ANN could capture complex relationship between the dependent variables (output such as bus arrival time) and a set of explanatory/independent variables (input such as traffic conditions and passenger demand) [40]. Therefore, the ANN technique could be very useful in prediction when it is difficult or even impossible to mathematically formulate the relationship between the input and output. However, the extent to which an ANN is trained could have significant impact on its prediction performance, especially in some applications where only small amount of data is available for training.

ANN Basics

The ANN is a network consisting of interconnected units called processing elements (PEs, also known as artificial neurons because it has certain resemblance to the neurons in the human brain). Each PE receives connections from other PEs and/or itself. The signals transmitted through the connections are scaled by adjustable parameters called weights. A weight is associated with every connection in the network.

In this study, we are exploring the relationship between bus travel times and various inputs such as time of the day, day of the week, and weather (precipitation). Therefore, the ANN should be designed to solve problem with function approximation type.

The multilayer perceptron (MLP) typed ANN architecture was chosen since it is generally easy to use and can approximate almost any input/output map. It has been widely used in countless applications. Its major disadvantages include slow training process and high demand on data amount. A typical MLP architecture with one hidden layer is shown Figure 11.

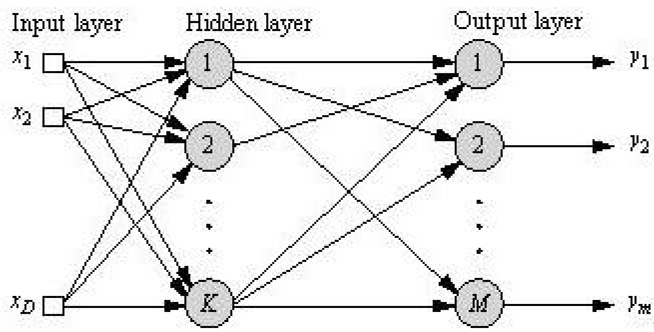


Figure 11 MLP with One Hidden Layer

Back-propagation is the most commonly used algorithm in training an ANN [41]. A back-propagation network (BPN) is trained in a supervised mode, i.e., the weights of the network is continually adjusted to incrementally reduce the difference between the output of the system and the desired response. Its general procedure is shown in Figure 12 [42]. For a single layer network, corrections are made for the weights in proportion to the error between the desired output (e.g., actual travel time) and the network output (e.g., predicted travel time). For a multiple-layer ANN, corrections have to be made for the weights from the first to the second layer, the second to the third layer, and so on. The stopping criterion could be a pre-set number of iterations, a specific output mean square error (MSE), or cross validation that is the most powerful one among them.

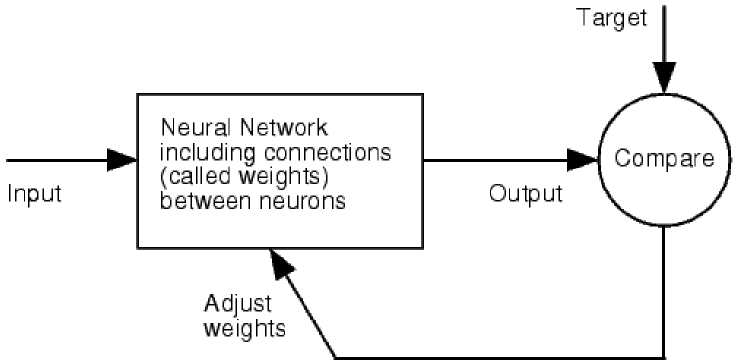


Figure 12 BPN Training Procedure

In this study, cross validation criterion was chosen since it stopped the training at the point of best generalization (i.e. the performance in the validation set) is obtained. A small part of the training data need to be set aside and used to test the ANN model. When the performance starts to degrade in the validation set (i.e., cross validation MSE started to increase), training should be stopped.

Processing elements can be combined into an ANN network in many different ways. Determining the number of hidden layers used in BPN is a trial and error process. Usually, one or two hidden layers are sufficient to create a model that is able to predict reasonably well. It is worth noting that increasing the number of hidden layers beyond two often undesirably reduce the network's ability to make better generalization or a better ANN model.

The primary performance measure of an ANN is the MSE, which is defined as the mean squared error between the predicted and actual travel times, as shown below. The lower the MSE, the better the model performs.

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{NP} \quad (3)$$

where

$P =$ number of output neurons

$N =$ number of samples in the data set

d_{ij} =desired output for sample i at neuron j

y_{ij} = network output for sample i at neuron j

Other performance measures include normalized mean squared error, percent error, etc.

Applicability

Using ANNs has an advantage over conventional prediction methods for it can handle complicated systems that are hard to formulate. Unlike regression, which needs an explicitly defined function to relate the input and the output, the ANN can approximate a function and associate input with specific output after being properly trained. This capability is extremely useful when the system is rather complex (such as transit operation) and/or it is impossible to specify a form of function to accurately represent the relationship between the input and output. Moreover, an ANN does not require input variables to be independent with each other, which could save substantial effort in data correlation analysis.

Data Requirement

To model an ANN, a large amount of data would be required. A general "rule of thumb" is that the number of exemples (training data records) should be at least three times of the number of network weights. The number of network weights can be adjusted via a number of approaches, such as reducing the number of hidden layers, reducing the number of processing elements (PEs) in each hidden layer, applying weight decay when using full synapse between layers, or choosing arbitrary synapse over full synapse. Currently, the amount of data that is usable in ANN modeling is relatively small. Therefore, reducing the number of weights in the network was used to satisfy the aforementioned data ratio. In addition, due to the limited data amount, the number of hidden layers is restricted to one.

However, the research team believes that with new APC data being added to the central database everyday, the data amount requirement can be satisfied eventually without applying those weight reduction measures.

Pre-Processing

Input and Output

The studied APC data provided by NJ Transit included a total of four different patterns on both service directions (inbound and outbound). The selected patterns are WMIAP, PAIWM, WM-AP, and PA-WM as described in Section 4.1. For each direction, there are 12 and 14 time points for patterns (PA-WM, WM-AP) and (PAIWM, WMIAP) respectively. Therefore, the prediction of bus arrival times for the four patterns need to be modeled separately.

Among those variables that may contribute to the variation of bus travel time between time points, the research team selected the following as the weight parameters: time of the day, day of the week, and weather (e.g., precipitation).

The output of the model will be the travel times on each segment of the route, i.e., between two consecutive time points. Then the arrival time can be calculated based on the departure time from previous time point and the estimated travel time to the subject time point.

Data Format

NeuroSolutions requires that all input files be saved as a coma delimited text file. Each trip in the data file would occupy one row in which travel time between time points, as well as time of the day, day of the week, and weather information are selected. All trips belonging to the same pattern for each direction are located in one input file. For the purpose of calculation convenience, the travel time has been converted to the number of seconds. A sample data file is shown in Figure 13.

```
TT1,TT2,TT3,TT4,TT5,TT6,TT7,TT8,TT9,TT10,TT11,DayOfWeek,TimeOfDay,Precipitation
638,630,405,263,669,1190,897,148,114,1251,327,WEDNESDAY,MP,N
649,580,436,197,534,747,793,251,172,739,292,MONDAY,LN,N
707,785,432,305,769,930,593,207,177,641,363,MONDAY,E,Y
607,543,401,252,792,1024,662,156,132,1153,333,THURSDAY,MP,N
743,665,500,359,916,1196,798,305,230,1326,429,THURSDAY,AP,N
774,868,474,442,793,1126,848,304,248,1056,341,TUESDAY,E,N
```

Figure 13 Sample Data File

<u>Modeling Procedure</u>

In this study, the NeuralExpert tool of NeuroSolutions was used to develop ANNs. It is a wizard that asks user questions and automatically builds the best network and configures the parameters and probes for the problem. The general procedure is outlined as follows.

Step 1: Identify the problem type as function approximation.

Step 2: Identify the input file.

Step 3: Specify input variables (e.g., time of the day, day of the week, and precipitation).

Step 4: Tag symbolic inputs. Due to the nature of the input variables in the study as symbolic rather than numerical values that is continuous, it is necessary to specify that all three variables are symbolic.

Step 5: Identify the file that contains data to model. This is the same as the input file based on the way we process data. Therefore, choose “use input file for desired file” and “shuffle data files” to randomize the file order.

Step 6: Select the columns to model, i.e., select those travel times, which are labeled, from TT1 to TT11 (for the patterns with 12 time points) or up to TT13 (for the patterns with 14 time points).

Step 7: Choose a level of generalization protection. This is to help the ANN perform better on new data in the training process. It is implemented by setting aside data used to determine when to stop training the ANN (called cross validation data set). Normal level with 20 percent cross validation data from the input file was chosen.

Step 8: Choose “out of sample testing”, i.e., set aside certain percentage of samples from the input file to test the ANN after training and cross validation. Due to limited size of samples, 3 percent was specified.

Step 9: Specify level of genetic optimization (e.g., “None”). Performing genetic optimization involves using large amount of data.

Step 10: Choose the level of neural network complexity as “Low”. This will establish an ANN with one hidden layer, which is preferred due to limited size of training data.

The wizard is likely to send a warning for the shortage of data afterwards. This problem can be dealt with additional adjustments as follows. The purpose of this procedure is to reduce the number of connections in the network, aiming to reduce the number of network weights.

Step 1: Check the weight decay box on the momentum inspectors associated with the synapses between the input and hidden layers and between the hidden and output layers. The default weight decay rate is 0.01.

Step 2: Add weight inspectors on these two synapses and show the weights during the training process.

Step 3: Train the ANN using different weight decay rate, and save the one with the best MSEs.

Step 4: Based on weights in the weight inspector, change full synapse to arbitrary synapse. Connect the PEs with input and output variables if the weight is high in absolute value.

Step 5: Calculate the number of network weights by adding number of weights from synapses between input and hidden layer and between hidden and output layer, and weights from the hidden layer. The number of weights for the synapses can be found from the Soma tab of the synapse inspector, while that for the hidden layer can be found from the Soma tab of the TahnAxon inspector. The total number of training samples should be at least 3 times of the number of network weights.

ANN Models

Four ANN models were established in this study to predict bus travel time by pattern and by direction, as shown in Table 11.

Table 11 Developed ANN Models

	Inbound	**Outbound**
Patterns (w/ 12 time points)	Model I (for WM-AP)	Model II (for PA-WM)
Patterns (w/ 14 time points)	Model III (for WMIAP)	Model IV (for PAIWM)

Model I

The network architecture shown in Figure 14 presents the elements in the ANN that have been addressed on the documentation of NeuroSolutions.

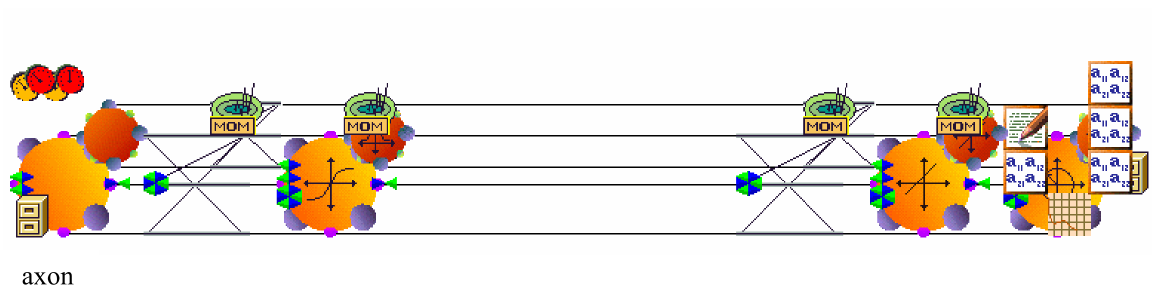


Figure 14 Network Architecture of Model I

The axon at the far left side is the input layer. It is connected with a hidden layer through a TahnAxon type transfer function and hidden synapse with 11 weights. There are 3 PEs in the hidden layer, which is connected to the output layer through output synapse with 11 weights. Therefore the total number of weights for this network is 25. The total number of data samples is 81, while 20 percent of these (16 samples) were used in cross validation, and 2 samples were used in testing. The training data file then has 63 samples. This number of samples is low compared to the recommended sample size (3 times of the total network weights). However, in order to evaluate all input variables, the network weights cannot be further reduced.

After the network has been established, multiple trainings were conducted and the best one (with the minimum MSE) was saved. Figure 15 shows the learning curve of the training process. The horizontal axis represents the number of epochs (i.e., the number of times that training data is presented to the network), while the vertical axis represents the MSE and the horizontal axis represents the number of iterations. It can be observed that the learning curve is rather smooth which indicates that the model performance is steadily improving even though very slowly after 200 iterations.

The network weights as generated by the software are shown in Table 12 as the output of the sensitivity analysis. Since all input variables in the study are symbolic type variables, they were split into multiple subvariables in the network.

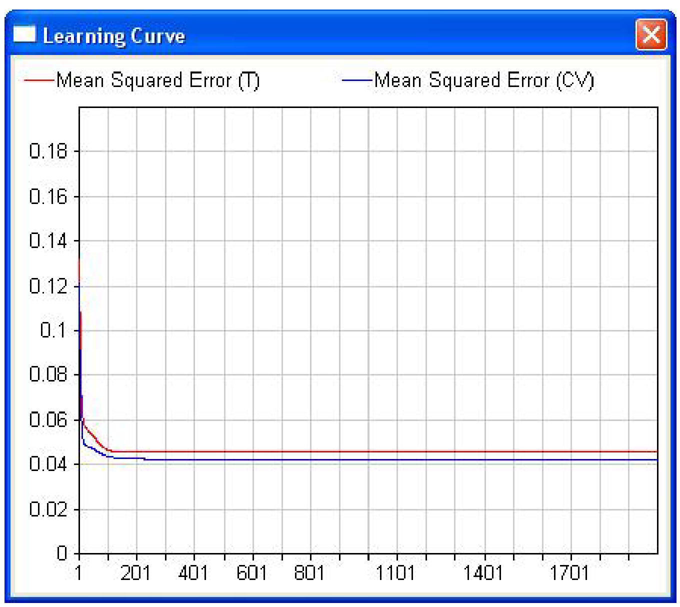


Figure 15 Learning Curves of Model I

Table 12 Values of Parameters in Model I

Input Variable		Weight	Cumulative Weight
Day of the Week	Monday	0.14	12.32
	Tuesday	4.33	
	Wednesday	1.91	
	Thursday	1.75	
	Friday	4.18	
Time of the Day	MP	5.91	81.14
	AP	18.12	
	E	15.78	
	LN	41.34	
Precipitation	Precipitation – N	3.26	6.54
	Precipitation – Y	3.28	

To evaluate the impact of the each variable, one can add the weights of all subvariables that belong to one original variable. For example, one should add weights for all days of a week to obtain the impact of day of the week on bus travel times. The cumulative significance of each variable is also shown in Table 12, from which one can observe that “time of the day” is the most significant factor in affecting bus travel times. Compared to “time of the day”, “day of the week” and “precipitation” do not have such significant impact.

Model II

The network architecture for Model II is similar to that of Model I as shown in Figure 14. The total number of data samples is 112, with which 22 samples (20 percent) were used for cross validation and 3 samples were used for testing. This leaves the number of training samples to be 89. The total number of network weights is 25, with 11, 3, and 11 weights at the hidden synapse, hidden layer, and output synapse, respectively. Therefore the training sample size can satisfy the recommended level.

The learning curve is shown in Figure 16, and the results of the sensitivity analysis are shown in Table 13. Similar to Model I, the training process seems to be smooth, and “time of the day” is the most significant one among all three input variables.

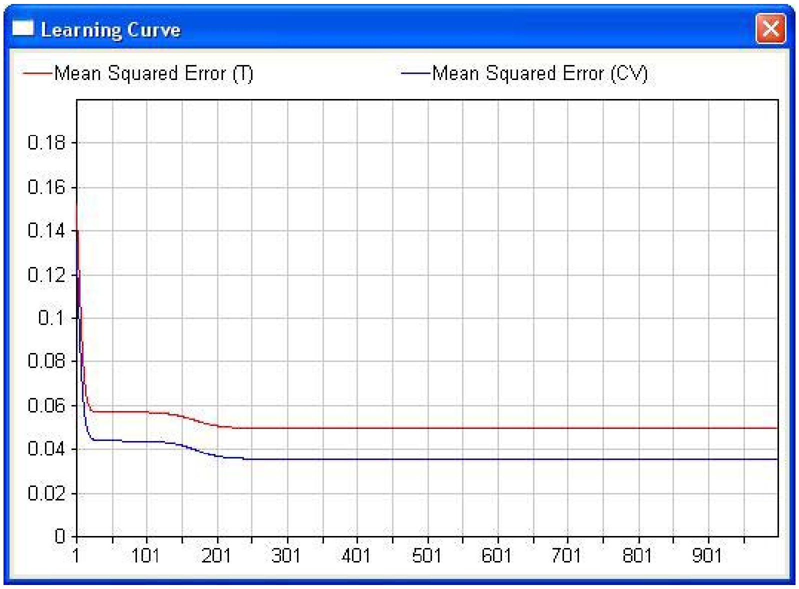


Figure 16 Learning Curves of Model II

Table 13 Values of Parameters in Model II

Input Variable		Weight	Cumulative Weight
Day of the Week	Monday	2.22	10.70
	Tuesday	2.88	
	Wednesday	0.33	
	Thursday	4.64	
	Friday	0.63	
Time of the Day	EM	18.05	80.79
	MP	22.23	
	AP	18.32	
	E	22.19	
Precipitation	Precipitation – N	4.25	8.51
	Precipitation – Y	4.26	

Model III

Model III was developed for the inbound pattern with 14 time points traveling inbound (WMIAP). Its network architecture remains similar to that of Models I and II, as shown in Figure 14.

The total number of data samples is 135, among them 27 samples (20 percent) were used for cross validation and 4 samples were used for testing. This leaves the number of training samples to be 104. The total number of network weights is 29, with 13, 3, and 13 weights at the hidden synapse, hidden layer, and output synapse, respectively. Thus, the training sample size can satisfy the recommended level.

The learning curve for Model III is shown in Figure 17, and the results of the sensitivity analysis is shown in Table 14. Similar to Models I and II, the training process seems to be smooth, and “time of the day” is the most significant one among all three input variables.

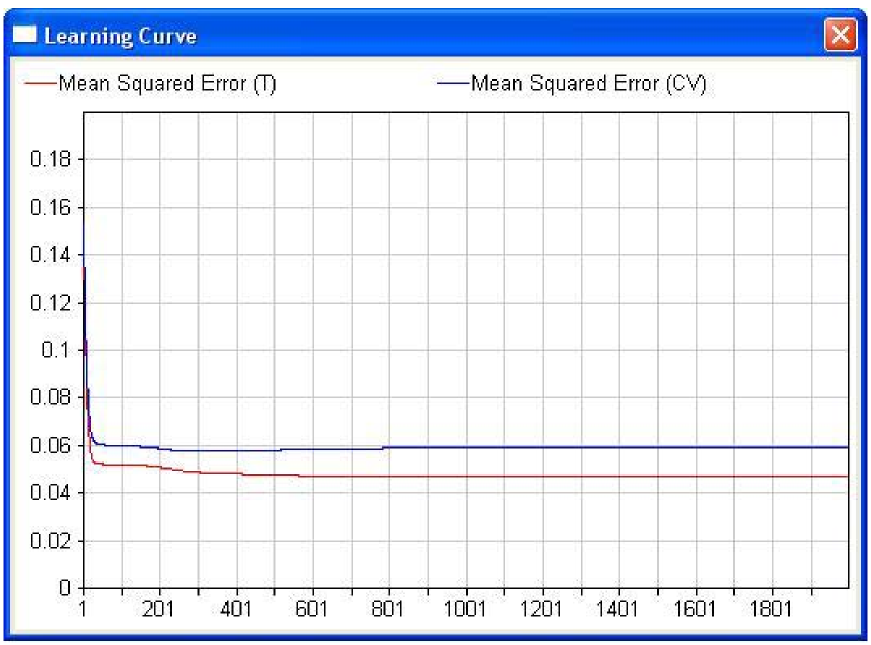


Figure 17 Learning Curves of Model III

Table 14 Values of Parameters in Model III

Input Variable		Weight	Cumulative Weight
Day of the Week	Monday	0.01	4.90
	Tuesday	0.75	
	Wednesday	2.61	
	Thursday	0.08	
	Friday	1.46	
Time of the Day	EM	22.50	91.49
	LM	4.55	
	MD	10.73	
	EA	15.02	
	E	13.34	
	LN	25.34	
Precipitation	Precipitation – N	1.80	3.61
	Precipitation – Y	1.81	

Model IV

Model IV was developed for the outbound pattern serving 14 time points (PAIWM). Its network architecture remains similar to that of models I, II, and III, as shown in Figure 14.

The total number of data samples is 121, among them 24 samples (20 percent) were used for cross validation and 4 samples were used for testing. This leaves the number of training samples to be 93. The total number of network weights is 29, with 13, 3, and 13 weights at the hidden synapse, hidden layer, and output synapse, respectively. Therefore, the training sample size can satisfy the recommended level.

The learning curve for Model IV is shown in Figure 18, and the results of the sensitivity analysis is shown in Table 15. Similar to Models I, II, and III, the training process seems to be smooth, and "time of the day" is the most significant one among all three input variables.

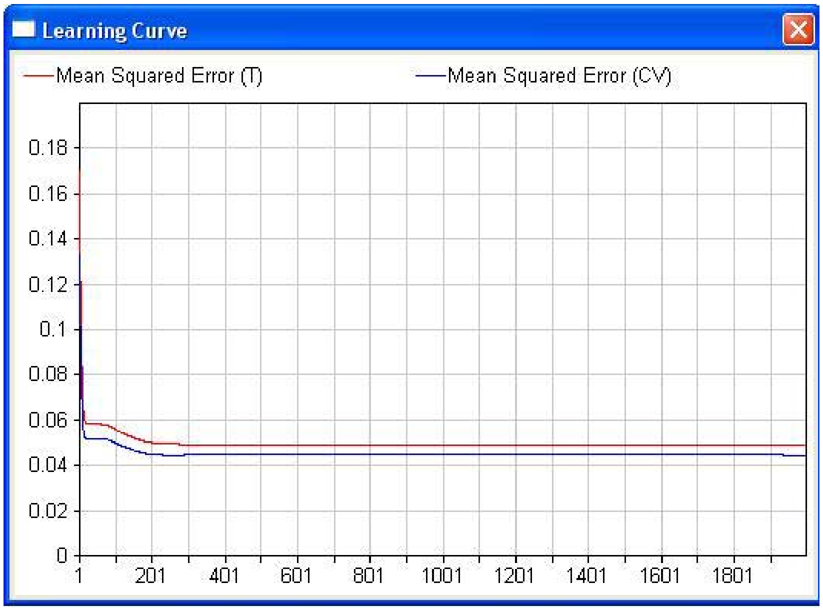


Figure 18 Learning Curves of Model IV

Table 15 Values of Parameters in Model IV

Input Variable		**Weight**	**Cumulative Weight**
Day of the Week	Monday	2.94	10.41
	Tuesday	2.12	
	Wednesday	0.76	
	Thursday	1.75	
	Friday	2.84	
Time of the Day	EM	26.04	88.02
	LM	3.89	
	MD	1.57	
	EA	25.49	
	AP	14.10	
	E	16.94	
Precipitation	Precipitation – N	0.78	1.57
	Precipitation – Y	0.78	

Kalman Filtering Algorithm

The ANNs developed in this study are based on historic data pool of bus trips. New data are added into that pool regularly. Training can then be conducted afterwards to ensure the ANN models up to date. However, this method does not have the dynamic feature to adapt to incident (non-recurring) condition.

A dynamic procedure was developed based on the Kalman filtering algorithm. It enables online adjustment of arrival time estimates for a particular trip based on its available travel time information up to the moment the estimation is conducted.

Let t_k denote the travel time from time point k to the given destination (i.e., the time point for which arrival time prediction is performed), $T_{k,k+1}$ denote the travel time from time point k to time point $k+1$, s_k denote the travel time from origin to time point k. Then the travel time from time point $k+1$ to the destination t_{k+1} can be calculated as $t_{k+1} = t_k - T_{k,k+1}$, and the travel time from origin to time point $k+1$ can be calculated as $s_{k+1} = s_k + T_{k,k+1}$.

If z_k denotes the observed travel time from origin to time point k, then $z_k = s_k$. Let $x_k = (t_k \quad s_k)^T$, the Kalman filter can be formulated as

$$x_{k+1} = \Phi_k x_k + A_k + w_k \tag{4}$$

$$z_k = H_k x_k + v_k \tag{5}$$

in which,

$$\Phi_k = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \qquad H_k = \begin{pmatrix} 0 & 1 \end{pmatrix}, \qquad A_k = \begin{pmatrix} -T_{k,k+1} \\ T_{k,k+1} \end{pmatrix}$$

w_k and v_k are white noises associated with the transition process and measurement, respectively. They are assumed to have zero mean and variances of Q_k and R_k, respectively.

The filtering procedure is outlined as follows.

Step 1: Initialize state variables. Set $x_0 = \begin{pmatrix} t_0 & s_0 \end{pmatrix}^T$, in which t_0 is the estimated total travel time from the origin to the destination, and s_0 is set to be 0 based on its definition.

Step 2: Initialize covariance P_0 when $k = 0$.

Step 3: State variable extrapolation.

$$x_{k+1}^{-} = \Phi_{k+1}\hat{x}_k + A_k = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} t_k \\ s_k \end{pmatrix} + \begin{pmatrix} -T_{k,k+1} \\ T_{k,k+1} \end{pmatrix} \tag{6}$$

in which $T_{k,k+1}$ can be obtained from estimates based on historical data.

Step 4: Covariance extrapolation.

$$P_{k+1}^{-} = \Phi_{k+1} P_k \Phi_{k+1}^{T} + Q_k \tag{7}$$

Step 5: Kalman gain computation.

$$K_{k+1} = P_{k+1}^{-} H_{k+1}^{T}\left(H_{k+1} P_{k+1}^{-} H_{k+1}^{T} + R_{k+1}\right)^{-1} \tag{8}$$

Step 6: State variable update.

$$\hat{x}_{k+1} = \hat{x}_{k+1}^{-} + K_{k+1}\left(z_{k+1} - H_{k+1}\hat{x}_{k+1}^{-}\right) \tag{9}$$

Stop, if time point $k+1$ is the destination. Otherwise, go to Step 7.

Step 7: Covariance update.

$$P_{k+1} = P_{k+1}^{-} - K_{k+1} H_{k+1} P_{k+1}^{-} \tag{10}$$

Go to Step 3.

PREDICTION EVALUATION AND ANYALYSIS

The prediction models developed in this study has two major elements: (1) travel time prediction using the developed ANN that was trained based on historical bus trip data collected by APC devices; and (2) dynamic adjustment to the time-till-arrival at downstream time points using the developed Kalman filter algorithm.

Performance of Artificial Neural Networks (ANNs)

The performance of the developed ANN model was tested using data that were never “seen” by the ANN. That is, the test data were not used to train or validate the ANN. For each ANN model developed in this study, 3 percent of the collected data were set aside as testing samples. The performance of the ANN model on the test data was evaluated using the minimum square error (MSE) measurement. Table 16 shows the MSEs for training, cross validation, and testing of each model.

Table 16 Performance Measures for ANN Models

Model	Training MSE	Cross Validation MSE	Test MSE
I	0.0908	0.0847	0.0421
II	0.0987	0.0712	0.1196
III	0.0934	0.1182	0.0724
IV	0.0985	0.0891	0.1220

Generally, the test MSE is expected to be larger than the MSE for either training or cross validation since the test data was new to the model. However, in several occasions (e.g., Models I and III) shown in table 16, the test MSE appears to be smaller. This might be caused by a small test sample size that makes the testing result relatively volatile. However, with the increase of testing samples in the data pool, the model performance shall be more stable.

During the process of ANN model development in this study, only a small amount of samples (3 percent) were applied as testing data. The recommended minimum ratio of training samples to network weights that is 3, was not sufficient even with such a small data was selected for testing the ANN. To evaluate the performance of the model, all data were used in the test process. The variation between scheduled and actual travel times and the variation between the predicted (ANN output) and actual travel times were compared.

Figures 19 through 26 show the spatial and temporal variations of prediction errors with all four ANN models. The average errors in these figures are calculated using Eqs. 11 and 12.

$$e_{ANN} = \frac{t_{ANN} - t_a}{t_a} \qquad (11)$$

Accordingly, the error between the scheduled and actual travel times can be found as:

$$e_S = \frac{t_S - t_a}{t_a} \qquad (12)$$

where

e_{ANN}: Prediction error from the ANN

t_{ANN}: Predicted travel time from the ANN

e_S: Prediction error of scheduled travel time

t_S: Scheduled travel time from the timetable

t_a: Actual travel time

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	NWK AIRPORT TERM A
9	NWK AIRPORT TERM B
10	NWK AIRPORT TERM C
11	BROAD ST & EDISON PL
12	PENN STATION BUS LANES

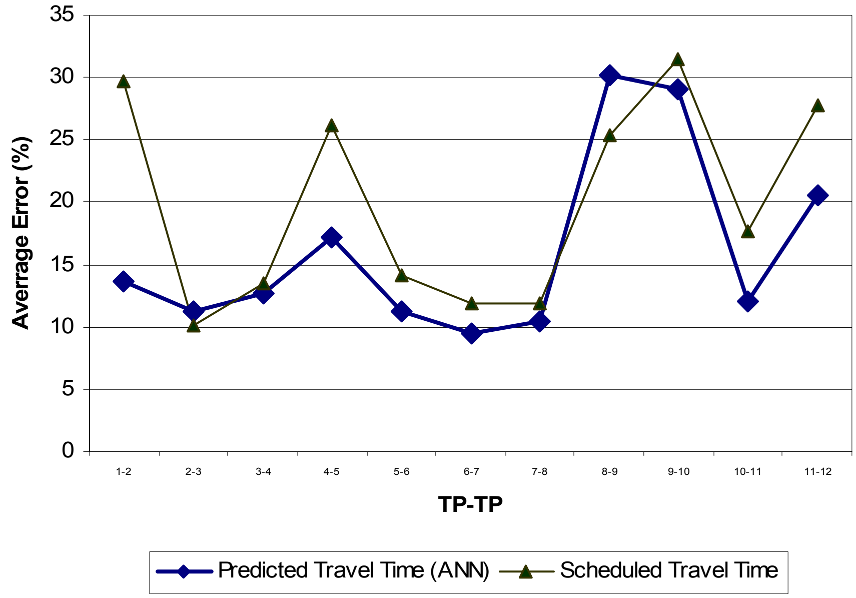


Figure 19 Predicted (Model I) vs. Scheduled Errors for TP-to-TP Travel Times

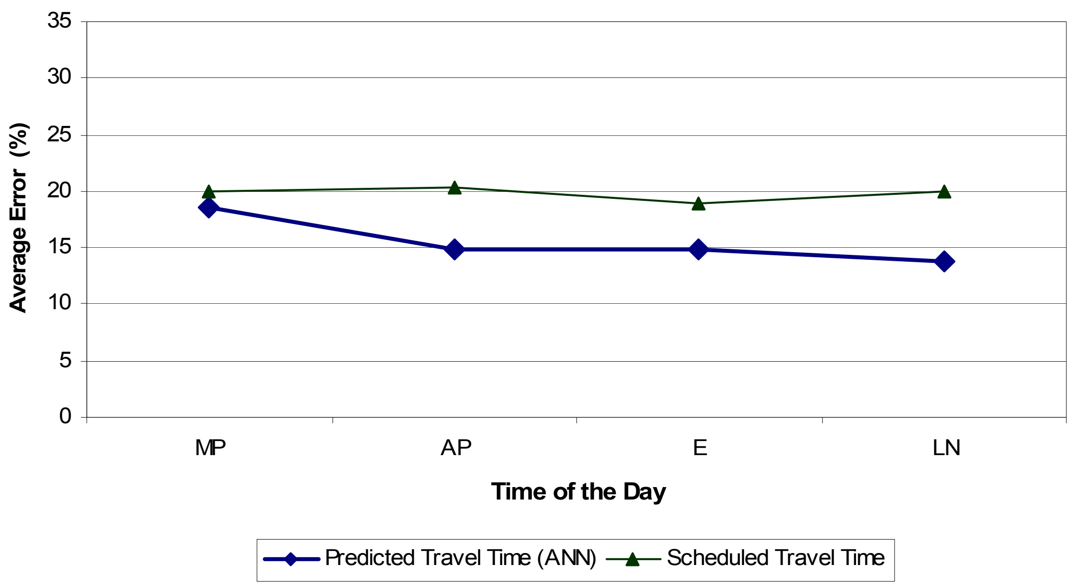


Figure 20 Predicted (Model I) vs. Scheduled Errors for Travel Times in Different Periods

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	BROAD ST & W JERSEY ST
7	SAINT GEORGES AVE & WOOD AVE
8	IRVING ST & BROAD ST
9	W INMAN AVE & ST GEORGES AVE
10	INMAN AVE & WOOD AVE
11	NJT METROPARK STATION
12	WOODBRIDGE CENTER MALL

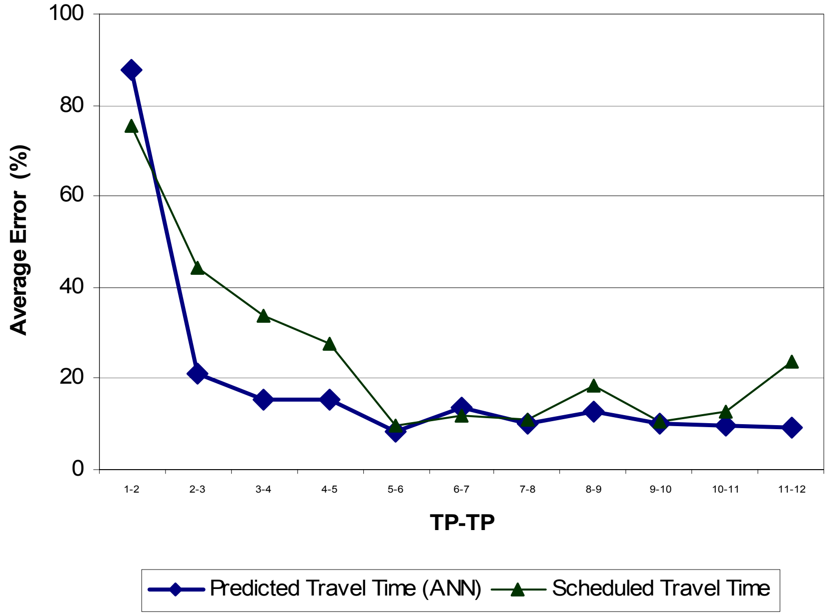


Figure 21 Predicted (Model II) vs. Scheduled Errors for TP-to-TP Travel Times

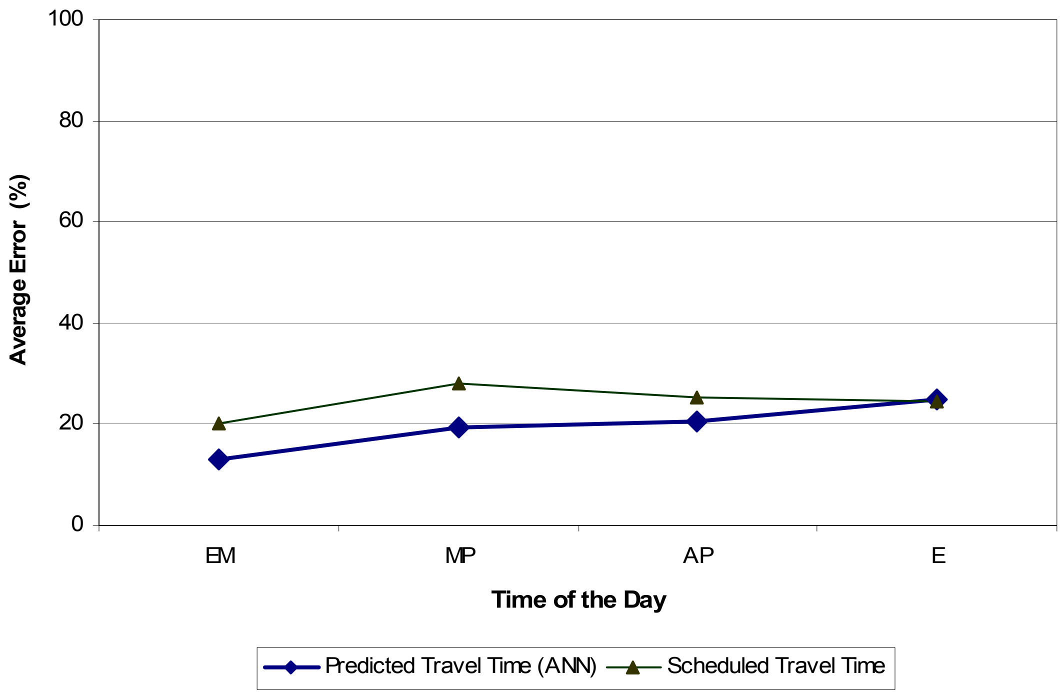


Figure 22 Predicted (Model II) vs. Scheduled Errors for Travel Times in Different Periods

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	IKEA
9	FEDERAL EXPRESS - NEWARK AIRPORT
10	NWK AIRPORT TERM A
11	NWK AIRPORT TERM B
12	NWK AIRPORT TERM C
13	BROAD ST & EDISON PL
14	PENN STATION BUS LANES

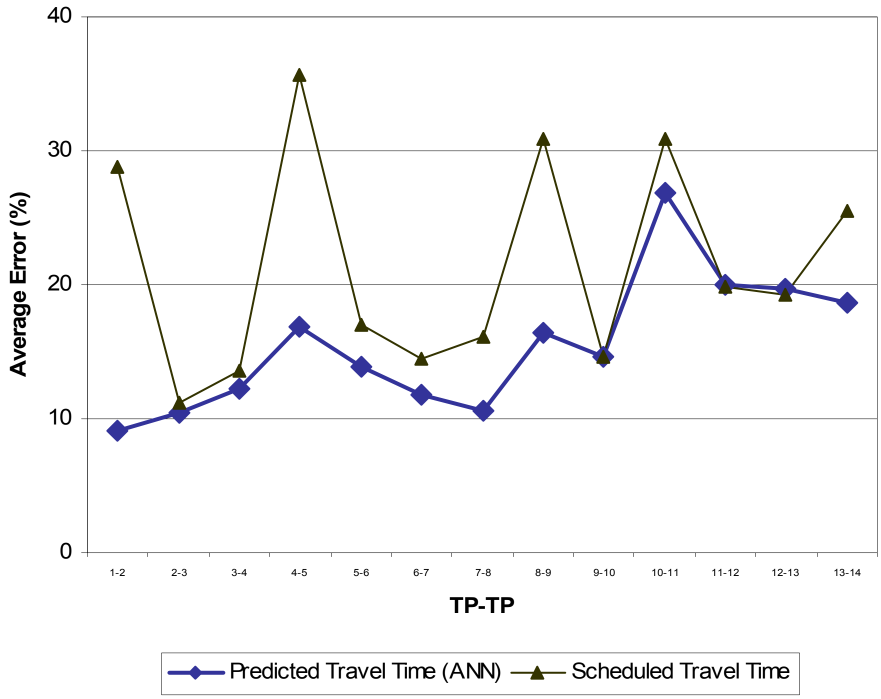


Figure 23 Predicted (Model III) vs. Scheduled Errors for TP-to-TP Travel Times

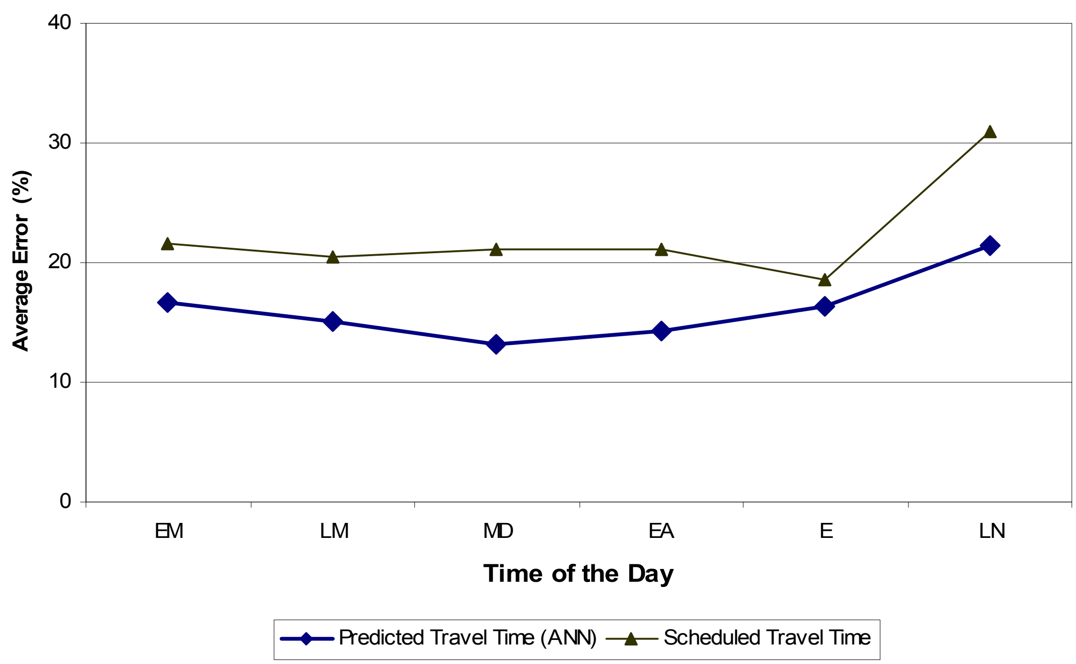


Figure 24 Predicted (Model III) vs. Scheduled Errors for Travel Times in Different Periods

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	FEDERAL EXPRESS - NEWARK AIRPORT
7	IKEA
8	BROAD ST & W JERSEY ST
9	SAINT GEORGES AVE & WOOD AVE
10	IRVING ST & BROAD ST
11	W INMAN AVE & ST GEORGES AVE
12	INMAN AVE & WOOD AVE
13	NJT METROPARK STATION
14	WOODBRIDGE CENTER MALL

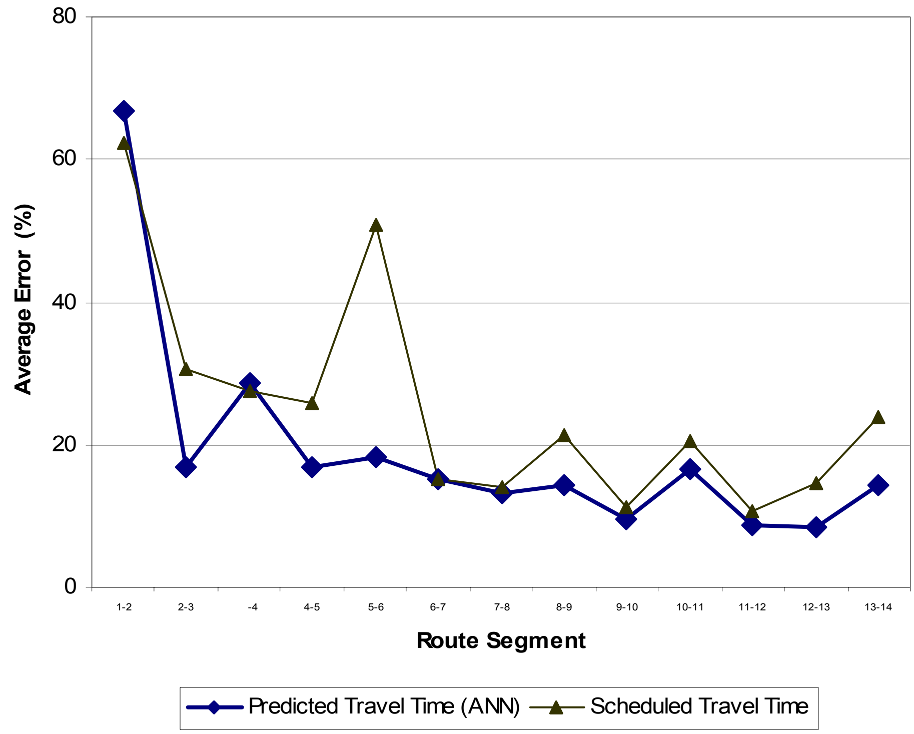


Figure 25 Predicted (Model IV) vs. Scheduled Errors for TP-to-TP Travel Times

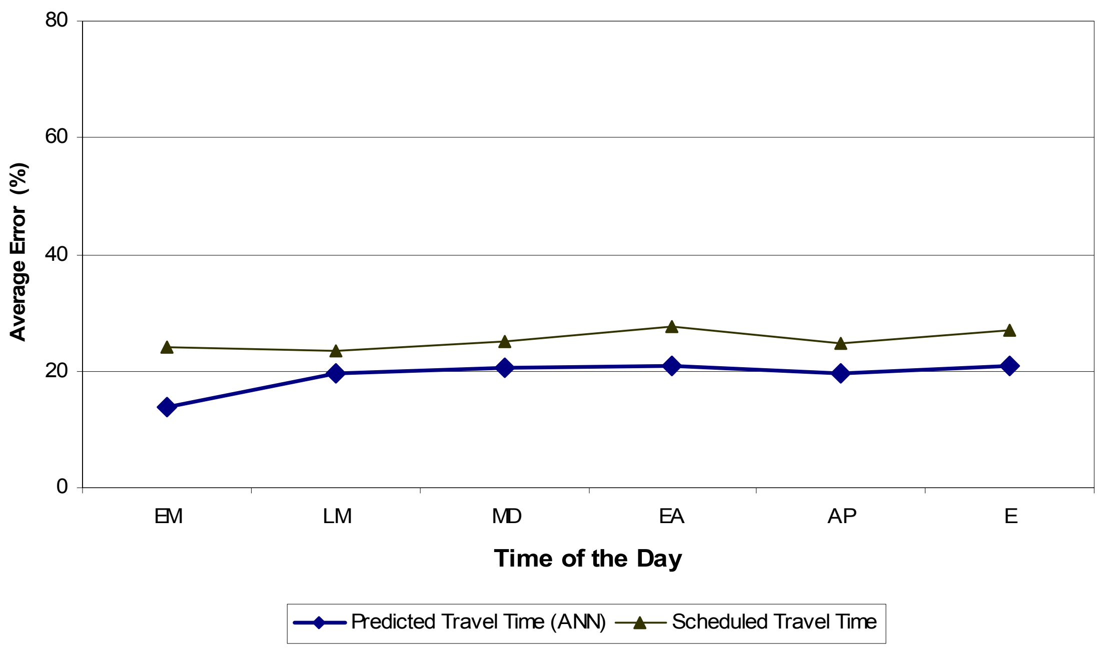


Figure 26 Predicted (Model IV) vs. Scheduled Errors for Travel Times in Different Periods

It was observed that, the ANN gave in general a better estimate of the travel time than that from the timetable since the average error of ANNs in most cases is less than that from the timetable. However, in a few cases, the timetable estimates were better than that from the ANNs. This might be attributable to two facts: (1) the limited available data for ANN model development; and (2) the error in original APC data.

Even though the stability of the ANN prediction was affected by the quality and quantity of the data, the research team believes that with more new data added into the APC database, the performance of the neural network models shall be further improved.

Performance of the Neural/Dynamic (N/D) Model

In this study, a neural/dynamic (N/D) model that integrates the Kalman filtering algorithm and an ANN was developed to dynamically adjust the predicted bus arrival time. Whenever a bus reaches a time point, the travel/arrival time prediction from a corresponding ANN can be adjusted according to real time information (e.g., the most updated travel/arrival times).

The estimated travel time to each downstream time point was updated when the most recent bus arrival information became available. For example, as a bus departs from time point 1, the ANN predicts the arrival times from first time point to all downstream time points. When the bus arrives at time point 2, the new prediction is based on the Kalman filter, while the prediction error at time point 2 will be taking into consideration.

Following the steps of the Kalman filter (KF) algorithm, travel times from the current stop to all downstream time points were predicted. The prediction information was then updated when the bus arrived at the next time point. For illustration purpose, a trip was selected as an example to analyze the performance of the developed Kalman filter algorithm. This trip was made during late night on a Friday under rain. And the prediction results were shown in Table 17.

When k=1, the Kalman filter algorithm was initialized using baseline estimates of travel time between time points. In Table 17, the ANN was used to predict travel time as baseline estimate for each destination. With the bus traveled to the next TP called TP(k+1), the travel time prediction to all downstream TPs, from TP(k+2) to TP12, were adjusted using the actual bus arrival information at TP(k+1). This process was repeated until the bus arrived at the final destination, TP12.

One should note that since s_k is defined as the travel time from the origin to the current time point k, it reflects the actual travel time and is independent to the travel time from the current TP to downstream TPs. Therefore, s_k were the same for all downstream TPs. Each cell in Table 17 represents the estimated state variable $\hat{x}_k = (\hat{t}_k \quad \hat{s}_k)^T$. For example, $k = 3$ meant that the bus reached TP3. For TP10, the predicted travel time from TP3 to TP10, was 3189 seconds, and the bus spent 1273 seconds traveling from the origin to TP3, (i.e., $\hat{s}_3 = 1273 \sec$). It meant that the predicted travel time from TP1 to TP10 was 4462(=3189+1273) seconds when the bus arrived at TP3. Thus, a more accurate arrival time of the bus of TP10 can be estimated.

The predicted vs. actual travel times and their difference from current TP to all downstream TPs were summarized in Table 18. It demonstrated that the prediction of arrival times to any downstream TP would be more accurate when the most updated bus arrival information became available.

Table 17 Travel Time Prediction (N/D Model) for One Trip (seconds)

k	TP1	TP2	TP3	TP4	TP5	TP6	TP7	TP8	TP9	TP10	TP11	TP12
TP1	0	670	1326	1793	2025	2605	3393	4058	4342	4516	5324	5588*
	0	0	0	0	0	0	0	0	0	0	0	0**
TP2		0	656	1123	1355	1936	2723	3388	3673	3846	4654	4918
		671	671	671	671	671	671	671	671	671	671	671
TP3			0	466	698	1278	2066	2731	3015	3189	3997	4261
			1273	1273	1273	1273	1273	1273	1273	1273	1273	1273
TP4				0	231	812	1599	2264	2549	2722	3530	3794
				1722	1722	1722	1722	1722	1722	1722	1722	1722
TP5					−1	580	1367	2032	2317	2490	3298	3562
					1926	1926	1926	1926	1926	1926	1926	1926
TP6						−1	786	1452	1736	1909	2717	2981
						2479	2479	2479	2479	2479	2479	2479
TP7							−1	664	949	1122	1930	2194
							3207	3207	3207	3207	3207	3207
TP8								−1	284	457	1265	1529
								3963	3963	3963	3963	3963
TP9									−1	173	981	1245
									4221	4221	4221	4221
TP10										−1	807	1071
										4369	4369	4369
TP11											−1	263
											5096	5096
TP12												−1
												5370

*: $\hat{t}_k$ Travel time from time point k to the given destination

**: $\hat{s}_k$ Travel time from origin to time point k·

To evaluate the performance of the Kalman filter, the arrival time predicted by the Kalman filter and ANNs, and their deviations from the actual travel time were compared. The predicted travel times from the origin (TP 1) to all downstream TPs obtained from the Kalman filter output were compared to the actual travel times between the same pairs of origins and destinations (downstream time points), and the prediction errors can thus be calculated. The prediction errors of the N/D model, ANNs, and timetable could be obtained from Eqs, 11, 12 and 13, respectively.

$$e_{ND} = \frac{t_{ND} - t_a}{t_a} \tag{13}$$

where

e_{ND}: Prediction error of the N/D model

t_{ND}: Predicted travel time from the N/D model

t_a: Actual travel time

Table 18 Predicted vs. Actual Bus Travel Times (Seconds)

Actual	*671*	*1271*	*1721*	*1925*	*2478*	*3205*	*3966*	*4220*	*4368*	*5093*	*5370*
	TP2	**TP3**	**TP4**	**TP5**	**TP6**	**TP7**	**TP8**	**TP9**	**TP10**	**TP11**	**TP12**
TP1	670	1326	1793	2025	2605	3393	4058	4342	4516	5324	5588*
	1	-55	-72	-100	-127	-188	-92	-122	-148	-231	-218**
TP2		1327	1794	2026	2607	3394	4059	4343	4517	5325	5589
		-56	-73	-101	-129	-189	-93	-124	-149	-232	-219
TP3			1739	1971	2552	3339	4004	4288	4462	5270	5534
			-18	-46	-74	-134	-38	-68	-94	-177	-164
TP4				1953	2534	3321	3986	4270	4444	5252	5516
				-28	-56	-116	-20	-50	-76	-159	-146
TP5					2506	3293	3958	4243	4416	5224	5488
					-28	-88	8	-23	-48	-131	-118
TP6						3265	3931	4215	4388	5196	5460
						-60	35	5	-20	-104	-90
TP7							3872	4156	4329	5137	5401
							94	64	39	-44	-31
TP8								4246	4420	5228	5492
								-26	-52	-135	-122
TP9									4394	5202	5466
									-26	-109	-96
TP10										5176	5440
										-83	-70
TP11											5359
											10.92

*: Predicted travel time

**: difference between predicted and actual travel time

Figure 27 indicated the prediction errors of the N/D model and the ANN for a particular trip (with 12 time points and made during late night on a Friday under rain). It was observed that for most downstream time points, the travel time predicted by the N/D model is much closer to the actual travel time than that predicted by the ANN. It is worth noting that for this particular trip, the ANN model did not provide better estimates of arrival times than the timetable (e.g., time points 5, 6, 9-12). Figure 28 shows the prediction errors of the developed N/D model, ANN Model III, and a timetable another trip pattern (inbound with 14 TPs). This trip was made in early afternoon on a Tuesday without rain. It can be observed that the N/D model outcomes were very close to the actual travel times, and it outperformed the ANN model.

It showed that the N/D model provided better estimates of bus arrival times at downstream TPs than the ANNs and timetable. Although the N/D prediction might be less accurate for example at TP1 to TP2 (Figure 28), in general, the prediction errors are less than 5 percent.

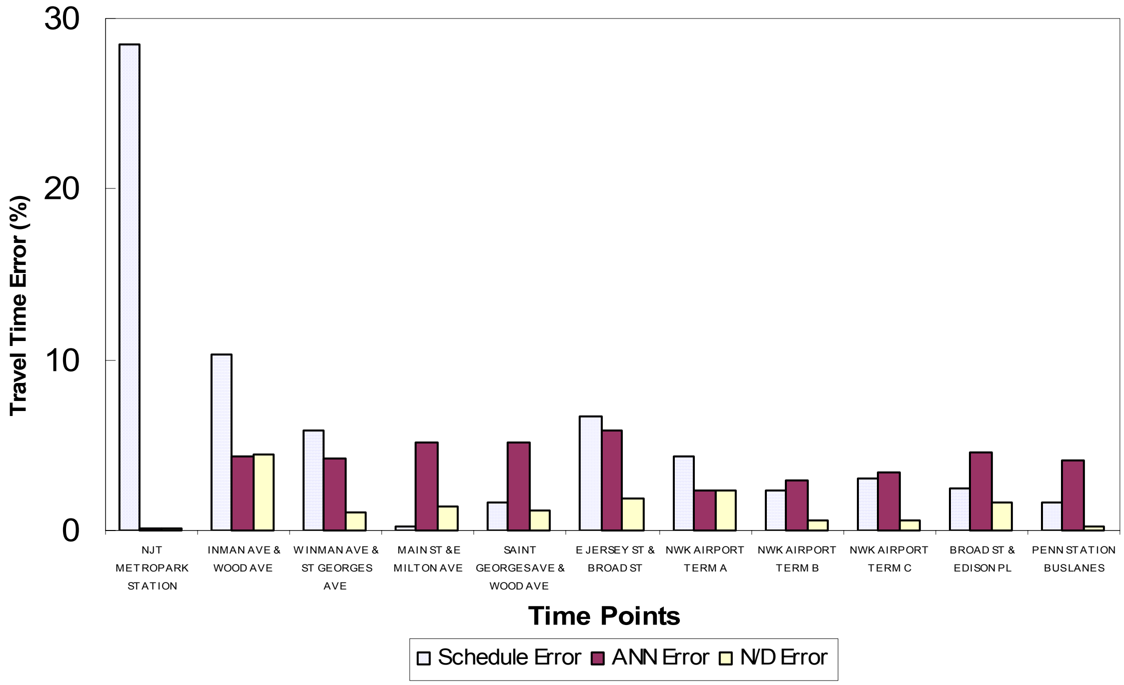


Figure 27 Prediction Errors from TP1 to All Time Points (Model I)

The deviation between the predicted and actual arrival times, as well as scheduled and actual arrival times at each time point were shown in Figures 29 through 36. It was observed that for each pattern, the deviation between the predicted and actual arrival times is smaller than that between the scheduled and actual arrival times at all time points. The boundary of the arrival time variations between schedule and actual travel times increases as the index of time points increases. This might be contributed by the variation of travel times propagated as the bus proceeded at further downstream stops. However, for the variations between the predicted and actual arrival times at time points was rather stable because the N/D model could dynamically predict bus arrival times based on the most updated information.

In addition to the evaluation of prediction performance of the variations between scheduled and actual travel time and the variation between predicted and actual travel times are compared for all the trips (e.g., inbound or outbound with 12 or

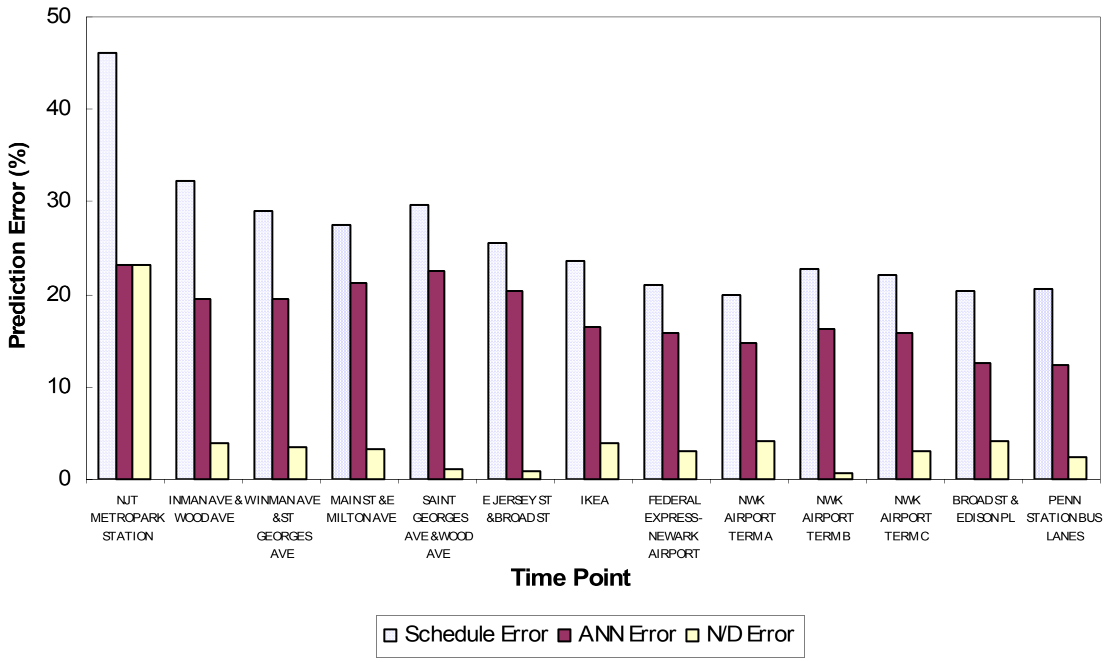


Figure 28 Prediction Errors from TP 1 to All Time Points (Model III)

14 time points). The prediction accuracy was evaluated by computing the root mean squared error (RMSE), which can be obtained from

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{14}$$

where

N = the number of test samples

y_i = actual travel time of sample i

$\hat{y}_i$ = ANN estimated travel time of sample i

The RMSEs are calculated for each bus route segment (i, defined as the segment between time points i and $i+1$).

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	FEDERAL EXPRESS - NEWARK AIRPORT
7	IKEA
8	BROAD ST & W JERSEY ST
9	SAINT GEORGES AVE & WOOD AVE
10	IRVING ST & BROAD ST
11	W INMAN AVE & ST GEORGES AVE
12	INMAN AVE & WOOD AVE
13	NJT METROPARK STATION
14	WOODBRIDGE CENTER MALL

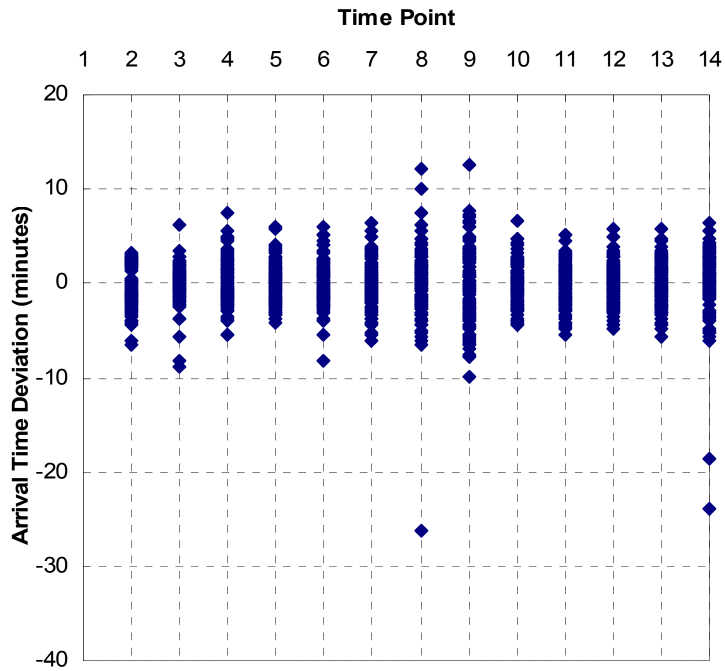


Figure 29 Difference between Predicted and Actual Arrival Times (Pattern PAIWM)

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	FEDERAL EXPRESS - NEWARK AIRPORT
7	IKEA
8	BROAD ST & W JERSEY ST
9	SAINT GEORGES AVE & WOOD AVE
10	IRVING ST & BROAD ST
11	W INMAN AVE & ST GEORGES AVE
12	INMAN AVE & WOOD AVE
13	NJT METROPARK STATION
14	WOODBRIDGE CENTER MALL

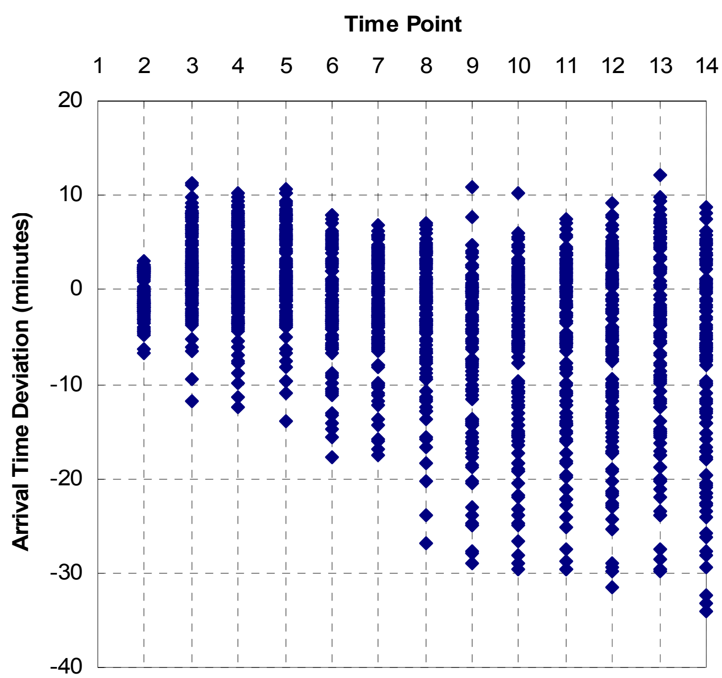


Figure 30 Difference between Scheduled and Actual Arrival Times (Pattern PAIWM)

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	IKEA
9	FEDERAL EXPRESS - NEWARK AIRPORT
10	NWK AIRPORT TERM A
11	NWK AIRPORT TERM B
12	NWK AIRPORT TERM C
13	BROAD ST & EDISON PL
14	PENN STATION BUS LANES

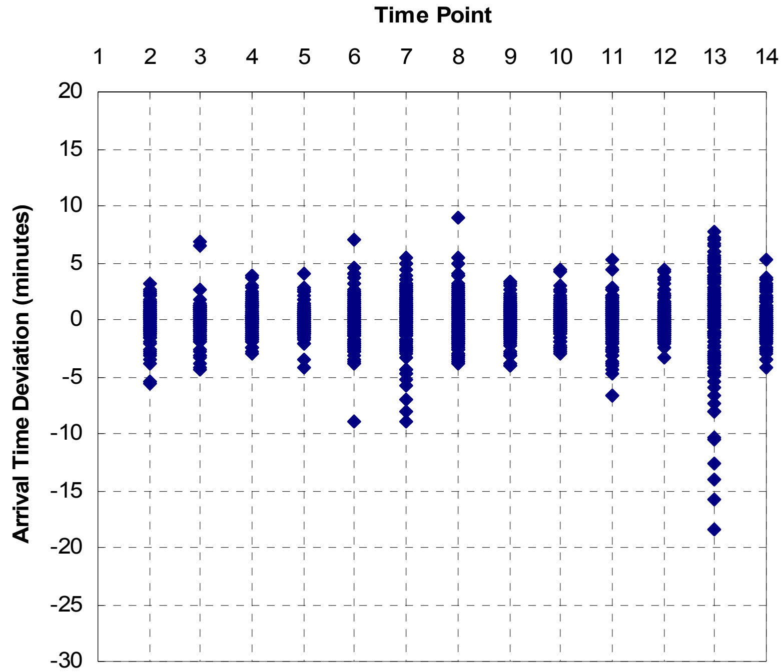


Figure 31 Difference between Predicted and Actual Arrival Times (Pattern WMIAP)

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	IKEA
9	FEDERAL EXPRESS - NEWARK AIRPORT
10	NWK AIRPORT TERM A
11	NWK AIRPORT TERM B
12	NWK AIRPORT TERM C
13	BROAD ST & EDISON PL
14	PENN STATION BUS LANES

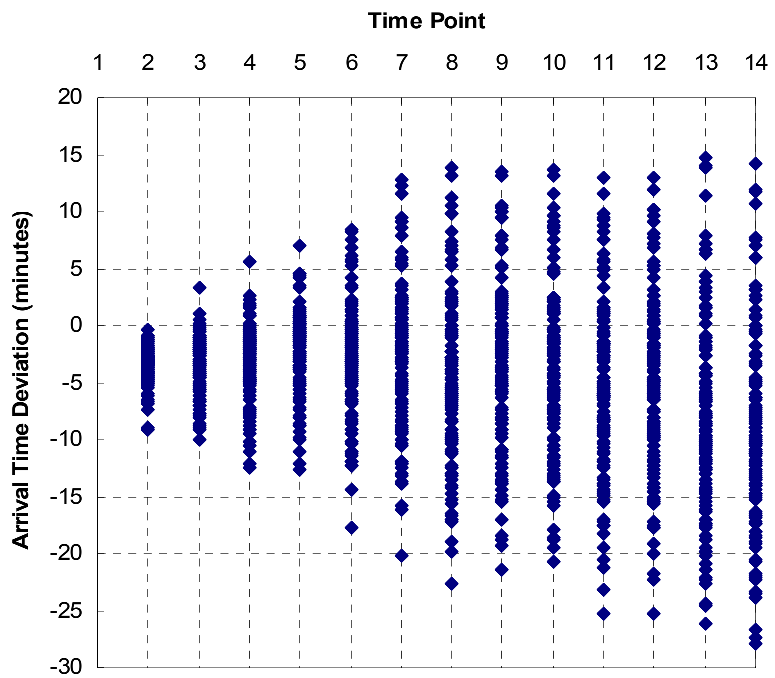


Figure 32 Difference between Scheduled and Actual Arrival Times (Pattern WMIAP)

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	NWK AIRPORT TERM A
9	NWK AIRPORT TERM B
10	NWK AIRPORT TERM C
11	BROAD ST & EDISON PL
12	PENN STATION BUS LANES

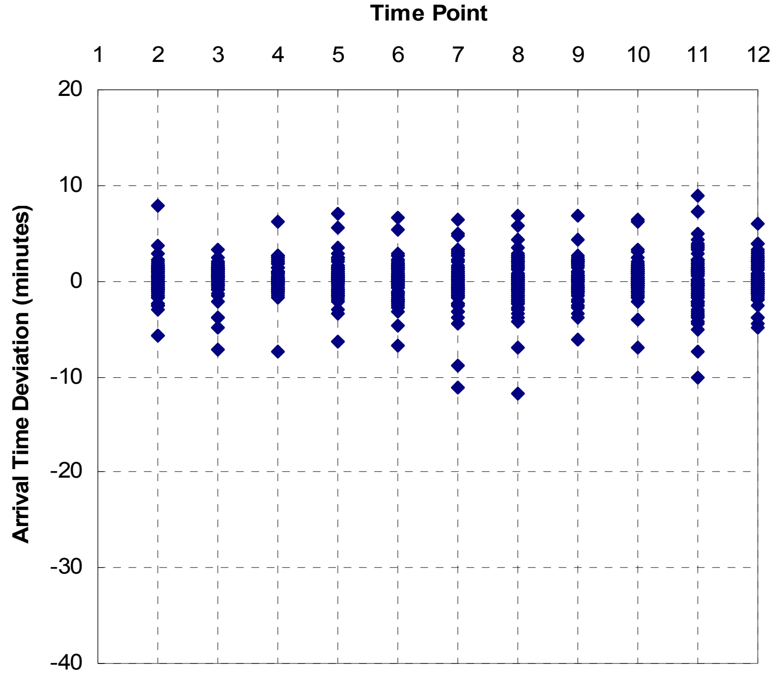


Figure 33 Difference between Predicted and Actual Arrival Times (Pattern WM-AP)

TP #	Description
1	WOODBRIDGE CENTER MALL
2	NJT METROPARK STATION
3	INMAN AVE & WOOD AVE
4	W INMAN AVE & ST GEORGES AVE
5	MAIN ST & E MILTON AVE
6	SAINT GEORGES AVE & WOOD AVE
7	E JERSEY ST & BROAD ST
8	NWK AIRPORT TERM A
9	NWK AIRPORT TERM B
10	NWK AIRPORT TERM C
11	BROAD ST & EDISON PL
12	PENN STATION BUS LANES

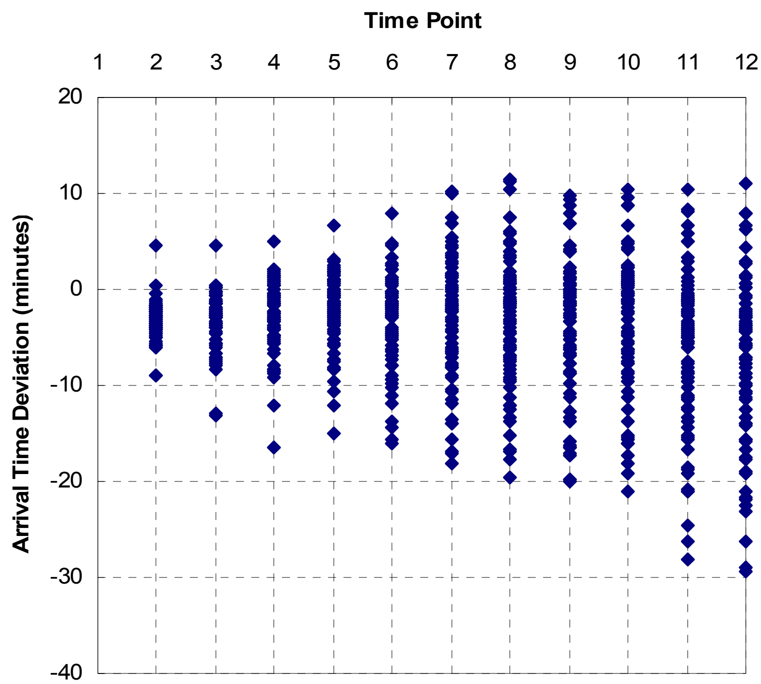


Figure 34 Difference between Scheduled and Actual Arrival Times (Pattern WM-AP)

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	BROAD ST & W JERSEY ST
7	SAINT GEORGES AVE & WOOD AVE
8	IRVING ST & BROAD ST
9	W INMAN AVE & ST GEORGES AVE
10	INMAN AVE & WOOD AVE
11	NJT METROPARK STATION
12	WOODBRIDGE CENTER MALL

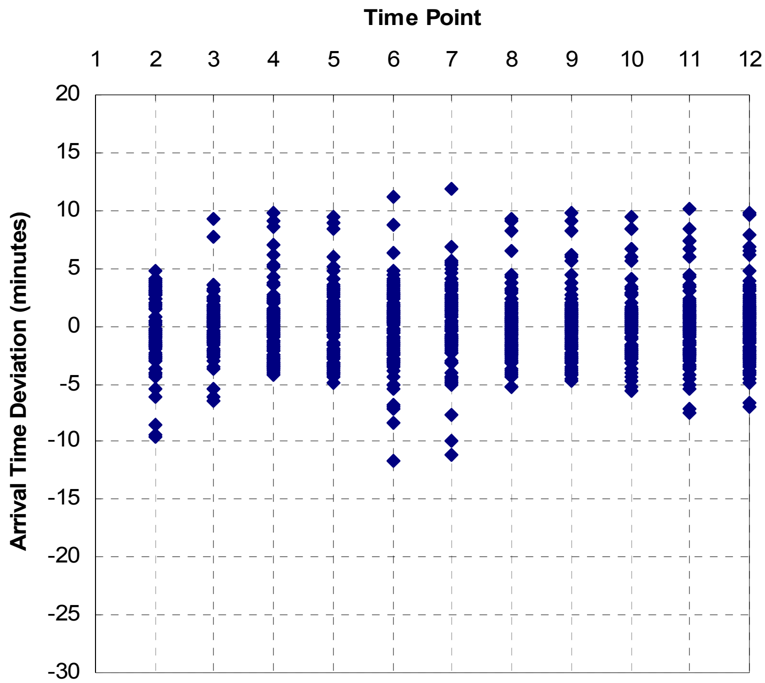


Figure 35 Difference between Predicted and Actual Arrival Times (Pattern PA-WM)

TP #	Description
1	PENN STATION BUS LANES
2	BROAD ST & BRANFORD PL
3	NWK AIRPORT TERM A
4	NWK AIRPORT TERM B
5	NWK AIRPORT TERM C
6	BROAD ST & W JERSEY ST
7	SAINT GEORGES AVE & WOOD AVE
8	IRVING ST & BROAD ST
9	W INMAN AVE & ST GEORGES AVE
10	INMAN AVE & WOOD AVE
11	NJT METROPARK STATION
12	WOODBRIDGE CENTER MALL

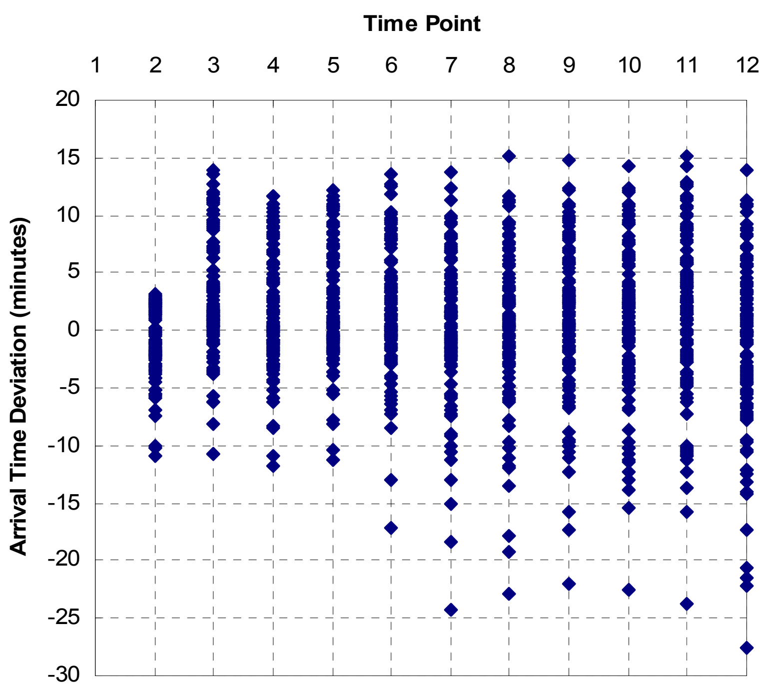


Figure 36 Difference between Scheduled and Actual Arrival Times (Pattern PA-WM)

Figures 37 through 40 show the performance comparison of the dynamic algorithm, the ANN models, and the bus timetable for trips originating from time point 1 and arriving at each downstream time points, for studied patterns WM-AP, PA-WM, WMIAP, and PAIWM, respectively.

It can be observed that from all trips statistic analysis, the N/D model, with a lower RMSE, always performs better than the ANN model. This is as expected since it has incorporated latest bus arrival information into the prediction. Also, the ANN generally give better indication of bus travel times than the timetable, except for outbound trips (pattern 1) arriving at time points 7 through12 from time point 1. For these particular trips, the maximum difference is less than 60 seconds.

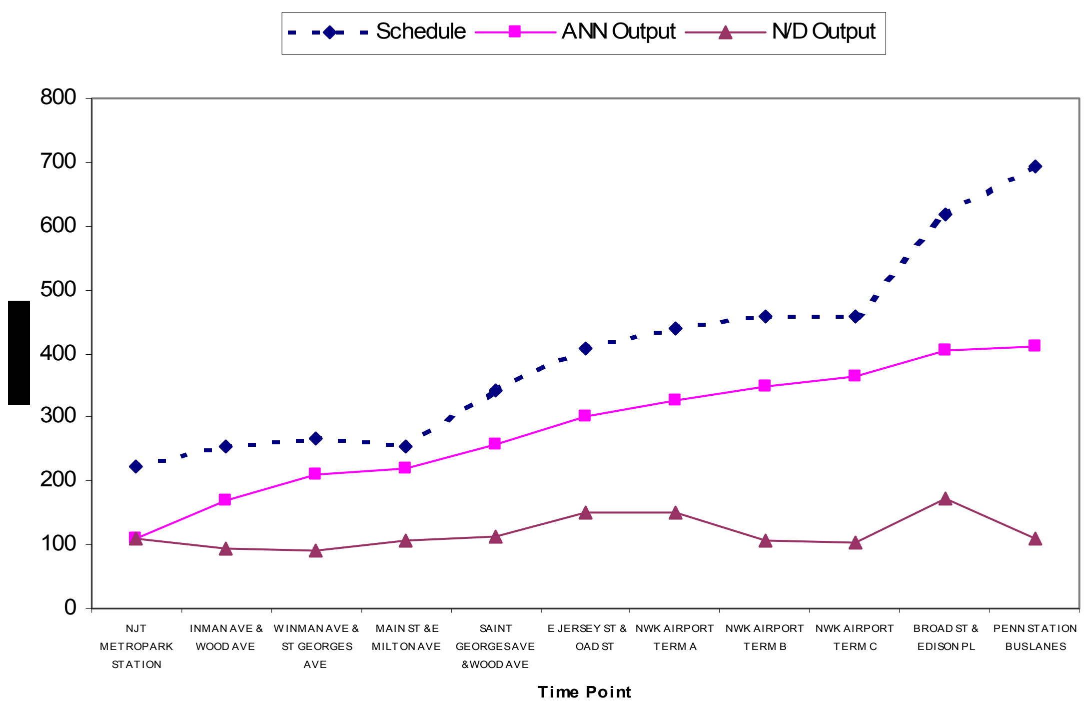


Figure 37 Performance Comparison (Pattern WM-AP)

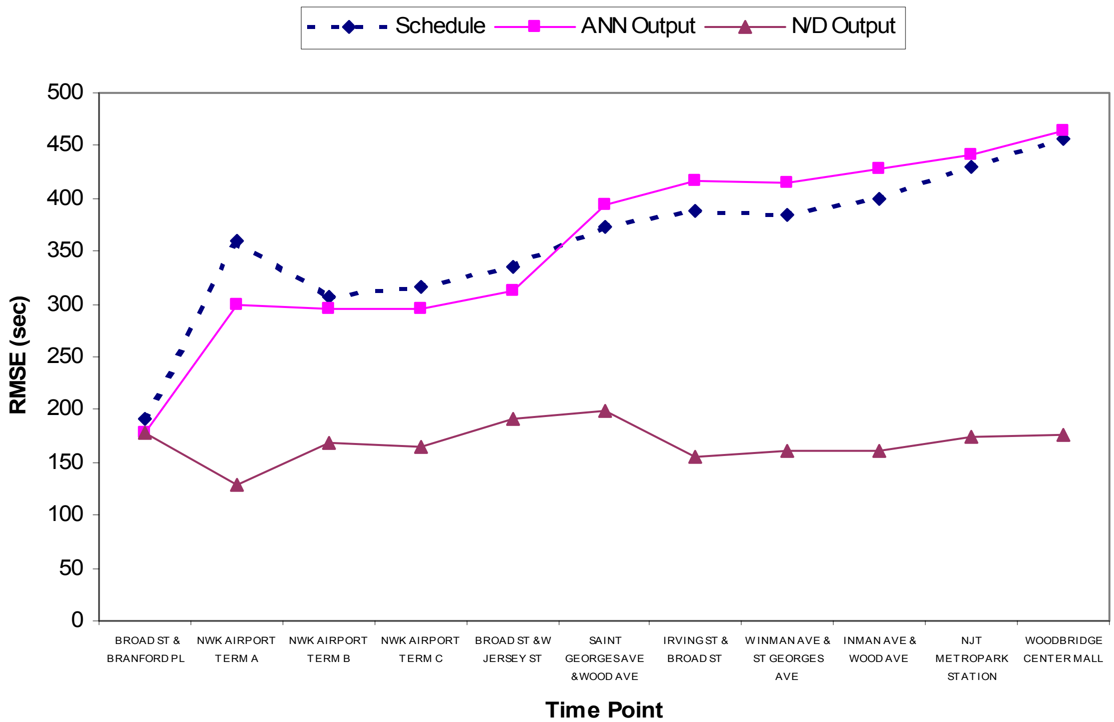


Figure 38 Performance Comparison (Pattern PA-WM)

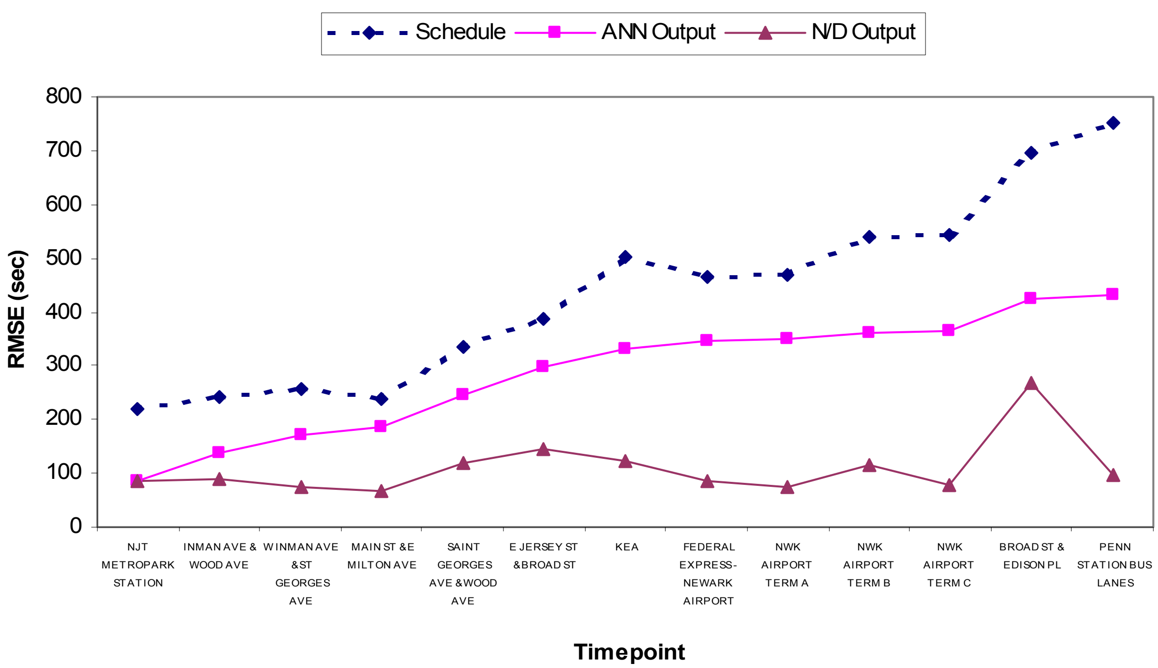


Figure 39 Performance Comparison (Pattern WMIAP)

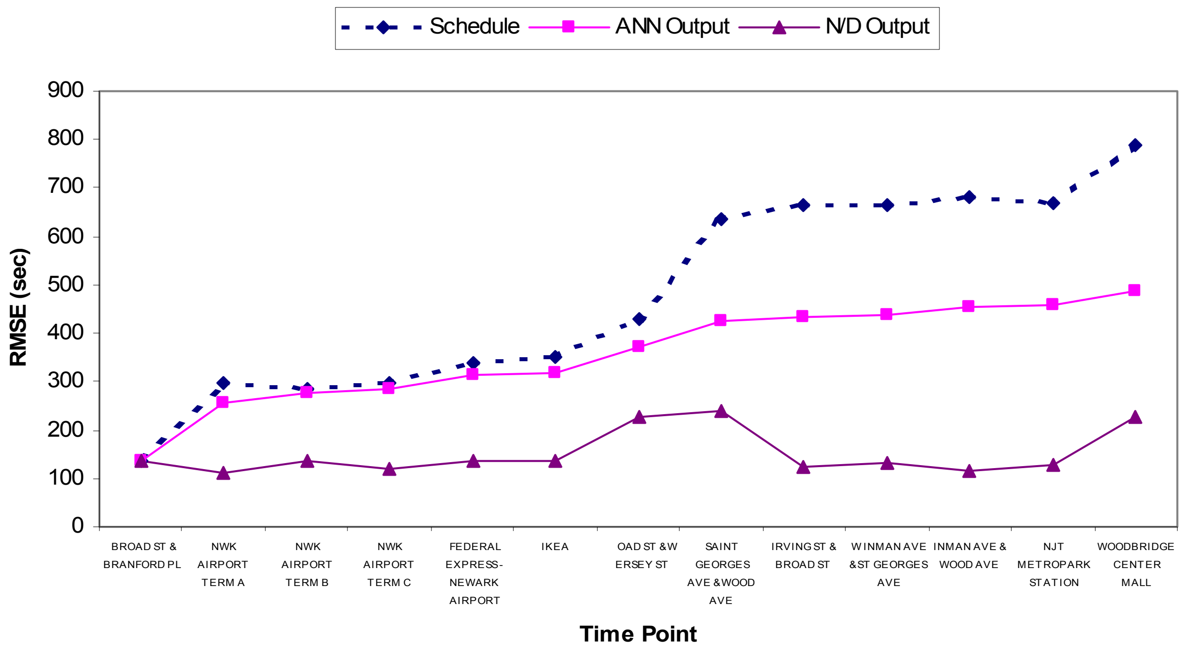


Figure 40 Performance Comparison (Pattern PAIWM)

One can also observe that the RMSEs of the ANN and the schedule show a trend of increase as the index of time points increases. This can be attributed to the error that propagates when the distance between the origin and destination is longer. Promisingly, the N/D model is generally stable with only few small scale hikes (e.g., Figures 29 through 32). The incorporation of the latest bus arrival information into the N/D model ensures higher prediction accuracy.

CHAPTER 8

CONCLUSIONS

In this study, the NJ Transit's APC data were applied in developing bus travel time prediction models. Though there were some inconsistent data existing in the APC data, the APC unit has demonstrated its effectiveness to collect detailed bus operational information (e.g., on/off passenger number, open/close time, etc). The data and the process procedure discussed in chapter 5, could generate accurate information for model development, (e.g., weather information, arrival times at time points, numbers of passengers boarding and alighting at time points and between them). The process of the APC data could be further developed as a standard procedure in the future study.

Artificial neural networks (ANN) were developed based on historic bus trip information for predicting bus arrival times. The developed ANNs have demonstrated their capability to model complex nonlinear systems, such as a model for bus travel times. In the developed Neural/Dynamic (N/D) model, the Kalman filtering algorithm has been integrated with the ANN because of its dynamic features to adapt to stochastic conditions in real time. Thus the developed N/D model could provide accurate prediction with data collected by APC units.

By given trip starting time (time of day), day of week, and weather (precipitation) condition, the developed ANN is able to generate estimated travel times between each pair of time points along the trip. The estimated travel time was then used as input to the developed N/D model to approximate the predicted travel time to a particular destination (any downstream time points).

After evaluating the developed bus travel time prediction models, it has shown that the ANN models generally gave a better estimation of travel times than that posed on the timetable. The N/D model outperformed the ANN models in most time points. The results demonstrated that the N/D model can significantly improve the error when predicting bus travel times.

It is necessary to note several issues that surfaced during the modeling process. The primary concern has been the insufficient data in training neural networks. In this study, the database only contains trips made during Year 2002. The amount of usable data is quite limited. Even though measures were taken to reduce the number of network weights in the ANN models, the recommended data amount to network weights ratio was still insufficient in certain cases. It is desirable to have more data to train and test the ANN models.

Another major concern has been the data quality. During pre-processing, it was found that large discrepancies exist in Year 2002 data. Such problems include inconsistent distance traveled between time points, inaccurate time point locations, incomplete trip records, etc. Corrections had to be made manually and some trip data had to be abandoned for model development purpose, which certainly contributed to the limited data size in the ANN modeling process.

With the increase in the amount of available data, we believe that the methodology developed in this study will become a powerful tool for bus arrival time prediction. Future study may explore the inclusion of other variables such as passenger counts, dwell times into the ANN model (they were not included because of the limited training samples).

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