# Dynamic Bus Arrival Time Prediction with Artificial Neural Networks

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**Abstract:** Transit operations are interrupted frequently by stochastic variations in traffic and ridership conditions that deteriorate schedule or headway adherence and thus lengthen passenger wait times. Providing passengers with accurate vehicle arrival information through advanced traveler information systems is vital to reducing wait time. Two artificial neural networks (ANNs), trained by link-based and stop-based data, are applied to predict transit arrival times. To improve prediction accuracy, both are integrated with an adaptive algorithm to adapt to the prediction error in real time. The bus arrival times predicted by the ANNs are assessed with the microscopic simulation model CORSIM, which has been calibrated and validated with real-world data collected from route number 39 of the New Jersey Transit Corporation. Results show that the enhanced ANNs outperform the ones without integration of the adaptive algorithm.

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Announcing the importance of the field

**CE Database keywords:** Predictions; Travel time; Neural networks; Buses; Simulation.



## Introduction

Public transportation planners and operators face increasing pressure in stimulating patronage through providing efficient and friendly service. Within the context of intelligent transportation systems, advanced public transportation systems (APTS) and advanced traveler information systems (ATIS) are designed to collect, process, and disseminate real-time information to transit users via emerging navigation and communication technologies (Federal 1998). One of the key elements in APTS/ATIS is a model to predict transit vehicle arrival times with reasonable accuracy. With quickly expended APTS related technologies [e.g., global positioning systems (GPS), automatic vehicle location systems (AVLS), and automatic passenger counters systems (APCS)], ATIS should provide timely vehicle arrival and departure information to passengers for scheduling their departure times and to transit operators to coordinate transfers (Kalaputapu and Demetsky 1995; Abdelfattah and Khan 1998; Federal 1998; Chien and Ding 1999a,b). For example, the negative impact of uncertain wait time suffered by passengers can be reduced. A study conducted by Ben-Akiva and Lerman (1985) has empirically shown that the wait time is more costly than the in-vehicle time.

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To achieve short-term vehicle arrival time prediction, the models developed with historic data cannot respond to dynamic conditions. It is desirable to develop advanced models, such as artificial neural networks (ANNs) for the dynamic prediction of vehicle arrival and departure times. In addition, stochastic traffic conditions on links and ridership variation at stops should be carefully considered. For evaluating the performance of the proposed ANNs, a comparison of predicted and simulated vehicle arrival/departure times generated from CORSIM (Chien and Ding 1999a,b) is conducted in the present study.

Giving overviews about the subject of the study

## Literature Review

Transit vehicle arrivals at stations/stops in urban networks are stochastic because travel times on links, dwell times at stops, and delays at intersections fluctuate spatially and temporally. The joint impact of the fluctuation deteriorates transit schedule adherence, lengthens the user wait time, and thus degrades the service quality. A sound model, which can predict vehicle arrival times and provide timely and accurate information to passengers, is desirable for mitigating such an impact. However, developing such a model that can adapt to time varying traffic and demand conditions is a challenging task.

A variety of prediction models developed in previous studies are reviewed and classified into univariate forecasting models, multivariate forecasting models, and ANNs. The univariate forecasting models are designed to predict a dependent variable through describing the intrinsic relationship with its historical data mathematically. The commonly used univariate forecasting models include probabilistic estimation and time series models (Okutani and Stephanedes 1984; Stephanedes et al. 1990; DeLurgio 1998). These methods usually have a short time lag while predicting in real time. The accuracy of time series models highly relies on the similarity between the real-time and historical traffic patterns. The variation of the historical average could cause significant inaccuracy in the prediction results (Smith and Demetsky 1995).

Unlike univariate models, multivariate models can predict and explain a dependent variable with a mathematical function



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formed by a set of independent variables. The commonly used multivariate models are regression models and state-space Kalman filtering models.

As a conventional modeling approach for predicting bus arrival times (Abdelfattah and Khan 1998), linear and nonlinear regression models could measure the simultaneous influence of various factors affecting the dependent variable via correlation and significance tests. To establish a regression model, all selected explanatory variables, independent between one and another, are significant to the dependent variable (usually measured by $t$-statistics). Such a requirement may limit the application of regression models to a transit system containing various highly intercorrelated (multicollinear) and time varying factors (Kalaputapu and Demetsky 1995). Faghri and Hua (1992) evaluated the applicability of artificial intelligence in transportation. Particularly addressed was the research potential of artificial neural networks. They demonstrated relatively promising results in a simple case study. A traditional linear regression analysis and two ANN models, adaptive linear element and back-propagation (BP), were used in trip generation forecasting. This particular case indicated that ANN models work better than the linear regression method.

Originating from the state-space representations in modern control theory, Kalman filtering models have been applied for predicting short-term traffic demand and travel times on freeways (Okutani and Stephanedes 1984; Stephanedes et al. 1990). Kalman filtering models have elegant mathematical representations (e.g., linear state-space equations) and the potential to adequately accommodate traffic fluctuations with their time-dependent parameters (e.g., Kalman gain). These models were effective for predicting the travel time one time step ahead, but they deteriorated when the forecasting had to be done over multiple time steps (Park and Rilett 1999).

As a prominent approach for solving complex problems, ANNs have been recently gaining popularity in transportation (Chang and Su 1995; Smith and Demetsky 1995; Wei and Wu 1997). ANNs, motivated by emulating the intelligent data processing ability of human brains, are constructed with multiple layers of processing units, named artificial neurons. The neurons contain activation functions (linear or nonlinear) and are highly interconnected with one another by synaptic weights. Information can be processed in a forward or feedback direction (e.g., feedforward or recurrent ANNs) through fully or partially connected topologies. Meanwhile, the synaptic weights can be adjusted to map the input-output relationship for the analyzed system automatically through a learning process (Hagan et al. 1996; Wei and Wu 1997). ANNs can be designed to incorporate the features of time series models (i.e., spatial-temporal ANN) or statistical models (i.e., associative Gaussian ANN). With such versatile parallel distributed structures and adaptive learning processes, ANNs appear to be a promising approach to describe complex systems where various time and location dependent factors are intercorrelated.

Unlike the aforementioned univariable and multivariable models, ANNs can be developed without specifying the form of the function, while the restrictions on the multicollinearity of the explanatory variables can be neglected. However, ANNs cannot reveal the input-output function explicitly. Instead, it is buried deeply within the networks, which may hinder the mathematical analysis and hypothesis tests. Due to limited theoretical guidelines, heuristic methods dominate the selection of input variables, network topology, and learning parameters. Meanwhile, the error surface of the learning problem is highly irregular with respect to the synaptic weights, with some parts fairly flat and others extremely curved. Therefore, the learning process is inherently delicate and is slow to converge to the optimal solution (Hagan et al. 1996), which impedes on-line training and adapting ANNs to real-time conditions.

Previous studies demonstrated that ANNs have the potential to accurately predict traffic conditions on freeways (e.g., traffic volumes, travel times, and speeds) (Dougherty et al. 1993; Hua and Faghri 1994; Smith and Demetsky 1995; Zhang et al. 1997) and urban streets (e.g., origin-destination flows, queue lengths, and bus schedule deviations) (Chin et al. 1994; Chang and Su 1995; Kalaputapu and Demetsky 1995). Kalaputapu and Demetsky (1995) developed ANNs with time series features for predicting bus schedule deviations. Based on the posted schedule and the output from their ANNs, bus arrival times can be estimated. In that study, the ANNs with different topologies, including feedforward and partial recurrent (e.g., Elman and Jordan nets), were evaluated by the data collected from an AVLS system of Tidewater Regional Transit in Virginia. The results suggested that the performance varied slightly among different topologies. Although only historical data on bus arrivals were considered as model inputs, the pioneer study gives us motivation to develop enhanced ANNs for dynamic bus arrival prediction, while real-time traffic (e.g., traffic volumes, speeds, and delays) and ridership variations can be accommodated.

Indicating a gap; Raising a question

**Table 1.** Previous Studies on Application of Artificial Neural Networks in Prediction

| Author/year | Predicted subject | Network structure | Decision variables |
|---|---|---|---|
| Dougherty et al. (1993) | Traffic congestion | Three-layer[b] | Flow, queue length, volume ratio |
| Chang and Su (1995) | Queue length at intersections | Three-layer | Flow, occupancy, speed, and historical queue length |
| Chin et al. (1994) | $O/D$ flow | Three-layer | Entering/existing traffic volumes |
| Hua and Faghri (1994) | Travel time | Two-layer[a] | Traffic volume/blockage index |
| Smith and Demetsky (1995) | Traffic volume | Three-layer | Historical volume/speed |
| Kalaputapu and Demetsky (1995) | Schedule deviation | Three-layer | Scheduled bus arrival time/ historical schedule deviation |
| Zhang et al. (1997) | Travel speed | Three-layer | Historical speed, density, and ramp entry rate |

[a]Two-layer: an input and an output layer.

[b]Three-layer: an input, a hidden, and an output layer.



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### Objective and Scope

Stating purpose of the study

The primary objective of this study is to develop models for accurately predicting bus arrival times in an urban network. First, two different ANN predictive models trained by link-based and stop-based data are proposed. Later, an adaptive algorithm is designed to integrate the ANNs for adjusting prediction errors dynamically. To evaluate the performance of the ANNs, a number of experiments are designed and analyzed with CORSIM (Ding et al. 2001). The reliability analysis for the proposed ANNs will be assessed by comparing predicted and simulated bus arrival times at various stops.

Comparing to previous work

### Model Development

Describing experimental procedures

Of the many topologies available for ANNs, the fully connected multilayer feedforward network with sigmoid activation functions is usually chosen to deal with complex transportation systems (Hagan et al. 1996). For training ANNs, a BP learning algorithm, called the generalized delta rule, is qualified (Kalaputapu and Demetsky 1995). Table 1 shows that many ANNs trained by the BP algorithm have been applied in predicting information, such as travel time, traffic volume, and queue length at intersections.

While developing ANNs, the objective function, defined as the sum of squares errors (SSE) over the entire set of $N$ training examples, is minimized by applying the BP algorithm

$$e=\frac{1}{2}\sum_{p=1}^{N}(y_p-\hat{y}_p)^2 \tag{1}$$

where $y_p$ and $\hat{y}_p$ represent simulated and predicted bus arrival times for the $p$th example, respectively. By applying the BP algorithm, a synaptic weight matrix $\mathbf{W}_i$ connecting neurons on the $i$th and $i+1$th layer can be optimized through minimizing $e$. Hagan et al. (1996) demonstrated that the amount of the adjustment $\Delta\mathbf{W}_{i,n}$ during the $n$th iteration can be determined by Eq. (2)

$$\Delta\mathbf{W}_{i,n}=-\eta\frac{\partial e}{\partial\mathbf{W}_{i,n}}+\gamma\Delta\mathbf{W}_{i,n-1} \tag{2}$$

where $\eta$, representing the learning rate ($\eta>0$), scales the step size in searching for the optimal solution. A large $\eta$ can speed up the learning process; however, the optimal solution may be missed because of wild oscillations in $\mathbf{W}_i$. Thus, the momentum rate $\gamma$ (ranging between 0 and 1) is introduced to regulate the change in $\mathbf{W}_i$ to prevent such oscillation. Rigorous theorems have been developed for choosing the optimal $\eta$, $\gamma$, and the number of neurons on a hidden layer for ANNs (e.g., ADALINE) containing linear activation functions. However, for ANNs with nonlinear activation functions (e.g., sigmoidal), heuristic and experimental procedures dominate the selection of values of these parameters (Hagan et al. 1996; Wei and Wu 1997).

The learning process of updating the synaptic weight matrix with the BP algorithm can be regarded as performing a nonlinear fitting operation on all training examples. The training examples are presented cyclically until the synaptic weight matrix converges, at which $e_r$ is minimized.

The BP algorithm needs to exercise extensive experiments to identify the proper parameters (e.g., learning/momentum rates and the number of neurons on each hidden layer). In addition, its

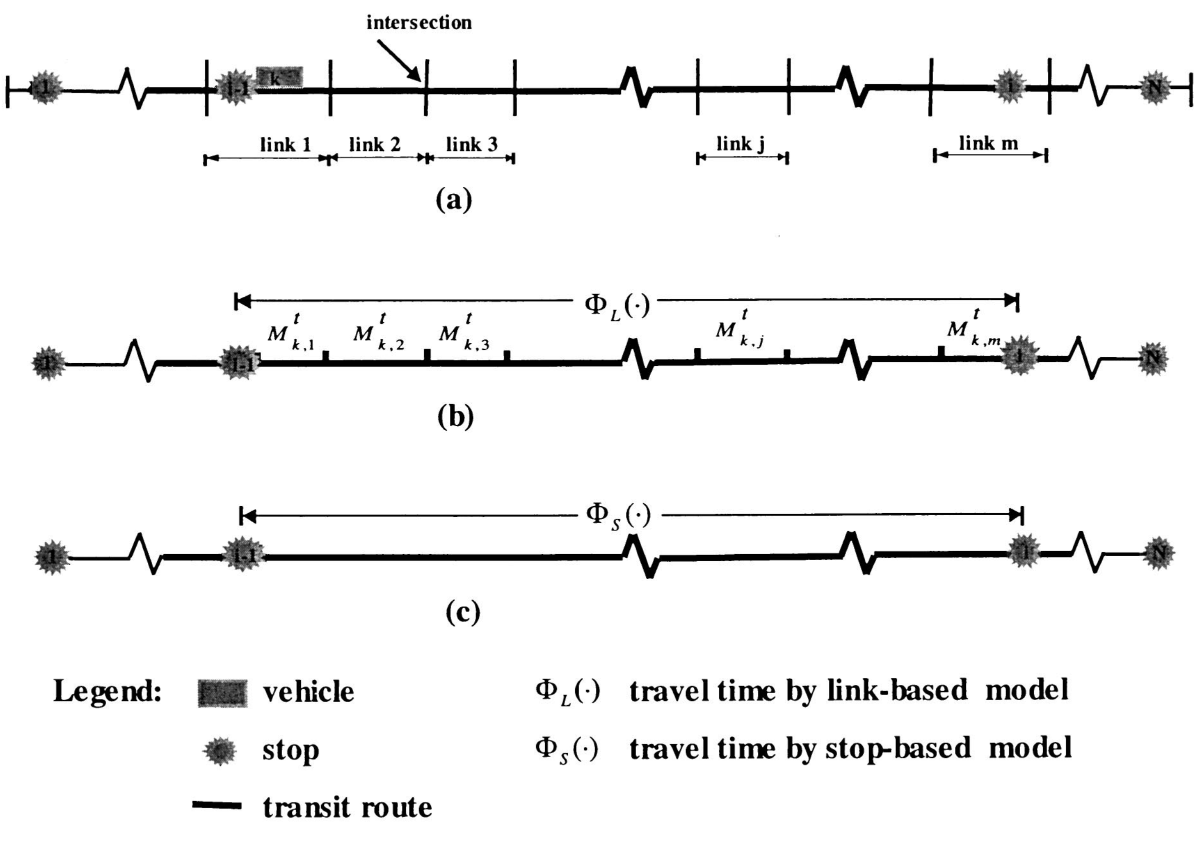


**Fig. 1.** Transit route segment with link-based and stop-based travel times: (a) segment between stops; (b) link-based travel time; (c) stop-based travel time



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convergence process for minimizing the intrinsically complex error function is lengthy. Therefore, the BP algorithm is difficult to apply on-line. This might limit the performance of ANNs, especially when the real-time conditions significantly deviate from those data used for training the ANNs. To improve the accuracy of the prediction results in a changeable environment is difficult. In this study, an adaptive algorithm is developed to justify prediction errors dynamically.

; Describing statistical procedures

### Link-Based Artificial Neural Network

The link-based ANN is designed to predict bus arrival times at any downstream stops by accumulating bus travel times on all traversed links between pairs of stops. Assume that there are links numbered from 1 through $m$ from stop $i-1$ to stop $i$, as shown in Fig. 1(a). At time $t$ in Fig. 1(b), the predicted arrival time $E_{k,i}$ for bus $k$ at stop $i$ can be determined by the sum of travel times $(\Sigma_{j=1}^{m} M_{k,j}^{t})$ on all $m$ links and the bus departure time $p_{k,i-1}$ at stop $i-1$. Thus

Justifying design priorities

$$E_{k,i}=p_{k,i-1}+\sum_{j=1}^{m} M_{k,j}^{t}; \quad \forall k,i \quad \text{and } p_{k,i-1}\geqslant t \tag{3}$$

where $p_{k,i-1}$=sum of predicted bus arrival time $E_{k,i-1}$ and dwell time $d_{k,i-1}$ of bus $k$ at stop $i-1$. The $p_{k,i-1}$ can be estimated by Eq. (4)

$$p_{k,i-1}=E_{k,i-1}+d_{k,i-1}; \quad \forall k,i \tag{4}$$

where $d_{k,i-1}$=function of headway between buses $k$ and $k-1$ and passenger demand at stop $i$ (Chien and Ding 1999a,b). Assume that $\Sigma_{j=1}^{m} M_{k,j}^{t}$ can be predicted by a link-based ANN, called $\Phi_L(\mathbf{X}^t)$. It is a function of vector $\mathbf{X}^t$ containing factors affecting link travel times (e.g., volumes, speeds, and delays) that can be obtained from traffic surveillance systems. The link-based ANN is developed based on the configuration shown in Fig. 2(a).

To predict dwell time at a stop, the number of boarding passengers has to be determined. Assume that passenger arrivals at stops follow Poisson distributions. The number of boarding passengers $B_{k,i-1}$ of bus $k$ at stop $i-1$ can be formulated as

$$B_{k,i-1}=\sum_{j=i}^{N} \bar{q}_{i-1,j}(a_{k,i-1}-p_{k-1,i-1}) \tag{5}$$

where $\bar{q}_{i-1,j}$ represents hourly demand from stop $i-1$ to stop $j\,(i\leqslant j\leqslant N)$. The term $(a_{k,i-1}-p_{k-1,i-1})$ denotes the headway between bus $k$ and bus $k-1$ at stop $i-1$. Note that $a_{k,i-1}$, the arrival time of bus $k$ at stop $i-1$, is either known or predictable by using Eqs. (3) and (4), in which the dwell time $d_{k,i-1}$ can be obtained from Eq. (6)

$$d_{k,i-1}=B_{k,i-1}t_b \tag{6}$$

where $t_b$ presents the average passenger boarding time. Thus, the departure time $p_{k,i-1}$ of bus $k$ from stop $i-1$ can be estimated by Eq. (4). With $d_{k,i-1}$ and the predicted travel time $\Phi_L(\cdot)$ of bus $k$ from stop $i-1$ to stop $i$, the bus arrival time $E_{k,i}$ at stop $i$ can be predicted.

### Stop-Based Artificial Neural Network

Unlike the link-based ANN, the stop-based ANN is developed by training aggregated stop-based data such as the means and standard deviations of volumes, speeds, and delays on the links between a pair of stops. As shown in Fig. 1(c), the predicted arrival time $E_{k,i}$ for bus $k$ at stop $i$ can be defined by the sum of the bus departure time $p_{k,i-1}$ at stop $i-1$ and the stop-to-stop travel time predicted by $\Phi_S(\cdot)$, as formulated in Eq. (7)

$$E_{k,i}=p_{k,i-1}+\Phi_S(\mathbf{Z}^t); \quad \forall k,i \tag{7}$$

where $\Phi_S(\cdot)$, the stop-based ANN shown in Fig. 2(b), is a function of vector $\mathbf{Z}^t$ consisting of the means and standard deviations of traffic volumes, speeds, and delays on the links between a pair of stops. Estimation of the bus departure time $p_{k,i-1}$ is similar to that discussed for the link-based ANN. By iteratively applying Eqs. (7) and (4), the bus arrival time $E_{k,i}$ at stop $i$ is predictable.

Articulating design choices

### Enhanced Artificial Neural Network

While applying ANNs to predict bus arrivals in real time, the data collected by traffic surveillance systems on links (e.g., detectors), at stops (e.g., AVLS transponders), and on vehicles (e.g., APCS) will be transmitted to the ANNs. The prediction results can then be generated and disseminated through ATIS to pretrip and en route passengers. Meanwhile, the difference (prediction error) between the simulated and predicted arrival times at stops can be detected, which might be caused by the discrepancy between the real-time data and those used for training the ANNs. To improve prediction accuracy, an adaptive algorithm, called enhanced ANNs, is developed to integrate both link-based and stop-based ANNs, for justifying prediction results in real time. The predicted arrival time $D_{k,i}$ of bus $k$ at stop $i$ by enhanced ANNs can be estimated by Eq. (8) as

$$D_{k,i}=E_{k,i}+K_{k,i}\Delta_{k-1,i}; \quad \forall k,i \tag{8}$$

where $E_{k,i}$ represents the arrival time predicted by either the link-based or the stop-based ANN. The $\Delta_{k-1,i}$, the prediction error, can be determined when bus $k-1$ arrives at stop $i$

$$\Delta_{k-1,i}=a_{k-1,i}-E_{k-1,i} \tag{9}$$

where $a_{k-1,i}$ and $E_{k-1,i}$ represent the simulated and predicted arrival times for bus $k-1$ at stop $i$.

To reduce the prediction error, the factor $K_{k,i}\,(0<K_{k,i}<1)$ is introduced to scale the adjustment of the prediction result from the ANNs. $K_{k,i}$ can be optimized by minimizing the covariant prediction error $P_{k,i}^{+}$ at stop $i$ (Gelb et al. 1977)

$$K_{k,i}=\frac{P_{k,i}^{-}}{P_{k,i}^{-}+R_{k,i}}; \quad \forall k,i \tag{10}$$

where

$$P_{k,i}^{-}=\mathbf{E}[(a_{k,i}-E_{k,i})^2] \tag{11}$$

and

$$P_{k,i}^{+}=\mathbf{E}[(a_{k,i}-D_{k,i})^2] \tag{12}$$

represent the covariance of the prediction errors generated from the ANNs and the enhanced ANNs, and are formulated in Eqs. (11) and (12), respectively. $R_{k,i}$, formulated in Eq. (13), is the covariance for the random noise (independent and zero mean) observed from bus arrival times at stop $i$

$$R_{k,i}=P_{k,i}^{+}/K_{k,i} \tag{13}$$

$R_{k,i}$ accounts for the effects of random drifting of the enhanced ANNs from the observed bus arrivals, which depends on the stochastic characteristics in specific transit systems. $P_{k,i}^{-}$, $P_{k,i}^{+}$, and $R_{k,i}$ are estimated and updated iteratively in real time to determine the optimal $K_{k,i}$ that helps the enhanced ANNs to adapt to



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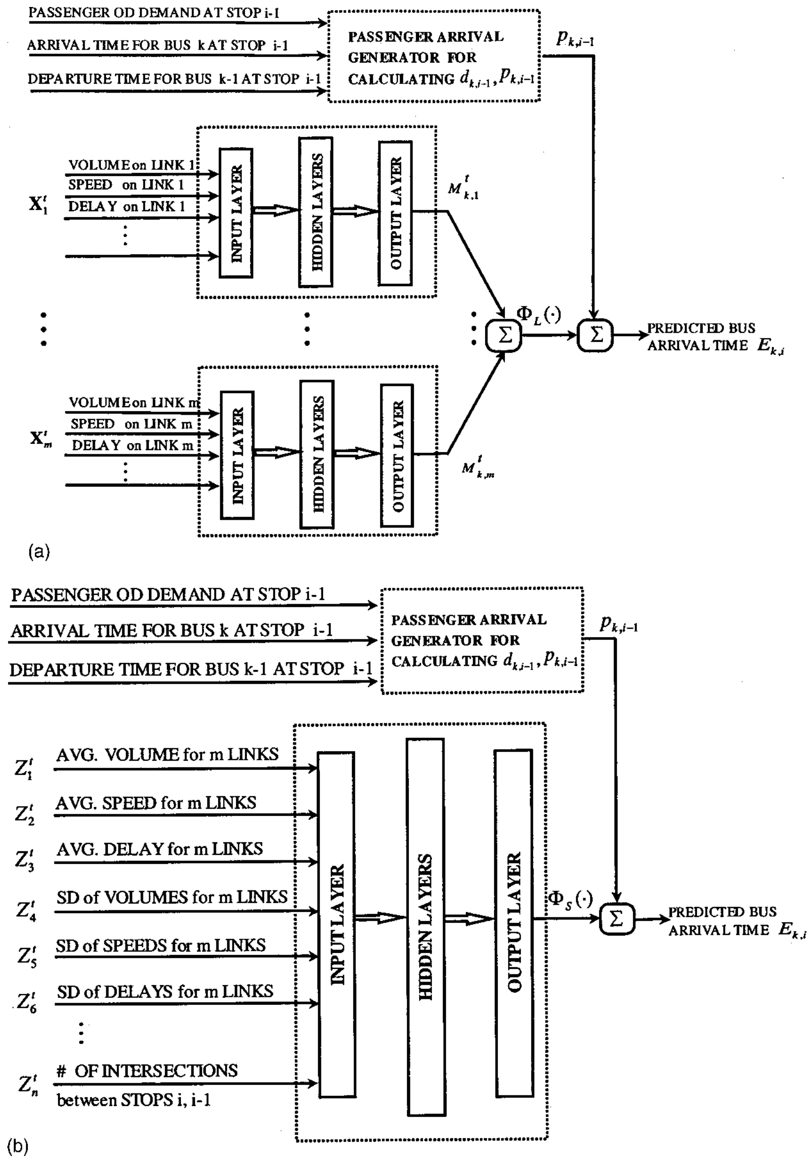


**Fig. 2.** Configuration of: (a) link-based model; (b) stop-based model

real-time situations by adjusting the prediction error when a bus departs from a stop. The benefit earned by applying the adaptive algorithm is in its computational efficiency; it can be integrated with ANNs to enhance the prediction performance while adapting to a dynamic environment without exercising a lengthy ANN retraining process.

# Justifying procedures or methodology

## Case Study

In this section, the proposed ANNs for predicting transit arrival times have been evaluated by simulating a 4.4-mi segment of route number 39 of the New Jersey Transit Corporation. The segment encompasses 30 intersections (of which 26 are signalized) and serves 14 stops per direction, as shown in Fig. 3. Training the ANNs requires a large amount of data, including both link-based and stop-based data (e.g., traffic volumes, speeds, and delays), and bus arrival and departure times collected under various traffic and demand conditions. Since GPS-based AVLS and traffic data of the analyzed route are not available in the study site, the microscopic simulation model CORSIM (Federal 1996) is applied to simulate bus operations and AVLS for generating real-time information.

### *Microscopic Simulation Model CORSIM*

The CORSIM based microscopic simulation program (Ding et al. 2001) is applied here to emulate bus operations and generate unobtainable real-time information used for training the proposed ANNs. CORSIM can simulate vehicle overtaking and merging maneuvers, passenger arrival distribution, and the interactions of transit vehicles with other vehicles competing for the right-of-way. It is a time-driven microscopic traffic simulator, in which individual vehicle movements are simulated every second for up to 19 time periods. Multiple time periods allow users to evaluate a changing traffic environment, signal timing, or transit operating strategies by inputting different variables. In addition, CORSIM is able to simulate the number of lanes, turn pockets, incidents, and a wide range of geometric and traffic flow conditions.

To develop the simulation model, the route geometry and traffic data including traffic counts, signal timing plans, and bus op-



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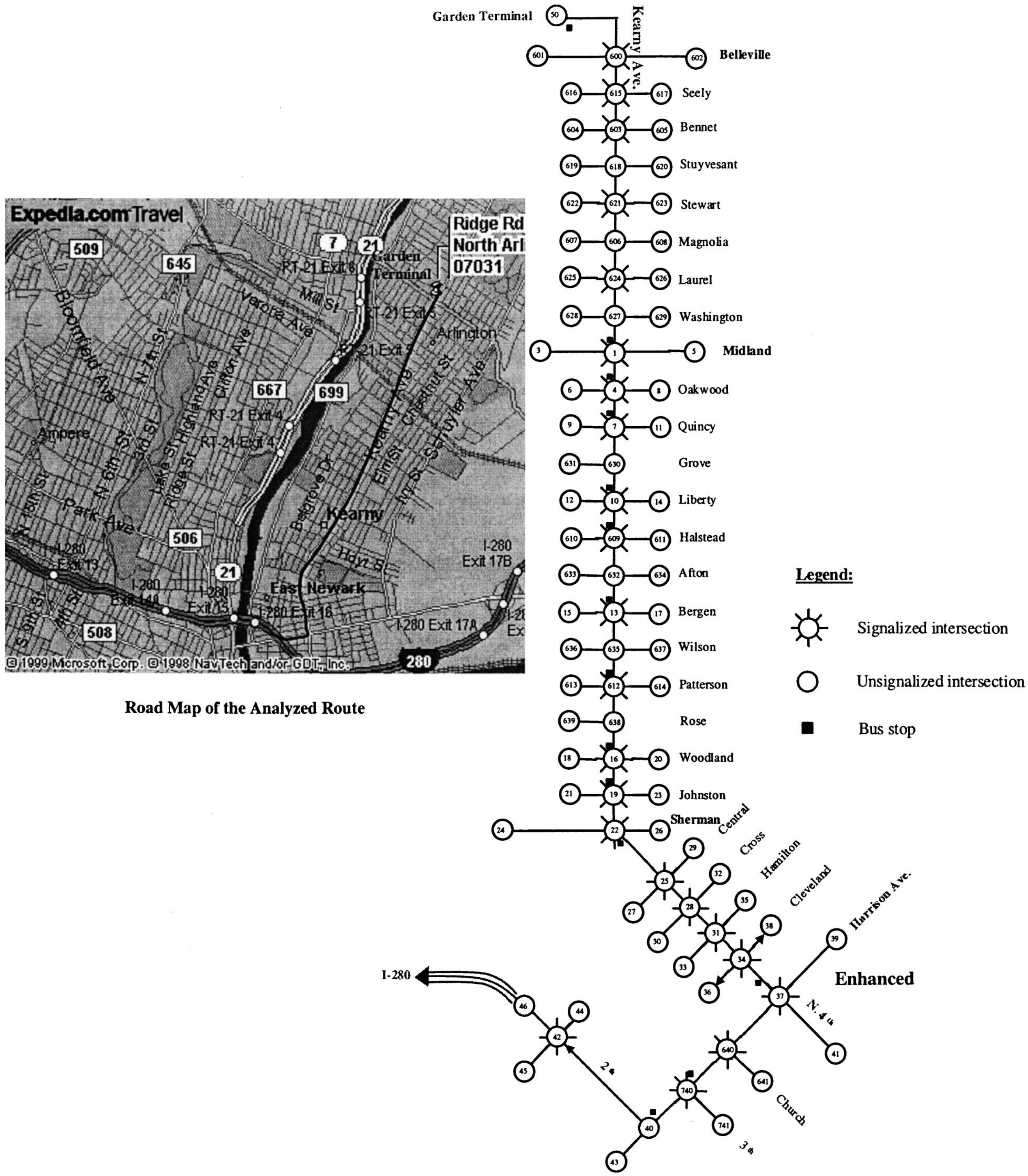


**Fig. 3.** Link-node diagram of New Jersey Transit route number 39

erational data have been collected from the analyzed route and the local government authority (e.g., cities of Newark, Kearny, and Harrison in New Jersey). Rigorous procedures of calibration and validation have been adopted to ensure that the simulation outputs, such as bus arrival/departure times, passenger boarding/alighting demands, and traffic conditions on links, are substantiated by field observations. The simulation model can therefore replicate transit operations adequately and provide a fairly reliable environment for extensively testing the developed ANNs under various traffic and demand conditions.

## Model Development

The data collected from the simulation results of the morning peak (7:30–9:30 a.m.) are used for training the ANNs. The simulation results consisting of link volumes, queues and speeds, and bus operational information (e.g., bus locations and delays, arrival/departure times, bus journey times, and boarding/alighting demands) collected from 24 buses have been analyzed. Factors affecting bus arrival times include traffic control devices, link lengths, stop spacings, traffic volumes/densities, vehicle speeds/



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**Table 2.** Variables Related to Link-Based and Stop-Based Models

| Variable | Definition |
|---|---|
| | (a) Variables related to link-based model |
| *LDIS* (ft) | Bus travel distance on a link |
| *LVOL* (vehicles/h) | Average link traffic volume |
| *LSPD* (mph) | Average link speed |
| *LDLY* (s/vehicle) | Average link delay |
| *LQUE* (s/vehicle) | Average link queue time |
| *PASS* (−) | Passenger demands at stops |
| | (b) Variables related to stop-based model |
| *SDIS* (ft) | Distance between stops |
| *SVOL* (vehicles/h) | Mean of LVOLs over all of the links between stops |
| *DVOL* (vehicles/h) | Standard deviation of LVOLs over all of the links between stops |
| *SSPD* (mph) | Mean of LSPDs over all of the links between stops |
| *DSPD* (mph) | Standard deviation of LSPDs over all of the links between stops |
| *SDLY* (s/vehicle) | Mean of LDLYs over all of the links between stops |
| *DDLY* (s/vehicle) | Standard deviation of LDLYs over all of the links between stops |
| *SINTE* (−) | Number of intersections traversed between stops |
| *PASS* (−) | Passenger demands at stops |

delays, and passenger boarding/alighting demands. After examining the factors identified above, potential explanatory variables for both the link-based and the stop-based ANNs are presented in Table 2.

The variables affecting bus link travel times include those related to traffic conditions, such as travel distance on a link (LDIS), average link volume (LVOL), average link speed (LSPD), average link delay (LDLY), average queue time on a link (LQUE), and passenger demands at stop (PASS). On the other hand, the variables affecting bus stop-to-stop travel times include aggregated traffic conditions over all of the links between a pair of stops. These are stop spacing (SDIS), mean and standard deviation of volumes (SVOL and DVOL), mean and standard deviation of speeds (SSPD and DSPD), mean and standard deviation of delays (SDLY and DDLY), number of intersections between a pair of stops (SINTE), and demands at stops (PASS).

The ANNs with different input variables listed in Table 3 have been trained by the BP algorithm, based on the data collected from the simulation. While training ANNs, different values of

**Table 4.** Correlation of Variables[a] Related to Link-Based ANN

| Variable | LVOL | LSPD | LDLY | LQUE |
|---|---|---|---|---|
| *LVOL* | 1 | −0.27 | 0.25 | 0.22 |
| *LSPD* | — | 1 | **−0.52** | **−0.67** |
| *LDLY* | — | — | 1 | **0.96** |
| *LQUE* | — | — | — | 1 |

[a]LDIS and PASS, and SDIS and PASS are not included in the correlation analysis, since they are chosen as input variables for each ANN in Table 3.

parameters (the number of hidden neurons, the momentum rate $\gamma$, and the learning rate $\eta$) are experimented. The results with respect to different combinations of hidden neurons are presented in Table 3. We found that for the link-based ANN, the lowest SSE over 380 training examples is achieved by model number 1 with variables LDIS, LVOL, LSED, LDLY, and PASS. For the stop-based ANN, the lowest SSE over 340 training examples is achieved by model number 8 that contains SDIS, SVOL, SSPD, SDLY, SINTE, and PASS.

The correlation analysis among the variables shown in Table 3 is conducted and presented in Tables 4 and 5. We found that for the link-based ANN, LDLY is correlated with LQUE (0.96) and LSPD (−0.52), while LSPD is correlated with LQUE (−0.67). For the stop-based ANN, SDLY is found to be correlated with SSPD (−0.73) and DDLY is correlated with DSPD (0.83), while SINTE is correlated with DVOL (0.65), DSPD (0.42), and DDLY (0.50), respectively. The selection of variables, however, was not confined strictly to the correlation constraints. For example, model number 8 contains both SSPD and SDLY, but the predicted result is superior to that from other models. The link-based (model number 1) and stop-based (model number 8) models are integrated with the adaptive algorithm to further improve the prediction accuracy.

## Model Evaluation

The developed ANNs are linked with the simulation model for the evaluation of arrival time prediction on New Jersey Transit route number 39. While simulating bus operations, prediction errors from the ANNs are evaluated when buses arrive at stops. In enhanced ANNs, the prediction errors are used for justifying the prediction results. The simulated and predicted bus arrival times

**Table 3.** SSE for Various Link-Based and Stop-Based Models

| Model number | Input variables | Number of hidden neurons | Number of training examples | SSE ($s^2$) |
|---|---|---|---|---|
| | (a) Link-based artificial neural network | | | |
| 1 | LDIS, LVOL, LSPD, LDLY, PASS | 6 | 380 | **0.0965** |
| 2 | LDIS, LVOL, LSPD, LQUE, PASS | 6 | 380 | 0.1108 |
| 3 | LDIS, LVOL, LSPD, PASS | 5 | 380 | 0.1108 |
| 4 | LDIS, LVOL, LDLY, PASS | 5 | 380 | 0.1104 |
| 5 | LDIS, LVOL, LQUE, PASS | 5 | 380 | 0.1108 |
| | (b) Stop-based artificial neural network | | | |
| 6 | SDIS, SVOL, SSPD, DVOL, DSPD, PASS | 7 | 340 | 0.0694 |
| 7 | SDIS, SVOL, SDLY, DVOL, DDLY, PASS | 7 | 340 | 0.0758 |
| 8 | SDIS, SVOL, SSPD, SDLY, SINTE, PASS | 7 | 340 | **0.0410** |
| 9 | SDIS, SVOL, SSPD, SINTE, PASS | 6 | 340 | 0.1103 |
| 10 | SDIS, SVOL, SDLY, SINTE, PASS | 6 | 340 | 0.0504 |



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**Table 5.** Correlation of Variables[a] Related to Stop-Based Artificial Neural Network

| Variable | SVOL | SSPD | SDLY | DVOL | DSPD | DDLY | SINTE |
|---|---|---|---|---|---|---|---|
| *SVOL* | 1 | −0.24 | 0.45 | 0.01 | −0.24 | 0.07 | 0.05 |
| *SSPD* | — | 1 | −0.73 | −0.06 | −0.03 | −0.28 | −0.28 |
| *SDLY* | — | — | 1 | −0.18 | −0.26 | 0.00 | 0.05 |
| *DVOL* | — | — | — | 1 | 0.36 | 0.42 | **0.65** |
| *DSPD* | — | — | — | — | 1 | **0.83** | **0.42** |
| *DDLY* | — | — | — | — | — | 1 | **0.50** |
| *SINTE* | — | — | — | — | — | — | 1 |

[a]LDIS and PASS, and SDIS and PASS are not included in the correlation analysis, since they are chosen as input variables for each ANN in Table 3.

at all downstream stops during 7:30–9:30 a.m. are collected for conducting a reliability analysis that is assessed by the root-mean square error (RSME) over all $N$ testing examples. The RMSE can be obtained from Eq. (14)

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

where $y_p$ and $\hat{y}_p$ represent the simulated and predicted bus arrival times for the $p$th example, respectively.

Figs. 4 and 5 depict the time-space diagram for a bus dispatched at the 1,939th simulation second (8:02:19 a.m.). From Figs. 4(a) and 5(a), we found that without integrating the adaptive algorithm, the stop-based ANN outperforms the link-based ANN, especially for predicting the travel time between a pair of stops with multiple intersections. In Figs. 4(b) and 5(b), we found that the arrival times predicted by the enhanced ANNs are more accurate than those predicted by the ANNs without the adaptive feature, especially for multistop prediction. This can be attributed to the efficiency of the error justification at each stop by the adaptive algorithm. The accuracy analysis of stop-to-stop travel times for 24 buses predicted by the two enhanced ANNs has been assessed and is shown in Fig. 6. Although both models can capture stop-to-stop travel times, slight differences are found at stops 3-4 and 5-6, where the enhanced link-based ANN outperforms the stop-based one. In contrast, at stops 1-2 and 11-12, the enhanced stop-based ANN outperforms the link-based one. This result is consistent with the observation from the ANNs without the adaptive feature.

The performance of the enhanced ANNs has been further investigated by comparing the RMSEs of predicted stop-to-stop travel times obtained from simulating 24 buses. In Table 6, the RMSEs from the two enhanced ANNs increase as the number of intersections between pairs of stops increases. The RMSE of the

Stating results or findings

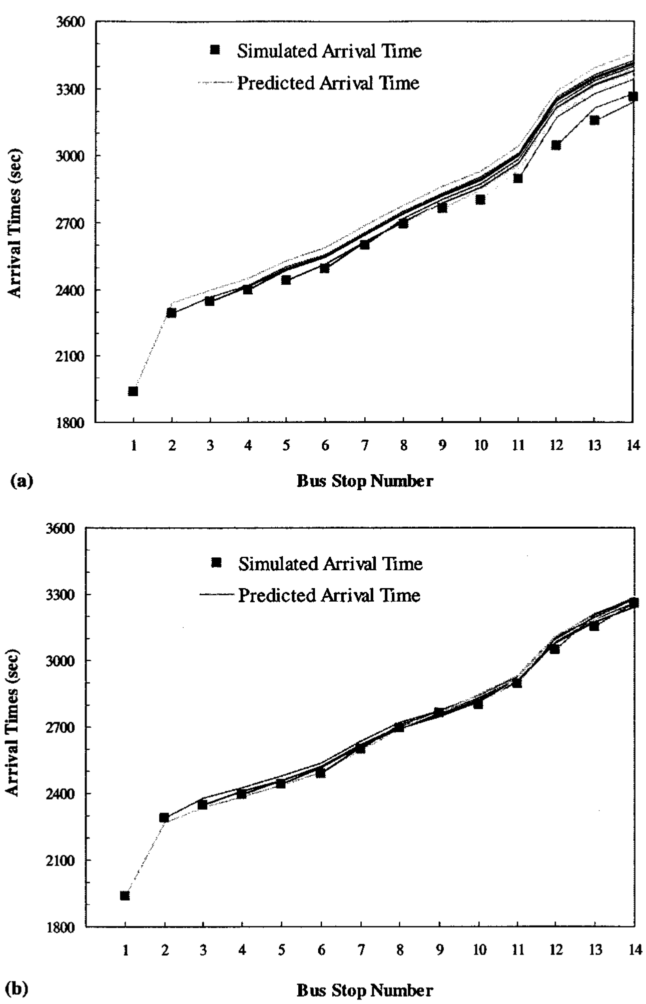


**Fig. 4.** Predicted and simulated bus arrival times: (a) with link-based model; (b) with enhanced link-based model

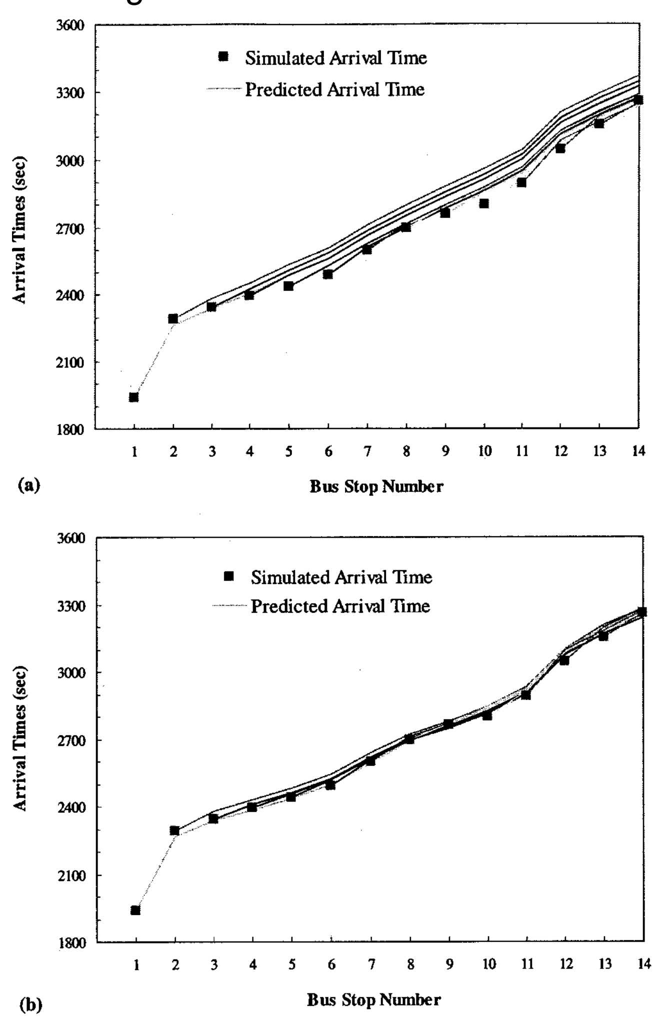


**Fig. 5.** Predicted and simulated bus arrival times: (a) with stop-based model; (b) with enhanced stop-based model



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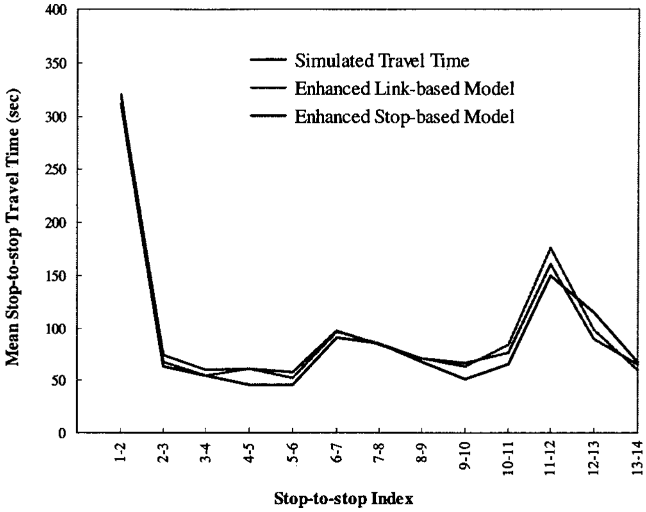


**Fig. 6.** Mean stop-to-stop travel times with enhanced models

enhanced link-based ANN increases from 14.5 to 72.26 s, while the number of intersections between stops changes from one to eight. Under the same condition, the RMSE of the stop-based ANN increases from 19.71 to 61.43 s. This indicates that the enhanced link-based ANN outperforms the stop-based one if the number of intersections between a pair of stops is relatively small. Table 6 also demonstrates great improvements in the prediction accuracy of the enhanced ANNs from their low RMSEs.

The resulting RMSEs for the predicted arrival times at various downstream stops (multistop prediction) are shown in Fig. 7. The RMSE increases as the number of stops traversed in between increases. This is because traffic conditions further downstream tend to be more stochastic and unpredictable, while the prediction error may be accumulated from upstream stops. Comparing Figs. 7(a and b), we found that the RMSEs of the enhanced ANNs are much lower than those of the ANNs without the adaptive feature. In addition, the enhanced stop-based ANN has a lower RMSE than the link-based one when the number of stops between the predicted origin and destination stops, which indicates that the enhanced stop-based ANN accommodates stochastic conditions at further downstream stops better than the link-based one.

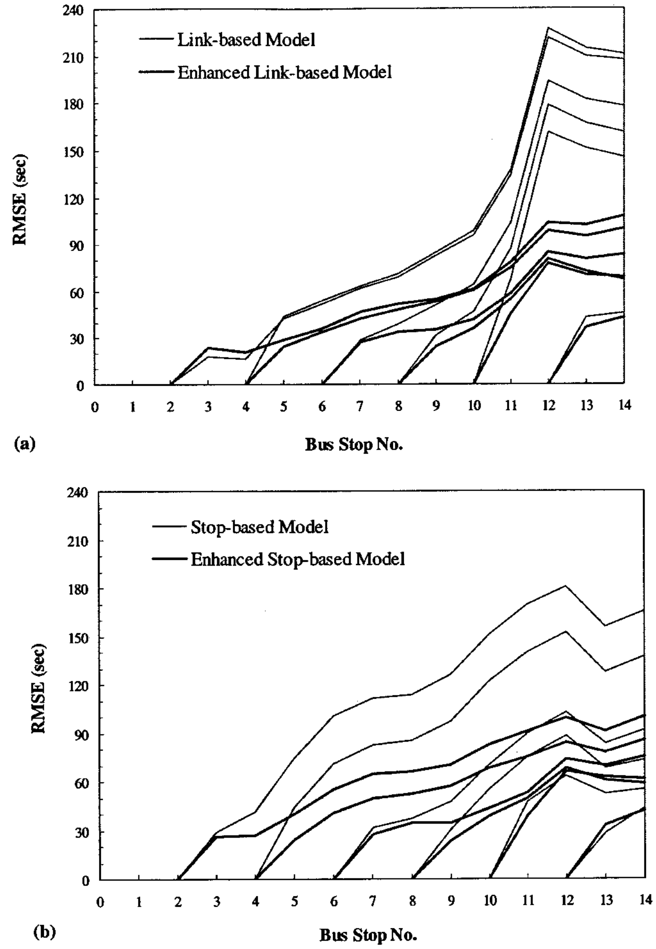


**Fig. 7.** RMSE of arrival times predicted from various stops: (a) with link-based model; (b) with stop-based model

## Conclusions and Future Research

One of the major stochastic characteristics in transit operations is that vehicle arrivals tend to deviate from the posted schedule. Poor schedule or headway adherence is undesirable for both users and operators, since it increases passenger wait/transfer times, discourages passengers from using the transit system, and de-

Explaining the results; Stating limitations; Summarizing

**Table 6.** Mean and Root-Mean Square Error (RMSE) of Stop-To-Stop Travel Times

| | | | | Mean (RMSE) (s) | | | |
|---|---|---|---|---|---|---|---|
| Stop-to-stop index | Stop-to-stop distance | Number of intersections | Simulated travel time (s) | Link-based artificial neural network | Stop-based artificial neural network | Enhanced link-based artificial neural network | Enhanced stop-based artificial neural network |
| 1-2 | 4,466 | 8 | 311.17 | **385.04 (82.50)** | 318.29 (63.91) | **320.63 (72.26)** | 319.46 (61.43) |
| 2-3 | 1,003 | 1 | 63.67 | 62.73 (18.06) | 78.79 (28.84) | 67.88 (23.74) | 73.79 (25.87) |
| 3-4 | 1,003 | 1 | 54.83 | 54.65 (13.43) | 72.40 (27.76) | 54.28 (14.5) | 60.28 (19.71) |
| 4-5 | 1,056 | 1 | 46.38 | 82.23 (43.83) | **82.59 (44.23)** | 61.27 (24.44) | **61.18 (24.27)** |
| 5-6 | 422 | 1 | 45.79 | 56.45 (23.69) | **73.71 (39.73)** | 52.18 (20.62) | **57.54 (26.98)** |
| 6-7 | 1,478 | 1 | 91.21 | 100.08 (28.96) | 102.93 (31.44) | 96.33 (27.58) | 97.07 (27.77) |
| 7-8 | 1,312 | 1 | 85.46 | 93.29 (32.83) | 88.64 (29.00) | 84.90 (25.93) | 83.81 (26.46) |
| 8-9 | 980 | 1 | 67.79 | 83.39 (31.75) | 81.93 (30.27) | 71.48 (24.32) | 70.94 (23.45) |
| 9-10 | 581 | 1 | 51.29 | 67.47 (30.68) | 78.10 (40.87) | 63.48 (28.01) | 66.59 (31.17) |
| 10-11 | 552 | 2 | 65.71 | 107.31 (67.67) | 86.05 (47.55) | 83.71 (45.37) | 76.88 (38.84) |
| 11-12 | 1,806 | 5 | 149.58 | **238.11 (121.34)** | 157.65 (44.17) | **175.44 (61.53)** | 160.81 (54.68) |
| 12-13 | 598 | 2 | 114.50 | 103.99 (43.04) | 87.52 (28.32) | 97.86 (36.94) | 89.86 (32.77) |
| 13-14 | 422 | 1 | 67.29 | 63.08 (34.94) | 75.91 (42.83) | 60.28 (35.23) | 65.19 (39.24) |



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grades the operation efficiency and productivity. This study developed enhanced ANNs that can dynamically predict accurate bus arrival information while considering stochastic traffic and demand variation. The performance of the enhanced ANNs was evaluated by simulation results generated from the enhanced CORSIM model. After simulating 24 buses operating on route number 39, the reliability analysis showed that enhanced ANNs can accurately perform for both single and multiple stop prediction. Moreover, the stop-based ANN is preferred when there are multiple intersections between stops, while the link-based one is more suitable for the pairs of stops with few intersections. An obvious extension is to develop a hybrid ANN model by integrating the link-based and stop-based models developed in this study. Thus, the accuracy of predicted bus arrival time information can be further improved.

To generate credible simulation results for developing ANNs, the CORSIM model has been calibrated and validated with real-time data (Ding et al. 2001). If real-time data collected from traffic surveillance systems and transit monitoring systems are available, the ANNs can be similarly developed to adapt to transit operations in a changeable environment. Maintaining headway and schedule adherence in transit operations, while controlling vehicles operating in dynamic urban networks, is another challenging task. The benefit evaluation of different operational control strategies (e.g., headway and schedule control) in conjunction with the implementation of the enhanced ANNs could be another potential extension of this study.

Stating implications of results

Suggesting further research

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