Using a Neural Network to Analyze the Impact of Passenger Activity on Bus Dwell Time and Travel Time

This paper applies neural network modeling approach to analyze the impact of passenger activities on bus dwell time and station-to-station travel time. Data used to develop the model was collected by onboard AVL/APC devices. Sensitivity analyses based on a trained neural network were performed to evaluate the relative significance of each passenger activity variable to variation of dwell time and/or station-to-station travel time. Transit providers can use these methods to identify the causes of schedule deviation and to develop improvement measures that are most effective to transit service.

by **Mei Chen and Xiaobo Liu**

INTRODUCTION

Bus operational performance has been an important topic in transit studies for decades. Extensive research has been conducted on the development of various performance measurements. For example, Henderson et al. (1991) generated regularity indices for evaluating transit performance. Strathman and Hopper (1993) analyzed operating measurements to assess bus on-time performance. Zolfaghari et al. (2002) developed a multi-attribute model for evaluating schedule and headway adherence for high and low-frequency services. These measurements help identify problems in bus operations and facilitate the design of effective technical and policy solutions. Some relevant applications include bus travel time prediction (e.g., Dailey et al. 2001, Shalaby and Farhan 2003, and Chen et al. 2004) real-time information on bus arrival (e.g., Koffman 1990 and Nelson 1994), and computer-aided dispatching (e.g., Strathman et al. 2000).

Although performance measures (such as on-time performance and travel time) are critical to long-term service planning, they are not detailed enough to portray service variability at the trip level. Part of the reason is that these measures were traditionally developed based on very limited data on transit operational and passenger activity. The significant costs associated with the collection of this data have seriously restricted its availability. However, a more effective diagnosis of contributing factors to bus service variability requires that such data be as detailed as possible.

With the development of advanced sensing and communication technology, transit operators are increasingly able to make real-time adjustments to service (e.g., using dynamic dispatching) to improve their services in the short term. A thorough understanding of the factors that are most significant to transit operation, particularly those that are controllable by transit providers, is necessary to facilitate decision-making on both short-term adjustment and long-term planning. However, only a limited amount of research is available under this context. Sterman and Schofer (1976) used the inverse of standard deviation of travel times to investigate factors affecting the reliability of urban bus services. Their results indicated that reliability was significantly degraded by increasing the route length, the intensity of intersection control, traffic volumes, and, with less certainty, bus passenger loadings. Guenthner and Sinha (1983) tested the statistical distributions of passenger boarding/alighting at the posted stops, based on which dwell time per person was modeled as a function of passenger boarding/alighting counts. Later, Guenthner and Hamat (1988) used data collected from Milwaukee, WI, to develop the distribution of adjusted bus arrival times. They also examined the characteristics of bus arrival times under the influence of different factors such as travel distance, location of peak load point, and headways. Rajbhandari et al. (2004) developed

a set of regression models to fit the relationships between bus dwell time and passenger boarding/alighting counts. The coefficients of determination were mostly around 0.7 for these models. While these studies offered interesting insights into the factors contributing to bus service variability, they were based on very limited data on passenger activities or they made certain assumptions on bus operation (e.g., fixed stop regime).

With increasing deployment of automatic vehicle location (AVL) and automatic passenger counter (APC) technology, large amounts of transit operation and passenger activity data (e.g., numbers of passengers boarding and alighting at each stop, as well as their corresponding time and location) have become available. Using data provided by these devices, a better understanding of the relationship between bus operating characteristics and passenger activities can be obtained. Based on this information, bus operators can develop effective strategies to improve bus operational control and planning in a complex traffic environment.

The objective of this study is to analyze the impact of passenger activities on bus dwell time and station-to-station travel time. The analyses used trip data recorded on a bus service route by onboard automatic passenger counters with AVL capabilities. The functional relationships between bus operating characteristics (such as dwell time and station-to-station travel time) and passenger activities were modeled by artificial neural network (ANN) models. This model enables transit operators to evaluate the relative significance of each passenger activity variable to the variation of dwell time and station-to-station travel time. Transit providers can use these methods to identify the causes of schedule deviation and potential measures that are most effective in improving transit service quality.

Data Description

The APC data were obtained from a reputable transit agency in the northeastern United States. The bus route under investigation operates through Essex, Union, and Middlesex counties in New Jersey, starting from Newark Penn Station and ending at Perth Amboy. The route is 29.5 miles between these two points and has 14 time points. The section starting from Newark Penn station and ending at Woodbridge Center Mall has 13 time points (TPs), and it was selected for this study because it has the largest amount of trip data among all the routes. In total, 167 bus trips were recorded between these two points during 2002. Scheduled travel time averaged 111 minutes, while actual travel time ranged from 90 minutes to 141 minutes. These trips were made during early morning, morning peak, late morning, mid-day, early afternoon, afternoon peak, and evening, as classified by the transit provider.

The onboard AVL/APC devices recorded much information related to bus operational and passenger activities, including the time and location of a door open/close event and the number of passengers boarding and/or alighting at each stop. Based on this information, various operational parameters such as passenger load between two stops, dwell time at each stop, cumulative dwell time and number of stops made between two stations, as well as station-to-station travel time, were estimated. Some of these estimates were subsequently used in the analyses.

CHARACTERISTICS OF PASSENGER ACTIVITIES

Temporal and spatial characteristics of passenger demand are critical factors in the design of transit service. The most detailed information on passenger demand on a bus line is in the form of boarding and alighting counts at each stop. This data provides information on transit station usage and busloads at all points along a route. While passenger counts are essential to transit scheduling and long-term service planning, few analyses have been performed to quantify their impact on transit operation.

As transit operators strive to improve service quality to attract more patrons, an in-depth understanding of the factors that are significant to on-time performance is extremely important. For a bus service route, passenger demand varies with time of day and along the route. Certain segments (portions of the route between two adjacent time points) may carry

significantly higher loads than do others. One may also observe frequent passenger boarding and/or alighting activities on some segments.

Based on AVL/APC data, one can analyze the temporal and spatial distributions of passenger activities using various statistical procedures. For example, multi-way analysis of variance (ANOVA) was used to demonstrate that temporal (i.e., time-of-day) and spatial (i.e., segment) factors were significant to passenger activity variables such as boarding/alighting counts and the number of stops made on a segment. Furthermore, multiple comparison tests were used to examine if the average boarding counts (or other passenger activity variables) were statistically different between the subcategories within a factor (such as morning peak and early afternoon under the time-of-day factor). These analyses help transit operators pinpoint the period and/or segment that experiences the most variation in passenger activities. These techniques help determine potential problems in bus operation and thus facilitate efficient allocation of limited resources in future service improvement.

DWELL TIME VARIATION ANALYSIS

Dwell time is an important parameter reflecting operating characteristics of transit service. It is traditionally defined as the time interval between the first and last passengers boarding the bus. The exact measurement of dwell time according to its original definition is very difficult in practice. Nevertheless, the time interval between door opening and subsequent door closing events derived from AVL/APC data can be considered as a valid approximation to dwell time. However, one should be cautious when making this assumption, because bus doors often remain open for extensive periods when the bus is at a terminal. This phenomenon was observed frequently in the data. Such a long interval does not reflect the level of passenger activities at terminals.

Generally, bus dwell time depends on various factors such as bus design (e.g., types and widths of doors, width of the aisle, and height of the floor from the platform), lifting policy, passenger load, and characteristics. For a given service route, dwell time is usually affected by the number of passengers boarding and/or alighting the bus, as well as the operational characteristics of service. If boarding and alighting are designated to separate doors and are allowed at the same time, dwell time is likely to be shorter than those operations with only one door available.

Currently, most bus transit services operate under a demand-stopping regime. That is, the bus driver will stop to pick up or drop off passengers along a route at the demand of a passenger onboard or along the route. While increasing the accessibility and attractiveness of transit service, this practice could cause dwell time, and subsequently station-to-station travel time, to be less predictable, especially when passenger demand evens out over the entire route segment.

An analytical tool that compares the relative significance of each input variable is needed. Considering the complex and stochastic nature of the transportation system, we developed artificial neural networks to approximate the functional relationship between dwell time (as model output) and passenger activities with associated temporal and spatial attributes (as model input). After the networks were trained and validated, sensitivity analyses were then conducted to examine the relative strength of each of the input variables.

In the following sections, the basic concept and procedure of neural network modeling, and particularly the concept of sensitivity analysis, will be introduced. They are followed by the application of such concepts in analyzing the relative significance of contributing factors to the variation of passenger dwell time.

Artificial Neural Network

The artificial neural network is an advanced computing model that enables adaptive and nonlinear learning. It is built from many processing elements that are interconnected with each other. It has been used in many applications to approximate functional relationships that would otherwise be difficult to model using other methods such as regression analysis. Fundamental concepts of neural network models can be found in Principe et al. (2000) as well as numerous other works.

A major advantage of neural network modeling is that it does not require functional forms to be explicitly specified. Nor does it require that input variables be independent of each other. These features are extremely beneficial to a traffic system in which most variables (e.g., passenger demand over time and/or along a route) are stochastic, and some input variables may be correlated with each other (such as passenger boarding and alighting counts and the number of stops made along the way). However, a neural network needs to be trained and validated using an extensive amount of data. With the advancement of technology, a large amount of data that records the operational characteristics of a transportation system is becoming increasingly available. Transit AVL/APC data is one example and the data requirement of neural network modeling is less likely to be a problem. For a comprehensive review of neural network applications in transportation system analysis, refer to Faghri and Hua (1992) for details. As far as transit system modeling applications, Ding and Chien (2000) developed neural network models to predict bus arrival time based on simulation data. Chen et al. (2003) and Chen et al. (2004) developed neural network models and combined them with Kalman filter algorithm to predict bus travel time using AVL/APC data. However, detailed information on passenger activity was not included in these models. Figure 1 shows a general architecture form for a neural network with one-dimensional output. The input variables located on the input layer are connected with the processing elements (PEs) on the hidden layer which are then connected to the processing element on the output layer.

Neural networks were developed to model the relationship between dwell time and passenger activities, as well as their associated temporal and spatial factors. Network input variables that describe passenger activities are passenger boarding count, alighting count, and the number of stops made on a segment. Also included in the model as input are symbolic variables, which are time-of-day and route segment. One additional channel is added to input for each unique symbol found in the data field. Each expanded channel of a given symbolic variable represents one symbol, with a "1" indicating the symbol is present and a "0" indicating the symbol is absent. As a result, each data sample will have only one channel set to "1" and the remaining channels set to "0" for a given symbolic input. The AVL/APC devices showed that data were collected on twelve segments during seven periods. Therefore, the time-of-day variable is expanded to seven channels and the segment variable expanded to 12 channels.

Figure 1: General Architecture of a Single Output Neural Network
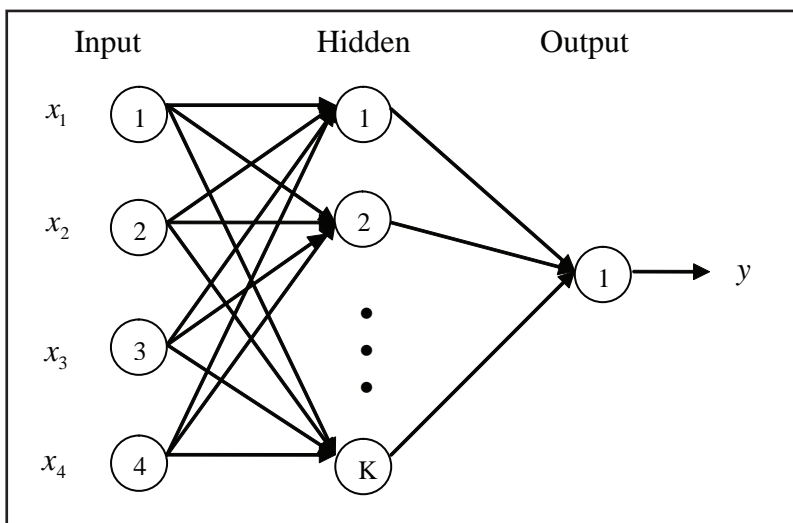
Performance Comparison. Various network topologies such as multi-layer perceptron and radial basis functions were tested with different transfer functions (e.g., tangent, sigmoid, etc.). Multiple test runs were conducted for each combination of network topology and transfer function, and the best-performing networks were saved. A commonly used performance measure is the mean squared error (*MSE*), which is defined as

$$(1) \quad MSE = \frac{\sum_{j=1}^{P}\sum_{i=1}^{N}(d_{ij} - y_{ij})^2}{NP},$$

Where P denotes the number of output processing elements, N denotes the number of exemplars in the data set, y_{ij} denotes the network output for exemplar i at the processing element j, and d_{ij} denotes the desired output for exemplar i at the processing element j. *MSE* is a measure of how well the network output fits the desired output.

However, *MSE* is closely related to the data for scale of output. Performance is not directly comparable between two models with different output data. To offset such impact, one can estimate the normalized mean squared error (*NMSE*) instead to obtain a standardized measure of performance. The NMSE is defined as MSE divided by the variance of the desired output, as follows,

$$(2) \quad NMSE = \frac{MSE}{\text{var}(\mathbf{d})}$$

where $\mathbf{d}$ represents the vector of desired output.

Another performance measure is the correlation coefficient (r), which examines the correlation between the network output and the desired output. It is defined as

$$(3) \quad r = \frac{\sum_i (y_i - \bar{y})(d_i - \bar{d})\big/N}{\sqrt{\sum_i (d_i - \bar{d})^2\big/N}\sqrt{\sum_i (y_i - \bar{y})^2\big/N}},$$

Where, y_i and d_i denote the network output and desired output for exemplar i, respectively; $\bar{y}$ and $\bar{d}$ denote their average respectively, and N denotes the number of exemplars in the data set. The closer the r value is to 1.0, the better the correlation is between the network output and desired output.

Preliminary analysis showed that the multiplayer perceptron (MLP) networks consistently outperformed the radial basis (RBF) networks when applied to this set of data. Therefore, only MLP networks were constructed in the formal analysis. Various combinations of input variables were tested with a different number of PEs and transfer functions. Table 1 shows several sample neural networks with the best-performance in modeling the dwell time as a function of passenger demand variables and time and spatial factors. With an *MSE* value of 282.4 (which corresponds to an average error of less than 17 seconds between estimated and measured dwell times), and an NMSE value of 0.18, the best-performing network produced a set of estimated dwell time that had a coefficient of correlation of $r = 0.91$ with the measured dwell time.

Sensitivity Analysis. After a model is trained and validated, sensitivity analysis can be performed to evaluate the significance of each input. The sensitivity of an output with respect to an input can be obtained through fixing the weights of a trained network and perturbing the input channel in a small amount while keeping other input constant. The corresponding change in the output is then measured. Two types of sensitivity measures were used in this study: raw sensitivity and relative sensitivity. Let I denote the number of input variables, J denote the number of output variables, x_i denote the value of the $i - th$ input, and y_i denote the value of the $j - th$ output. When other input variables are unchanged, the perturbation of the $i - th$ input of Δx_i will cause the value of the $j - th$ output to change by Δy_j. The raw sensitivity of the $i - th$ input with respect to the $j - th$ output can be expressed as $\frac{\Delta y_j}{\Delta x_i}$.

In addition to the raw marginal impact of an input, one may need to find the relative strength of each input variable. Relative sensitivity is defined as the percentage effect that a particular input has on an output. It can be expressed as $I \times J$ matrix, in which column j ($j \in [1,...,J]$) contains the percentage effect of all input variables on the $j - th$ output. The sum of all entries for

any column should be 100%. The percentage effect of each input variable on a particular output was estimated through normalizing the raw sensitivities associated with this output. It should be noted that the raw sensitivities of all channels associated with a symbolic input variable (e.g., time-of-day and segment) should be averaged before renormalization.

Sensitivity measures describe the effect of a given input on an output. Larger sensitivities imply higher significance in mapping. For transit operators, identifying factor(s) that are most significant to the operation will provide decision support for potential service improvement. From the neural network modeling perspective, sensitivity analysis can be used to identify the least important input(s) to the network output. The analyst may then consider excluding these inputs from the model if the performance of the network does not deteriorate considerably after the exclusion. This could be a very useful tool in reducing the size of the neural network to save on data collection and computation cost. In this study, this concept was implemented in the preliminary evaluation of neural network models.

For the best-performing neural network, model 1 in Table 1, the relative sensitivity for each of the input variables was estimated and shown in Figure 2. The boarding count on a segment was the most significant input of the model. It accounted for more than 45% of

Table 1: Performance Measures of Neural Network Models

Model No.	Topology	Number of PEs in the Hidden Layer	Transfer Function	MSE	NMSE	r
1	MLP	7	tanh	282.4	0.18	0.91
2	MLP	5	tanh	283.3	0.23	0.89
3	MLP	7	sigmoid	284.1	0.24	0.87

Figure 2: Relative Sensitivity of Total Dwell Time with Respect to Input Variables
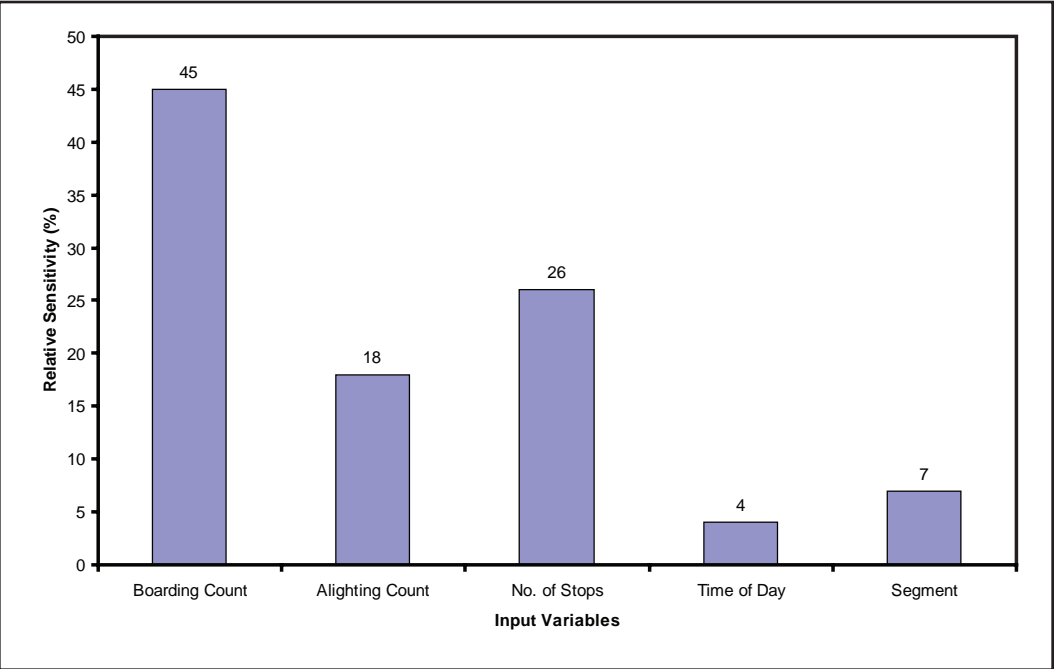
the changes in dwell time caused by giving a small perturbation for all inputs. Meanwhile, the alighting count by segment was not as significant – it only accounted for about 18% change. This observation is consistent with bus operating characteristics. It usually takes a longer time for passengers to board because each of them needs to pay the fare once on the bus.

The number of stops made on a segment was the second most significant factor to the change of total dwell time – at a relative sensitivity of 26%. This variable reflects both the distribution of passenger demand along the route and the transit-stopping regime. The bus service route from which the trip data was collected was operating under a demand-stopping regime, i.e., the buses stopped at any location (as deemed safe by the operators) that the passengers on board or along the route demanded. Under this operating policy, the spatial distribution of passenger demand along the route determines the number of stops to be made on each segment.

Compared to passenger activity measures, temporal and spatial factors were the least significant input variables (with the lowest relative sensitivity values). Therefore, they may be excluded from the input variable set to reduce the size of the network. Subsequent training and validation runs confirmed that the performance of the updated network was not affected significantly. The *MSE* increased slightly to 284 while the coefficient of correlation dropped slightly to 0.85.

TRAVEL TIME VARIATION ANALYSIS

A very important piece of information needed for transit operational analysis is station-to-station travel time, which is crucial to obtaining operating speed and reliability of service for planning potential service improvement. In this study, neural networks were also developed to model the relationship between station-to-station travel time and passenger activities. Input variables included boarding count, alighting count, number of stops made on a segment, and total dwell time on a segment, as well as temporal and spatial factors.

The network was trained and validated for multiple times (10 times in this study) using various combinations of transfer functions and a number of PEs in the hidden layer. Sensitivity analysis was performed on the network for each combination. Those input variables with the least significance were excluded from the input, and the network was re-trained and re-validated. This process continued until the performance of the neural network (measured by MSE and correlation coefficient) started to deteriorate significantly.

After extensive test runs, it was found that the models with total boarding count, total alighting count, number of stops made, and total dwell time, as well as temporal and spatial factors had the best overall performance and computational efficiency. The MSEs and NMSEs were consistently lower than in models with other combinations of input variables. Table 2 shows the performance of selected models with relatively good performance. For all scenarios tested, the MLP network with a single hidden layer outperformed the MLP network with multiple hidden layers and all of the RBF networks that were tested. Therefore, only MLP networks with a single hidden layer are shown in the table.

The best performing model (no. 8 in Table 2) is the single hidden layer (with 5 PEs) MLP network with a tangent transfer function. With an MSE value of 1304, which corresponds to an average error of 36 seconds on station-to-station travel time estimation, and an NMSE of 0.07, the network output showed a very strong linear correlation with the measured station-to-station travel time.

As described earlier, the sensitivity of an output (i.e., station-to-station travel time) with respect to an input can be estimated by calculating the change in output caused by a small perturbation of each input variable while keeping other inputs fixed at their current values. Figure 3 shows relative sensitivities with respect to each of the input variables for the best performing model (no.8). The segment variable incorporates several critical factors such as segment length, geometric condition, and traffic control settings that affect bus-running time substantially. It was the most

Table 2: Performance Comparison Between Various Neural Network Models

Model No.	Topology	Number of PEs in the Hidden Layer	Transfer Function	MSE	NMSE	r
4	MLP	10	tanh	1354	0.14	0.92
5	MLP	7	tanh	1357	0.15	0.92
6	MLP	7	tanh	1312	0.13	0.93
7	MLP	5	tanh	1312	0.13	0.93
8	MLP	5	tanh	1304	0.07	0.96

Figure 3: Relative Sensitivity of Station-to-Station Travel Time with Respect to Input Variables
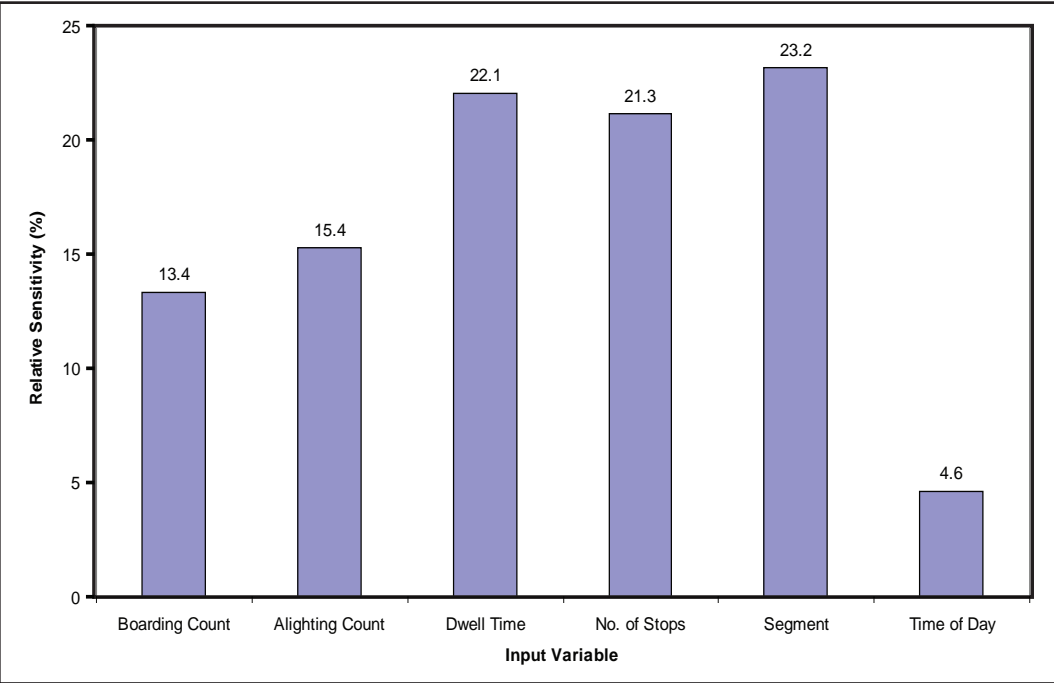
significant input to the variation of travel time for this bus route. Dwell time was the second most important input. It reflected station-standing time to allow passenger boarding and alighting. The number of stops made on a segment was the next significant input, representing the distribution of passenger demand along the route. While they had similar relative sensitivities values, these three factors apparently contributed significantly more than any other input variables, with a total combined relative sensitivity of more than 66%. On the other hand, station-to-station travel time was less sensitive with respect to changes in boarding and alighting counts.

The temporal (i.e., time-of-day) factor did not have a significant impact on travel time variation. However, its exclusion from the input caused significant deterioration of network performance. Specifically, the correlation coefficient, r, dropped to 0.82 after it was removed from the input, and the MSE increased to 2016. Therefore, the exclusion of the temporal factor from the input was not recommended under this circumstance.

CONCLUSIONS AND PRACTICAL IMPLICATIONS

This paper analyzed the impact of passenger activities on bus dwell time and station-to-station travel time. Artificial neural network models were developed to approximate functional relationships between input and output variables. This modeling approach was chosen because it does not require an explicit functional form or independence among input variables. This is a significant advantage over other methods such as regression, especially where many variables may be correlated with each other (such as boarding count and number of stops made). Neural network models demonstrated good performance with reasonable values of MSE and high correlation coefficients between the network output and actual measurements.

Among all of the variables describing passenger activities, boarding count was the most significant contributor to the variation of dwell time. While this was no surprise to practitioners, the observation confirmed the significance of the model. The next significant input was the number of stops made on a segment, which was also quite significant to station-to-station travel time. This observation can provide some insight into transit operation. Because station-to-station travel time is highly sensitive to total dwell time and the number of stops made on a segment as shown in Figure 3, transit operators may want to look for ways to control the number of stops made on a segment. This is especially important when passenger demand reaches a higher level that calls for more frequent stopping under a demand-stopping regime. Here, transit providers should consider switching to on-call stopping or even fixed stops to concentrate on passenger boarding/alighting at a smaller number of locations along the route. This will not only shorten dwell time, but will also significantly help reduce station-to-station travel time (or increase operating speed).

The relative sensitivity of each input factor produced by the neural network models can serve as an indicator of the importance of each input. Sensitivity analysis can help decision-makers identify factors that warrant the most attention and resources in future service improvement efforts. For example, with additional data on geometric condition and traffic-control devices along the service route, the transit provider can use the same technique to further identify significant contributors to variation in service reliability and thus develop appropriate strategies for service improvement. For instance, if the sensitivity analysis indicates that traffic signal density is a significant contributor to travel time variation, a signal priority for buses might be considered if possible. Clearly, these observations and conclusions are site-specific. Nevertheless, the analytical procedures used in this study can be applied to any transit route with AVL/APC data.

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Mei Chen, Ph.D., *is an assistant professor in the Department of Civil Engineering at the University of Kentucky. Her research interests include transportation network analysis, travel demand forecasting, simulation and forecasting, and public transit. She received her Ph.D. in Transportation from New Jersey Institute of Technology in 1999.*

Xiaobo Liu, Ph.D., *works at Edwards and Kelcey as a transportation modeler for transportation planning and operational analysis. His works mainly focus on corridor planning, capacity/safety analysis, operations simulation and optimization as well as regional travel modeling. He received his Ph.D. in Transportation from New Jersey Institute of Technology in 2004.*