An Artificial Neural Network Method for Length-based Vehicle Classification Using Single-Loop Outputs

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ABSTRACT

Classified vehicle volumes are important inputs for traffic operation, pavement design, and transportation planning. However, such data are not available from single-loop detectors, the most widely deployed type of traffic sensor in the existing roadway infrastructure. Several attempts have been made to extract classified vehicle volumes from single-loop measurements in recent years. These studies use estimated speed for length calculation and classify vehicles into bins based on the calculated vehicle lengths. Due to the stochastic features of traffic flow, however, deterministic mathematical equations based on certain assumptions for speed calculation typically do not work well for all situations and may result in significant speed estimation errors under certain traffic conditions. Such errors accumulate when estimated speeds are used in vehicle length calculations and degrade the accuracy of vehicle classification. To solve this problem, we develop an artificial neural network method to estimate classified vehicle volumes directly from single-loop measurements. The proposed neural network is very simple. It is a three-layer neural network with back-propagation structure. This method is tested using data collected from several loop stations on I-5 over a long duration. The results show that the proposed artificial neural network model produces reliable estimates of classified vehicle volumes under various traffic conditions.

Key words: single loop, dual loop, vehicle classification, and artificial neural network.

1. INTRODUCTION

Large trucks, buses, and recreational vehicles are typically associated with slow acceleration, inferior braking, and large turning radius. The *Highway Capacity Manual (1)* requires adjustments to the volumes of these vehicles in highway design and capacity analysis. Due to the heavy weight of these vehicles when they are fully loaded, their impact to pavement life time is significant and the volumes of these vehicles are indispensable inputs for pavement design and maintenance *(2)*. From safety perspective, these large vehicle volumes are also desirable because statistics show that large vehicles have higher accident risk and traffic accidents with these vehicles involved are more severe. For example, although large trucks are only 4% of total registered vehicles in the U.S., they account for 8% of all vehicles involved in fatal crashes *(3)*. Therefore, classified vehicle volumes are important for traffic operation, pavement design, transportation planning.

Although recently developed traffic detectors, such as Video Image Processor (VIP), Triple-Technology traffic detector (TT-298), etc., are capable of measuring classified vehicle volumes, they are not widely available in the existing roadway infrastructure. Single-loop detectors are ubiquitously available, but they cannot provide classified vehicle volumes unless upgraded to dual-loop detectors. A single-loop detector merely measures vehicle count and lane occupancy directly. When two single-loop detectors are placed several meters apart on one traffic lane, they form a dual-loop detector. A dual-loop detector produces vehicle speed and length in addition to single-loop measurements. In the Washington State Department of Transportation (WSDOT) dual-loop detection system, vehicles are classified into four categories based on their lengths: Bin 1 represents vehicles shorter than 26 ft (7.92 m); Bin 2 includes vehicles from 26 ft (7.92 m) to 39 ft (11.89 m) long; Bin 3 vehicle lengths range from 40 ft (12.19 m) to 65 ft (19.81m); and Bin 4 contains vehicles longer than 65 ft (19.81 m) *(4)*. Though dual-loop detectors are ideal for collecting speed and vehicle-classification data, there are too few of them on our current freeway systems to meet practical needs. Upgrading a single-loop detector to a dual-loop detector requires putting in another single loop to pair up with the existing single loop. The cost for such an upgrade is expensive considering the hardware cost and the indirect cost resulted from lane closure. This implies that using single-loop measurements to estimate classified vehicle volumes is of practical significance.

This paper describes a new Artificial Neural Network (ANN) method, developed at the Smart Transportation Applications and Research Laboratory (STAR Lab) in the University of Washington, for bin-volume estimation using single-loop data. Before presenting the details of the ANN method in the methodology section, related studies are briefly introduced. Numerical test results and discussion on the performance of this ANN method are described in the section follows the methodology. The final section concludes this research effort and proposes further research topics.

2. PREVIOUS WORK

A single-loop detector outputs vehicle volume and lane occupancy periodically. For example, the WSDOT loop detection system reports data every 20 seconds and the California

Department of Transportation (Caltrans) loop detectors outputs data every 30 seconds. These aggregated interval measurements can be used to calculate the mean effective vehicle length (defined as sum of vehicle length and the single-loop length) using Equation (1) when vehicle speeds are constant and known.

$$\bar{l} = \frac{O(j)}{N(j)} \cdot s(j) \tag{1}$$

Where j = time interval index; N = vehicle count per interval; O = lane occupancy (percentage of time loop is occupied by vehicles); and s = speed for vehicles. Lane occupancy and vehicle count are direct measurements of single loops, but s must be estimated.

Many algorithms have been developed to estimate traffic speed from single-loop outputs. Several of these algorithms were based on the Athol's speed estimation formula *(5)*. These studies focused on improving speed estimation accuracy by choosing the right speed estimation parameter (commonly referred to as the *g* factor) or preprocessing single-loop data before applied to Athol's speed estimation formula. For example, Coifman et al. (*6*) recommended using the median lane-occupancy per vehicle for speed estimation. Wang and Nihan *(7)* suggested a filtering process to screen out intervals with long vehicles and using only short-vehicle measurements for speed calculation. Coifman *(8)* suggested calibrating *g* in free flow condition when traffic speed is known and applying the calibrated *g* for speed estimation in other time periods. Hellinga *(9)* proposed to calibrate *g* using the nearby dual-loop measured mean effective vehicle length. Wang and Nihan *(10)* opted to estimate mean effective vehicle length using a log-linear regression model that was calibrated using data from dual-loop stations.

Many researchers, such as Mikhalkin (*11*), have sought sophisticated filtering methods to improve speed estimates. Dailey (*12*) considered random errors in the measurements and used a Kalman filter for speed estimation. Pushkar et al. (*13*) developed a cusp catastrophe theory model to estimate speed. Sun and Ritchie *(14)* proposed a linear model to estimate individual vehicle speeds using slew rates of single loop inductive waveforms. They concluded that their proposed algorithm performed better than conventional speed estimation methods.

Though the estimated speed enables vehicle-length calculation and length-based vehicle classification, few studies were found to address vehicle classification issues using single-loop data. Wang and Nihan *(10)* built a log-linear model to estimate mean effective vehicle length using statistical moments of occupancy and volume. This estimated mean effective vehicle length gave one potential means of classifying vehicles with single-loop data. Kwon *(15)* developed an algorithm to estimated truck volumes in multi-lane freeway using lane-to-lane speed correlation. Cheung et al. *(16)* proposed a vehicle classification method using magnetic sensors. Mittal *(17)* proposed a statistical approach to estimate truck volumes on state highways. Sun et al. *(14)* used waveforms to extract vehicle lengths for vehicle re-identification. However, their algorithm requires a single-loop detector to output waveforms, which the majority of the existing single-loop detector cards cannot produce. This may seriously hinder the application of this method. Wang and Nihan *(7)* proposed a vehicle classification method based on the nearest neighbor decision rule for classifying vehicles into two categories (short vehicle and long vehicle) using single-loop measurements. While this algorithm produced reasonably accurate vehicle classification, the classification categories were rough. It would be better to classify vehicles into the four categories as has been done by the WSDOT dual-loop detectors. To reach such a goal, new research efforts are required.

3. METHODOLOGY

3.1 Artificial Neural Network (ANN)

Due to the stochastic features of traffic flow, deterministic mathematical equations based on certain assumptions for speed calculation typically do not work well for all situations and may result in significant speed-estimation errors under certain traffic conditions. When estimated speed is used in vehicle-length calculation, the secondary estimation procedure will generate significant errors cumulated from each estimation steps. Such problems, however, cannot be overcome by deterministic mathematical equations. ANN appears to be an effective solution for such a problem.

ANN is a powerful data modeling tool that is able to capture and represent complex input/output relationships and characteristics, such as associativity, self-organization, generalizability, and noise- and fault-tolerance *(18 and 19)*. Along with the development of computing science, the modern information processing technologies, such as genetic algorithm, expert systems, etc., ANN technologies have developed fast. ANN has been extensively used in many transportation studies and proven to be an effective solution to problems too complicated to be represented and optimized by conventional mathematical methods *(20, 21, 22, and 23)*. Therefore, we propose to use ANN for capturing the complicated relationships between single-loop measured variables and classified vehicle volumes under various traffic conditions.

3.2 ANN Architecture and Algorithm

Based on the observed traffic characteristics and the efforts of trial and error, we design a three-layer, feed-forward ANN with the architecture of back-propagation (BP), one of the most popular and stable network architectures, to estimate classified vehicle volumes from single-loop measurements. Standard back-propagation is a gradient descent algorithm; for our problem we adopt the Levenberg-Marquardt algorithm as the training rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back-propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. Properly trained BP networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input similar to the input vectors used in training can lead to an output close enough to the correct output. This generalization property makes it possible to train a network with a representative set of input pairs and get good results without training the network using all possible input and output pairs.

Following this idea, vehicle classification can be conducted independently without applying the estimated speed data. This kind of straightforward estimation avoids accumulating errors resulted from the inaccurate speed estimates. For this study, vehicles are divided into four classes that are consistent with the four bins used by the WSDOT detection system. The four length-based vehicle categories are described in Table 1.

TABLE 1 Four Length-Based Vehicle Categories Used By The WSDOT

Classes	Range of length	Vehicle types
Bin1	Less than 26 ft (7.92 m)	Cars, pickups, and short single-unit trucks
Bin2	From 26 ft (7.92 m) to 39 ft (11.89 m)	Cars and trucks pulling trailers, long single-unit trucks
Bin3	From 40 ft (12.19 m) to 65 ft (19.81 m)	Combination trucks
Bin4	Longer than 65 ft (19.81 m)	Multi-trailer trucks

In order to mine more associated relationships between a series of single-loop measurements and the corresponding bin volumes, we employ multi-dimensional input vectors to train the proposed ANN. Also, different structures are adopted to best fit the specific properties of each vehicle category. For instance, the neural network for estimating Bin 1 volume is designed to have 19 nodes in the input layer: 1 node for the time stamp input and 9 pairs of nodes for inputting single-loop measurements (volume and lane occupancy) over a three-minute period (there are nine 20-second intervals in a three-minute period). As a rule, a network with too few hidden units only occasionally discovers hidden dependencies in data sets and the network is likely to produce a significant number of errors. On the other hand, a network with too many hidden units tends to memorize all data instead of finding the associated relations and this often leads to an ineffective model with remarkable network errors. The hidden layer of this study is designed to have 35 nodes in order to provide the capacity for approximating and converging with the proposed ANN and to balance other factors of the sample data set. The output layer contains one node for Bin 1 volume output. The network structure for Bin 1 volume estimation can be briefly expressed as 19-35-1. Analogously, similar design procedures have been conducted for other vehicle categories. For each bin category, a different network structure distinguished by the number of nodes on the hidden layer is applied to discover and store the implicit interrelationships among single-loop measurements and the bin volume. Their input vectors are the same with that of Bin 1, which consists of one time stamp, nine continuous 20-second-sampling volumes and nine corresponding occupancies in 3 minutes. The network structures for estimating the volumes of Bin 2, Bin3, and Bin4 are designed as 19-8-1, 19-5-1, and 19-21-1, respectively, based on the characteristics of the data and results of trial and error. The entire network architecture is shown in Figure 1.

Though different network structures are proposed for estimating volumes of different vehicle categories, the same calculation procedure is adopted and implemented for all the four networks. This calculation procedure is described as follows.

Every element of the input vector is assigned an independent weighting factor w. The sum of the weighted inputs and the constant are transformed by a function $f(x)$ of the hidden layer. We use the differentiable tan-sigmoid transfer function $f(x)=\frac{1+e^{-x}}{1-e^{-x}}$ to generate their output to the hidden layer. The output of the input layer to hidden node i is:

$$o_i = f(w_i * X^T + \theta_i) = f(\sum_{j=1}^{N} \omega_{ij} x_j + \theta_i) \tag{2}$$

where, o_i is the output of the tan-sigmoid transfer function, $w_i = [\omega_{i1}, \omega_{i2}, \cdots, \omega_{iN}]^T$ is the vector of weights, θ_i is a constant for node *i*, and $X = [x_1, x_2, \cdots, x_N]^T$ is the vector of input activations.

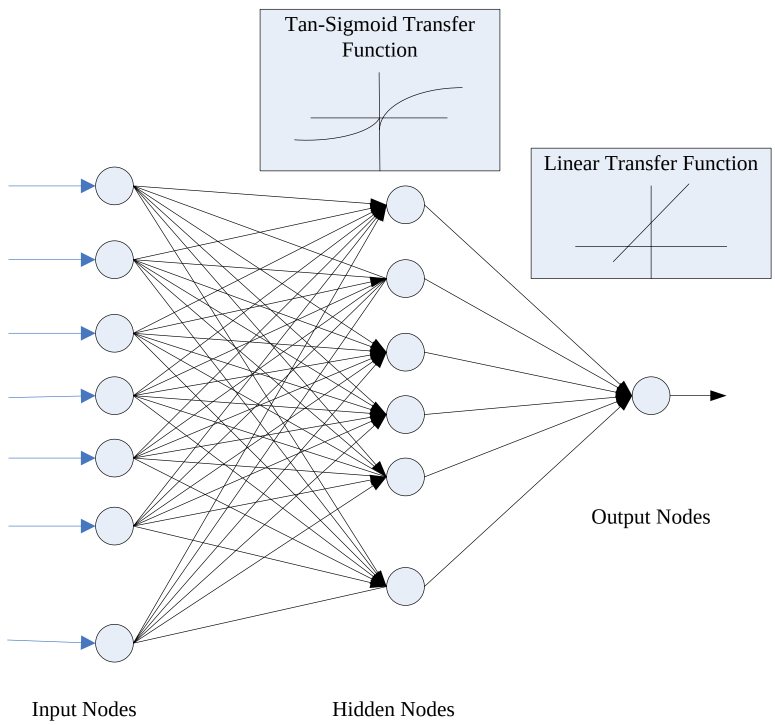

FIGURE 1 The architecture of the proposed artificial neural network model.

Similarly, a linear function is employed for the output layer

$$l(x) = kx + b \tag{3}$$

where *k* is the scope and b is the intercept of the linear function *l(x)*.

The output of the only node on the output layer is

$$y = l(\sigma * O^T + \eta) = l(\sum_{r=1}^{R} \delta_r o_r + \eta) \tag{4}$$

where $\sigma = [\delta_1, \delta_2, \cdots, \delta_R]^T$ is the vector weights, $O = [o_1, o_2, \cdots, o_R]^T$ is the vector of outputs from the hidden layer, η is the constant and y is the output of network.

After the neural network structure is set, the most important thing is to prepare the training data set and train the network. The training data set must be carefully selected so that the ANN can learn all the relationships through the training process. The designed BP learning phase consists of a forward phase followed by a backward phase. The optimal objective is to minimize the sum of squared errors at the layer at the output side. To do so, the gradient of the error with respect to the weights is found and the weights are adjusted backward toward the layer at the input side. For example, if a neuron is on the hidden layer, it is necessary to calculate the responsibility of the neuron's weights to the final error. To do this, the error at the output neurons is taken and propagated backwards through the current weights, e.g., the same weights used to propagate the activation forward. Adjustment to the neuron's weighting factors is needed if the responsibility exceeds a certain threshold. Then the training process is repeated until the specified stopping criteria are satisfied; that is, when the rate of change of the mean squared error is sufficiently small or the mean squared error is sufficiently small, the training stops, and the validation and testing process will be conducted successively *(24).*

The flow chart of the calculation procedure is shown in Figure 2. The main steps of this procedure are as follows:

1. Initialize the weights to small random values.
2. Specify the training vector pair (input—time series of volumes, occupancies, and time stamp and the corresponding output—detected bin volume) from the training set and present the input vector to the inputs of the network.
3. Calculate the actual outputs (estimated bin volume) as the forward phase.
4. According to the difference between actual and desired outputs (error), adjust the weights to reduce the difference (in a way that minimizes the error). This is the backward phase.
5. Repeat steps 2 through 4 for all training vector.
6. Repeat from step 2 until the error falls within the threshold value (the error for the entire set is acceptably low).
7. Stop the procedure of training and apply the network for bin-volume estimation.

After the neural network is properly configured and trained, it is ready for bin volume estimates.

4. ESTIMATION EXAMPLES AND DISCUSSION

To demonstrate the effectiveness of the proposed method, numerical experiments were conducted. Two loop stations on I-5 were selected for the test. Details of the stations are summarized in Table 2. Each station contains a dual-loop detector for each lane. One of the two single loops of a dual-loop detector is used as the single-loop data source and the dual-loop measured bin volumes are employed to verify the results from the proposed ANN.

The training data set was merely from ES-163R, a dual-loop station at Southbound I-5 under the NE 130th St over bridge. Fifteen days data, from April 30 to May 13, 1999, were used for the training process. The training data set included single-loop measured volume and occupancy as well as the bin volumes produced by the corresponding dual-loop detectors.

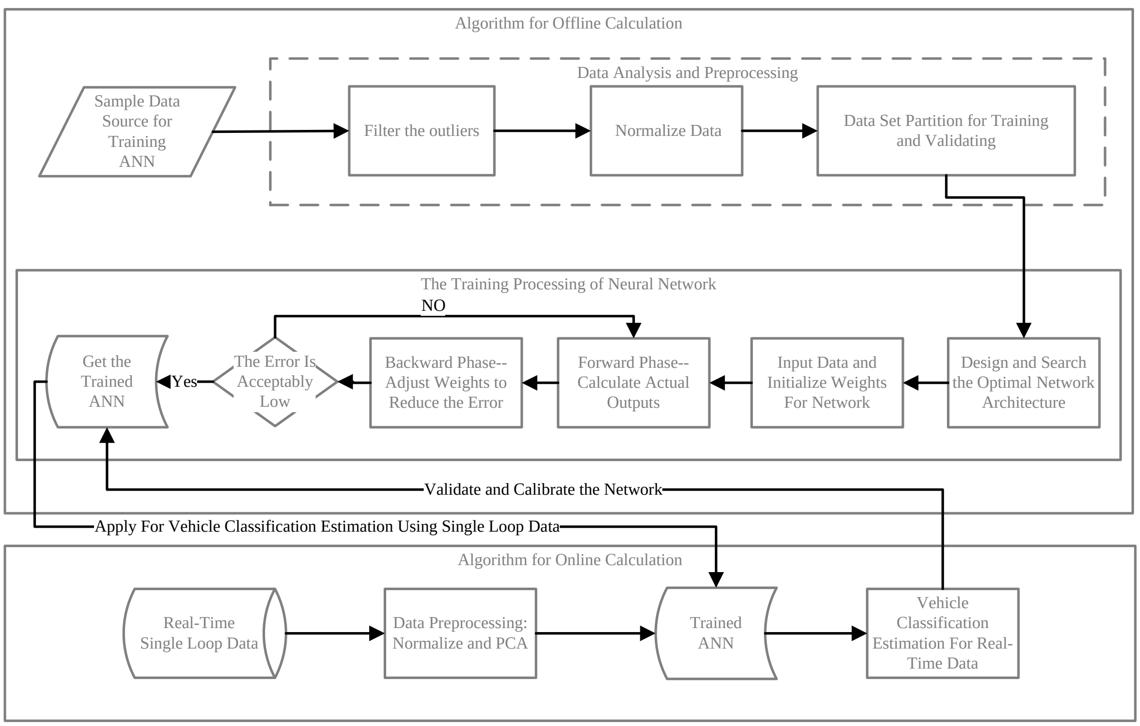

FIGURE 2 Flow chart of the ANN algorithm.

As mentioned earlier, the proposed ANN takes all nine 20-second interval measurements over a 3-minute period as inputs and outputs the bin volume for the 3-minute period. The internal associations among the input data and between the input data and the output data are mined and remembered by the ANN through the training process. To improve the rate of convergence and precision of approximation, the training set was normalized by setting the average of the set to zero and unifying its standard deviation. The Levenberg-Marquardt algorithm was employed by the training process. The entire ANN method was implemented by NeuroIntelligence, a special ANN software tool.

TABLE 2 Selected Loop Detectors For Example Study

Station code	Location	Lane No. (From right)	Dual-loop Code[1]	Single-loop Code[1]
ES-209D	SB I-5 & 156th St. SW	2	_MN__T2	_MN___2
ES-163R	SB I-5 & NE 130th St.	3	_MS__T3	MMS___3

[1] The WSDOT uses exactly 7 characters as loop code to indicate its location and purpose.

To verify the effectiveness of the proposed ANN and its temporal and spatial transferability, the trained ANN was applied to several test data sets. These test data were collected under various traffic conditions and time periods at the different locations. Interval volumes and occupancies measured by single-loop detectors were used for estimating classified vehicle volumes. The actual bin volumes measured by the corresponding dual-loop detectors were employed to check the results. Figures 3 and 4 show the estimated bin volumes and dual-loop observed bin volumes for May 13, 1999 (Thursday) at station ES-163R. Due to the low volumes (typically smaller than 2 per 3-minute period) in Bin 2 and Bin 3, results were integrated to 15-minute periods for comparisons and the results are shown in Figure 4. In addition to the general comparisons displayed in Figure 4, Figure 3 provides comparisons for the observed and estimated Bin-1 volumes at a higher level of resolution (3-minute level). We can see that the two curves overlap and synchronize very well with each other. Since single loop provides vehicle counts for all four bins, if Bin-1 volume is estimated accurately, the total large-vehicle volume, which contains Bin 2, Bin 3, and Bin 4, can be accurately determined consequently.

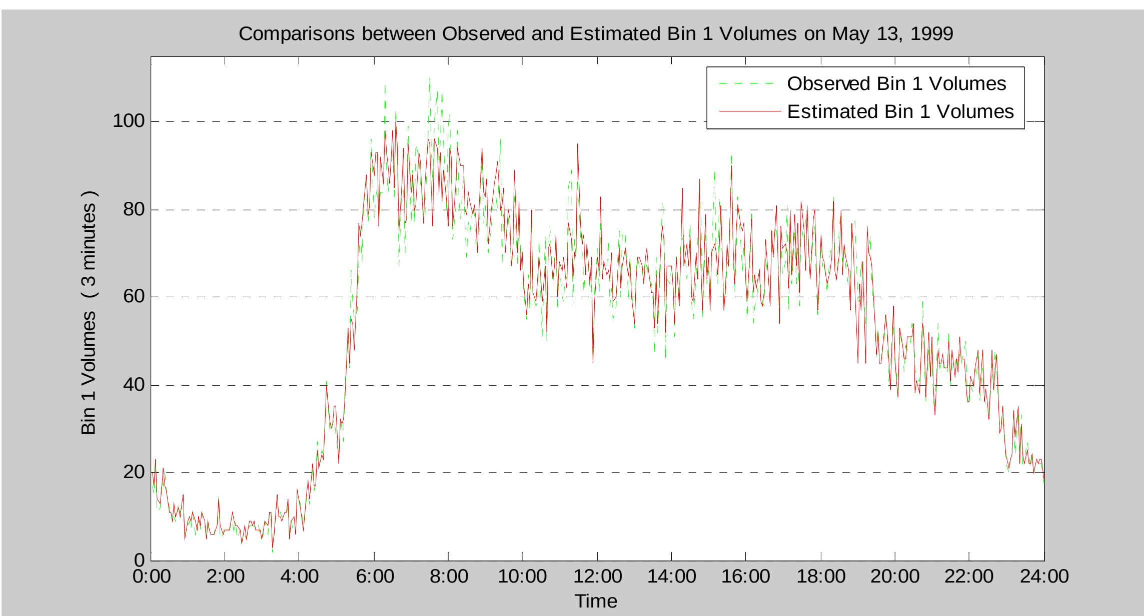

FIGURE 3 Comparisons between observed and estimated Bin 1 volumes at 3-minute level for detector of ES-163R: _MN___2 on May 13, 1999.

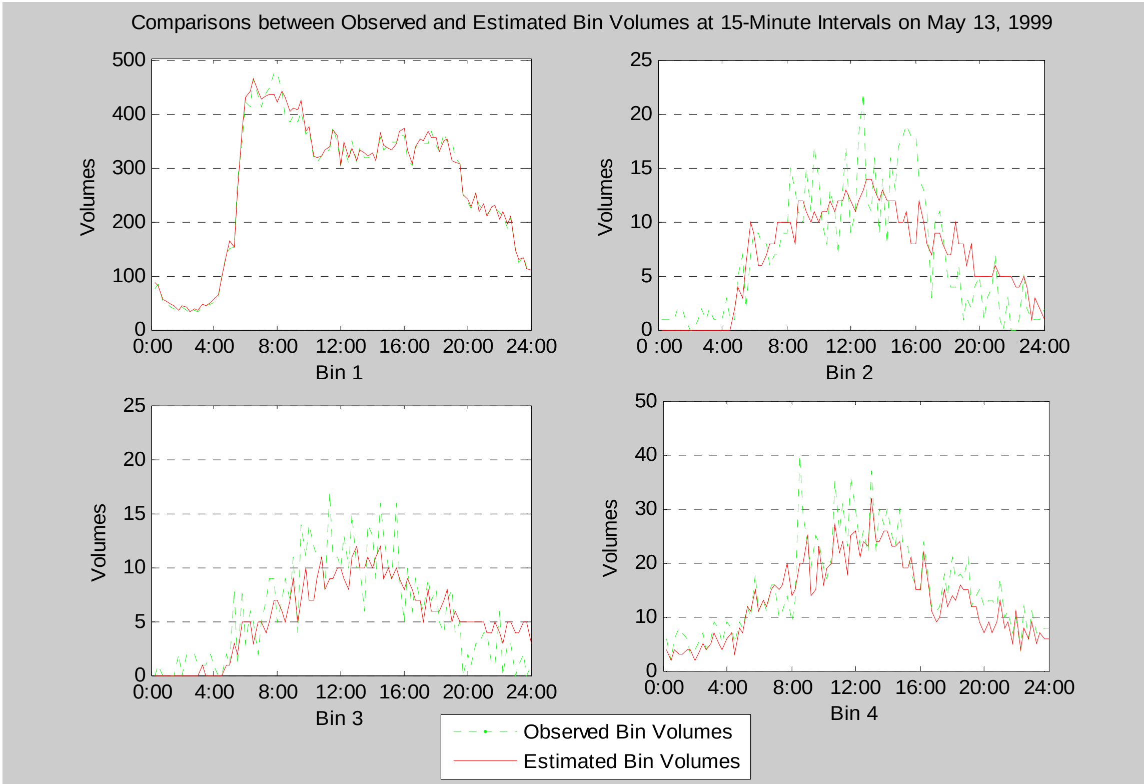

FIGURE 4 Comparisons between observed and estimated bin volumes at 15-minute level for detector of ES-163R: _MN___2 on May 13, 1999.

The same comparison curves for station ES-209D on May 10, 2004 are shown in Figure 5. We noticed that the estimated volumes for Bin 2 and Bin 3 were significantly larger than the observed Bin 2 and Bin 3 volumes during the afternoon peak period (16:00-18:00). This was probably because of the heavy congestion in this period. When traffic is heavily congested, vehicle speed is significantly lower, which causes unusually long on-times of shorter vehicles mistakenly identified as longer vehicles by the ANN model. Due to the relatively low volumes in Bin 2 and Bin 3, the impacts of such misclassifications were noticeable. Under such seriously congested conditions, a feasible solution is to re-train the ANN model using data collected under the congestion conditions. The ANN model will achieve better performance when the training data sets are collected from situations closer to the application scenario.

To facilitate the comparison between the estimated bin volumes and the observed bin volumes, we define a statistical variable, estimation error, as the observed bin volume minus the estimated value for each 3-minute period. Means and standard deviations of estimation error in each test case are calculated for the purpose of examining the temporal and spatial transferability of the ANN model. In order to evaluate the strength of association and synchronization between the observed data series and the estimated data series, correlation coefficients (R-value) were also computed. All these results are summarized in Table 3 and Table 4.

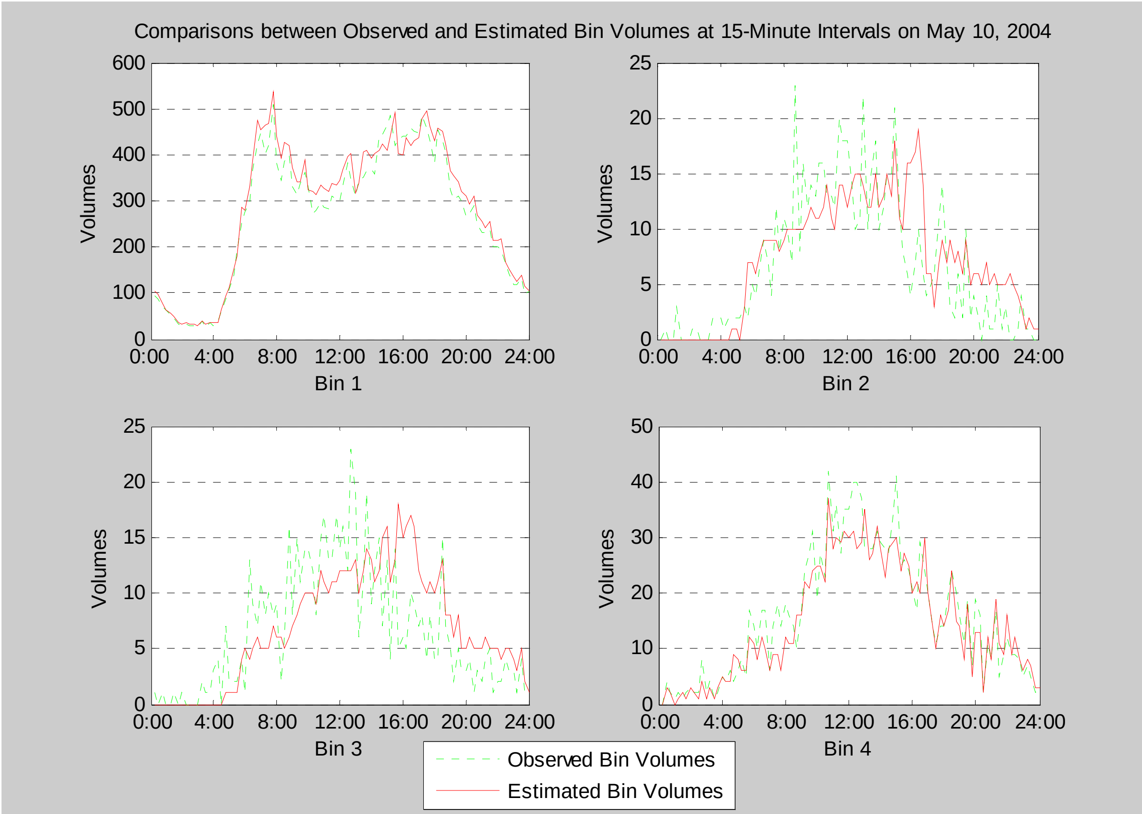

FIGURE 5 Comparisons between observed and estimated bin volumes at 15-minute level for detector of ES-209D: _MN___2 on May 10, 2004.

As can been seen from the comparison figures and statistics, this ANN model provided reasonably accurate bin-volumes for the test locations and days, especially for Bin 1 and Bin 4. The comparison curves for different days for station ES-163R indicated that the proposed algorithm yielded favorable results for bin volumes. As shown in Table 3, the means of estimation errors for Bin 1 were smaller than 0.6 for all the five days tested at station ES-163R, and the standard deviations were less than 6 with the estimation periods of 3 minutes. The R-values for Bin 1 were greater than 0.97, which indicate that the estimated and observed bin volumes are highly correlated. The estimation accuracy for Bin 1 was the best. Results for other bin volumes were also reasonably good. The result for Bin 4 was better than those for Bin 2 and Bin 3. The reason that the estimation results for Bin 2 and Bin 3 contained larger error was possibly because of the lower volumes in these two categories. The relatively smaller training samples for these two bins may leave many associations un-captured in the ANN model, and hence result in larger uncertainty in volume estimations of Bin 2 and Bin 3. However, considering the time lag between dual-loop and single-loop reported data and the possible errors with the dual-loop data, the difference between the estimated bin volumes and the observed bin volumes might have been exaggerated. From practice perspective, the estimated results are acceptable and applicable.

TABLE 3 Statistical Comparison Of Estimation Errors And Correlation Coefficients Between Measured And Estimated Bin Volumes At The Interval of 3 Minutes For Different Days At Station ES-163R

Time Periods	ES-163D											
	Bin 1			Bin 2			Bin 3			Bin 4		
	Mean	STD[1]	R[2]	Mean	STD	R	Mean	STD	R	Mean	STD	R
May 13, 1999	-0.47	4.68	0.99	0.07	1.4	0.54	0.09	1.13	0.57	0.44	1.31	0.83
September 6, 1999	-0.33	3.6	0.99	0.09	0.97	0.33	0.19	0.87	0.41	0.06	0.83	0.73
September 7, 1999	-0.29	4.95	0.99	0.38	1.37	0.53	0.6	1.31	0.45	0.53	1.24	0.85
September 8, 1999	-0.34	5.95	0.97	0.22	1.51	0.43	0.46	1.42	0.3	0.44	1.68	0.71
September 9, 1999	-0.59	4.43	0.98	0.24	1.26	0.52	0.49	1.34	0.36	0.33	1.44	0.79

[1] Standard deviation. [2] R is the correlation coefficient that describes the strength of the association and synchronization between measured and estimated bin volumes.

TABLE 4 Statistical Comparison Of Estimation Errors And Correlation Coefficients Between Measured And Estimated Bin Volumes At The Interval of 3 Minutes For Different Days At Station ES-209D

Time Periods	ES-209D											
	Bin 1			Bin 2			Bin 3			Bin 4		
	Mean	STD[1]	R[2]	Mean	STD	R	Mean	STD	R	Mean	STD	R
May 10, 2004	-3.17	8.88	0.96	-0.10	1.49	0.52	-0.03	1.48	0.49	0.29	1.67	0.81
May 11, 2004	-4.04	9.95	0.95	0.02	1.50	0.50	0.04	1.45	0.45	0.47	1.77	0.78
May 12, 2004	-3.89	9.38	0.96	0.02	1.46	0.50	-0.04	1.40	0.43	0.72	1.91	0.76
May 13, 2004	-2.83	10.54	0.94	0.06	1.69	0.51	-0.02	1.41	0.50	0.51	1.90	0.75
May 14, 2004	-1.98	12.55	0.92	-0.09	1.73	0.44	0.19	1.65	0.48	0.58	2.21	0.71
May 15, 2004	-1.76	9.44	0.95	-0.35	1.05	0.36	-0.30	0.92	0.34	-0.29	1.34	0.52
May 16, 2004	-2.17	8.30	0.96	-0.27	0.89	0.36	0.01	1.08	0.38	-0.14	0.92	0.67
May 17, 2004	-1.40	11.31	0.94	0.05	1.54	0.51	0.02	1.55	0.42	0.28	2.00	0.72
May 18, 2004	-1.75	13.94	0.91	0.18	1.81	0.47	0.16	1.61	0.51	0.79	2.40	0.74
May 19,2004	-2.01	10.49	0.98	0.14	1.40	0.59	0.18	1.27	0.56	0.43	1.98	0.80

[1] Standard deviation. [2] R is the correlation coefficient that describes the strength of the association and synchronization between measured and estimated bin volumes.

Estimation accuracies for days from Sept. 6 to Sept. 9, 1999 were comparable to that for May 13, 1999, a day from the period when the training data set was collected. This indicates that no significant error was observed when the trained ANN was applied to a different time period at the location from where the training data set was generated.

One dual-loop detector at station ES-209D was randomly selected to test the spatial transferability of the proposed ANN model. Ten days data, from May 10 through May 19, 2004, were collected for the test. Test results are summarized in Table 4. We can see that the means and standard deviations of estimation error became larger and R-values also decreased slightly. The largest mean of estimation error was -4.04 for Bin 1 at this station, about 9% of the average Bin-1 volume over a 3-minute course. Estimation accuracies for other bins are slightly lower than that of Bin 1 with the largest relative estimation error below 24.6%. Considering that the data set used for this test was collected five years after the training data set and at a different location, this test result is very favorable. This concludes that the proposed ANN model is robust and can be applied to different stations on I-5 with reasonable accuracy. However, better accuracy can be obtained if the ANN is tuned with recent data to adapt to the traffic pattern changes.

5. CONCLUSIONS

Due to the size and weight carried, trucks, buses, and recreational vehicles have inferior performance compared with passenger cars. Classified vehicle volume data are important input for traffic operation, pavement design, and transportation planning. However, classified vehicle volumes are not directly measured by the ubiquitously deployed single-loop detectors. Estimating classified vehicle volumes from single-loop outputs is of practical significance.

Several studies have tackled this problem using traditional analytical methods. However, these methods require either special hardware installations or estimate speed first before vehicle classification. Deterministic mathematical equations used for speed calculation are typically based on certain assumptions and they do not work well for all situations due to the stochastic features of traffic flow. Significant errors result if these equations are used for speed estimation under certain traffic conditions. When estimated speed is used in vehicle-length calculation, the estimation error accumulates and this degrades the accuracy of vehicle classification. To overcome this problem, we proposed an ANN method in this paper. The proposed ANN has three layers with back-propagation architecture. Vehicle classification categories employed by this study were consistent with the four-bin classification system currently used by the WSDOT dual-loop detection system. To achieve the best bin volume estimates, a specific neural network is designed and configured for each vehicle category. The proposed ANN is trained and tested using data collected from loop detector stations on I-5 in the greater Seattle area.

Our test results indicate that the proposed ANN method worked stably and effectively for the studied stations. The estimated bin volumes were reasonably accurate and can be applied to transportation practice. The temporal and spatial transferability tests showed that the proposed ANN is robust and can be applied to estimate bin volumes during different time periods and at different loop stations on I-5 without introducing significant errors. However, since all of the test-stations were from I-5, we cannot conclude that the proposed ANN is spatially transferable before conducting more tests using data from different routes.

Although the proposed ANN method produced favorable bin volumes, further improvements to its performance are possible through optimizing its network design and training, especially under heavily congested conditions. Additionally, more accuracy tests using data from different types of road and different areas also help understand the spatial transferability of the proposed method.

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