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Development of MLR, ANN and ANFIS Models for Estimation of PCUs at Different Levels of Service

S. Srikanth[1*] **and A. Mehar**[2]
1. Research Scholar, Department of Civil Engineering, National Institute of Technology, Warangal, India
2. Assistant Professor, Department of Civil Engineering, National Institute of Technology, Warangal, India

Corresponding author: *ssseelamsrikanth@gmail.com*

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ABSTRACT

Passenger car unit (PCU) of a vehicle type depends on vehicular characteristics, stream characteristics, roadway characteristics, environmental factors, climate conditions and control conditions. Keeping in view various factors affecting PCU, a model was developed taking volume to capacity ratio and percentage share of particular vehicle type as independent parameters. A microscopic traffic simulation model VISSIM has been used in present study for generating traffic flow data which some time very difficult to obtain from field survey. A comparison study was carried out with the purpose of verifying when the adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and multiple linear regression (MLR) models are appropriate for prediction of PCUs of different vehicle types. From the results observed that ANFIS model estimates were closer to the corresponding simulated PCU values compared to MLR and ANN models. It is concluded that the ANFIS model showed greater potential in predicting PCUs from v/c ratio and proportional share for all type of vehicles whereas MLR and ANN models did not perform well.

1. Introduction

The road traffic in India is highly heterogeneous comprising vehicles like Buses, Trucks, Auto-Rickshaws, Bikes/Scooters, Cycles, and Rickshaws etc. which comprise of wide ranging static and dynamic characteristics. Due to the highly varying physical dimensions and speed characteristics, it makes difficult for vehicles to maintain traffic lanes and forces to occupy any convenient lateral positions over the road width based on the availability at any instant of time. Traffic flow is defined as numbers of vehicles passing a section of road way or traffic lane per unit time. The definition is more standardized by considering passenger cars traffic stream rather than vehicles traffic stream under mixed traffic. Measurement of traffic flow under heterogeneous traffic conditions is usually carried out by converting individual vehicle type count into equivalent passenger cars units.

Two basic principles should be applied for the estimation of PCU values of the vehicles on any of the roadway types, as part of capacity analysis. The first principle links the concept of passenger car equivalency to the level-of-service (LOS) concept. The second principle emphasizes the consideration of all factors that contribute to the overall effects of the vehicles on traffic stream performance. Therefore, LOS concept is applied in this study to estimate the PCU value of each vehicle type. PCU of a vehicle type depends on vehicular characteristics, stream characteristics, roadway characteristics, environmental factors, climate conditions and control conditions (Anand et. al. [1]). Keeping in view various factors affecting PCU, a simulation model was developed taking volume to capacity ratio and percentage share of particular vehicle type as independent parameters. VISSIM software was used to simulate various varying factors in traffic for the development of model. VISSIM is a microscopic and behaviour-based traffic simulation models develop to analyse the full range of functionally classified roadways and public transportation operations.

Multiple Linear regression (MLR), artificial neural network (ANN) and ANFIS models proposed considering the effect of volume to capacity ratio (v/c) and the percentage share of vehicle type (P) on PCU of vehicle type. Multiple Linear Regression method attempts to model the relationship between two or more independent or explanatory variables and a response variable by fitting a linear equation to observed data. ANNs are computing systems having an input layer, one or more hidden layers and an output layer of neurons (Tracey et al., [2]). Although ANN is a powerful technique for modeling various real-world problems, it has its own shortcomings. If the input data are ambiguous or subject to a relatively high uncertainty, a fuzzy system such as ANFIS may be a better option [Moghaddamnia et al., [3].

Jang [4] first proposed the ANFIS method and applied its principles successfully to many problems [Lin and Lee [5]]. ANFIS is a scheme that uses the learning capability of ANNs to derive fuzzy IF–THEN rules with appropriate fuzzy set membership functions (Tay and Zhang [6]). The main strength of ANFIS in comparison with ANNs is that it generates linguistically interpretable IF–THEN rules. ANFIS models capture the relationship between input and output data by establishing fuzzy language rules, while ANNs do so in form of trained connection weights. Furthermore, it is reported that constructing an ANFIS model is less time-consuming than an ANN model (Azamathulla et al., [7]).

The objectives of this study was to develop and compare the capabilities of ANFIS, ANN, and MLR models to estimate PCU values of different vehicles by using volume to capacity ratio and percent share.

2. Literature review

Various studies have been performed by the researchers to estimate and analyse PCU factors for different vehicle types using many approaches. Some of them utilised traffic simulation models to find PCUs under a wide range of traffic and geometric conditions. Therefore a short discussion of the previous literature has been made in this section.

Keller et al. [8] developed passenger car equivalents through network simulation. Authors developed and tested a macroscopic traffic simulation model to derive passenger car equivalents for large size vehicles by taking vehicle size, traffic volumes and signal timing as important factors. The results obtained showed the estimated PCEs increased linearly as the traffic volume increases up to high levels. Ramanayya [9] opinioned that the standard for capacities followed in western countries cannot be directly applied as PCU of a vehicle type varies with levels-of-service and traffic composition. The equivalent design vehicle unit for different vehicle types estimated for different vehicle types increases with increase in the percentage of slow moving vehicles at a given level-of-service. Fan [10] applied constant v/c method to calculate PCEs values. Elefteriadou et al. [11] calculated PCU values on two lane highways and arterial roads based on simulation results. Authors developed formulated speed-flow curves with uniform traffic volume and with mix traffic volume. Simulation run performed by selecting subject vehicle type with incremental proportions by removing some passenger cars in the traffic stream. PCU values have been derived by comparing the points on the curves at same average speed level. Karim et al. [1] developed a method for estimation of PCU for different classes of vehicles on Malaysian roads. Authors analysed the effect of speed and headway on PCU values of different vehicle types under mixed traffic and used headway ratio, speed ratio and width ratio of cars to subject vehicle types for estimating PCUs.

Chandra and Kumar [12] studied the effect of lane width on PCU values of more than five vehicle types. A new concept called dynamic PCU was used to estimate the PCU factor of all types of vehicles that uses projected area and speed data for finding PCUs. It was found that the PCU of a vehicle type increases linearly with the width of the carriageway. However, the sensitivity was different for different vehicles. Wider roads lead to the greater freedom of movement which results in greater speed differentials between a car and a vehicle type and thus PCU value increases. Arasan and Arkatkar [13] examined the effect of traffic volume and road width on PCU of a vehicle under heterogeneous conditions using simulation model. HETEROSIM was used to study the vehicular interactions at micro-levels and simulated traffic over a wide range volume. Bains et al. [14] simulated Indian Expressway sections for evaluating Passenger Car Unit of different vehicle categories at different volume terrain conditions using micro-simulation model, VISSIM. Authors found that the PCUs decrease with increase in volume to capacity ratio. PCU of a subject vehicle category also decreases when its proportional share increases in the traffic stream. Mehar et al. [15] estimated PCU values of five vehicle types on interurban multi-lane highways. Dynamic PCU method was used to estimate PCUs. PCU values are also estimated at different LOS under varying traffic mix. The traffic simulation model VISSIM used for generating traffic flow after proper calibration. PCU values for different vehicle types were suggested at different LOS on four-lane and six-lane divided highways. Mehar et al. [16] studied the effect of traffic composition on the capacity of multilane highways using micro simulation model VISSIM. VISSIM software was calibrated using speed and flow data and found capacity values for different combinations of the mix in the traffic stream. The study proposed generalised equations to determine the capacity value at given composition.

Recently, researchers have used ANN and ANFIS techniques for development of models in various fields of civil engineering. Khademi et al. [17] used MLR, ANN, and ANFIS techniques for determination of the displacement of a concrete reinforced building. Authors found that ANN and ANFIS models show great accuracies in estimating the displacements whereas MLR model did not show acceptable accuracy. Jiang et al. [18] used ANN based approach for modeling the concrete corrosion processes in sewers. It found that ANN model performed better than a MLR model. Mashhadban et al. [19] used ANN and PSOA are used to generate a polynomial model for predicting self-compacting concrete (SCC) properties. The obtained results showed that PSOA integrated with the ANN is a flexible and accurate method for prediction of mechanical properties of fiber reinforced SCC properties. Zhou et al. [20] used ANN and ANFIS to predict compressive strength of hollow concrete block masonry prisms. The results showed that the proposed models have excellent prediction ability with insignificant error rates. Behfarnia and Khademi [21] used ANN and ANFIS models for estimation of 28-day compressive strength of concrete for 160 different mix designs. From the results, it is found that ANN model is recognized to be more fitting than ANFIS model in predicting the 28-day compressive strength of concrete. Biswas et al. [22] used ANN to develop a volume-based speed prediction model for individual vehicle category. Results showed a great deal of agreement between the predicted and the observed speeds.

3. Methodology

3.1. Multiple linear regression (MLR)

Linear regression is one of the oldest statistical techniques, and used in many researches (Guisan et al., [23]). The basic linear regression model has the form of equation 1.

$$Y = \alpha + X^T \beta + \varepsilon \tag{1}$$

Where Y denotes the dependent variable, α is a constant called the intercept, X =(X1,…,Xn) is a vector of explanatory variables, β ={ β1,…,βn} is the vector of regression coefficients (one for each explanatory variable), and ε represents random measured errors as well as any other variation not explained by the linear model. When calibrating a regression model, one tries to minimize the unexplained variation by the use of one of the estimation techniques such as the least-squares algorithm (Guisan et al., [23]). In this study, the statistical software EXCEL was used to develop the MLR models by considering dependent variable as PCU and independent variables are V/C ratio and proportional share.

3.2. Artificial neural network (ANN)

Neural networks represent simplified methods of a human brain and can be replaced with the customary computations which finds the problems difficult to solve. The artificial neural network obtains knowledge through learning. The same way as the human brain, ANN utilizes examples to learn. Artificial neural networks have been used broadly in the various engineering applications because of their ability to offer a worldwide practical method for real-valued, discrete-valued, and vector valued functions [24]. The general structure of ANN is shown in

Figure 1. The network contains three different layers namely input layer, hidden layer, and an output layer.

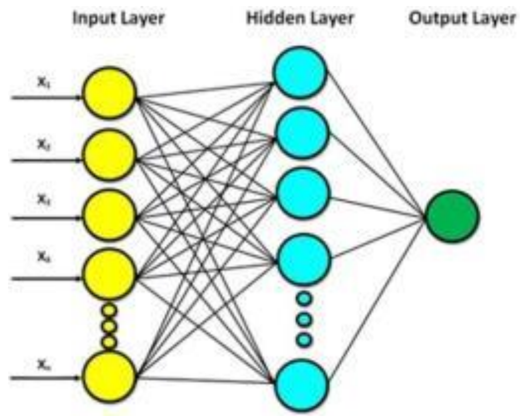

Fig. 1. Structure of ANN model

In this study, the Alyuda NeuroIntelligence software was used to develop the ANN models. The procedure of development of ANN model of this study is shown in Figure 2.

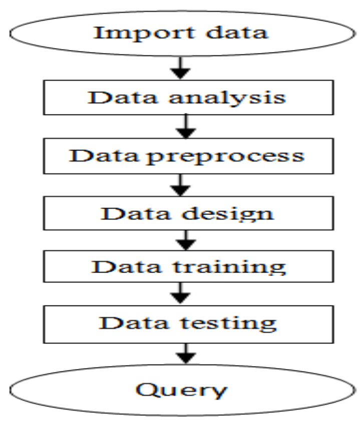

Fig. 2. Flowchart for development of ANN model

First, the basic data was input into the Alyuda NeuroIntelligence software. The function of analysis was activated. Among the data input in the software, 70% of them were selected as the training samples. The software would arrange them into a basic model for the subsequent training procedure. 15% of the data were selected for testing, and 15% of them were selected for verification. The Alyuda NeuroIntelligence software would automatically divide and arrange the input data in the input layers to [-1, 1] and output data in the output layer to [0, 1] and this process is called Data Preprocessing. In terms of the design, Alyuda Neuro Intelligence automatically generalized frameworks and presented the optimal neural network framework as reference. After many simulation trainings were completed, selected the best algorithm based on minimum absolute error training error. For data training chosen the best algorithm, Absolute error as zero and number of iterations as 10000 to obtain the output values and achieve the optimal convergence effect and the highest accuracy. After the data training simulation, the predicted data and actually input data were verified. The predicted value, actual value and the instantaneous predicted value were mutually compared for verification. The results could be used to verify the accuracy of the predicted value trained from the network model. From query, got the ANN model output values for a given input.

3.3. ANFIS

ANFIS is identified as a solution for different complex problems. ANFIS is a class of adaptive, multi-layer and feed-forward networks which is comprised of input–output variables and a fuzzy rule base of the Takagi–Sugeno type [25]. The structure of ANFIS is shown in Figure 3. The structure of ANFIS has contained five different layers. Layer 1 takes the responsibility for fuzzification of input feature values in the range of 0 to 1. Any node in the Layer 2 multiplies the incoming signals and sends the results out. The membership values are getting normalized in the Layer 3. Layer 4 can establish the relationship between the input and output values, and Layer 5 is also called the de-fuzzification layer consists of one single node which generates the summation of all incoming signals from previous node and results in a single value. In this layer, each rule output is added to the output layer [24,25].

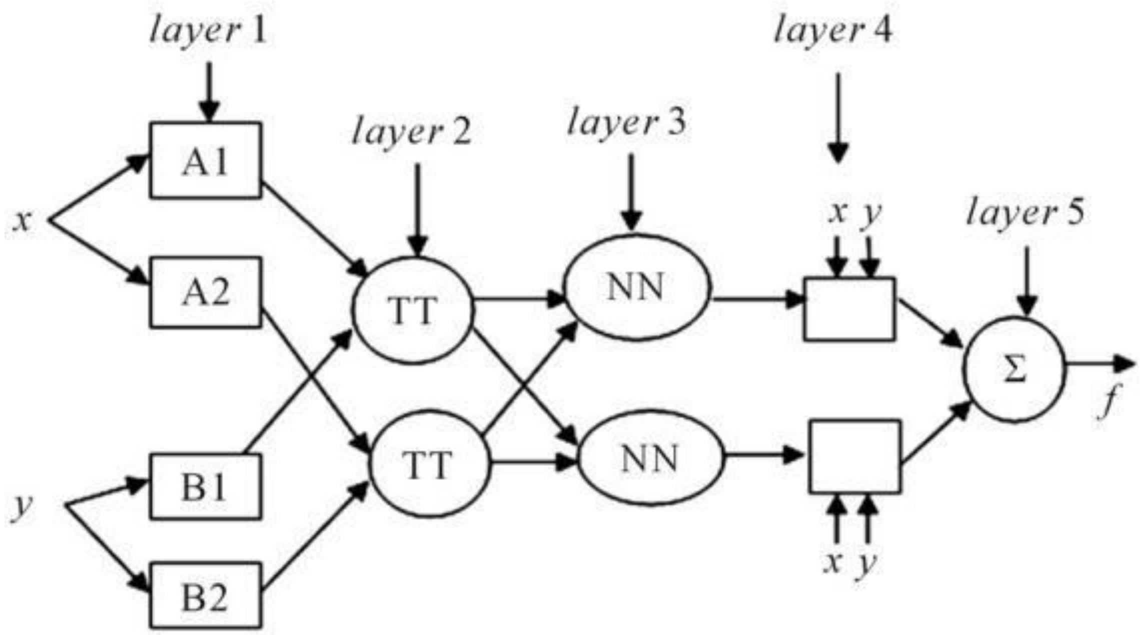

Fig. 3. Structure of ANFIS model

In this study, the MATLAB was used to develop the ANN models. The procedure of development of ANFIS model of this study is shown in Figure 4.

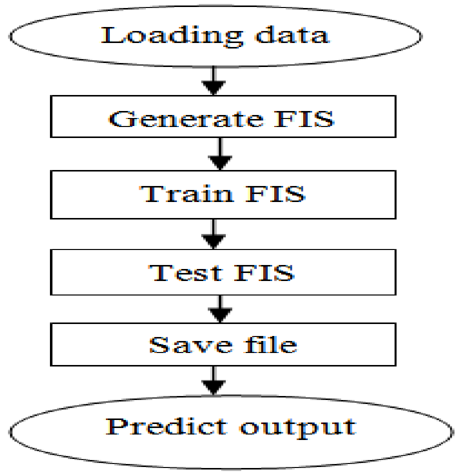

Fig. 4. Flowchart for development of ANFIS model

In a preliminary analysis, evaluated a command genfis1 with different types of membership functions (including gbellmf, gaussmf, gauss2mf, psigmf, dsigmf, pimf, trapmf, and trimf) and different numbers of epochs to get the best training performance with minimum squared error. The command genfis1 generates a Sugeno-typeFIS structure as initial conditions (initialization of the membership function parameters) for ANFIS training. Hybrid learning algorithm was also employed to optimize the learning procedure of the ANFIS models in each trial. The hybrid learning algorithm is a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters in emulating a training data set. Finally, the trimf with 3 numbers of membership functions was used for the adaptive system analysis.

4 Collection of field data and analysis

Field data was collected for present study on four-lane divided National Highway (NH) known as NH 163, Warangal to Hyderabad. The traffic flow data on section I was collected near Bibinagar village whereas traffic flow data on section II was collected near Madikonda village. The highway sections having paved shoulder in good condition with 1.5 m width. Traffic flow data on sections was collected by using video-graphic method. Data collection was performed for a period of 4 hours from 8 AM to 12 PM on a typical weekday under clear weather conditions. A trap length of 50 metres was marked on section of highway to estimate the speed of vehicles. All the vehicles were classified into seven categories namely, Standard car (CS), big utility car (CB), Two-wheeler (2W), Three-wheeler (3W), Heavy Vehicle (HCV), Multi-axle vehicle (MAV) and Bus (B). Standard car (CS) is defined as Passenger car in present analysis.

The speed parameter values and traffic composition on section I is given in Table 1. PCU values for different vehicle types are estimated by taking speed and area ratio of standard car to subject vehicle. Equation (2) estimates the PCU value of i^{th} (subject vehicle type) vehicle. This method is called as dynamic PCU proposed by Chandra and Sikdar, which is effectively used for interrupted and uninterrupted traffic conditions.

$$PCU = \frac{V_c/V_i}{A_c/A_i} \tag{2}$$

Where, PCU_i is PCU of the ith vehicle, V_c/V_i is speed ratio of the car to the ith vehicle and A_c/A_i is space ratio of the car to the ith vehicle.

Table 1. Speed data and traffic composition on section-I.

Vehicle Type	Section-I	
	Average speed(Kmph)	Composition (%)
CS	64	20
CB	67	6
LCV	48	7
HCV	42	4
TW	45	45
3W	41	12
B	45	3
MAV	39	3

5. Simulation analysis

Microscopic traffic flow simulation model VISSIM has been used in the present analysis to perform simulation analysis. For development of base model, a straight link of 1.4 km was created in VISSIM where only 1.0 km of centre part was considered for data analysis and 0.2 km length on either side of the stretch was considered as buffer link. Link was created with two lanes of 3.5 m width and shoulder lane of 1.5 m. To measure the simulated speed a section of 50 m was created at appropriate distance away from the point of vehicle input. The lateral and overtaking behaviours in VISSIM were modified as per left sided rule to truly replicate the non-lane based traffic conditions. Primarily, the model was run based on its default setting of parameters with basic field input data such as desired speed of each vehicle types and volume in veh/hr as per field observation. The simulation data was extracted for 1 hr and output was compared with field data. The comparison was made on basis of field traffic volume and speed distribution profile of vehicles. The comparison of traffic volume and speed profile of one of the vehicle types is depicted in Figure 5. Field traffic volume obtained at 5 min interval was compared with simulated volume at the same interval. Simulation output based on the default parameters settings has resulted large differences with the field data and it can be inferred that the VISSIM at default values of parameters not able to reflect field traffic flow behaviour.

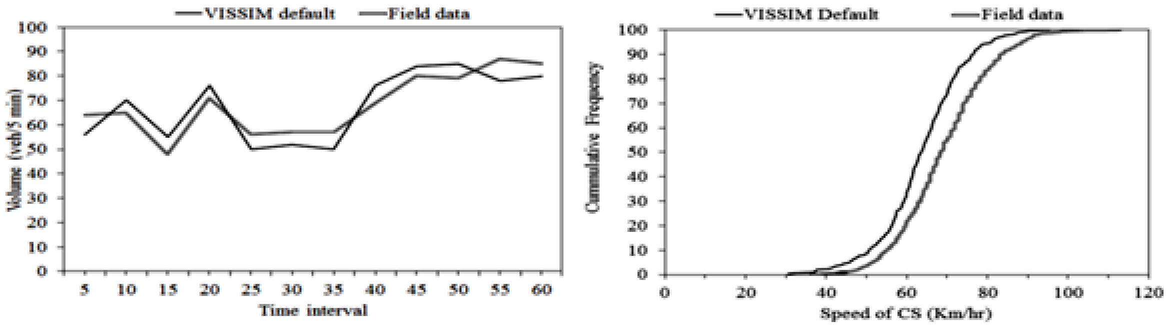

Fig. 5. Comparison of traffic volume and speed profile.

6. Calibration of VISSIM

VISSIM is used in the study for generating sufficient amount of speed and traffic flow data to determine the capacity. Among ten different driver behaviour parameters (CC0 to CC9) given in Wiedemann Model 99 only two of them namely; CC0 (standstill distance) and CC1 (time headway) are found to be significant as the traffic flow reaches to capacity [Mehar et al. [2013]]. These two parameters also governs the safety distance between the vehicles. Therefore, capacity obtained from default values of these two parameters may not be reliable unless calibration is performed using field data. Default values of CC0 and CC1 parameters are 1.5 m and 0.9 sec respectively. The values of CC0 and CC1 parameters are also depending on composition of traffic under mixed traffic condition. Hence, field traffic composition observed at the Section I was used as basis to perform calibration of VISSIM model.

Mehar et al. [2014] calibrated CC0 and CC1 parameters for vehicle type homogeneous traffic situation to find capacity of four lane divide highway. The simulation runs were performed under homogeneous type of vehicles such as ‘All CS’, ‘All CB’, ‘All HV’, ‘All 2W’,and ‘All 3W’. The CC0 and CC1 values as determined for each vehicle type through homogeneous type traffic simulation are given in Table 2 with their respective capacity values.

Table 2. VISSIM parameters for homogeneous traffic stream [Mehar et al. [26]].

Homogeneous vehicle type	Simulated capacity	Calibrated values	
		CC0 (m)	CC1 (sec)
SC	4950	1.17	1.1
BC	3385	1.5	1.4
2W	9540	0.3	0.3
3W	2950	1.5	0.9
HV	1245	2.4	1.7

The above driver behaviour parameters (CC0 and CC1) for each vehicle type were used for the base model to replicate the mixed traffic behaviour. CC0 and CC1 parameters are most influence parameters to estimate the capacity using VISSIM. The traffic regulations were chosen as "left-side traffic" to replicate the Indian traffic conditions. The lateral behaviour of each vehicle type was also adjusted such that their desired position at free flow is on any lane. A new link behaviour type "Mixed traffic" was created in which each vehicle type class and its driving behaviour was added in this category. This behaviour type was selected in Link data for the created link. Field volumes were given as input from lower (100 veh/hr) to higher (7000 veh/hr) levels along with composition of vehicle types as observed in the field. The simulation was run for about 10800 simulation seconds. For evaluation files related to vehicle record, travel time and vehicle inputs were chosen to get the required output.

The travel time of each vehicle type over the trap length obtained from the simulation was used to calculate the speed of each vehicle type. The average speed of each vehicle type obtained from field data and simulated data were compared and is shown in Figure 6. Fine tuning of VISSIM parameters was confirmed as speed values fall under acceptable limits of percentage error (5%). Hence VISSIM model may be used for further study.

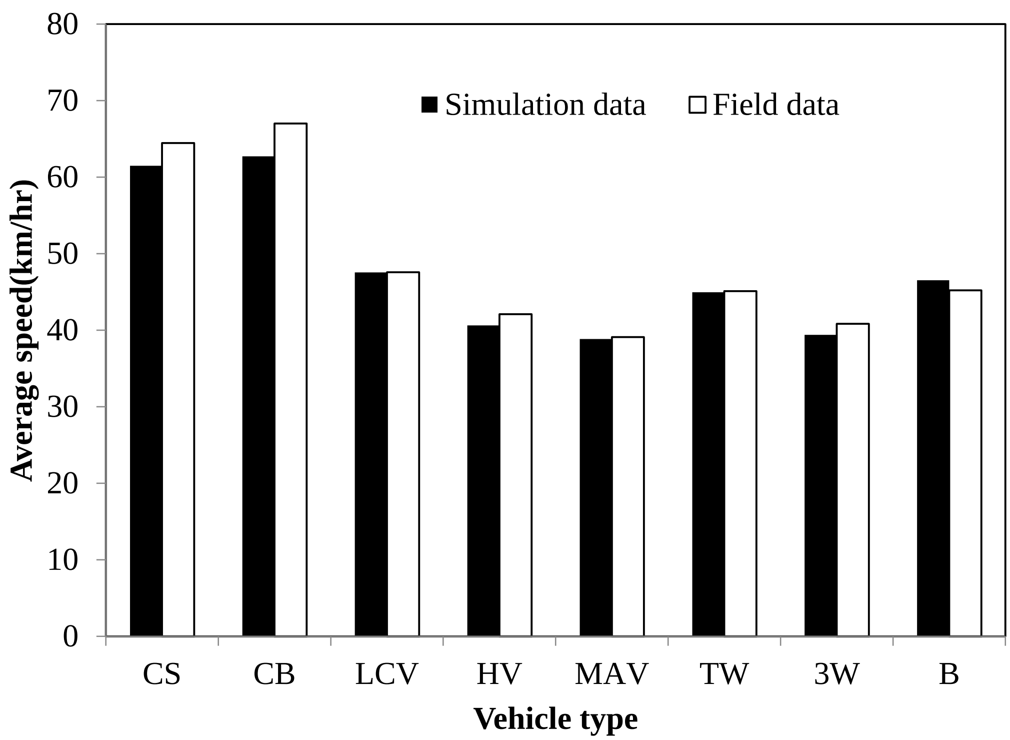

Fig. 6. Average speed of each vehicle type for the simulated data and field data

7. Development of PCU model

Section-II was considered for the development of model. Only two vehicle types (subject vehicle and standard car) were simulated at a time with 10% subject vehicle and 90% standard car (CS). Similarly, the simulation was done at 20% and 30% subject vehicle proportions. Traffic volume was increased from lower to higher volume levels (100 vph to 6000 vph) and simulation was run for 2 hrs. From the simulation output, the speed-flow curve was developed for each scenarios and capacity was estimated in veh/hr. The maximum volume for each vehicle type scenario, under varying proportional share was obtained on speed volume curve. Maximum volume obtained under varying proportional share of subject vehicle type mixed with standard car traffic stream is mentioned in Table 3.

Table 3. Simulated capacity on four-lane divided section and share of second vehicle type

% share	Maximum Volume (vph)						
	CB	TW	3W	LCV	HV	MAV	BUS
10	4512	5208	4320	4452	3900	3936	3984
20	4236	5388	4224	4248	3600	3312	3600
30	4260	5544	4224	4152	3360	2988	3264

The maximum volume as obtained on speed-volume curve likely to be reduced with increase in percentage share of vehicle types like CB, HV, MAV, LCV, BUS, 3W. The reduction in capacity is mainly due to the different size and different operating capabilities required by subject vehicle types are compared to standard cars. However, the addition of amount of vehicle type TWs has increased the capacity of section due to their less space occupancy and good manevouerabiity. The determined capacity values are used to estimate the critical volume ratios. These critical volume ratios are estimated as the ratio of volume to capacity value of the simulated section using speed-volume curve. For example, speed –volume for 30% LCV+70% cars is shown in Figure 7. This figure shows the demarcated lines at the volume levels upto which the average stream speeds are consistently reduced. The change in stream speed resulted in change in the traffic flow. Thus, volume to capacity ratios were estimated and level of service boundaries are defined. The procedure was followed for each vehicle type scenarios.

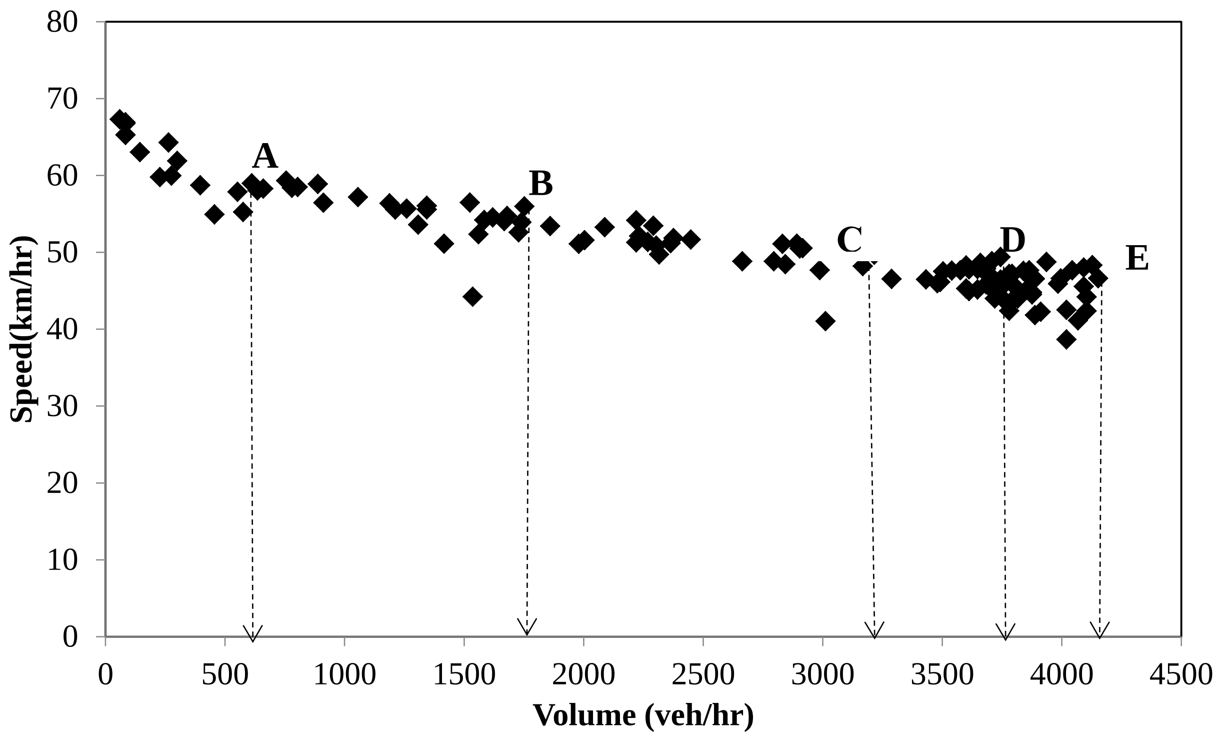

Fig. 7. Determination of v/c ratio corresponding to different Levels of Service for LCV at 30% of its own proportion

8. Estimation of PCU values at different v/c ratio and % share

Initially the PCU value of each vehicle type was estimated by using Dynamic PCU method. The PCU value of each vehicle type at different V/C ratio and at different percentage share was found for the development of the model. For the development of model independent parameters having no correlation are required. It was found that there was no correlation between volume to capacity ratio and the percentage share of vehicle type. Hence, these independent parameters were used for the development of MLR, ANN and ANFIS models.

9. Results and discussion

The descriptive statistical characteristics of the PCU data for different types of vehicles were derived through SPSS 16 software and are given Table 4. Histograms of different vehicles also plotted using SPSS 16 for understanding the distribution of PCUs and is shown in Figure 8. Figure 8 revealed that there was little variability in the sample distributions of the variables used in this study to develop prediction models.

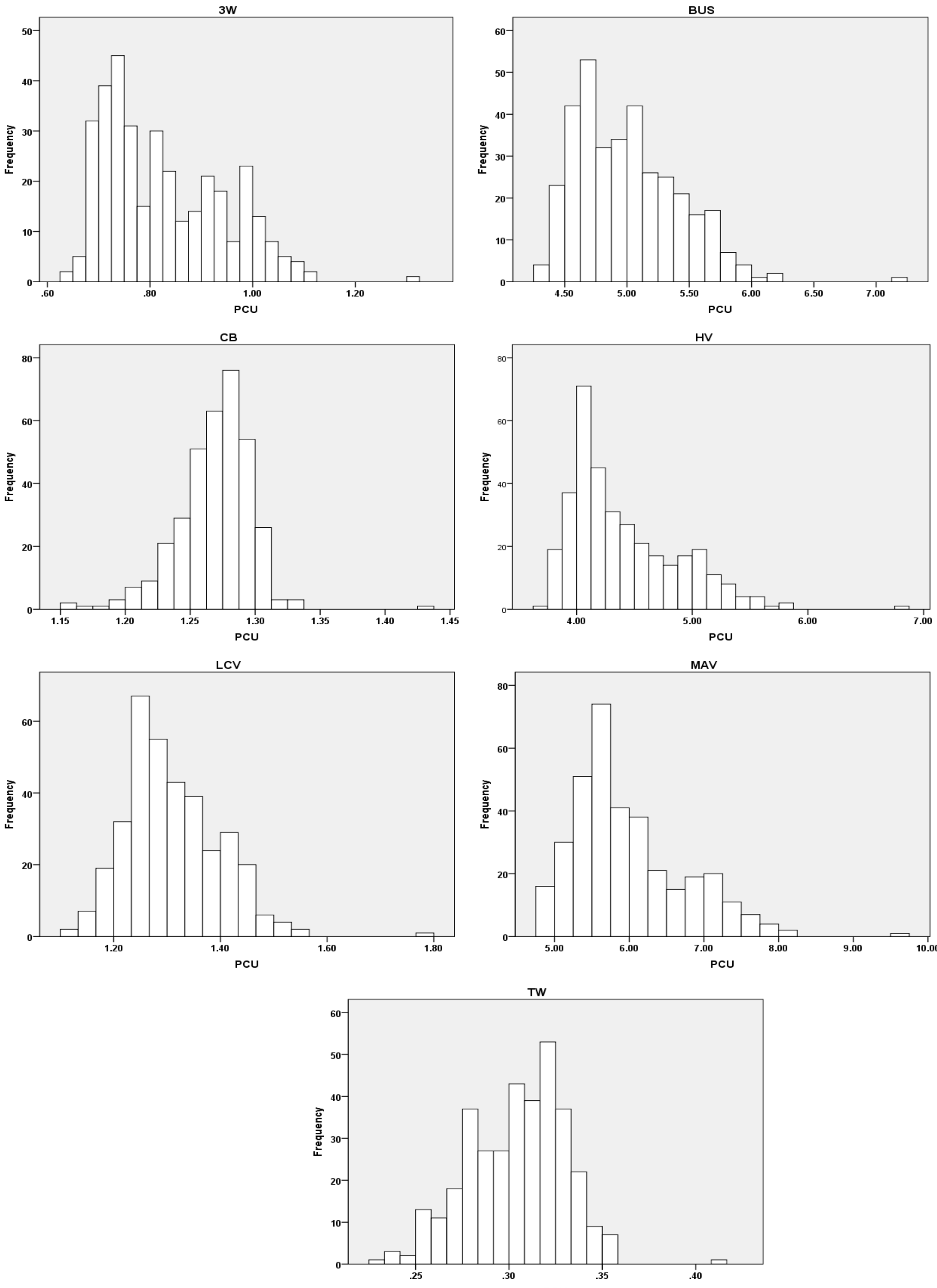

Fig. 8. Histograms of different vehicle types

Table 4. Descriptive statistics of PCUs

Vehicle type	PCU			
	Maximum	Minimum	Average	Standard deviation
TW	0.42	0.23	0.30	0.03
3W	1.31	0.64	0.82	0.13
CB	1.42	1.16	1.27	0.07
LCV	1.80	1.11	1.31	0.09
HCV	6.81	3.69	4.40	0.47
BUS	7.24	4.31	5.00	0.42
MAV	9.71	4.76	5.98	0.75

MLR models were developed for all type of vehicles by considering v/c ratio and % share as input variables and is given in Table 5. In the table 5 value 0.00 indicates the P-value. According to the evaluation indices, it appears that the conventional regression models were to some extent poor in predicting PCUs.

Table 5. Multiple Linear Regression (MLR) models for PCUs

Predictor	Vehicle types						
	TW	3W	LCV	CB	HCV	BUS	MAV
Intercept	0.357 (0.00)	1.095 (0.00)	1.518 (0.00)	1.2 (0.00)	5.78 (0.00)	6.07 (0.00)	8.06 (0.00)
V/C ratio	-0.062 (0.00)	-0.316 (0.00)	-0.22 (0.00)	0.079 (0.00)	-1.41 (0.00)	-1.08 (0.00)	-2.16 (0.00)
% share	-0.0006 (0.00)	-0.00215 (0.00)	-0.0025 (0.00)	-----	-0.0149 (0.00)	-0.013 (0.00)	-0.022 (0.00)
R-square	0.36	0.49	0.32	0.33	0.77	0.4	0.518
Adjust R-square	0.35	0.485	0.32	0.32	0.77	0.39	0.516

To produce the best results by the network, several architectures including different number of hidden layers, distinct activation functions as well as different combination of neurons in each hidden layer was utilized in training of all ANN models. Tables 6 summarize the best architectures, activation functions and number of iterations used in the network to obtain the best results for all types of vehicles.

Table 6. Characteristics of the best structure of ANN architecture

Vehicle type	Best architecture	Best algorithm	Training error	Iterations
TW	4-5-1	Conjugate Gradient Descent	0.011494	10000
3W	4-4-1	Conjugate Gradient Descent	0.035779	10000
CB	1-7-1	Quick Propagation	0.017115	10000
LCV	4-4-1	Quick propagation	0.030412	10000
HCV	4-7-1	Conjugate Gradient Descent	0.157045	10000
BUS	4-8-1	quick propagation	0.15271	10000
MAV	4-10-1	Quasi-Netwon	0.21338	10000

Table 7 indicated the results of statistically performance and optimal architecture of ANFIS networks. The combination of Trimf and constant MFs for input and output layers, respectively, and hybrid as learning method produced the better consequences rather than the application of other combinations for all types of vehicles. The 50 epochs was used to train the model for lower RMSE training error for all vehicle types except TW. The 70 epochs was used to train the TW type vehicle model.

Table 7. Characteristics of the best structure of ANFIS architecture

Vehicle type	Optimization algorithm	Training error	Epochs
TW	Hybrid	0.022568	70
3W	Hybrid	0.081484	50
CB	Hybrid	0.069125	50
LCV	Hybrid	0.084698	50
HCV	Hybrid	0.20302	50
BUS	Hybrid	0.35374	50
MAV	Hybrid	0.51569	50

10. Comparison of MLR, ANN and ANFIS models

The RMSE and MAPE statistical tools were used to compare the accuracy of the ANFIS, ANN and MLR models in estimating the PCU. Comparison of the performances of ANFIS, ANN and MLR models for estimation of PCU of different vehicle types in training period are presented in Table 8. ANFIS showed the best estimation performance; namely, the lowest RMSE values were obtained when the data was modelled using ANFIS. When the calculated MAPE values were taken into consideration; however, ANN was observed to exhibit the best prediction performance because the lowest MAE values were obtained. On the other hand, the MLR had the lowest accuracy regarding the RMSE and MAE statistical accuracy testing tools. These results meant the behaviour of the inputs and output was non-linear. Prediction capability of ANFIS models is better than the ANN and MLR models. Based on these results; therefore, the ANFIS model can be suggested for estimation of PCU values.

Table 8. Comparison of performances of the MLR, ANN and ANFIS models

	Linear regression		ANN		ANFIS	
Vehicle type	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
TW	0.44	0.49	0.38	0.48	0.22	0.10
3W	1.74	0.72	1.48	1.07	0.19	0.09
CB	0.91	0.60	0.94	0.80	0.86	0.34
LCV	1.32	0.71	1.17	0.82	0.04	0.00
HCV	3.45	0.88	1.19	1.85	0.24	0.07
BUS	5.32	0.65	3.91	1.77	0.35	0.07
MAV	12.51	31.75	6.07	3.70	0.59	0.55

11. Conclusions

The following conclousions were made from the present study.

- Microscopic traffic simulation model VISSIM used to generate field traffic condition for development of linear PCU equations. The PCU equations are established by using dynamic PCU expression.
- Volume to capacity ratio and traffic mix both were found as significant variables for PCU estimation. PCU equations established for each vehicle type include the effect of varying volume to capacity ratios. However, the effect of percentage share is not significantly observed on PCU values of vehicle type CB under lower to higher traffic volume conditions.
- Histograms revealed that there was variability in the distributions of PCU of different vehicle types.
- According to the evaluation index (R^2), it appears that the conventional regression models were to some extent poor in predicting PCUs.
- In ANFIS model, the combination of Trimf and constant MFs for input and output layers, respectively, and hybrid as learning method produced the better consequences rather than the application of other combinations for all types of vehicles.
- ANFIS showed the best estimation performance; namely, the lowest RMSE and MAPE values were obtained when the data was modelled using ANFIS compared to ANN and MLR.
- ANFIS model estimates were closer to the corresponding simulated PCU values compared to MLR and ANN models.
- It is also concluded that the ANFIS model showed greater potential in predicting PCUs from v/c ratio and proportional share for all type of vehicles whereas MLR and ANN models did not perform well.

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