COMPARATIVE STUDY OF MLR, ANN AND ANFIS MODELS FOR ESTIMATION OF PCUS AT DIFFERENT VOLUME TO CAPACITY RATIOS

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Abstract

PCU models are developed in the present study by taking volume-to-capacity ratios and percentage shares of vehicle types. Field data collected on four-lane highway sections are analysed to develop speed-flow relations. A microscopic traffic simulation model VISSIM is also deployed for generating traffic flow data after calibrating it for mixed traffic conditions. PCUs of different vehicle types at six lane and eight lane divided highways are also estimated. The effect of number of lanes on PCUs was studied, and it was observed PCU of each vehicle type decreases with increase in the number of lanes and at a different level of service. The Adaptive neuro-fuzzy inference system (ANFIS), Artificial neural network (ANN) and Multiple linear regression (MLR) models are used for development of PCU Models from the results obtained through VISSIM simulation. A comparative study was performed with PCU obtained from different models reveals that the ANFIS model showed greater potential in predicting PCUs at varying v/c ratios and proportional share of vehicle types in the traffic stream. The models developed in the present study may be used for developing algorithms which describe traffic flow behaviour under mixed traffic conditions with better accuracy and precision.

Keywords: PCU, MLR, ANN and ANFIS

Introduction

Roadway traffic in India is highly heterogeneous that comprises of different vehicle types with 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 thereby they occupy any convenient lateral positions over

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the road width. Traffic flow is defined as numbers of vehicles passing through a section of roadway 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 conditions. The measurement of traffic flow under heterogeneous traffic conditions is usually carried out by converting classified vehicular count into equivalent numbers of 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*., 1999).

Keeping in view the various factors affecting PCU, a PCU models were developed in the present study by taking volume to capacity ratios and percentage shares of particular vehicle types into consideration. VISSIM software was used to simulate the mixed traffic flow after calibrating it by using field observed input parameters such as traffic volume, speed and vehicle composition. Validation of VISSIM model was also performed with different set of field data for the development of PCU models under controlled traffic flow conditions.

Three different approaches are used for the estimation of PCU values of vehicle types as observed in the field namely, MLR, ANN and ANFIS models. For estimation of PCU of a vehicle type, the parameters such as volume to capacity ratio (v/c) and percentage share (P) of own vehicle type are considered in all the methods.

The MLR 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*., 2011). 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*., 2009).

Jang (1993) first proposed the ANFIS method and applied its principles successfully to many problems (Lin and Lee, 1995). 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, 1999). 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*., 2009).

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.

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.

Ramanayya (1988) 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 (1990) applied constant v/c method to calculate PCEs values. Karim *et al*. (1999) 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 (2003) 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. Arasan and Krishnamurthy (2008) used simulation technique for four-lane divided road to quantify the impedance caused to traffic flow by the different categories of vehicles in heterogeneous traffic in terms of PCU using simulation technique and also to study the effect of road width and traffic volume on PCU values of vehicles. From the results obtained it was found that the PCU value of a vehicle significantly changes with change in traffic volume. Aggrawal (2008) used fuzzy model for estimation of PCU values in heterogeneous traffic conditions. Proposed fuzzy model have four inputs namely pavement width, shoulder condition, directional split and slow moving traffic and provides a crisp value of PCU for bus. Arasan and Arkatkar (2010) 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*. (2012) 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*. (2013) 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*. (2015) 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. Mardani *et al*. (2016) proposed concept of a stream equivalency factor was suggested to convert a heterogeneous traffic stream into homogeneous stream. A simple linear equation was developed using the field data to calculate equivalency factor for a known traffic volume and composition.

Method

MLR Technique

Linear regression is one of the oldest statistical techniques, and used in many researches (Guisan *et al*., 2002). The basic linear regression model has the form of Equation 1.

$$Y = \alpha + X^T \beta + \varepsilon \qquad (1)$$

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.*, 2002). 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.

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 (Khademi *et al.*, 2017). 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.

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

First, the basic data was input into the Alyuda NeuroIntelligence software. Among the data input in the software, 70% of them were selected as the training samples, 15% of the data were selected for testing, and 15% of them were selected for verification. The software would arrange training samples into a basic model for the subsequent training procedure. 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). In terms of the design, Alyuda NeuroIntelligence 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. After the data training simulation, the predicted data and actually input data were verified. The predicted value from software and actual values 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.

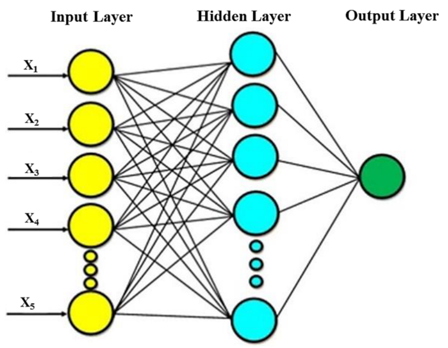


Figure 1. Structure of ANN model

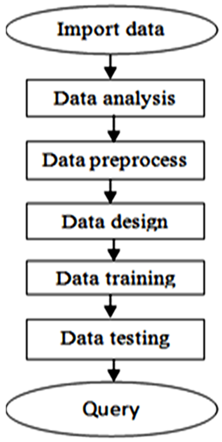


Figure 2. Flowchart for development of ANN model

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 (Khademi *et al*., 2016). The structure of ANFIS is shown in Figure 3.

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.

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 backpropagation 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.

Field Data and Analysis

The study locations are selected as sections of different National Highways in India. Four different sections of divided highways were selected, and traffic survey was performed to collect speed and flow data under different roadway and traffic conditions. Details of study locations are given in Table 1. Video graphic method was used for collecting the field data, and recording of traffic operation was under clear weather conditions for minimum 3 to 4 h on

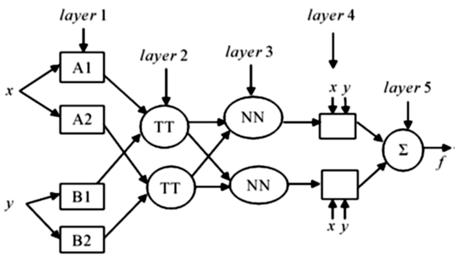


Figure 3. Structure of ANFIS model

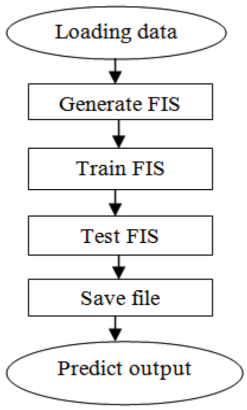


Figure 4. Flowchart for development of ANFIS model

Table 1. Study locations details

Section	Highway No.	Name	Type of highway	Type of shoulder	Properties
Section-I	NH 202	Bibinagar	4 lane divided	paved	CW: 7.0 m SW: 1.5m
Section-II	NH 202	Madikonda	4 lane divided	paved	CW: 7.0 m SW: 1.5m
Section-III	NH 16	Vijaywada-Guntur	6 lane divided	paved	CW: 10.5 m SW: 1.8m
Section-IV	NH-8	Delhi-Gurgaon	8 lane divided	paved	CW: 14.0 m SW: 1.8m

* CW= Carriageway width, SW= Shoulder width

typical weekdays. A trap length of 50 m was marked on the highway sections to estimate the average speed of vehicles. Vehicle type survey was also done, and clear dimensions of different vehicle types are measured. The information of vehicle type is shown in Table 2. All the vehicles were classified into seven categories namely, Standard car (CS), big utility car (CB), Two-wheeler (2W), Three-wheeler (3W), Light Commercial Vehicle (LCV), Heavy Vehicle (HV), Multi-axle vehicle (MAV) and Bus (B). Standard car (CS) is defined as Passenger car in present analysis.

Classified volume count at every 1 min interval was made by playing recorded videos. The speed of the vehicle types was also measured by noting down travel time in each 1 min interval from videos. Thus total traffic volume and composition data were obtained from each section. The average speed estimated at every 5 min was used an estimation of PCU values for each vehicle types. Speed data characteristics on each section are given in Tables 3 and 4. PCU values for different vehicle types are

Table 2. Dimensions of vehicles

Vehicle Type	Length (m)	Width (m)	Projected Area (m^2)
Standard Car (CS)	3.6	1.70	6.12
Big Car (CB)	4.6	1.80	7.82
Light Commercial Vehicles (LCV)	4.3	1.56	6.71
Heavy Vehicles (HV)	6.7	2.30	15.41
Multi Axle Vehicles (MAV)	11.5	2.42	27.83
Two-Wheeler (TW)	1.97	0.74	1.46
Three Wheeler (3W)	3.20	1.30	4.16
Bus (B)	10.6	2.40	25.44

Table 3. Traffic characteristics of sections

Vehicle Type	Section-I		Section-II		Section-III	
	Average speed (Kmph)	Composition (%)	Average speed (Kmph)	Composition (%)	Average speed (Kmph)	Composition (%)
CS	66.59	32	64	20	83.3	22
CB	69.8	7	67	6	75.1	10
LCV	49.8	3	48	7	60.1	4
HV	46.7	4	42	4	51.9	5
TW	50.02	45	45	45	56.5	49
3W	39.5	5	41	12	49.4	2
B	50.47	4	45	3	66.1	5
MAV	…….	…..	39	3	50.9	3

Table 4. Details of vehicle types on eight-lane section

Vehicle type	Average speed (kmph)	Composition (%)
CS	83	35
CB	84	22
HV	66	15
TW	67	28

estimated by taking speed and area ratio of standard car to subject vehicle. Equation (2) estimates the PCU value of ith(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.

$$PCU_i = \frac{V_c / V_i}{A_c / A_i} \qquad (2)$$

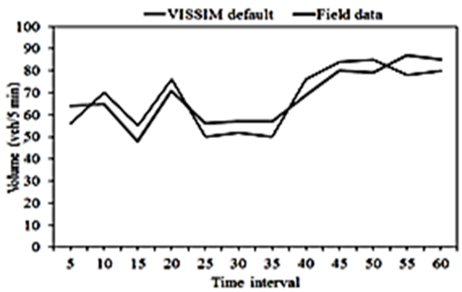
Where, PCU_i is PCU of the i^{th} vehicle, V_c/V_i is speed ratio of the car to the i^{th} vehicle and A_c/A_i is space ratio of the car to the i^{th} vehicle.

Simulation Analysis

Microscopic traffic flow simulation model VISSIM is used in to perform simulation analysis. A straight link section of 1.4 km was created with buffer zone of about 0.2 km length on either side of the stretch. Link was created with 2 lanes of 3.5 m width and shoulder lane of 1.5 m for each direction of travel. The lateral and overtaking behaviours in VISSIM were modified as per left sided rule to truly replicate the non-lane based traffic conditions. Travel time section of 50 m was created at appropriate distance away from the point of vehicles input for measurment of speed. The volume count section was also created between the travel time sections (entry and exit). Primarily, the model was run based on its default setting of parameters with basic field input data such as desired speed distribution of each vehicle types and total volume in veh/hr/dir as per field observations. The simulation data was extracted for 1 h 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.

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



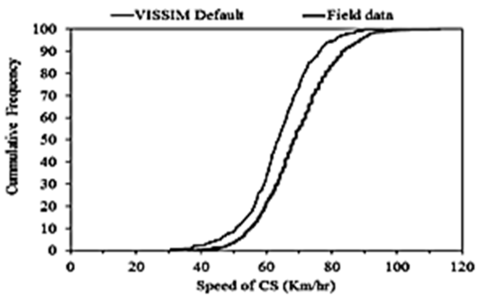


Figure 5. Comparison of traffic volume and speed profile

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.

VISSIM is used in the study for generating sufficient amount of speed and traffic flow data to determine the capacity. Among the ten different driver behaviour parameters (CC0 to CC9) of Wiedemann Model 99, only two of them namely; CC0 (standstill distance) and CC1 (time headway) are found to be significant for affecting capacity as these parameters are governing the safety distance between the simulating vehicles (Mehar *et al*., 2013). Default values of CC0 and CC1 parameters are 1.5 m and 0.9 sec respectively. The CC0 and CC1 parameters values are affecting due to the vehicle composition of vehicle types under mixed traffic conditions. Therefore, capacity obtained from default values of these two parameters may not be reliable unless calibration is performed using field volume, speed and traffic composition.

Mehar *et al*. (2014) calibrated CC0 and CC1 parameters for homogeneous vehicle type 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 5 with their respective capacity values.

Field traffic composition as observed in the field at Section I was used as basis to perform calibration of VISSIM model.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. Traffic volume in veh/hr/dir was given as input as per field observations 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.

Table 5. VISSIM parameters for homogeneous traffic stream (Mehar *et al*., 2014)

Homogeneous vehicle type	Simulated capacity	Calibrated values	
		CC0 (m)	CC1 (sec)
CS	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

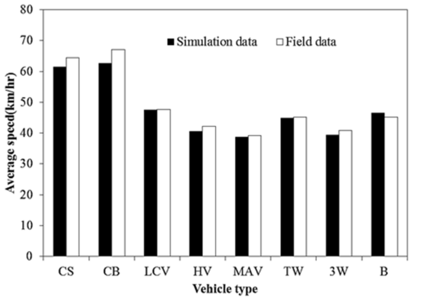


Figure 6.Average speed of each vehicle type for the simulated data and field data

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 veh/hr/dir to 6000 veh/hr/dir) and simulation was run for 2 h. The traffic volume was increased at the rate of 500 veh/hr/dir for every 10 min. and for the last volume increment was given as 1000 veh/hr/dir. 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 6.

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

Table 6. Simulated capacity on four-lane divided section and share of second vehicle type

% share	Maximum Volume (veh/hr/dir)						
	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

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 up to 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.

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 Level of Service (LOS) and different percentage share was found for the development of the model. The variation of PCU with volume to capacity ratio is shown in Figures 8 and 9.

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 model. MLR model was proposed considering the effect of volume to capacity ratio (v/c) and the percentage share of vehicle type (P) on PCU of vehicle type. The PCU values obtained by Dynamic PCU method at different LOS and

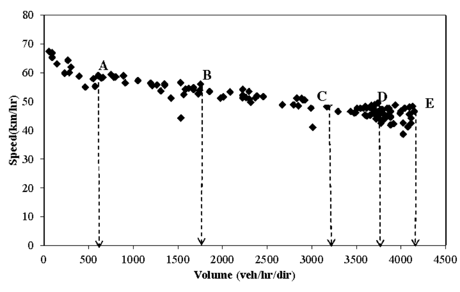


Figure 7. Determination of v/c ratio corresponding to different Levels of Service for LCV at 30% of its own proportion

different percentage share are regressed against the v/c ratio and percentage share. The PCU value of each vehicle type has been proposed by the following equations obtained from MLR. The generalised equation is given by Equation 2.

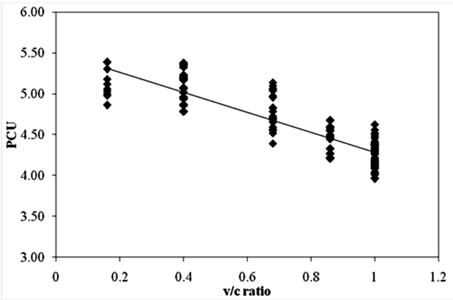


Figure 8. Variation of PCU at different v/c ratio for 10% HV

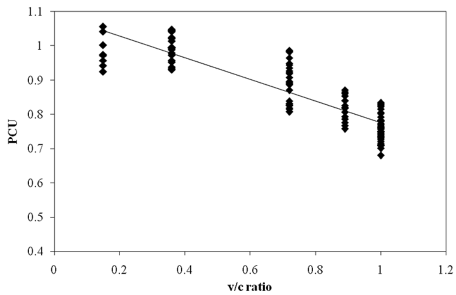


Figure 9. Variation of PCU at different v/c ratio for 10% 3W

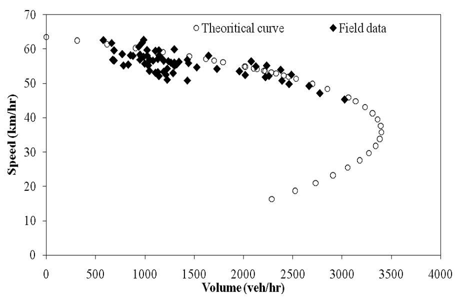


Figure 10. Speed-flow curve for the section on NH 202 (Bibinagar)

$$PCU_i = a + b*(v/c) + c*P_i \quad (1)$$

$$PCU_{HV} = 5.82 - 1.398*(v/c) - 0.017*P_{HV} \quad (2)$$

$$PCU_{TW} = 0.357 - 0.063*(v/c) - 0.001*P_{TW} \quad (3)$$

$$PCU_{CB} = 1.20 + 0.078*(v/c) \quad (4)$$

$$PCU_{MAV} = 8.061 - 2.162*(v/c) - 0.023*P_{MAV} \quad (5)$$

$$PCU_{3W} = 1.096 - 0.316*(v/c) - 0.002*P_{3W} \quad (6)$$

$$PCU_{BUS} = 6.069 - 1.082*(v/c) - 0.013*P_{BUS} \quad (7)$$

$$PCU_{LCV} = 1.518 - 0.223*(v/c) - 0.003*P_{LCV} \quad (8)$$

It was observed that the ‘p’ value representing the effect of volume to capacity ratio and the ‘p’ value representing the effect of percentage share (P) of vehicle type were significant as the values were less than 0.025. It means that v/c ratio and % share have significant effect on PCU. But for CB, the 'p' value corresponding to % share was 0.344 which is greater than 0.025 which means that it has no significant effect on the PCU value of CB. Hence, only the v/c ratio was used in the equation for CB.

Verification of PCU Model

The model developed has been validated by considering another section in Bibinagar which is a four-lane divided highway with paved shoulder on NH 202 (Warangal to Hyderabad). The section has a paved shoulder of width 1.5 m and a carriageway width of 7 m. The PCU value of different vehicle types on this section was determined by using the Dynamic PCU method and also by modelled PCU equations. The capacity of this section is 3399 veh/h. The speed-flow curve of this section is shown in Figure 10. The variation in PCU of HV and TW estimated by Dynamic PCU method and Modelled PCU equations is shown in Figures 11 and 12, respectively. It was observed that for a particular volume range there is more variation in PCU estimated by Dynamic method whereas very less variation is observed for the PCU values estimated by Modeled equations.

PCU on 6-lane and 8-lane Divided Highway Section

The PCU value of each vehicle type on Section-II (Vijayawada-Guntur Highway, NH 16) was estimated by using the modelled equations. It is a 6-lane divided highway with paved shoulder of 1.8 m wide. The capacity obtained for this section was 6864 pcu/h. The PCU of each vehicle type for this section are shown in Table 7. It was observed that as the v/c ratio increases the PCU of all vehicle types decreases except for CB. This may be because of less difference in the speed between CB and CS.

Similarly, 8-lane section with paved shoulder of 1.8 m wide on Delhi-Gurgaon expressway has been considered for estimating the PCU of each vehicle type using the modelled equations. The PCU value was determined by using the proposed equations. It was again observed that as the v/c ratio increases the PCU of all vehicle types decreases except for CB. This might be because of higher speed of CB when compared to CS. The PCU of different vehicle types were shown in Table 8.

The PCU value of different vehicle types on six-lane section and eight-lane section were compared. It was found that as the no. of lanes increases the PCU decreases. This decrease is shown in Figures 13 and 14. On an average, there was a decrease of 1.8% in the PCU value of HV and a decrease of 3.5% in PCU of CB as the no. of lanes increased. Similarly, the same trend is observed for other vehicle types also.

Similarly, the comparison of PCU of different vehicle types was made on 4-lane, six-lane and eight-lane sections. It was also found that as the no. of lanes increased the PCU decreased for all vehicle types. There was a decrease of 2.3% in PCU of HV with the increase in no. of lanes i.e. from four-lane to six-lane and a decrease of 1.8% with the increase in number of lanes from six-lane to eight-lane. The decrease is shown clearly in Figure 15.

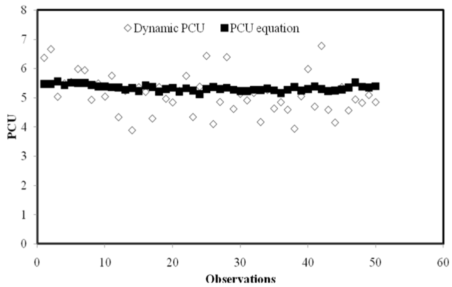


Figure 11. PCU of HV from the two methods

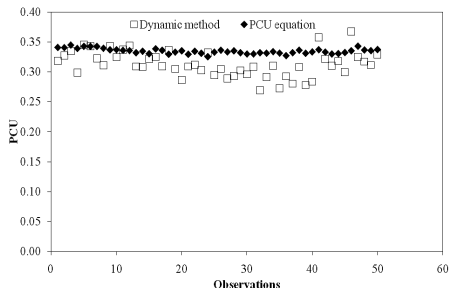


Figure 12. PCU of TW from the two methods

Table 7. PCU of each vehicle type on six-lane section obtained by modelled equations

v/c ratio	CB	LCV	BUS	MAV	HV	TW	3W
0.24	1.22	1.45	5.74	7.45	5.41	0.31	1.00
0.52	1.24	1.39	5.44	6.84	5.02	0.30	0.91
0.74	1.26	1.34	5.20	6.36	4.71	0.28	0.85
0.93	1.27	1.30	5.00	5.96	4.45	0.27	0.79
1.00	1.28	1.29	4.92	5.81	4.35	0.27	0.76

Table 8. PCU of different vehicle types on eight-lane section

v/c ratio	PCU values		
	CB	HV	TW
0.14	1.21	5.37	0.33
0.36	1.23	5.06	0.32
0.66	1.25	4.64	0.3
0.89	1.27	4.31	0.29
1	1.28	4.17	0.28

Development of MLR, ANN and ANFIS Models

The descriptive statistical characteristics of the PCU data for different types of vehicles were derived through SPSS 16 software and are given Table 9. Table 9 revealed that there was little variability in the sample distributions of the variables used in this study to develop prediction models. MLR models were developed for all type of vehicles by considering v/c ratio and % share as input variables and is given in Table 10. 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.

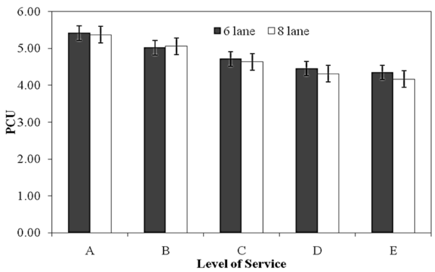


Figure 13. Effect of number of lanes on PCU of HV

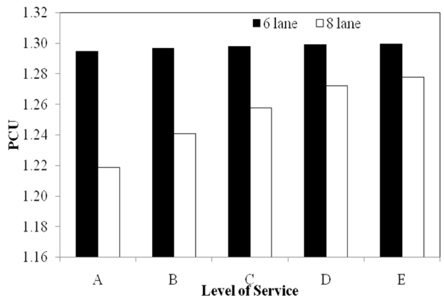


Figure 14. Effect of number of lanes on PCU of CB

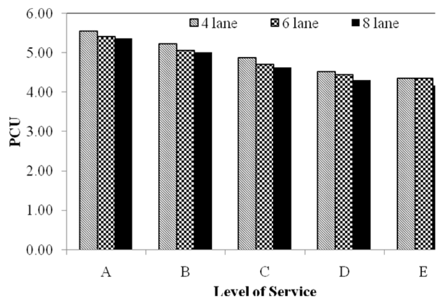


Figure 15. Decrease in PCU of HV with increase in number of lanes

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. Table 11 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 12 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.

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 13. 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 accurate and precise PCU values.

Conclusions

The following conclusions 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

Table 9. 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
HV	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

Table 10. Dimensions of vehicles

Predictor	Vehicle types						
	TW	3W	LCV	CB	HV	BUS	MAV
Intercept	0.357	1.095	1.518	1.2	5.78	6.07	8.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
V/C ratio	-0.062	-0.316	-0.22	0.079	-1.41	-1.08	-2.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% share	-0.0006	-0.00215	-0.0025	-----	-0.0149	-0.013	-0.022
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(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

Table 11. 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
HV	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

by using dynamic PCU expression.

• Volume-to-capacity ratio and traffic composition are found statistically significant for estimating PCU. PCU models are proposed for each vehicle types selected as a subject vehcile under the influence of volume-to-capacity ratios and its own proportional share in the traffic stream. However, the effect of percentage share is not statyistically significant on PCU of vehicle type CB from lower to higher traffic volume levels.

• The model has been verified by comparing the variation in PCU calculated by Dynamic method and modelled equations. It was observed that for a particular volume range the variation in PCU is more for PCU estimated by Dynamic method when compared with that estimated by proposed equations.

• The effect of number of lanes on PCU was studied, and it was observed PCU of each vehicle type decreases with increase in number of lanes and at a different level of service.

• 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 provides the better accuracy then MLR and ANN model values for all the subject vehicle types as the PCU values estimated from the ANFIS model are closer to the simulated PCU values.

• It is also concluded that the ANFIS model showed a greater potential in predicting PCUs using volume-to-capacity ratio and proportional share for vehicle type than the conventional methods.

Table 12. 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
HV	Hybrid	0.20302	50
BUS	Hybrid	0.35374	50
MAV	Hybrid	0.51569	50

Table 13. Comparison of performances of the MLR, ANN and ANFIS models

Vehicle type	Linear regression		ANN		ANFIS	
	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
HV	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

• The models developed in the present study may be used for developing algorithms which describe traffic flow behaviour under mixed traffic conditions with better accuracy and precision.

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