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Establishing Relationship between Travel Parameters and Trip Rate (All Modes) Using Artificial Neural Networks

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Abstract

Trip rate is defined as the ratio of the Total number of trips generated per day to the Total population of the considered area. While considering a city as a study area it is difficult to relate the amount of trips that originate in that study area and the amount of trips attracted towards the study area in a conventional manner. This study brings out some basic Travel parameters that helps in estimating the number of trips in a study area. Relationship between Travel parameters and Trip rate has been established using Artificial Neural Network (ANN) using different learning functions which reflects its performance level. In this study we have used learning functions TRAINLM, TRAINSCG which provided better results in establishing the relation between Trip rate and Trip rate parameters.

Keywords: *- Artificial neural network, Trip rate (all-modes), Independent variables (Travel parameters) Trainlm, Trainscg, Multi-layer Feed Forward network, Feed Forward back propagation network.*

I. INTRODUCTION

Estimated vehicular trips and person trips are important inputs for many analysis and decision-making processes. Every study area has its own type of traffic. Some areas have a high percentage of Vehicular trips where the number of trips made by the person is comparatively less. In case of some other areas the number of motorized trips is less based on the local governance and living standards of the people. The above mentioned cases have a better discipline regarding the type of the traffic in that area. It is convenient for a transportation engineer to plan the road infrastructure in these cases as the Trip Generation model preparation can be simulated by giving prior importance to one mode of traffic. Mixed traffic pattern has its own complexities so importance is to be given to both vehicular trips and person trips while planning to an area with equal proportions of vehicular and person trips. This paper focuses on bringing out the combined behaviour of vehicular trip rate and person trip rate using some parameters of the study area which are listed below in Table 1. Combined Impact of vehicular trip rate and person trip rate is labelled as **Trip rate (all-modes)** and the impact due to vehicular trip rate alone is labelled as **Trip rate (motorized).** Selected parameters of the study area are labelled as **Travel parameters.** These Travel parameters are considered as independent variables and the parameter **Trip rate (all-modes)** is considered as dependant variable which changes with the variation in the Independent Variable.

Table 1: Various Trip rate parameters

Travel Parameters	
Population(lakhs)	Congestion index
Area(sq.km)	Per capita income
Population Density	Male%
Trip length(km)	Female %

II. ARTIFICIAL NEURAL NETWORK

Back propagation Algorithm (Trainlm): Levenberg–Marquardt backpropagation (Trainlm) algorithm locates the minimum of a multivariate function that can be expressed as the sum of squares of non-linear real-valued functions. It is an iterative technique that works in such a way that performance function will always be reduced in each iteration of the algorithm. This feature makes Trainlm the fastest training algorithm for networks of moderate size.

Scaled Conjugate Gradient (Trainscg): This does not require line search at each iteration step like other conjugate training functions. Step size scaling mechanism is used which avoids a time consuming line search per learning iteration. This mechanism makes the algorithm faster than any other second order algorithms. The Trainscg function requires more iteration to converge than the other conjugate gradient algorithms, but the number of computations in each iteration is significantly reduced because no line search is performed.

III. METHODOLOGY

Cities which are densely populated and have a good share of trips per day have been selected in this study. Data related to these 30 cities regarding various travel parameters have been obtained using various sources & surveys. Population (lakhs-2001), Area (sq.km), Population Density, Trip length (km), Congestion index, Per capita income, Male%, and Female % are the travel parameters considered. These **Travel parameters** are now used to bring out relation with **Trip Rate (all modes)** using **Artificial Neural Networks.**

1. The selected eight **Travel parameters** are considered as inputs for the artificial neural network.
2. The network structure which is to be processed is made final.
3. The travel parameters selected are sent through a multi-layer perceptron network then trained accordingly using the type of learning functions available.
4. Weights and biases are automatically updated based on the network structure adopted.
5. Outputs are saved which interpret the outcome of the training process.
6. This process is repeated for required number of iterations until the results are favourable and the final network is saved.

7. Once after getting final network sample data points are given to the same network and outputs are examined for performance of the network.

IV. NETWORK MODELLING

Two layer perceptron Network:

As the name suggests, it consists of two layers. The architecture of this class of network, besides having the input and the Output layers, also has one Intermediate layer called hidden layers. The computational units of the hidden layer are known as hidden neurons. The hidden layer does intermediate computation before directing the input to the output layer. The structure of proposed network is represented in the figure 1. Our Network is comprised of eight inputs which pass through 10 neurons of the hidden layer and output is obtained after required iterations and minimum error is obtained.

The network has been trained using two different algorithms and two transfer functions which are 1. Back propagation Algorithm (Trainlm). 2. Scaled Conjugate Gradient (Trainscg) & 1. Tan-sigmoid & 2. Pure linear transfer functions

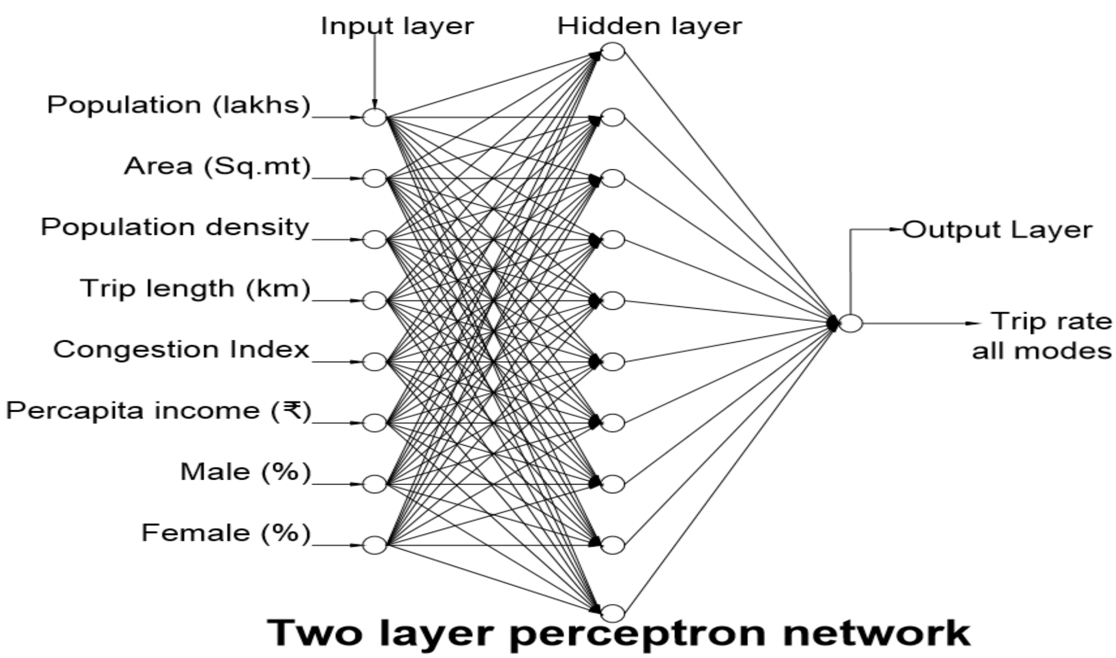


Figure 1: Model of the proposed neural network

V. RESULTS

Table 2: Training & Testing Data Size

Input Data Size	Training set	Validation set	Testing set
30*8	20*8	5*8	5*8

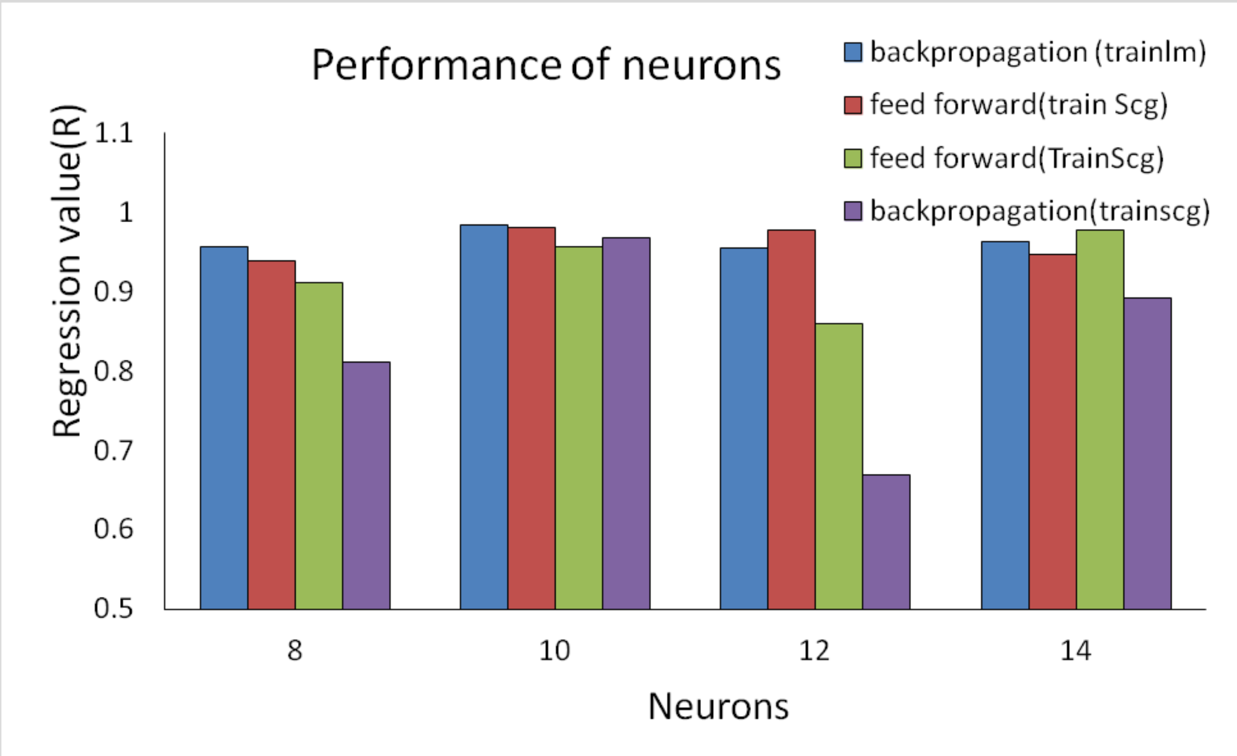
Table 3: Travel parameters Data of 30 cities

City Name	Population(In Lakhs-2001)	Area (sqkm)	Population Density	Trip Length (km)	Congestion Index	Per capita income (Rs)	Male %	Female %
Gangtok	0.92	77	1194.80	2.2	0.21	36,075	52	48
Panaji	0.97	23	4217.39	2.4	0.07	26,075	51.09	48.09
Shimla	1.73	100	1730	3	0.12	21,348	54.98	45.02
Pondicherry	5.08	290	1751.72	3	0.2	74,720	49.08	50.92
Bikenar	6.4	270	2370.37	2.7	0.2	50,775	52.62	47.43
Raipur	7.19	188	3824.46	3.1	0.3	52,689	50.39	49.6
Bhuvaneswar	8.44	233	3622.31	4	0.34	25,584	53.14	46.85
Chandigarh	9.66	150	6440	4.6	0	26,710	55.01	44.99
Hubli Dharwad	9.68	200	4840	4	0.24	37,576	50.47	49.47
Guwahati	10.6	264	4015.15	4.2	0.33	40,260	52.13	47.86
Amritsar	10.85	150	7233.33	4.6	0.2	50,640	52.94	47.06
Trivendram	11.22	310	3619.35	4.9	0.24	102,000	47.9	52.09
Madurai	11.85	732	1618.85	5.4	0.1	46,050	50.24	49.47
Agra	13.69	200	6845.00	4.6	0.07	35,650	53.52	46.47
Bhopal	14.58	320	4556.25	4.6	0.2	58,230	52.17	47.86

Kochi	18.18	730	2490.41	5.7	0.17	48,125	49.31	50.68
Patna	18.36	235	7812.77	4.5	0.23	45,230	52.72	47.28
Varnasi	18.95	250	7580.00	5.1	0.41	40,560	52.26	47.73
Nagpur	21.13	270	7825.93	5.2	0.3	81,225	51.25	48.74
Jaipur	26.8	544	4926.47	6	0.31	95,904	52.34	47.66
Kanpur	27.16	597	4549.41	5.7	0.34	306,000	53.69	46.3
Surat	30.9	680	4544.12	6	0.32	52,030	55.94	44.05
Pune	42	700	6000.00	6.2	0.2	22,178	52.22	47.77
Ahmadabad	59.34	1330	4461.65	6.2	0.3	75,115	52.5	47.49
Hyderabad	63.83	900	7092.22	7.9	0.36	77,277	51.18	48.81
Chennai	70.14	1189	5899.07	8.8	0.36	21,885	50.36	49.63
Bangalore	86.25	1279	6743.55	9.4	0.4	110400	52.2	47.79
Kolkata	147.38	1851	7962.18	10.1	0.4	26,710	52.41	47.58
Delhi	138.5	1758	7878.27	10	0.47	135,820	53.58	46.41
Mumbai	177.02	4355	4064.75	12	0.47	430,548	54.59	45.4

Model architecture selection:

For selecting the number of neurons that are to be adopted for this problem, we have processed the data by starting with 8 neurons and increasing two neurons in ascending there up to 14 and calculated the value (R) for different training functions and selected 10 neurons as the optimum solution for solving this network.



From the graph if we observe the blue curve (obtained while the data is processed using Trainlm function with backpropagation algorithm), for increase from 8 neurons to 10 neurons the R value is moderately varying but the same value has come down while moving from 10Neurons to 12Neurons and gained it previous value while processing with 14 Neurons. Coming to the orange curve (obtained while the data is processed using Trainscg function with Feed Forward algorithm) the performance has got stabilised a lot more than the blue curve and also the value R processed with 10 neurons has been almost near to the blue curve. Similar trend is seen in the other curve giving a clear idea of how many neurons the network requires to predict an optimum solution for our problem.

By using the assigned network structure along with training Functions Levenberg Marquardt Optimization TRAINLM and scalar conjugate gradient TRAINSCG, with 10 neurons in the Hidden Layer four combinations have been tested which are:

- Feed Forward Algorithm with Trainlm as training function.
- Feed Forward Algorithm with Trainscg as training function.

- Feed Forward back propagation algorithm with Trainlm as training function.
- Feed Forward back propagation algorithm with Trainscg as training function.

Table 4: R value obtained while varying the neurons for the four combinations

neurons	R Value (R)			
	Back propagation Trainlm	Feed Forward Trainscg	Feed Forward (Trainlm)	Back propagation (Trainscg)
8	0.956	0.93781	0.91070	0.811
10*	0.983	0.98048	0.95560	0.967
12	0.953	0.97654	0.85952	0.669
14	0.962	0.94615	0.97645	0.892

*selected neurons for the model network

Table 5: performance (M.S.E) & correlation (R) for different training functions

Algorithm	Training function	M.S.E	epochs	R
Back Propagation	Trainlm	0.003	3	0.983
Feed Forward	Trainscg	0.003	26	0.980
Feed Forward	Trainlm	0.009	1	0.955
Back Propagation	Trainscg	0.003	15	0.967

Feed Forward Algorithm Using Trainlm:

This network consists of Trainlm which is the training function which updates the weights and biases of the ongoing process and stops the process when the error is minimum. The performance of the neural network is determined by the mean squared error & data division is random. MSE value is 0.009 at epoch 1.The overall R(R) is=0.955.

Feed forward algorithm using Trainscg:

This network consists of Trainscg which is the training function which updates the weights and biases of the ongoing process and stops the process when the error is minimum. The performance of the neural network is determined by the mean squared error & data division is random. MSE value is 0.003 at epoch 26.The overall R(R) is=0.980.

Feed Forward back propagation algorithm using Trainlm:

This network consists Trainlm which is the training function where learning occurs in a training phase i.e.., errors of a target is back propagated from output to the inputs and weights are adjusted accordingly. Once the back propagation learns it can be tested on second set of inputs. The performance of the neural network is determined by the mean squared error & data division is index. MSE value is 0.003 at epoch 3.The overall R(R) is=0.983.

Feed Forward back propagation algorithm using Trainscg:

This network consists of Trainscg which is the training function where learning occurs in a training phase i.e.., errors of a target is back propagated from output to the inputs and weights are adjusted accordingly. Once the back propagation learns it can be tested on second set of inputs. The performance of the neural network is determined by the mean squared error & data division is index. MSE value is 0.003at epoch 15.The overall R(R) is=0.967.

Variation between surveyed values and network trained values for the four combinations has been plotted by taking the 30 cities on X-axis and trip (rate all-modes) on Y-axis values ranging from 0-2 as in figures 2.

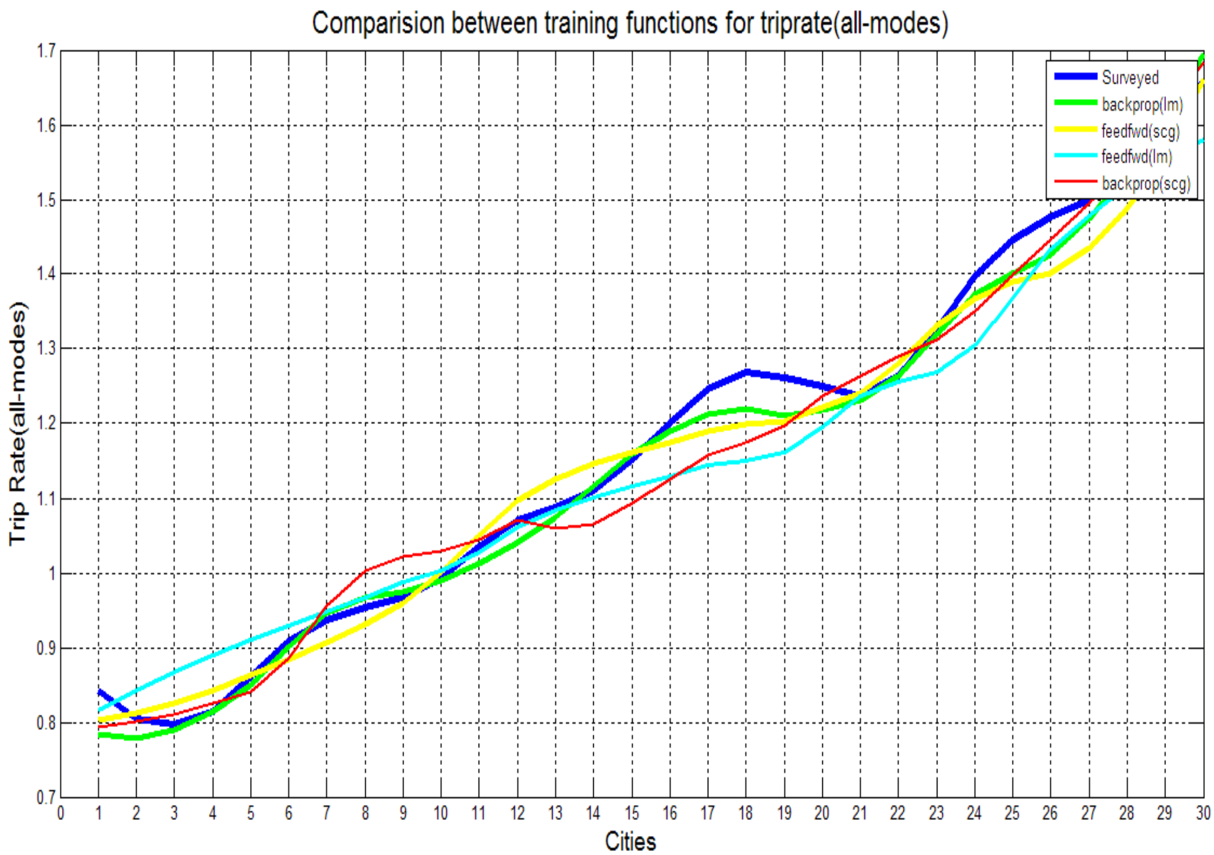


Figure 2: Variation between predicted values (training functions) vs surveyed values

VI. CONCLUSIONS

After testing the four combinations it was found:

1. Trainlm has performed well Using the Feed Forward Back Propagation algorithm producing predicted trip rate value with a R value 0.995

2. Trainscg has deteriorated its level of performance while processed with Feed Forward Back Propagation algorithm.

3. Trainlm has performed well using the Feed Forward algorithm producing predicted trip rate value with a R value 0.955.

4. Trainscg has performed well Using the Feed Forward algorithm producing predicted trip rate value with a R value 0.98

5. Results conclude that Trainlm has successfully predicted trip rate values

which confirms Artificial Neural Networks can be adopted for the problems of similar data size.

6. Trainscg has provided optimum prediction of trip rate values for both the network structures which stand by Trainlm.

7. Trip Rate Values have been success fully predicted while using ANN which are far better than the conventional R process.

8. Relationship between Travel parameters and Trip rate (all modes) has been established using Artificial Neural Network (ANN) using different Training functions.

9. ANN has helped us in establishing boundary conditions for the prediction of trip rates related to a particular city.

10. This analysis is helpful for a town planner to know the trip rate and plan the infrastructure accordingly.

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TERMINOLOGY

Trip Rate: The ratio of the Total number of trips generated per day to the Total population of the considered area.

Trip Rate (All Modes): Number of trips including walk per person of that study area.

Trip rate (motorized): Number of trips excluding walk per person of that study area.

Trip Length: the distance travelled for a trip in Kilometres.

Congestion Index: CI=1-(observed speed on major corridors/Posted speed limit (i.e. 30kmph).

Population density: Ratio of population to the area in equivalent units.

Per-capita Income: it is calculated by taking a measure of all sources of income in the aggregate (such as GDP or Gross national income) and dividing it by the total population.

Male %: percentage of male in the study area.

Female%: percentage of female in the study area.

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