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Trip Distribution Model for Delhi Urban Area Using Genetic Algorithm

Shivendra Goel[1], J.B. Singh[2], Ashok K. Sinha[3]

[1]Research Scholar, Shobhit University, Meerut 250110, India, shivendragoel@gmail.com
[2]Professor, Shobhit University, Meerut 250110, India, jbs.tomar@shobhituniversity.ac.in
[3]Professor,ABES Engg. College,Ghaziabad 201009, India, aksinha@computer.org

Abstract. As the society evolves it generates transport demand. An estimate of the volume of trips between zones is a necessary step in transportation studies. The classical transportation planning methods are based on simple extrapolation of trends. Some mathematical models like linear programming models have also been used by researchers for estimating traffic generation for future period. This paper presents a model for trip distribution in Delhi Urban Area using Genetic Algorithm. This model has been used for trip distribution in all zones of Delhi Urban Area. This model is applied on the real set of data on passengers trips generated and passengers trips attracted in all zones of Delhi Urban Area, which in turn gives satisfactory results which can be applicable in current and future scenarios. This work analyzes and compares the result of this model with Linear programming model for trip distribution.

Keywords: Genetic Algorithm(GA); Linear programming models; GA Based Trip Distribution model; Delhi Transport Corporation
(DTC).

1 Introduction

1.1 Different Phases of urban Transportation Planning

Trip generation is the first step in the conventional four-step urban transportation Planning process, widely used for forecasting travel demands. It predicts the number of trips originating in or destined for a particular traffic analysis zone. Urban area is divided into several traffic zones which are the clusters of households and socio-economic activities.
Trip distribution (or **destination choice** or **zonal interchange analysis**), is the second component (after trip generation, but before mode choice and route assignment) in the traditional four-step urban transportation planning process. This step matches trip makers' origins and destinations to develop a "trip table" a matrix that displays the number of trips going from each origin to each destination. Gravity model, entropy maximization models are widely used for trip distribution analysis [15].
Mode choice analysis is the third step in the conventional four-step urban transportation Planning process. Trip distribution's zonal interchange analysis yields a set of origin destination tables followed by;
Mode choice analysis allows the modeler to determine which mode of transport will be used.

Traffic assignment concerns the selection of routes between origins and destinations in transportation networks. It is the fourth step in the conventional urban transportation planning process.

Trip distribution models are intended to produce the best possible predictions of travelers' destination choices on the basis of trip generation and attraction information for every travel zone and generalized cost of traveling between each pair of zones [6].

Many scientific disciplines have contributed toward analyzing problems associated with the transportation problem, including operation research, economics, engineering, Geographic information science and geography. It is explored extensively in the mathematical programming and engineering literatures.

Estimating trip distribution for future period is a challenging task. George Dantzig[1] adapted the simplex method to solve the transportation problem formulated earlier by Hitchcock and Koopmans, but this simplex method is used by researchers for estimating trip distribution generation for future period[2-5].

The Linear programming based transportation models are applicable only to problems where the constraints and objective function are linear. Secondly, the most serious disadvantage of linear programming models is their failure to deal with demand uncertainties in any explicit way.

The subsequent section of this paper is organized as follows. Section 2 focuses on the proposed model of the trip distribution problem using Genetic Algorithm. This model presents a method for estimating the parameters, describes the main characteristics of the data used for calibration. Section 3 sets out the main results of the calibration process based on real set of data of Delhi Urban Area. Section 4 compares the result of proposed model with Linear programming model for trip distribution. Finally, Section 5 sums up the main conclusions of our analysis.

2 Proposed Solution

Genetic Algorithm based Trip distribution model is developed for solving the above stated problem. This model uses the goodies of Genetic Algorithm in Trip distribution. Model is stated as follows:

Fij={Pi,Aj,Cij}

Where:

Fij=trip distribution., Pi=total passengers generated at I, Aj=total passengers attracted at j.

Cij=Cost of Passenger trip from zone i to zone j.,i=number of origin zones., j=number of desitnation zones.

The implementation of the above model is as follows:

$$\sum_{j=1}^{m} Fij=Pi \quad i=1,2\ldots\ldots n \qquad \ldots..(i)$$

$$\sum_{i=1}^{n} Fij=Aj \quad j=1,2\ldots\ldots m \qquad \ldots..(ii)$$

Now, fitness function returns min (y) such that.

$$y=\sum_{i=1}^{n}\sum_{j=1}^{m} (Cij*Fij) \qquad \ldots.(iii)$$

Selection Operator. The selection operator chosen is the Roulette wheel selection. In roulette wheel selection individuals are assign a probability of being selected based on their fitness criterion, $p_i = f_i / \sum f_j$, Where pi is the probability that individual i will be selected, fi is the fitness of individual i, and $\sum f_j$ represents the sum of the fitness of all individuals in the population. Alike to using a roulette wheel, fitness of an individual is represented as in proportion slice of wheel. Wheel is then spinning and the slice underneath the wheel when it stops determines which individual becomes a parent[21].

Crossover ERO. Standard crossover operator is chosen for manipulating the above representation. This operator is ERO (Edge Recombination crossover Operators) are designed to manipulate permutations. ERO is an operator that creates a path that is similar to a set of existing paths (parents) by looking at the edges rather than the vertices [16,21].

Mutation Rate. Mutation becomes significant at what time after some generations the number of different strings decreases because burly individuals start dominating. In a condition of burly dominance of a few strings, the crossover operator alone would not bring any changes and the search for a best solution would be ended. To partially move the search to new locations in the solution space, mutation operator randomly alters genes. A mutation rate of 0.15 was taken for genetic algorithm. The number of generations considered in the algorithm was 1000.

3. Results

Following **Table 3.1** shows the data of Trips Generation and attraction from each zone and **Table 3.2A** and **Table 3.2A** shows the data of Fare (in Rs.) from one zone to another DTC and **Figure1** shows the flow chart of the work and **Table 3.3** A and **Table 3.3B** is computed based on the proposed solution shows the number of passenger trips from one zone to another.

3.1. Result Comparison with Linear Programming Model

The model in section 2 is also implemented in Linear Programming [18]. Proposed Genetic Algorithm model for trip distribution and the Linear Programming Model for trip distribution are applied on the above set of inputs. It gives the following results shown in table 4.1.

The Linear Programming model is as follows:

$$\text{min cost } z=\sum_{i=1}^{n} \sum_{j=1}^{m} (C_{ij}*T_{ij})$$

Subject to:

$$\sum_{j=1}^{m} T_{ij}=P_i \quad (i=1,2\ldots\ldots n)$$

$$\sum_{i=1}^{n} T_{ij}=A_j \quad (j=1,2\ldots\ldots m)$$

Where:

T_{ij}=trip distribution., P_i=total passengers generated at i,A_j=total passengers attracted at j.
C_{ij}=Cost of Passenger trip from zone i to zone j., z=min cost.
i=number of origin zones., j=number of desitnation zones.

Table 4.1

Particulars	**Linear Programming Based Model.**	**GA Based Trip Distribution model**
Status of Solution	Infeasible	Feasible
Number of results achieve in 81 Links of each connected Zones	9	76

The above result show in Table 4.1 shows that result achieved from Linear Programming Based Model is not up to the mark as the number of input variables increases in the above said problem it gives Infeasible solution.

Conclusion

Genetic Algorithm Based Trip Distribution model is proposed and applied on the real set of data which gives satisfactory solution which is easily applicable and compared with other models as well, as in this paper one can easily observed that a Linear Programming based model gives infeasible solution for the complex problems as stated above.

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Table 3.1[11-12]

Zones	No. of passengers trips Generated from each Zone 2005	No. of passengers trips Attracted at each Zone 2005
North	1730400	1742229
West	1239400	1247895
North	1050200	1082715
South	1039600	1070185
North	413040	387163
Central	449850	364808
South	1079600	1090338
East	417710	420582

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South	655870	669756
Total	8075670	8075670

Fig1: Flow Chart of the Work

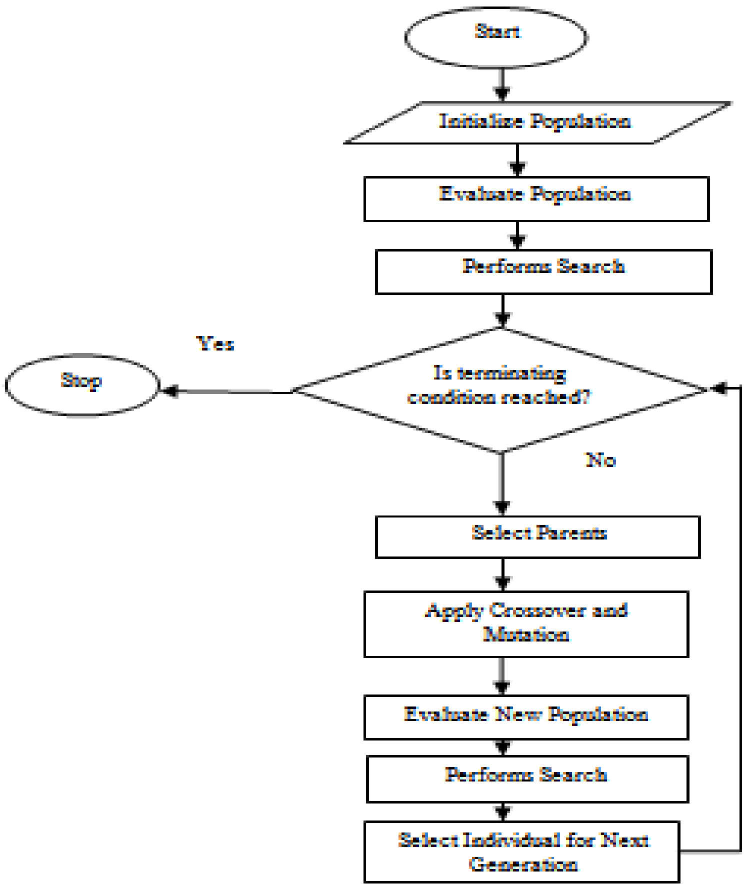

Table 3.2A [11] Fare (in Rs.) from one zone to another DTC

	North-West	West	North-East	South-West
North-	5	10	15	15
West	10	5	15	10
North-	15	15	5	15
South-	15	10	15	5
North	10	15	10	15
Central	10	10	10	10
South-	15	15	15	15
East	15	15	10	15
South	15	15	15	10

Table 3.2B [11] Fare (in Rs.) from one zone to another DTC

	North	Central	South-East	East	South
North-	10	10	15	15	15
West	15	10	15	15	15
North-	10	10	15	10	15
South-	15	10	15	15	10
North	5	10	15	10	15
Central	10	5	10	10	10
South-	15	10	5	10	10
East	10	10	10	5	15
South	15	10	10	15	5

Table 3.3A

Zones	**North-West**	**West**	**North-East**	**South-West**	**North**
North-West	311362.2	255176.24	193723.56	204619.64	102607.29
West	228355.73	207938.77	155817.9	155925.33	74638.957
North-East	206580.07	168001.77	139392.48	134685.36	57646.102
South-West	215947.05	142818.54	148187.49	127592.1	70667.657
North	137912.11	56694.95	70954.626	97627.821	nil
Central	118064.18	56255.003	79815.038	55539.371	nil
South-East	216067.9	171129.77	156765.22	132039.11	57385.51

East	117445.73	53699.248	75392.432	84361.317	8187.8002
South	190494.01	136180.71	62666.247	77794.59	32426.054

Table 3.3B

Zones	**Central**	**South-East**	**East**	**South**
North-West	141148.23	232265.14	132562.79	156934.92
West	54718.191	189071.99	80578.686	92354.446
North-East	61650.691	120431.3	60874.884	100937.33
South-West	56589.008	110693.21	56926.154	110178.79
North	269.72442	40538.431	nil	21392.96
Central	nil	83045.249	13806.873	57981.452
South-East	78684.484	140181.66	67371.104	59975.242
East	nil	88480.943	10646.496	12023.845
South	11859.551	85630.076	842.04374	57976.718