International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 08 Issue: 09 | Sep 2021 www.irjet.net p-ISSN: 2395-0072

TRAVEL DEMAND FORECASTING MODEL

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ABSTRACT: *Taking into consideration that travel has grown significantly over the previous few decades and this rise in travel seems to continue. This leads to the result of a wide range of factors which upsurges the demand for travel. After all this travel can only take place if there are appropriate facilities like roads, buses, trains, cycles, etc. The presence of those, their cost, and the quality of service they suggest also affect how much travel takes place, where, when and by what means. The connection between demand and supply of services and facilities is complex and a detailed analysis is beyond the scope of this project, which focusses on the factors affecting travel demand and forecasting the long run travel demand of Rajahmundry, East Godavari district, which is the most populous district within the state of Andhra Pradesh. Noticeably within the last decades, the modeling techniques of travel demand estimation have been developed substantially. The external trip estimation is vital but usually ignored in the travel demand modeling process. Our project aims to identify and estimate the main variables that affect the travel demand in low population areas, and to develop models to predict them. A special questionnaire had been prepared depending on interviews of passengers in Rajahmundry. We have selected the GLM procedure which offers the most fitted and precise approach for developing several trips with suitable data collection like Population, Total distance between origin and destination (Km), Area (Km2), Population density, Average personal income, Trip purpose, Trip time, Trip origin and destination, Trip frequency, Questionnaire data. The final demand models have statistics within the acceptable regions and. also, they are conceptually reasonable.*

Key Words: (Travel demand, Trip Estimation, Questionnaire, Generalized Linear, Modeling, Trip Origin and Destination, Trip Frequency and Travel demand forecasting)

1.INTRODUCTION

1.1General

1.2 Factors that affect travel demand

The demand for travel has to do with the movement of people and goods that they would choose under certain conditions, taking into account factors such as the mode of transport, the quality and convenience of transportation, and prices based on demand. Travel demand forecasting may be the key component of the transportation engineer's technical repertoire which enables the engineer to forecast the volume of traffic that a particular element of transport will use in the future, regardless of whether it is an existing highway or a potential light rail route.

i)Social Economic Factors:

· Lifestyles

· Number of people (residents, employees, and visitors).

· Age

· Incomes

ii)Social Demographic Factors:

· Incomes

· Tourist activity

· Number of jobs

iii)Prices:

· Road tolls

· Fuel prices and taxes

· Vehicle taxes & fees

· Parking fees

· Public transport fares

iv)Transport options:

· Automobile

· Cycling

· Walking

· Public transit

· Taxi services

· Ridesharing

v)Service quality:

· Safety and security

· Waiting conditions

· Delay

· Relative speed and Reliability

· Comfort

· Parking conditions

vi)Land use:

· Roadway design

· Transit service proximity

· Walkability

· Connectivity

1.3 ADVANTAGES

1. You'll gain the following valuable insights

The forecast will make you get into the habit of looking at past and real-time data to predict future demand. And by doing so, you will be able to better anticipate fluctuations in demand. it will give you an idea of the health of your company and give you the opportunity to correct the course or make changes.

2. You'll learn from past mistakes

You don't start from scratch after every forecast. Even if your prediction didn't come close to what ultimately happened, it does give you a place to start. It's common to review where and why things didn't go as planned. Your forecasts should eventually improve. Most importantly, you'll get into the habit of thinking about past performance as a whole.

3. It can decrease costs

When done right, anticipating demand will help you fine-tune your processes to increase efficiency throughout the supply chain. Because you are better able to predict what customers will want and when they want it, you will also be able to reduce excess inventory levels, thus increasing overall profitability.

1.4 DISADVANTAGES

I) Forecasts are never 100% accurate

Let's face it: it's hard to forecast the future. Even if you have a great process in situ, your forecasts will never be right. Some products and markets simply have a high level of instability. And generally, there is just an endless number of things that influence demand.

ii) Can be time-consuming and resource-intensive

Forecasting involves a lot of data collection, data organization, and coordination. Companies typically employ a team of demand planners who are responsible for creating the forecasts. But to get it right, demand planners need substantial input from sales and marketing teams. In addition, it is not uncommon for the processes to be manual and labor intensive, which takes a lot of time. Fortunately, if you have the right technology in place, this is much less of a problem.

iii) It can be expensive too

On a related note, hiring a team of demand planners is a significant investment. Add to this the cost of using good quality tools, the upfront costs may increase. But investing in advanced software, high-quality talent, and robust forecasting processes is just that - an investment. We are confident that you will see a return when all of this is done right.

1.5 DIFFERENT METHODS TO MEASURE TRAVEL DEMAND

i) Multiple linear regression

ii) Generalized linear modeling

iii) GIS& GRID

iv) microscopic travel demand orchestrator

v) Fourier series

vi) Network modeling

vii) Neural network approach

viii) Multiple discrete-continuous choice

1.6 OBJECTIVE

The aim of this project is to identify and select the main variables that affect the travel demand, and to develop models to predict them in the East Godavari district.

FIG 1: RAJAHMUNDRY DISTRICT

1.7 TRIP GENERATION

The first step in travel forecasting is trip generation. This step uses land use, population, and economic forecast information to estimate how many trips will be made to and from each area. This is done separately depending on the purpose of the trip. The possible purposes are business trips from home (work trips that start or end at home), shopping trips from home, other trips home, school trips, non-travel (trips that end at home), truck trips, and taxi trips. The trips are calculated based on the characteristics of the zones. Trip productions are based on household characteristics such as the number of people in the household and the number of vehicles available. Trip attractions are generally based on the level of employment in an area.

Some of the assumptions in a trip generation are as follows:

- Independent decisions. Trip behavior is a complex process in which one household member's decisions are often dependent on others in the household. This interdependence does not count as the start of the journey.
- Limited trip purposes. With no over four to eight trip purposes, a simplified trip pattern outcome. All shopping trips are treated the same whether shopping for groceries or lumber.
- Combinations of trips are overlooked. Travelers may often combine a variety of purposes into a sequence of trips as they run errands and link activities together. This can be called trip chaining and is a complex process.

1.8 TRIP DISTRIBUTION

Trip generation only finds the number of trips that start or end in a particular area. The journey distribution process links the end of the journey to form a pattern of origin and destination. Travel distribution is used to represent the process of choosing a destination. Distributing the path results in a large increase in the amount of data to be processed; the origin and destination tables are very large. The most commonly used procedure for trip distribution is called the gravity model. The gravity model takes the trips produced in one area and distributes them to other areas based on the size of the other areas and on the distance from the other areas. An area with a large number of tourist attractions will receive a greater number of distributed trips compared to one with small tourist attractions. The distance to possible destinations is the other factor used in the gravity model. The number of trips to a particular destination decreases with the distance from the destination.

Some of the assumptions for the trip distribution are as follows:

• Constant trip times: For the model to be used as a forecasting tool, it must be assumed that the average trip lengths that occur now will remain constant in the future.

• Using automobile travel times to represent "distance". The gravity model requires a measure of the distance between zones. This is almost always based on automobile travel times rather than transit transport travel times and leads to a wider distribution of trips

• Limited effect of socio-economic cultural factors. The gravity model only distributes trips according to the size of the trip ends and travel times between trip ends.

1.9 TRAFFIC ASSIGNMENT

Once trips were split into highway and transit trips, the precise path that they use to travel from their origin to their destination should be found. These trips are then assigned to that direction in the step known as traffic assignment. Traffic assignment is the maximum time-ingesting and data extensive step withinside the system and is finished in a different way for highway trips and transit trips.

Some of the assumptions in traffic assignment are the following:

• Delay takes place on links. Most traffic assignment approaches anticipate that put-off takes place at the links in place of intersections. This is a great assumption for via roads and freeways however now no longer for highways with extensive signalized intersections.

• Travel simplest takes place in the network. It is believed that each one journey starts and ends at a single factor in a zone (the centroids) and takes place only at the links included withinside the network. Not all roads' streets are protected withinside the community nor are all feasible trip beginning and end factors included. The zone/network system is a simplification of reality.

• Capacities are simplified. To decide the potential of roadways and transit systems requires a complex process of calculations that take into account many factors. In maximum tour forecasts that is significantly simplified.

• Time of day variations. Traffic varies appreciably at some point of the day and at some stage in the week. The travel demand forecasts are made on a daily basis for a typical weekday after which transformed to top hour conditions.

• Emphasis on top hour tour. As defined above, forecasts are finished for the height hour. A forecast for the height hour of the day does now no longer offer any data on what's taking place the alternative 23 hours of the day.

2. METHODOLOGY

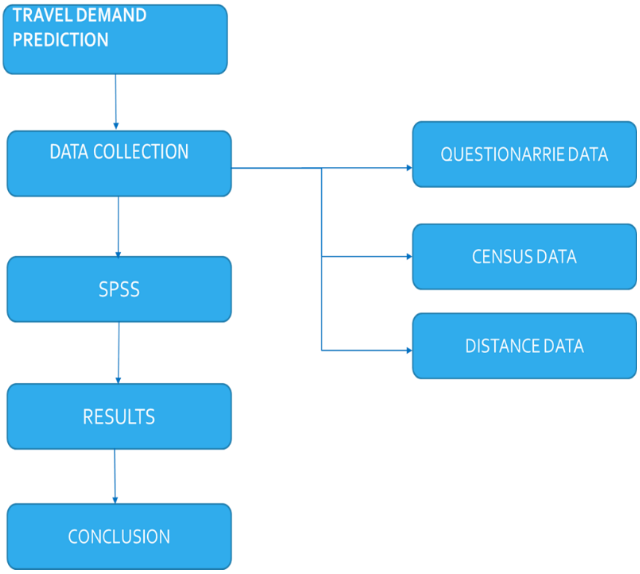


FIG 2: METHODOLOGY FLOW CHART

3. DATA COLLECTION

3.1 GENERAL

Four-step modeling, an important tool for forecasting demand and future performance of a transportation system, has been developed to assess large-scale infrastructure projects. Therefore, four-step modeling is less suitable for managing and controlling existing software. As these models are applied to large systems, they require information on travelers in the area affected by the system, where the data requirements are very high and can take years for data collection, data analysis, and the development of models. In order of planning and a systematic approach to accurate data collection and processing are required. This chapter covers three important aspects of data collection, namely survey design, household data collection, and data analysis. Finally, a brief discussion of other important surveys is also presented.

It is also important to know the purpose of the study and the details of the modeling approaches, as the demand for data is affected by them. In addition, many practical considerations such as the availability of time and money also have a big impact on the design of the survey. In this section, we will discuss the basic information required by data collection, defining the study area, dividing the area into zones, and the characteristics of the transport network.

The next step in the survey is the design of the questionnaire. Good design will ensure better respondent response and significantly improve data quality. Questionnaire design is more of an art than a science. However, few guiding principles can be established. The questionnaire must be simple, direct, must take the least time, and must be the least restrictive for the respondent. The traditional household survey of which it has three main sections; family characteristics, personal characteristics, and trip details.

3.2 SITE SELECTION:

Stretches selected for the roadside interviews are the following:

1) AV Road.

2) Market Road.

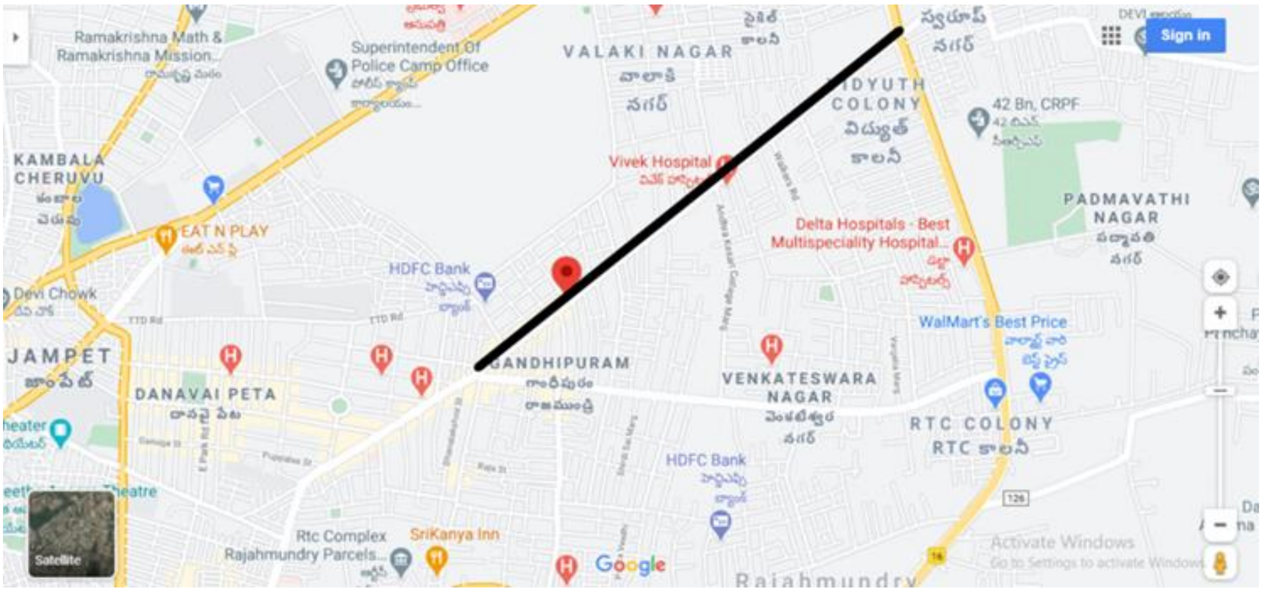


FIG 3: STRETCH 1- AV ROAD

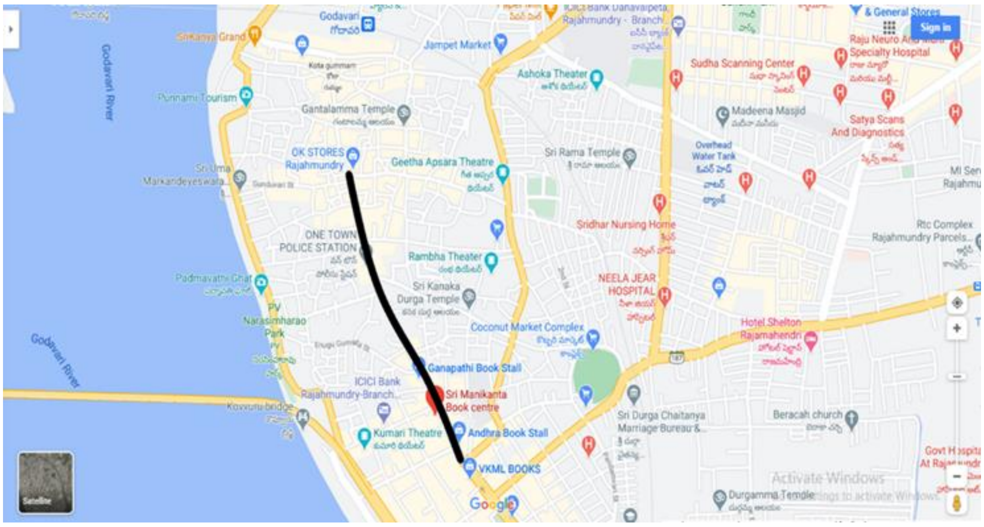


FIG 4: STRETCH 2 -MARKET ROAD

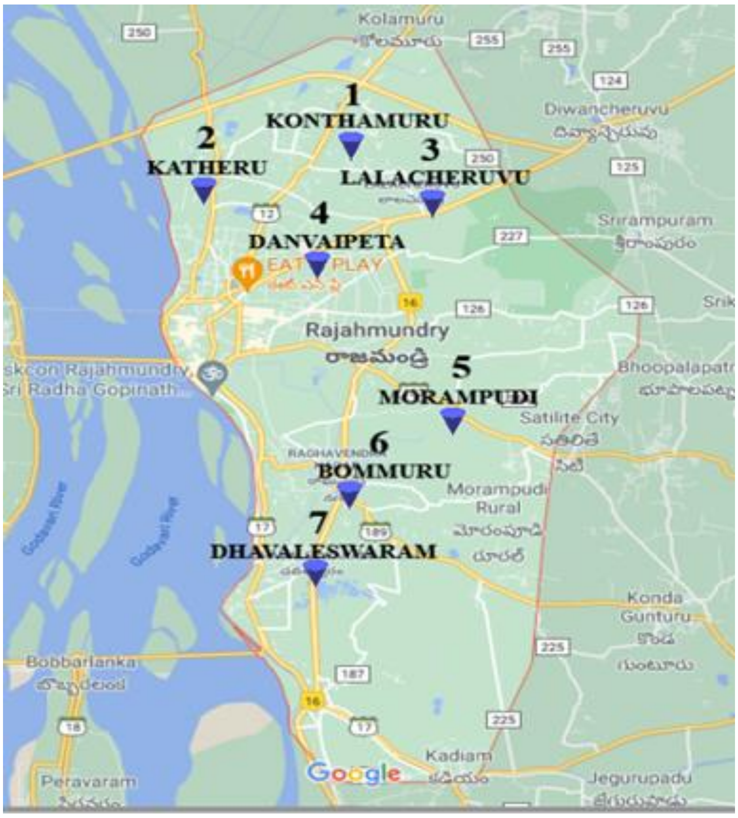


FIG 5: AREAS

3.3 DATA COLLECTION

According to the census of India (2011) Population data, Annual average income, Area, Density of population for the places like Konthamuru, Dhanvaipet, Katheru, Lalacheruvu, Morampudi, Bommuru, Dowleswaram have been collected. There are two types of data sources to be discussed.

They are the following: -

1. Questionnaire data
2. Distance data
3. Census data

QUESTIONNAIRE DATA: - A unique questionary has been prepared to conduct the on-road interview of passengers at AV road and Market Road. The time of interviews is from morning 8:00 A.M and evening 5-7:00 P.M in two months that is from February to march. Each form concerns an interview with one person and contains the following data: trip origin governorate, residence governorate and district, trip destination governorate, time and date of the trip, trip purpose, and trip frequency in the year, access mode time, and egress mode time.

DISTANCE DATA: - Distance between origin and destination was measured by Google earth maps with knowledge of the exact district's name and their locations on maps. These distances are so important and effective aspects that affect the number of personal trips per year and represent the main independent variable.

CENSUS DATA: - Census of India (2011) Population data, Annual average income, Area, Density of population for the places like Konthamuru, Dhanvaipet, Katheru, Lalacheruvu, Morampudi, Bommuru, Dowleswaram (All places are in Rajahmundry) have been collected.

CODE	GOVERNANTE	POPULATION	AREA (km2)	DENSITY(persons/km2)	Avg.persanal income(EP/year)
1	Konthamuru	20747	6.58	3153	180000
2	Katheru	20,124	5.43	3703	300000
3	Lala cheruvu	5394	1.43	3778	300000
4	Danvaipet	117692	7.86	14978	500000
5	Morampudi	18109	5.37	3371	400000
6	Bommuru	10100	3.67	2751	250000
7	Dowleswaram	23454	8.4	2792	200000
		30802.85714	5.534285714	4932.285714	304285.7143

FIG 6: Codes and properties of all governorates

VARIABLE	SYMBOL	MAX	MIN	AVG
I-Total distance between ori gin and destination in km	Dr	19	3.4	8.68
Population of origin 2020 in person	Pop o	117692	18109	3082
Population of destination 2020 in person	Pop d	117692	18109	3082
Area of origin in km^2	A0	8.4	1.43	5.53
Area of destination in km^2	Ad	8.4	1.43	5.53
Poputation density of origin in person/km^2	Den o	14978	2751	4932.28
Population density of destination in person/km^2	Den p	14978	2751	4932
Average personal income For origin in EP/year	Inc o	600000	180000	318572
Average personal income for destination in EP/year	Inc d	600000	180000	318572
Total time in minutes	T o	23	10	14

FIG 7: VARIABLES AND SYMBOLS FOR EACH PERSONAL TRIP

4.DATA ANALYSIS:

This type of modeling is used successfully worldwide in accident prediction. This model was used, but in a different way, to fit travel demand data. The mathematical form included all independent variables separately. To do this, the natural logarithm of all these variables was taken to create a powerful relationship between the frequency of trips and each of the former items. It made it possible to examine the effect of all independent variables on the annual personal trips separately.

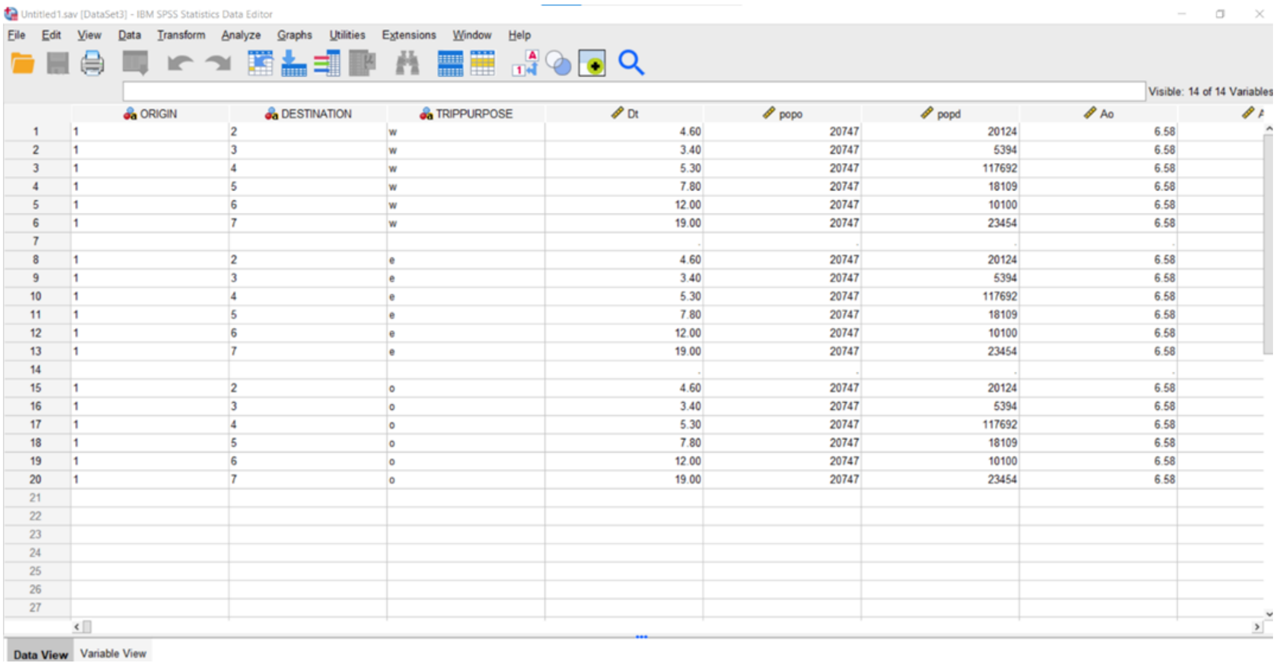
$$\mathrm{Tr} = \exp(\beta_0) \times X_1^{\beta_1} \times \cdots \times X_n^{\beta_n}$$

A normal distribution with a log link function was chosen to model these data. This form takes the following shape:

This form satisfied two main conditions: (1) This model must yield logical results (non-negative). Also, at Xi = 0 the number of trips must be zero. (2) The logarithmic link function that can linearize this way for the aim of coefficient estimation should exist.

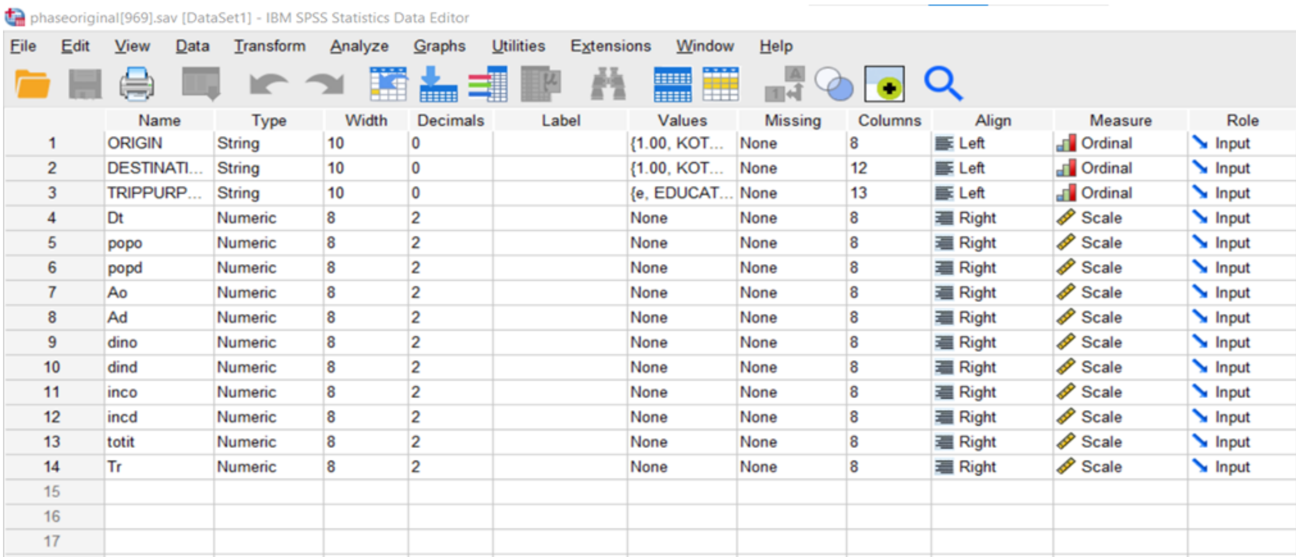
This model form was executed using the generalized linear model procedure in the SPSS software.

SPSS applied the outmost log-likelihood technique to estimate the regression coefficients, Wald Chi-squared statistics, and p-values. The model with the minimum and highest R2 value was selected.



	ORIGIN	DESTINATION	TRIPPURPOSE	Dt	popo	popd	Ao
1	1	2	w	4.60	20747	20124	6.58
2	1	3	w	3.40	20747	5394	6.58
3	1	4	w	5.30	20747	117692	6.58
4	1	5	w	7.80	20747	18109	6.58
5	1	6	w	12.00	20747	10100	6.58
6	1	7	w	19.00	20747	23454	6.58
7				.	.	.	.
8	1	2	e	4.60	20747	20124	6.58
9	1	3	e	3.40	20747	5394	6.58
10	1	4	e	5.30	20747	117692	6.58
11	1	5	e	7.80	20747	18109	6.58
12	1	6	e	12.00	20747	10100	6.58
13	1	7	e	19.00	20747	23454	6.58
14				.	.	.	.
15	1	2	o	4.60	20747	20124	6.58
16	1	3	o	3.40	20747	5394	6.58
17	1	4	o	5.30	20747	117692	6.58
18	1	5	o	7.80	20747	18109	6.58
19	1	6	o	12.00	20747	10100	6.58
20	1	7	o	19.00	20747	23454	6.58

FIG 8: PLACE 1 MODEL DATA (PLACE 1 AS ORIGIN)



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	ORIGIN	String	10	0		{1.00, KOT...	None	8	Left	Ordinal	Input
2	DESTINATI...	String	10	0		{1.00, KOT...	None	12	Left	Ordinal	Input
3	TRIPPURP...	String	10	0		{e, EDUCAT...	None	13	Left	Ordinal	Input
4	Dt	Numeric	8	2		None	None	8	Right	Scale	Input
5	popo	Numeric	8	2		None	None	8	Right	Scale	Input
6	popd	Numeric	8	2		None	None	8	Right	Scale	Input
7	Ao	Numeric	8	2		None	None	8	Right	Scale	Input
8	Ad	Numeric	8	2		None	None	8	Right	Scale	Input
9	dino	Numeric	8	2		None	None	8	Right	Scale	Input
10	dind	Numeric	8	2		None	None	8	Right	Scale	Input
11	inco	Numeric	8	2		None	None	8	Right	Scale	Input
12	incd	Numeric	8	2		None	None	8	Right	Scale	Input
13	totit	Numeric	8	2		None	None	8	Right	Scale	Input
14	Tr	Numeric	8	2		None	None	8	Right	Scale	Input

FIG 9: VARIABLE VIEW

phaseoriginal[969].sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

Visible: 14 of 14 Variables

	ORIGIN	DESTINATION	TRIPPURPOSE	Dt	popo	popd	Ao	Ad	dino	dind	inco	incd	totit	Tr	var	var	var
1	2.00	1.00	w	4.60	20124.00	20747.00	5.43	6.58	3703.00	3153.00	300000.00	180000.00	13.00	210.00			
2	3.00	1.00	w	3.40	5394.00	20747.00	1.43	6.58	3778.00	3153.00	300001.00	180000.00	10.00	211.00			
3	4.00	1.00	w	5.30	117692.00	20747.00	7.86	6.58	14978.00	3153.00	500000.00	180000.00	11.00	250.00			
4	5.00	1.00	w	7.80	18109.00	20747.00	5.37	6.58	3371.00	3153.00	400000.00	180000.00	12.00	260.00			
5	6.00	1.00	w	12.00	10100.00	20747.00	3.67	6.58	2751.00	3153.00	250000.00	180000.00	17.00	254.00			
6	7.00	1.00	w	19.00	23454.00	20747.00	8.40	6.58	2792.00	3153.00	200000.00	180000.00	23.00	310.00			
7	2.00	1.00	e	4.60	20124.00	20747.00	5.43	6.58	3703.00	3153.00	300000.00	180000.00	13.00	210.00			
8	3.00	1.00	e	3.40	5394.00	20747.00	1.43	6.58	3778.00	3153.00	300001.00	180000.00	10.00	152.00			
9	4.00	1.00	e	5.30	117692.00	20747.00	7.86	6.58	14978.00	3153.00	500000.00	180000.00	11.00	250.00			
10	5.00	1.00	e	7.80	18109.00	20747.00	5.37	6.58	3371.00	3153.00	400000.00	180000.00	12.00	320.00			
11	6.00	1.00	e	12.00	10100.00	20747.00	3.67	6.58	2751.00	3153.00	250000.00	180000.00	17.00	360.00			
12	7.00	1.00	e	19.00	23454.00	20747.00	8.40	6.58	2792.00	3153.00	200000.00	180000.00	23.00	250.00			
13	2.00	1.00	o	4.60	20124.00	20747.00	5.43	6.58	3703.00	3153.00	300000.00	180000.00	13.00	210.00			
14	3.00	1.00	o	3.40	5394.00	20747.00	1.43	6.58	3778.00	3153.00	300001.00	180000.00	10.00	230.00			
15	4.00	1.00	o	5.30	117692.00	20747.00	7.86	6.58	14978.00	3153.00	500000.00	180000.00	11.00	250.00			
16	5.00	1.00	o	7.80	18109.00	20747.00	5.37	6.58	3371.00	3153.00	400000.00	180000.00	12.00	260.00			
17	6.00	1.00	o	12.00	10100.00	20747.00	3.67	6.58	2751.00	3153.00	250000.00	180000.00	17.00	310.00			
18	7.00	1.00	o	19.00	23454.00	20747.00	8.40	6.58	2792.00	3153.00	200000.00	180000.00	23.00	250.00			
19																	
20																	
21																	

FIG 10: PLACE 1 MODEL DATA (PLACE 1 AS DESTINATION)

PLACE 1 AS ORIGIN:

WORK PURPOSE: -

Tr = exp(8.58) x Dt-0·007 *Popd0.0021 *Ad -0.104 *dind-0.00146* Incd 0.0001

Pivot Table Parameter Estimates

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SansSerif 9

Parameter Estimates

Parameter	B	Hypothesis Test: Wald Chi-Square	Hypothesis Test: Sig.
(Intercept)	5.637	74.035	.000
Dt	-.007	1.662	.000
popo	0[a]	.	.
popd	2.084E-5	2.981	.000
Ao	0[a]	.	.
Ad	-.104	7.588	.000
dino	0[a]	.	.
dind	.000	2.307	.000
inco	0[a]	.	.
incd	1.471E-6	1.246	.000
totit	0[a]	.	.
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 11: EDUCATION PURPOSE:

Tr = exp(4.870) *Dt-0·067 *Popd-0.00321 *Incd 0.023

Pivot Table Parameter Estimates

Parameter Estimates

Parameter	B	Hypothesis Test	
		Wald Chi-Square	Sig.
(Intercept)	4.851	72.035	.000
Dt	-.067	1.235	.000
popo	0[a]	.	.
popd	-.003	2.580	.000
Ao	0[a]	.	.
Ad	.000	.000	.000
dino	0[a]	.	.
dind	.000	.000	.000
inco	0[a]	.	.
incd	.023	1.124	.000
totit	0[a]	.	.
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 12

OTHER PURPOSE:

Tr = exp (4.250) * Dt-0·007 * Ad -0.024 *dind0.002* Incd 0.023

Pivot Table Parameter Estimates

Parameter Estimates

Parameter	B	Hypothesis Test	
		Wald Chi-Square	Sig.
(Intercept)	4.256	72.035	<.001
Dt	-.007	1.235	<.001
popo	0[a]	.	.
popd	.000	.000	.000
Ao	0[a]	.	.
Ad	-.024	3.254	<.001
dino	0[a]	.	.
dind	.002	2.356	<.001
inco	0[a]	.	.
incd	.023	1.124	<.001
totit	0[a]	.	
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 13

PLACE 1 AS DESTINATION:

WORK PURPOSE: -

Tr = exp (4.562) x Dt0·012 *Popo0.000021 *Ao -0.269 * Inco 0.00029

Pivot Table Parameter Estimates

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Parameter Estimates

Parameter	B	Hypothesis Test	
		Wald Chi-Square	Sig.
(Intercept)	4.562	84.035	<.001
Dt	.012	1.372	<.001
popo	7.686E-5	8.477	<.001
popd	0[a]	.	.
Ao	-.269	10.393	<.001
Ad	0[a]	.	.
dino	-.001	8.864	<.001
dind	0[a]	.	.
inco	1.240E-6	4.953	.003
incd	0[a]	.	.
totit	0[a]	.	.
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 14: EDUCATION PURPOSE: -

Tr = exp (4.376) x Dt-0·029 *Popo0.00012 *Ao -0.010 *dino0.0001* Inc0 0.**0001**

Pivot Table Parameter Estimates

File Edit View Insert Pivot Format Help

Parameter Estimates

Parameter	B	Hypothesis Test	
		Wald Chi-Square	Sig.
(Intercept)	4.376	77.763	.000
Dt	-.029	18.289	<.001
popo	6.400E-5	30.202	<.001
popd	0[a]	.	.
Ao	-.010	18.935	.005
Ad	0[a]	.	.
dino	.000	.000	.000
dind	0[a]	.	.
inco	1.572E-6	20.086	.002
incd	0[a]	.	.
totit	0[a]	.	.
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 15: OTHER PURPOSE: -

Tr = exp (4.376) *Dt-0·029 *Popo0.00016 *Ao -0.010 *dino-0.001* Inco0.0001

Pivot Table Parameter Estimates

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Parameter Estimates

Parameter	B	Hypothesis Test Wald Chi-Square	Sig.
(Intercept)	4.376	77.763	.000
Dt	-.029	18.289	<.001
popo	6.400E-5	30.202	<.001
popd	0[a]	.	.
Ao	-.010	18.935	.005
Ad	0[a]	.	.
dino	-.001	8.235	<.001
dind	0[a]	.	.
inco	.000	.000	.000
incd	0[a]	.	.
totit	0[a]	.	.
(Scale)	1		

Dependent Variable: Tr
Model: (Intercept), Dt, popo, popd, Ao, Ad, dino, dind, inco, incd, totit

a. Set to zero because this parameter is redundant.

FIG 16

Trip purpose	R square value
work	0.789
education	0.856
other purpose	0.756

FIG 17 FOR 3 EQUATIONS

G	H
Trip purpose	R square value
work	0.765
education	0.723
other purpos	0.852

FIG 18 FOR 2ND 3 EQUATIONS

CONCLUSION

Our project presents the identification and estimation of the main variables influencing travel demand in areas with low population density. The research concerns the district of Rajahmundry in Andhra Pradesh. The most important conclusions of this article are, GLM models give better and safer results and for all models, the negative sign of the coefficients for Dt and Totit means that Tr increases continuously as these variables decrease. This conclusion is rational and in accordance with logic. The derived models are useful and functional for future planned trips, especially in the Rajahmundry district. Future trips vary considerably depending on the variation of specific independent variables such as population for origin and destination areas, average personal income for origin, and destination areas over internal (urban) distances. Therefore, the number of personal trips in the future can be easily calculated by integrating the main independent variables in the derived models. Finally, future research should be conducted to expand all aspects of this research using comprehensive field data from various governorates to perform more in-depth models and analyzes of travel demand. This definitely improves the transportation system in Rajahmundry.

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