TRIP GENERATION MODELING OF ILORIN CITY, NIGERIA, USING GIS AND ARTIFICIAL NEURAL NETWORK

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Abstract: Ilorin's traffic situation, while not as severe as larger cities like Lagos, Ibadan, and Port-Harcourt, is showing signs of bottlenecks and congestion. Travel demand modeling is important for effective transportation planning. This study develops Artificial Neural Network (ANN) trip generation (production and attraction) models using household and trip characteristics, population data, and maps of the base year (2022). The models had high accuracy values of 0.999873850524 and 0.999999999903 with low error values of 0.058 and 0.0000000419 for trip production and attraction respectively. The models were then used to foresee trip production and attraction for the horizon year (2032).

Keywords: congestion, transportation planning, travel demand, mathematical model, Artificial Neural Network, GIS, trip generation.

1. INTRODUCTION

Transportation infrastructures must be planned and built to meet the increasing transportation needs of a region due to factors such as population growth, urbanization, and income per capita [1]. Rather than continuously expanding infrastructures, engineers and planners should estimate future needs and then design infrastructures that can functionally meet those needs for a long time. Continuous transportation planning helps engineers evaluate existing infrastructures and determine whether they need expansion or removal [2].

Travel demand modelling is a principal part of transportation planning which predicts future travel patterns by collecting and analyzing current travel behavior data to form predictive mathematical models [3]. The conventional travel demand modelling technique includes four steps, namely, trip generation, trip distribution, modal split, and trip assignment. Trip generation is the term used to describe the process of estimating the number of trips originating from or destined for each traffic analysis zone in a particular study area [4].

Artificial Neural Networks (ANNs), a subset of Machine Learning, are capable of learning from and modelling extensive datasets using algorithms that mimic human brain neurons, enabling them to perform complex tasks with remarkable precision [5-7]. Artificial Neural Networks (ANNs) are data-driven models comprising interconnected neurons that communicate through weights and biases [8]. The standard neural network architecture involves three key layers: the input layer, responsible for representing input variables; hidden layer(s) with intermediate nodes

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and neurons that partition input values using weights and biases, passing the results through an activation function for final output determination; and the output layer, which collects activation function outputs from previous nodes [5, 8].

ANNs are praised for their ability to learn from data, eliminating the need for complex mathematical modelling [6, 7]. Recent advancements in this field include the development of specialized ANN architectures. Zhang et al. [9] introduced the attention graph convolutional sequence-to-sequence model (AGC-Seq2Seq) for traffic speed forecasting, outperforming other models like ARIMA and ANNs in terms of prediction accuracy. Kataev et al. [10] used Convolutional Neural Networks to estimate pedestrian traffic, contributing to the development of smart cities and efficient transport networks. Slimani et al. [11] found that Multi-Layer Perceptron neural networks perform well in traffic forecasting. Olayode et al. [6] effectively employed ANNs to predict traffic flow at signal-controlled intersections in South Africa using a comprehensive dataset.

In travel demand modeling, Etu and Oyedepo [7] achieved significant success in modeling trip generation in Akure city, Nigeria, by employing the Radial Basis Function (RBF) Neural Network. They noticed the RBF neural network's remarkable accuracy in this urban context. Their study underscores the necessity of shifting from conventional modeling techniques, like regression analysis, in transportation planning applications to embrace artificial intelligence. Artificial intelligence methods, particularly neural networks, surpass the limitations of traditional approaches and deliver enhanced results. This study aims to develop a trip generation model of Ilorin City using GIS and Artificial Neural Network. GIS and ANN have proven to be powerful tools for maps analysis and data modelling respectively in various fields [7, 12]. Currently, no travel demand model exists for Ilorin City, hence, this study creates a trip generation model which is the first step of the conventional travel demand modelling process. Based on its objectives, this study delineates Ilorin into traffic analysis zones (TAZs) using GIS; collects household and traffic data about each zone (for base year 2022); analyses the data statistically; models the analyzed data; and forecasts future traffic or trips (for 2032) from and to each zone.

2. METHODOLOGY

2.1. The Study Area

Ilorin had an estimated population of 777, 667 in 2006 and a projected population of 1,287,267 in 2022 and is the 7th largest city by population in Nigeria [13]. It is located along 8.4679° N and longitude 4.5656° E. The city comprises of twenty political wards. Ilorin has a well-developed intra-city public transit system, and the city's major roadways are in good condition. For this study, Ilorin is delineated into 8 TAZs as shown in Figure 1.

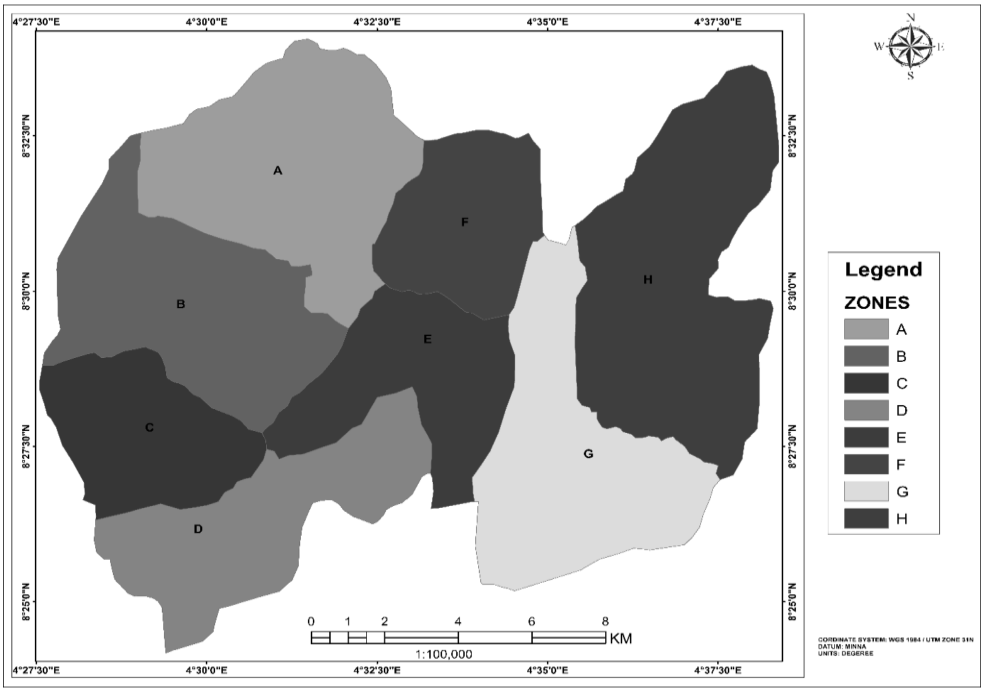

Fig. 1**.** Map of Ilorin: showing the TAZs for the study.

2.2. Data Collection and Analysis

2.2.1. Data Sourcing

The secondary data of the study area include population figures, land use characteristics and geographical maps. Primary data include household/demographic characteristics, socio-economic characteristics, traffic volume and composition and travelers' trip-making characteristics such as number of trips per week, trip purpose and route choice, among others. The secondary data was obtained from the Kwara State Chapter of the National Populations Commission, other government agencies, and GIS. The primary data was obtained from household surveys (origin-destination surveys). Household surveys required the administration of questionnaires.

2.2.2. Ilorin Population and Population Growth Rate

Ilorin had a population of 777,667 in 2006 [13]. Using the population figure and 3.2 % growth rate (as shown in Table 1 [13, 14]), the projected population of Ilorin in 2022 is 1,287,267. Projected population (2022 and 2032) for each TAZs was calculated using this growth rate.

Table 1. Growth Rates of Different Variables (yearly).

Variable	**Growth Rate (%)**
Population	3.2
Employment	2.3
Income	4.1
Value of Land	32

2.2.3. Survey Sampling Technique

The systematic random sampling technique [15] was used for this survey. The technique suggests that one in *n* households (e.g. one in every ten households) on a street can be chosen for the sampling, that is, for questionnaire administration. However, Yamane's adjusted formula was used to control the total number of samples collected per zone.

The Adjusted Yamane's Formula [16] is defined as follows:

$$n = \frac{N}{1+NE^2} \tag{1}$$

$$E = \frac{\rho e}{t} \tag{2}$$

where n is the sample size, N is the population size, E is the adjusted margin of error, ρ is the number of deviations that includes all possible values in the range, e is the error or precision level, t is t-value for the selected confidence level (1.96 for 95% confidence level):

a. for categorical variables (e.g. gender data)
   $\rho = 2$ and e = 0.05

b. for continuous variables (e.g travel data like the data used in this study)
   $\rho = 4$ and e = 0.03

2.2.4. Data Analysis and Maps Design

Data analysis for this study was done using Microsoft Office Packages such as Microsoft Office Excel (version 365) as the major analytical tool and Microsoft Word (365) where necessary. This study used GIS Software, specifically ArcGIS, for maps generation, analysis, production and design.

2.3. Delineation into Traffic Analysis Zones (TAZs)

Using ArcGIS software, Ilorin was divided into 8 zones in order to facilitate easy spatial observation and quantification of land use and economic factors which influence the travel characteristics of the city. Traffic analysis zones are expected to have common administrative (political) boundaries such as political wards. Hence, the political wards covered by Ilorin would be considered with respect to the land uses, population distributions and administrative boundaries.

2.4. Trips Generation Modelling

2.4.1. Variables selection and model used

In this study, Artificial Neural Network is used for trip generation as it gives more accurate modelling/forecasting results than traditional models [7]. The final variables considered for modelling were chosen with the aid of Pearson correlation analysis.

2.4.2. ANN Model

The study constructed ANN models from Python Programming Language on Google Colab Notebook. Python codes were utilized to complete all the necessary steps involved in the ANN model creation process. An additional set of codes was required to utilize the established model for predicting the trip generation estimates for the year 2032. The modelling process utilized various programming libraries and machine learning tools, namely Keras, Pandas, Numpy, Tensorflow, Sklearn, and the Google Colab library. These tools were integrated on the open-source Google Colab Notebook for optimal performance.

3. RESULTS AND DISCUSSION

3.1. Traffic Analysis Zones

The TAZs created (Figure 1) consists of the 20 administrative wards in Ilorin. The population of each zone is calculated by the sum of the population of the constituent wards. The result is shown in Table 2. Sampled population was determined using Yamane's adjusted formula. Afterwards the data was collected based on the TAZs and analyzed.

The data analysis unveiled key insights about Ilorin. On average, each household in Ilorin consisted of 6.51 individuals, with an approximate income of 240,000 naira. Daily household travel averaged at 11.7 trips, of which 81 % were home-based (9.5 trips) and 19 % were non home-based (2.2 trips). Furthermore, the primary mode of transportation in Ilorin was passenger cars, representing 53 % of total vehicle trips, followed by buses (25 %), tricycles (14 %), and motorcycles (8 %).

Table 2. Ilorin wards population for 2006 and 2022.

Zones	**Population (2006)**	**Population (2022)**	**Population targeted for Sample**	**Numbers of Households for Sample**
1	161,786	267,803	267	53
2	215,279	356,350	267	53
3	43,084	71,317	266	53
4	42,341	70,087	266	53
5	139,425	230,789	266	53
6	133,410	220,833	266	53
7	23,028	38,118	265	53
8	19,314	31,970	265	53
Totals	**777,667**	**1,287,267**	**2128**	**426**

3.2. Pearson Correlation Analysis

The variables considered for the correlation analysis are Total Zonal Trips (TT), Household Size (HS), Household Income (HI), Average Age (AG), Number of employed members (NE), Number of Students (NS), Number of Vehicles (NV), Number of members above age 12 (N12), Number of Males (NM), Number of Females (NF) and Ownership of Drivers' License (DL). The result of the analysis is shown in Table 3.

Table 3. Ilorin wards population for 2006 and 2022.

	TT	*HS*	*AG*	*HI*	*NE*	*NS*	*NV*	*N12*	*NM*	*NF*	***DL***
Trips/Household	1.00										
Av. Household Size	0.92	1.00									
Av. Age	0.22	0.11	1.00								
Av. Income	0.60	0.61	0.64	1.00							
No Employed	0.78	0.70	0.56	0.78	1.00						

No of Students	0.40	0.58	-0.52	-0.05	-0.14	1.00					
No of Vehicles	0.72	0.56	0.74	0.64	0.88	-0.21	1.00				
No of above 12yrs	0.92	0.87	0.30	0.61	0.69	0.44	0.74	1.00			
No of Male	0.60	0.71	0.47	0.49	0.62	0.11	0.65	0.60	1.00		
No of Female	0.77	0.79	-0.24	0.44	0.44	0.71	0.23	0.70	0.13	1.00	
Driver's License	0.77	0.67	0.64	0.70	0.92	-0.05	0.96	0.82	0.63	0.40	1.00

Total Trips (TT) is the dependent variable. After comparing the correlation coefficients of the independent variables, Zonal Population and Average Household Income are the independent variables for trip production modeling while Number of Employment or employed person [4] is the independent variable used for trip attraction modeling.

3.3. Total Zonal Trips (person trips) per day

Next, Households count (number of households) was estimated using populations and average household sizes for each zone (from household survey data) while the total trips for each zone was estimated by the product of households count and trips per household (as shown in Table 4).

Table 4. Values for estimating total zonal trips/day.

TAZ	Population (2022)	Trips per Household	Av. Household Size	Households count	Total Zonal Trips/day
Zone 1	267803	13.510	7.4	36190	488565
Zone 2	356350	12.587	6.4	55680	701568
Zone 3	71317	13.820	7.3	9769	134812
Zone 4	70087	10.463	5.8	12084	126882
Zone 5	230789	9.456	5.8	39791	378015
Zone 6	220833	11.818	6.4	34505	407159
Zone 7	38118	10.254	6.3	6050	62315
Zone 8	31970	12.750	7.0	4567	58458

3.4. Trip generation modeling

Artificial Neural Network (ANN) is the tool in focus for creating trip generation model for this study. Trip production and attraction for 2022 (Tables 5 and 6) and after 10 years' time (2032) were determined (Tables 8 and 9) in this step. In order to achieve this, the trip attraction/production parameters (independent variables) for 2022 were extracted from survey data while those for 2032 were calculated using growth rates shown in Table 1. The zonal income is expressed in Nigerian Naira (N).

For trip production, total zonal trips were calculated from household survey data as shown in Table 5.

Table 5. Base Year (2022) Parameters.

TAZ	Trip production		Trip attraction
	Population	Average Zonal Income (*1000)	Employment
Zone 1	267803	237	92950
Zone 2	356350	203	148553
Zone 3	71317	293	35107
Zone 4	70087	242	30473
Zone 5	230789	191	86808
Zone 6	220833	241	92856
Zone 7	38118	181	13907
Zone 8	31970	348	13925

In order, to estimate the trip attraction for each zone first, the relationship between trips generated (dependent variable) by all the zones and the number of employment (independent variable) was established using regression analysis. The regression model equation (equation (3)) was then used to estimate the trip attraction for each zone by plugging in the individual values of employment for each zone.

$$\text{Trip attraction (base year)} = -16250.32 + 4.8345*\text{Employment} \quad (3)$$

Table 6. Total person trips/zone for production/attraction for 2022.

TAZ	Total Zonal Trips (Production)	Total Zonal Trips (Attraction)
Zone 1	488565	442804
Zone 2	701568	704250
Zone 3	134812	166772
Zone 4	126882	123458
Zone 5	378015	387787
Zone 6	407159	431512
Zone 7	62315	42580
Zone 8	58458	58610

3.4.1. ANN Modeling for Trips generation

The base year variables and trips values were used to build trip generation models for both production and attraction of the base year. This was carried out using Artificial Neural Network (ANN). The ANN models were then used to generate or predict the trip production and attraction for 10 years' time.

3.4.2. ANN Model Architecture

After considering various types of ANN architecture, the multilayer perceptron (MLP) neural network was chosen. It is a simple sequential model with sets of 3 layers namely the input layer, the hidden layer(s) and the output layer. This type is in Figure 2. This architecture was used for both models.

ANN model training requires a lot of iterations involving changing of the model architecture parameters (called parameters tuning) until the desired or most acceptable performance or accuracy is achieved. In this study, the architecture that gave the best result is composed of:

- One input layer of 8 nodes;
- One hidden layer of 16 nodes;
- One output layer of 1 node (since the dependent variable, y, being predicted is one value).

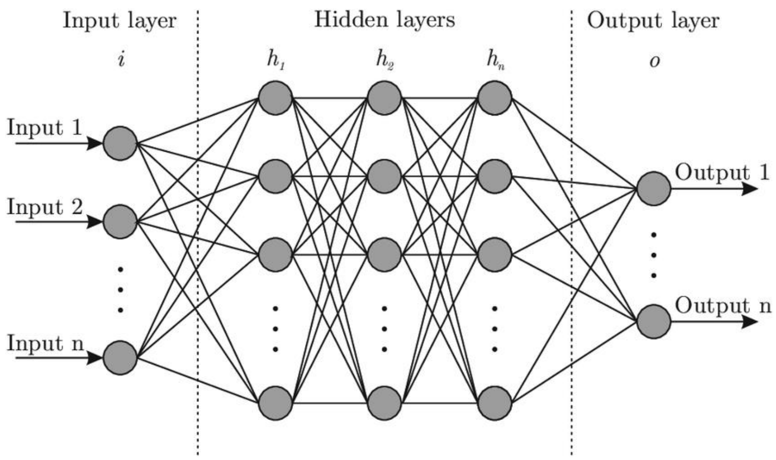

Fig. 2. General MLP architecture: showing input, hidden and output layers, and neurons.

3.4.3. ANN Model Training, Testing and Validation

Neural networks generally require a large amount of data for model training, hence the production and attraction data in this study was transformed into a data of over 500 rows using the mean and standard deviation of the original data. This gives a larger data with the same characteristics as the original ones. This new data is then used to build, train and test the ANN model.

The input data was split into training and testing datasets in proportions of 80 % and 20 %, respectively. The validation split (done internally by the network during the training process) was 20 % of the input data. Neural network does validation separately and simultaneously with training process; hence, the validation data percentage is not affected by the training and testing data split. It helps to improve the model performance by fine-tuning, the model after each epoch or cycle of training.

3.4.4. Model Accuracy

The model’s accuracy was determined using the r-square value, mean absolute error, and mean squared error. They were calculated using respective Keras and Python programming functions. The accuracy/error values for trip production and attraction models are presented in Table 7.

Table 7. ANN model accuracy and performance.

Accuracy measure	**Trip Production model**	**Trip Attraction model**
R-squared value	0.9998738505241817	0.9999999999033522
Mean Absolute Error (MAE)	0.17869409918785095	0.00015423298464156687
Mean Square Error (MSE)	0.05813134089112282	4.199481651312453e-08

This demonstrates that the model performed very accurately and can be considered reliable for predicting future values of trip generation (production and attraction) for Ilorin City.

Table 8. Predicted parameters for 2032 using ANN model.

	Trip production		Trip attraction
TAZ	Population	Average Zonal Income (*1000)	Employment
Zone 1	366955	354	116682
Zone 2	488285	304	186482
Zone 3	97721	437	44071
Zone 4	96036	362	38253
Zone 5	316237	286	108973
Zone 6	302594	360	116564
Zone 7	52231	270	17458
Zone 8	43807	520	17481

3.5. Forecasted Trip Production/Attraction After 10 years (2032)

Using the ANN model as built by Python programming language on Google Colab environment, the future trip production and attraction were predicted (Table 9) from 2032 independent variables or parameters (Table 8).

Table 9. Anticipated production and attraction for 2032 using ANN model.

TAZ	Total Zonal Trips (Production)	Total Zonal Trips (Attraction)
Zone 1	773424	547851
Zone 2	1035824	884952
Zone 3	297207	196811
Zone 4	237874	168684
Zone 5	621305	510581
Zone 6	649255	547280
Zone 7	108424	68150
Zone 8	251378	68261
Totals	3974691	2992570

4. CONCLUSION

This investigation developed a trip generation model for Ilorin City using GIS and Artificial Neural Networks (ANNs). The study may serve as a first step towards developing a city-travel demand model. GIS constitutes an extremely powerful map design tool while ANN is known for giving high accuracy results when used to model complex data. The city has been carefully delineated into eight traffic analysis zones (TAZs) using GIS. Zone centroids were then selected for each TAZs. The delineation and centroid selection based on administrative boundaries (such as political wards), major road networks and intersections, among other things. Household and trips data were collected using questionnaires administration based on the traffic analysis zones and sampling methods (Yamane’s adjusted formula and systematic random sampling method). The data collected was then analyzed.

The analysis of the data revealed that the overall average household size in Ilorin was 6.51 persons; average household income was approximately 240,000 naira; average household daily trips was 11.7 (9.5 or 81 % home-based and 2.2 or 19 % non home-based trips). Moreover, the analysis showed that cars are the most predominantly used travel mode by travelers in Ilorin with car trips taking 53% share of the total trips, followed by bus, tricycle and motorcycle, with 25 %, 14 % and 8 %, respectively. Among the correlations examined using Pearson Correlation analysis, it was found that household size and the number of household members above 12 years old exhibited the highest correlation, both scoring 0.92 in relation to total trips. Conversely, the average age of household members displayed the lowest correlation, with a score of 0.22 concerning total trips.

ANN was used to develop a trip generation model for the city based on 2022 household and trips data. The models' performance was evaluated using R-square score, mean absolute error and mean squared error. The results of the study show that the ANN trip generation model gave R^2 values of 0.9998738505241817 for trip production and 0.9999999999033522 for trip attraction and with very low error values of 0.058 and 0.00000004199 respectively. This shows that the ANN model developed in this study is very accurate and reliable for predicting future trips.

The ANN model was then used to predict trip generation for 2032 in each of the 8 zones. The forecast generated a total of 3974691 person trips per day for production and 2992570 person trips per day for attraction. The predicted values are, therefore, accurate and reliable and can be used for the trip distribution stage or any subsequent study that relies on them. Also, transportation planners can rely on these models and the predicted trip generation values in designing transportation systems for the city including pavement construction, signal timings and intersection designs, provision of mass transit systems, management of vehicle emissions, and so on.

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