

Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2023) 000–000

World Conference on Transport Research - WCTR 2023 Montreal 17-21 July 2023 Development of 3W-LOS Prediction Model for Urban Roadways using Adaptive Neuro Fuzzy Interface System

Subhada Nayak^a, Mahabir Panda^b, Prasanta Kumar Bhuyan^{c*}

^aPh.D. Scholar, National Institute of Technology, Rourkela- 769008, India ^bProfessor, National Institute of Technology, Rourkela- 769008, India ^cAssistant Professor, National Institute of Technology, Rourkela- 769008, India

Abstract

In order to transform cities into more liveable, safe, and sustainable places, we must shift our mobility paradigms. As one auspicious concept amongst urban transportation facilities, para transit modes facilitate urban transportation into small, efficient, and affordable vehicles that are flexibly operated on any infrastructure i.e. specifically motorized three-wheelers being the most prominent subject vehicle of para-transit mode in India, yielding the potential to make public transit more convenient, affordable, and sustainable all at once. Considering this, service quality prediction for motorised three-wheelers at urban roadways is analysed involving the data collected from 50 road segments from 5 cities. Adaptive Neuro Fuzzy Interface System (ANFIS) is used for the development of Three-Wheeler Level of Service (3W-LOS) prediction model, which simplifies the complex andwide input space. For the above quantitative parameters as road geometric features, flow parameters of traffic, built environment factors are considered and also for predicting the service level qualitative survey is done. Information of the survey participant (age, sex, driving experience, type of vehicle, education qualification, frequency of travel, etc.). A set of attributes are shown to drivers about road segment LOS and are asked to rate the facility on a Likert scale of 1-6 where, '1' indicates 'highly dissatisfied' and '6' indicates 'highly satisfied'. Overall satisfaction score (OS) of road links, taking the average of driver's rating is obtained. The coefficient of determination for training and testing is found to be 0.8809 and 0.8239 respectively by using the ANFIS output for 3W-LOS prediction over Indian roadway segments.

Keywords: Three-wheeler Level of Service; Adaptive neuro fuzzy interface system; Heterogenous traffic; Gaussian membership functions

*Corresponding author. Tel.: 8328890702 *E-mail address: bhuyanp@nitrkl.ac.in*

2352-1465 © 2023 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0) Peer-review under responsibility of the scientific committee of the World Conference on Transport Research – WCTR 2023.

1. Overview

The three-wheelers, which are shared or hired, assist people who do not use private transportation and are not served by the existing public transportation system. Because they have smaller engine capacity and higher mileage than a standard Car Taxi, they serve the needs of a segment of society by operating as cheap taxis. An auto-rickshaw is better than a car since it transports the same number of passengers while using one-third of the parking space andhalf the space while travelling. Because it is one-third the weight of a car, it wears out the road far less, needs fewer tyres and rubber, and consumes one-third of national resources to manufacture. All of this contributes to a reduction in indirect pollution. They pollute far less per passenger than cars because they have a small engine. They can't go faster than 50 km/h due to the engine's small size, so they stick to city speed restrictions and can also control the speeds of others. In comparison to cars, they cannot readily cause deadly accidents among pedestrians and bicyclists because to lower speeds and lesser weights. As a result, three-wheeler use in Indian cities should be promoted as much as feasible. Hence, the demand for an efficient private mode of transportation is gradually increasing to manage the necessities of both personal and professional life being a novel para-transit mode. On the other hand, managing road networks has been dreadfully challenging due to limited space and resources, as the modal shift effectively increases congestion and overcrowding in roadways operating environment.

Unlike developed countries, the complexity of traffic movement in emerging countries like India is basically due to its heterogeneity in traffic stream and presence of weak/loose lane discipline. The traffic mix in Indian scenario includes vehicle classes ranging from buses, motorized three-wheelers to the hand/animal driven carts, having diverse operational features. Drivers rarely ever adhere to any kind of lane discipline, and the drivers of non- motorized vehicles and large trucks tend to share the through lanes. Furthermore, some vehicles are involved in using the available lateral gaps to overtake other vehicles and try to be at the starting of the queue even during saturation flow. Because of this, peak-hour traffic tends to expand unpredictably and become more congested. Thereby, planning, designing and management of any transportation system has become an important issue for a comfortable ride of motorized three-wheeler drivers. The most fundamental entity of a road network is a road link. It is also popularly known as "mid-block segment", as it is the section of roadway that stretches longitudinally between two boundary intersections, which may or may not be operated by signal controls. The urban roadways are classified in to two categories, i.e. one-way or two-way based on the direction of through movement of vehicle stream with or without the presence of a median. The operating conditions of urban mid-block segments are investigated in this study to assess the performance of urban road links for motorized three-wheeler perspective. All the variables (quantitative) are listed for collection of datasets from selected urban road segments, under a heterogeneous mix traffic condition.

The geometrical parameters affecting 3W-LOS includes Effective Road width, Pavement condition index, Median width, Presence of median, Direction of travel, Number of lanes in eachdirection, Presence of dedicated bike lanes, Presence of grade-separated sidewalk, Shoulder width etc. Geometric data can be measured directly from the field using a measuring tape, and some factors can be assessed visually. Again, Traffic parameters in the study includes Average travel speed (S_{avg}) , Composition of three-wheeler vehicles in total traffic in %, Composition of slow and heavy vehicles in total traffic in %, Peak hour motorized traffic (PMV), On-street pedestrian volume in % etc. and this study incorporates various auxiliary variables identified in thepilot survey that have a substantial impact on the ease of driving and cause obstruction or delay in vehiclemovement. These includes Median crossing pedestrians in numbers, Roadside commercial activities, or Land use pattern (LU), Obstruction due to On-street parking (P), Hindrance due to frequently stopped heavy vehicles ahead (HF), Average delay caused due to presence of slow and heavy vehicles (D) etc. Among all the possible variables taken for preparing the dataset, the most influencing parameters are selected for model formation usingsignificant variable selection technique. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is being used for delivering three- wheeler service level prediction model for heterogeneous traffic condition in mid-block sections. The ANFIS model has the benefit of possessing both numerical and language information, which is a distinct advantage. In addition to this, ANFIS takes advantage of the ANN's capacity to categories data and recognize patterns. There is less of a need for the user to rely on memory with the ANFIS model, and it is more user-friendly than the ANN. The steps involved for 3W-LOS modelling are defining input-output variables (influencing parameters (V_i) with two-tailed significance (p)<0.001), defining fuzzy sets for input values $(f(V_i))$, defining fuzzy rules (Weights towards rules and input functions (W_i)), create and train the neural network using Gaussian membership function. The research shows that ANFIS has been effectively deployed to adapt course materials to a variety of learning contexts.

Standard error measures were used to assess the ANFIS model's efficiency, illuminating thebest configuration for enhanced forecasting. The findings of the MATLAB simulation suggest that the performance of the ANFIS approach is both beneficial and simple to put into practice. Fuzzy Logic and Neural Network are two different approaches to machine learning. ANFIS is an approach that combines the advantages of these approaches into a single approach. The ANFIS is operational because it uses the learning methods of neural networks to fine- tune the parameters of a fuzzy inference system (FIS).

To be convinced of the degree of the need for improved infrastructure, the service quality provided by existing roadways must be analyzed methodically. This study aims to provide an appropriate technique for assessing the 3W-LOS offered in this regard. 3W-LOS describes the operational circumstances and degree of satisfaction of motorized three wheelers on roads with geometric and traffic flow conditions. Several scholars have constructed mathematical models commonly referred to as LOS models for the prevalent road infrastructure conditions in developed nations. However, due to varying circumstances, these models may not be well adapted in countries like India, where urban road traffic is highly varied, resulting in complicated interactions between different types of vehicles. Hence, satisfaction level perceived by motorized three wheelers is influenced by several types of vehicles passing them or the composition of vehicular traffic. Along with this, geometric details of existing roads are also quite different. The subsequent section provides a concise summary of the study's context. This is followed by a discussion of thestudy's methodology, data sources, and development approach. The statistical significance and validation criteria of the developed ANFIS model are examined and explained in depth.

Nomenclature

2. Review of Literature

2.1 General

Currently, the planning, construction, and administration of any transportation system are focused on providing automotive drivers with a pleasant journey. In developing nations like as India, roadway facilities oftenresult in uncontrolled traffic growth and peak-hour congestion. In addition, there are several additional engineering aspects that affect drivers' satisfaction levels on urban roadways in developing nations in addition to speed and delay. As a result, the performance of urban roadways under heterogeneous traffic flow circumstances cannot be quantified by infrastructure construction based on homogeneous traffic flow models.

Some study has defined the LOS requirements for urban street infrastructures in underdeveloped nations. Deshpande, Gartner and Zarrillo, (2010) indicated that volume-weighted averages can calculate arterial street LOS. The progression performance frontier helps analysts analyze performance tradeoffs from preferentialconsideration of one path over another. Level of service trials use a two-lane wide level tangent road stretch with 35% nonmotorized vehicles and 65% motorized vehicles. As per Singh and Abu-Lebdeh, (2009), LOS is defined by automobile and motorized two-wheeler speeds, concentration, and road occupancy. LOS I, LOS II, LOS III, and LOS IV are determined through benchmark road (Road I) and traffic composition (Level I) simulations. Choocharukul, Sinha and Mannering, (2004) applied an ordered probit model to the LOS for the roadway. The authors came to the conclusion that the HCM's use of traffic density as the sole metric of performance may not

correctly represent the perspectives of people who drive on the roads. Chatterjee S., (2017) The level of service (LOS) is a qualitative word for transportation facility operating. Quantitative service measures are needed to assess a facility's operational status. That facility's MOE is its quantitative foundation. Flannery, Wochinger and Martin, (2005) suggested that drivers' opinions and other qualitative elements be included into LOS estimates. Dowling *et al.*, (2008) presented four LOS models to forecast the quality of service for four different types of urban transportation (automobile, transit, bicycle, and pedestrian). Flannery, Wochinger and Martin, (2005) developed a cumulative logit model that predicts automobile driver's perceptions of service quality based on presence of medians, landscaping, progress, and posted speeds. Papadimitriou *et al.*, (2019) identified and analysed the perceived highway LOS of road users with respect to traffic conditions.

Faezi *et al.*, (2011) created a system for predicting motorbike performance using logistic regression. A rider's perception of the importance of volume, total lane width, pavement surface quality, and speed was most strongly influenced by these variables. There has been some study on how to calculate LOS on urban streets with variable traffic volumes. Maitra, (1999) By using a fundamental diagram of speed-flow, as well as operational and volume characteristics of mixed traffic, we developed an empirical model to estimate congestion levels on urban road sections. Based on the volume to capacity ratio, Marwah and bhuvanesh singh, (2000)classified LOS into four groups based on the behaviour of heterogeneous traffic flow rates. Chen *et al.*, (2009) summarized LOS as: level of traffic facility provided and level of traffic operation. Mohapatra, Bhuyan and Krishna Rao, (2012) On the basis of speed data, a hybrid approach comprised of the evolutionary algorithm and Fuzzy C-Means clustering was used to determine the ranges of six LOS categories. This study came to the conclusion that both the physical aspects of the environment and its surrounding environment have an influence on excellent LOS. Patnaik and Bhuyan, (2016) determined LOS categories using genetic programming clustering.

2.2 Motorized three-wheeler in India

Despite the fact that both public and private transportation services offer a quick and dependable means of transportation, there are some gaps that they are still unable to fill, including late-night and early-morning travel, travel up to the destination, travel in rural areas and small cities, and more as per Hook and Fabian, (2009). These considerations made Paratransit, or informal public transportation, a crucial part of people's daily lives. Three Wheelers are the most common and most popular para-transit mode. The demand for three-wheelers has surely increased due to a variety of factors, including a high demand for travel, an expanding population, an increase in the number of workplaces, an increase in the number of trips each trip, and a lack of parking spaces. As per Sriraman *et al.*, (2006) three-wheeler mobility is significantly hindered by the presence of other vehicles since the performance and operating characteristics of these vehicles differ from those of other vehicles in the traffic stream at a signalized intersection. The number of vehicles in the intersection at any given time, the type of vehicles, and their acceleration capabilities all affect how long it takes for them to pass through the intersection and how much delay they produce.

2.3 Prediction Models and service level

The HCM (2000) methodology was used to estimate urban street LOS, and it was shown that it could only explain 35% of the variance1in mean driver rating. As a result, the cited authors concluded that current LOS methodologies do not fully reflect drivers' perceptions of service quality, as drivers evaluate service quality in a variety of ways, including travel efficiency, sense of safety, and aesthetics like travel time, average speed, number of stops, delay, number of signals, lane width, tree presence, and landscape quality. By combining the findings of user perception research into the LOS framework, HCM, (2010) refined the theory and definition of LOS. LOS is described as a quantitative stratification1of a performance measure or measurements that characterize service quality, according to HCM 2010. In a video laboratory research survey, a group of travelers is asked to rate the driving conditions on a scale of "very good" to "very poor," or anything along those lines. These qualitative ratings are translated to numeric numbers during data processing.

The fundamental technique for measuring LOS in HCM, on the other hand, has essentially remainedunchanged throughout time. HCM 2010 includes NCHRP project 3- 70, which aims to provide multimodal LOS approach for urban streets. According to the NCHRP 3-70 study, "stops per mile" and "left turn lane presence at signalized intersections" had the highest statistical significance for predicting automobile LOS of urban Street Segments. As a result, techniques that focus on establishing multimodal LOS are ideally adapted to it.

The HCM, (2016) is focused on calibration using capacity and speed adjustment parameters that took into account driver demographic effects. Instead of "average travel speed as a percent1of free-flow speed," the service measure for urban street facilities was modified to "average travel speed." For LOS A and LOS B, the relevant threshold values were reduced to 80 percent of free-flow speed. New adjustment parameters for parking activities, which affect free-flow speed estimation, were added to the approach for evaluating urban street segments with midsegment lane blockage. For intersection operations, mid-segment lane blockage, and downstream spillback, the saturation flow adjustment parameters were introduced. In order to assess the driver's satisfaction level at an unsignalized intersection, the delay at the intersection is used as a key input parameter. Deshpande, Gartner and Zarrillo, (2010) proposed three ways for assessing LOS on an urban artery that are methodical and precise in incorporating the effects of coordination. In conjunction with the HCM-2000 (TRB, 2000) technique, the cyclic coordination function (CCF) and related coordination adjustment factor (CAF) were employed to quantify the quality of progression (QOP). The authors proposed three different methods for estimating LOS: LOS analysis using average delay for the entire artery, LOS analysis using average trip speed with cyclic coordination factors, and CAF as a QOP performance indicator. Jena *et al.*, (2017) created an empirical model to evaluate Automobile1Users' Level of Service (ALOS) under varying traffic flow situations. The suggested methodology employs an ordinal logit analysis to model participants' ordered replies and identify which service category a segment provides for automotive use. Amaral, (2013) attempted to estimate the Level of Service of e-bike, escooter, and bicycle riders in mixed traffic mid-block bicycle lanes. With the use of ordered probit models, researchers were able to determine how users of e-bikes, e-scooters, and bicycles feltabout the level of comfort they had while riding their respective vehicles. The findings revealed that those who rode electric bicycles and scooters were more likely to experience feelings of unease when compared to people who rode bicycles. Comfort levels for cyclists improved as the width of the mid-block bicycle lane rose, but theselevels declined when the number of two-wheeled vehicles on the road increased. It was also comforting for bikersto have separate lanes for motorised vehicles, bicycles, and pedestrians. Clustering Large Application (CLARA) was utilised by Das and Bhuyan, (2017) to classify urban streets into a variety of types based on free flow speed (FFS). Vast amounts of second by-second speed data are acquired using the Global Positioning System1(GPS), and GIS was utilised to handle the large amount of data. FFS ranges for several urban street classes and speed ranges for different LOS categories were defined in the study, and the values were found to be lower than HCM, (2000) indicated. In addition, the average trip speed ranges in each LOS category (given as a % of free flow speed) nearly match the percentages shown in HCM, (2010).

The research suggests that the application of the afore mentioned approaches in emerging nations is dubious. This is due to the fact that speed and journey time are not the only factors determining the driving experience of drivers. In this research, the effects of a number of significant elements, such as roadside business operations, parking turnover, interruptions by non-motorized vehicles and public transportation, etc., are ignored. In addition, regardless of travel behaviour, any approach would be susceptible to significant rejection. Therefore, this research investigated the relationship between a variety of road characteristics and drivers' perceptions of pleasure in a mixed traffic flow situation. By investigating a novel methodology to assess the service quality service quality of motorized three-wheelers supplied by urban road segments, the current methodologies are validated.

3. Procedure

3.1 General

Transportation planners should concentrate on the characteristics of the transportation system that have the most impact on road users' satisfaction levels. Level of service (LOS) models are generally accepted as the standard way for assessing the operational performance of any transportation infrastructure. The Highway Capacity Manual (HCM), which is the manual that is used the most often, is followed in practically every area of the globe. This manual specifies LOS to be measured in terms of how satisfied the users are. Nevertheless, information concerning user perception is not included into the choices that are made about investments in developing countries.

Data set preparation and study location

India is home to many castes, cultures, religions, and languages. Because of this, drivers around the nation drive differently. Driver comfort will also be affected by traffic, road infrastructure, geometric designs, and driving environments in different parts of India. This research examined 50 road segments in five Indian cities to build a reliable three-wheeler level of service model. The study sites were urban residential and commercial sectors. Driving is safer and more pleasant on roads with a median and no steeper slopes at horizontal bends. In each of thesecities, the way people drive and how the roads are laid up are distinct, indicating that the traffic flow is distinct.

The necessary quantitative data sets were gathered from 50 urban roadway segments in five cities in India namely; Bhubaneswar (Odisha): The city has a literacy rate of 93.15 percent, which is greater than the national average of 75 percent, With an average road density of 11.82 square kilometres, the city has over 1,600 kilometresof roadways, Jhansi (Uttar Pradesh): The city's literacy rate is 75.05 percent, The city is at the crossroads of four national highways: NH-27 from Gujarat to Assam, NH-75 from Gwalior to Rewa through Chhatarpur, NH-44 from Jammu to Kanyakumari, and NH-39 from Jammu to Kanyakumari., Visakhapatnam (Andhra Pradesh): The city hasa large network of roadways with a total length of 2,007.10 km, with the major highways NH16 and NH5 as well as a section of the Golden Quadrilateral system bypassing the city, Latur (Maharashtra): Road connectivity is strong, with fourlane highways being built connecting Mumbai, Pune, Nagpur, Nanded, Satara, Kolhapur, Sangli, and Aurangabad. The city of Latur is bisected by NH 361, a national highway that runs through it. Latur Municipal transport (LMT) is an intra-city bus service which covers almost all parts of the city. Udgir (Maharashtra): the cityis well connected by road to all major villages and cities, with buses operated by the Maharashtra State Road Transport Corporation (MSRTC). The city is crossed by NH-50, while NH-63 is currently under construction.

The traffic patterns and composition, as well as the road networks, vary amongst these five cities. Consequently, these data sets may accurately depict the variability of traffic streams. The research that was done allowed for the collection of fundamental knowledge on the constraints that come with using older methodologies toassess the quality of urban street services in the presence of highly variable traffic flow circumstances. Driver comfort on urban streets can be influenced by factors such as road geometry and traffic operations according to a field study conducted on the streets. The road geometrical data sets, including effective road width, width of median, and shy distance, were measured using a measuring tape. Infrequently, only one-way traffic flow is authorized when the number of lanes for one direction of traffic varies from one to four, with two-way traffic flow. During morning (8.00-11.00 a.m.) and evening (4.00–7.00 p.m.) rush hours, the traffic flow on a particular street was captured by a high-resolution video camera. Table 1 lists all quantitative data obtained from urban road links, along with their associated units. The geometric parameters like road width, effective road width, width of median (if present), shy distance, shoulder width etc., were cross verified from Google earth to avoid any manual errors and errors due to approximation. Pavement surface quality, road markings, camber/cross slope etc., were investigated through field observation. Pavement surface quality was expressed on a Likert scale (1-5), with 1 being worst and 5 being the best pavement surface quality. Number of lanes in the carriageway were counted manually and expressed in numbers, presence of median was expressed as 1 while absence was 0.

During the data collection process, high-resolution video cameras mounted on the tripod stands were employed to capture the traffic flow parameters such as traffic volume and composition of different types of vehicles in traffic mix. The camera was placed at high elevation sites such as a foot over bridges or a terrace of tall structures. So that the camera could clearly capture traffic movement along the road. The most critical 15-minute period of traffic flow within an hour was considered. The most critical 15-minute period of traffic flow within an hour was considered. All the recorded clips were played in Kinovea software on the monitor and each category of vehicles was counted separately for peak 15-minute duration. On-street pedestrian volume was also counted from the recorded video clips. Average travel speed was calculated from recorded video clips by dividing the trap length by the time taken by the vehicle to cross the trap section. The average delay was calculated as the difference between the travel time needed to pass a certain section of road at reduced speed due to the presence of heavy and slow-moving vehicles ahead and the travel time to pass the same length of roadway without their presence.

The built-environmental parameters are taken which affect the driving behaviour of drivers are such as: roadside commercial activity, illegal on-street parking, presence of slow-moving heavy vehicles, percentage of non-motorized vehicles in the traffic mix, median crossing pedestrian, opposite encounters etc., cause hinderance or delay to the traffic. The obstruction in driving caused due to illegal on-street parking is quantified by visualizing the percentage of the road length occupied by the parked vehicles in each approach. The type of land use pattern across the investigated approaches was used to determine the hindrance in driving caused by roadside commercial density. In this study the land use pattern is categorized in three categories: (i) Residential areas with low commercial activities, (ii) Mixed land-use areas, combination of residential and commercial areas, and (iii) Purely commercial areas with high commercial activities. The number of heavy vehicles present in the traffic mix were counted through a video laboratory survey and expressed as a percentage of the total traffic. Also, the number of non-motorized vehicles present in the traffic stream were counted through a video laboratory survey and expressed as a percentage of total traffic volume in each approach. Similarly, the number of pedestrian crossing median and opposite encounters were counted through a video laboratory survey and expressed in numbers.

3.2 Influencing Variable selection

Spearman's correlation is characterized as the nonparametric version of Pearson correlation coefficient. It simply measures the degree 37 of association between both continuous and discrete ordinal variables. The collecteddatabase in this study contains both continuous variables (traffic volume, average speed, and delay etc.) and ordinalor categorical variable (Pavement condition index, perceived 3W-LOS scores, On street parking, hindrance etc.). Hence Spearman's correlation is applied in this study to examine the correlation between output and input variables. Spearman's correlation coefficient or Spearman's rho (ρ) is a statistical measure of the strength of a monotonic relationship, established between two variables 'x' and 'y', where 'x' is independent and 'y' is the dependent variable. The assumed data sets used are ordinal, interval or ratio level. This 'p' value close to 1 or -1 indicates strong correlation between two variables positively or negatively. A 'ρ' value of zero indicates, there exists no relation at all. At the same time, any variable having ' $p' > 0.6$ is ignored to avoid multi-collinearity among different input parameters used in the model development.

3.3 ANFIS 3W-LOSModeling Approach

In ANFIS method, the model combines the learning capabilities of a neural network and reasoning capabilities of fuzzy logic in order to increase predicting ability. This model, instead of learning output function, it learns input space for more accuracy. ANFIS model divides the whole wide input space according to their behavior in the sharedspace with output space.

The network structure may be broken down into two parts: premise and consequence. The architecture is made of five levels, as indicated in Fig.1. The first layer processes the input values and finds the membership functions that correspond to those values based on those values. The term "fuzzification layer" is widely used to refer to this layer. The membership degrees of each function are calculated using the set of parameters specified in the premise, namely a,b,c. The second layer is responsible for creating the rule-based firing strengths.

The second layer is designated as "rule layer" due to its function. The third layer is responsible for normalising the calculated firing strengths by dividing each value by the overall firing strength. The fourth layer accepts the normalised data and the result parameter set p,q,r as input. This layer returns the defuzzified values, which are then sent to the final layer, which returns the final output. The first layer of an ANFIS network explains the distinction between it and a standard neural network. In general, neural networks use a stage of data pre-processing in which thecharacteristics are transformed into normalised values between 0 and 1.

A neural network for ANFIS does not need a sigmoid function, but it performs the preprocessing phase by turning numeric inputs to fuzzy values.

Syntax: f is = anfis(trainingData) f is = anfis(trainingData,options) $[$ fis,trainError $] =$ anfis $($) $[$ fis,trainError,stepSize $]$ = anfis $($ [fis,trainError,stepSize,chkFIS,chkError] = anfis(trainingData,options)

fis = anfis(trainingData) generates a single-output Sugeno fuzzy inference system (FIS)

The training algorithm models the training data set using a combination of the least-squares and backpropagation gradient descent techniques.

fis = anfis(trainingData,options) tunes an FIS using the specified training data and options

An initial FIS object to tune; Validation data to avoid data overfitting; Training algorithm settings; and whether to provide training progress information.

4. Result and Discussion

The number of field-observed independent input variables may or may not have a substantial impact on perceived 3W-LOS scores. As a result, Spearman's correlation analysis was used to choose relevant variables to predict output from a set of independent variables and a dependent variable (perceived 3W-LOS scores). Following that, the value of Spearman's correlation coefficient or Spearman's rho (ρ) between each independent variable and perceived 3W-LOS scores was estimated, and its significance (p-value) was assessed. In the 3W-LOS model development process, input variables with two-tailed significance $(P) < 0.001$ are taken into account.

However, one (or more) of the selected variables is shown to be substantially linked with certain significant variables. These types of factors explain the same kind of variation in perceived 3W-LOS score, with the variable with the strongest correlation with model output explaining the most variation. This is referred to as "multi- collinearity." To eliminate multi-collinearity among input variables, the variable with a higher value with a perceived 3W-LOS score is chosen for model development, while the alternate variable(s) is neglected from further analysis. Results obtained from this analysis are presented in Table No.2.

The Spearman's correlation analyses revealed a total of six significantly identified variables with two-tailed significance (p), Such as Peak hour traffic volume per effective width (PHV/W_{eff}) , Average three- wheeler travel speed (Savg), Pavement condition Index (PCI), average delay (D), On-street Parking turnover (P), and Hindrance factor (HF).

Variables	Correlation with percieved 3W-LOS				Significance		
Average three- wheeler travel speed (S_{ave})		0.788			0.000		
Peak hour traffic volume per effective width (PHV/W_{eff})		-0.653			0.000		
Percentage of Motorised three-wheelers(3w)		-0.510			0.000		
average delay (D)		-0.687			0.000		
On-street Parking turnover (P)		-0.582		0.000			
Hindrance factor (HF)		-0.456		0.000			
Correlation among input variables (ρ) value							
Variables	S_{avg}	PHV/W_{eff}	3W	P	D	HF	
S_{avg}	1.000						
PHV/W_{eff}	0.342	1.000					
3w	-0.223	-0.304	1.000				
P	-0.468	-0.459	0.184	1.000			
D	-0.600	-0.158	0.110	0.466	1.000		
HF	-0.370	-0.119	0.320	0.373	0.441	1.000	

Table 2: Spearman's Correlation among input variables and 3W-LOS

In this study, the ANFIS model has developed to get nonlinear association between input and output variables of

Fig.2: ANFIS input-output variable insertion

roundabout entry capacity using the neuro-fuzzy toolbox integrate in MATLAB version R 2013 a. The above said six variables such as Average three-wheeler travel speed (S_{avg}), Peak hour traffic volume per effective width (PHV/W_{eff}), Percentage of Motorized three-wheelers(3w), average delay (D), On-street Parking turnover (P) and Hindrance factor (HF) are given as an input as Fig.2, to the ANFIS model in the MATLAB to establish the relationship between these input variables and entry capacity (Qe) of roadway segment.

Within the framework of the ANFIS model, there are a total of five distinct levels. When grading the input ranges in the first layer, the input membership functions are applied to the input parameters. After that, the weights are distributed throughout the varying ranges of the second layer's input variables. The standardised weighted input data is then applied to the third phase of the process. This procedure is carried out while training is being provided.

Fig. 3(a): ANFIS training data set index

Fig. 3(b): ANFIS Training and Testing information with epochs

(Fig.3) to the ANFIS system itself.

Fig. 4: ANFIS Rules for each input and output

The following layer takes the weighted input data from the third layer and shifts them such that they may flow through the rules that have been specified (Fig.4). Following this, the outputs that were generated from the rules are recorded, and then the defuzzification process of the system is used to turn the combinations of all of these outcomes into the required output value. ANFIS five-layer architecture is shown in Fig.5.

Fig.5: ANFIS five-layer architecture

In this study, the combination of least squares and back propagation error method i.e. hybrid algorithm is used to train the ANFIS based model.

ANFIS model details: Parameters for model development

Start training ANFIS ...

No. of nodes $= 1503$ No. of linear parameters = 729 No. of non-linear parameters = 54 Total no. of parameters $= 783$ No. of training data pairs = 36 No. of testing data pairs = 24 No. of fuzzy rules = 729 Optimization method: Hybrid1 Error tolerance $= 0.01$ $Epochs = 100$

Fig. 6: ANFIS modelling approach, testing-training \mathbb{R}^2 graphical representation

By adjusting parameters such as the input membership function (Gaussian, constant, Pi, Trapezium, Sigmoidal, Triangular, and Generalized Bell shape), the output membership function (constant and linear), the defuzzification method (weighted sum and weighted average), the number of training cycles, and the number of nodes in the network, we are able to analyse the results and determine the best topology of an ANFIS model with a respectable prediction capability of 3W- The best ANFIS model is the one with the greatest coefficient of determination (R2). The ANFIS output/3W-LOS score is extracted, and a linear regression model is applied to check for co-efficient of determination of testing and training data and the result is as shown in Fig. 6. To assess the performance of the proposed model, several statistical parameters are applied in this study. The Mean Absolute Deviation (MAD), Mean Square error (MSE), Root mean square error (RMSE) and Mean Absolute Percentage Error (MAPE) are applied to judge the prediction performance of the proposed model and valued as MAD= 0.038909, MSE=0.318171, RMSE= 0.564066, MAPE= 7.282766 respectively. = $(W_i)^*$. $(p_k V + q_k Percieved_{3W-1})$ $L + r_k$, i

Mathematically ANFIS model prediction can be summarized as:

The structure of ANFIS may be broken down into five distinct levels. First-layer processing involved using input membership functions to assign grades to input parameters over a range.

\n Layer 1: Fuzzy Membership
\n
$$
3W - LOS(O_i)^1 = \mu_{Ai}(V), i = 1, 2, \ldots
$$
\n

\n\n (1) $3W - LOS(O_i)^1 = \mu_{Bi}(Percieved_{3W-LoS}), i$ \n

$$
3W - LOS(Oi)2 = Wi
$$

Layer 2: Weights
$$
= \mu_{Ai}(x) X \mu_{Bi}(Percieved_{3W-LOS}) , i = 1,2, ...
$$
 (3)

Layer 3: Normalized weights

Layer 4:

$$
3W - LOS(Oi)3 = (Wi)* = \frac{Wi}{\sum Wi} , i = 1, 2, ...
$$
 (4)

$$
3W - LoS(Oi)4 = (Wi)*. Fi = (Wi)*. (pkV + qkPercieved3W-LoS + rk), i = 1,2, ...
$$
 (5)

Layer 5: Defuzzification by summing output of all rules

$$
3W - LOS(O_i)^5 = \sum_{i=1}^{n} (W_i)^*.F_i^* = (W_i)^*. (p_k V + q_k Percieved_{3W-LOS} + r_k), i
$$

= 1,2, ...

Equation no. (6) gives the ANFIS output, the model calculated 3W-LOS value.

5. Concluding Remarks

This study reveals that the service quality of urban roadways has been assessed since the nineties. LOS models which are developed for developed countries will fail to quantify the LOS in developing countries due to heterogeneity, no lane discipline of drivers, etc., For evaluating LOS in developing countries like India there is no standard handbook like "HCM", is available. Three Wheelers are the most common and most popular para-transit mode. The demand for three-wheelers has surely increased due to a variety of factors, including a high demand for travel, an expanding population, an increase in the number of workplaces, an increase in the number of trips each trip, and a lack of parking spaces, as a result, the current study aimed to validate existing methodologies by constructing new 3W-LOS models for user-friendly road networks and efficient traffic management at road intersections.

Spearman's ρ was determined for the array of service attribute to know significant variables. Resulting significant variables with two-tailed significance (P) < 0.001 for 3W-LOS are observed to be PHV/W_{eff} , S_{avg}, 3W, D,

P, and HF. A positive ρ value of S_{avg} indicates that, satisfaction level of driver increases with increase in average speed. On the other hand, negative ρ value of 3W, D, P, PHV/W_{eff}, and HF indicate that, satisfaction level of driver's decreases with increase in Percentage of motorized three- wheelers, average delay, On-street parking, traffic volume per effective width and Hindrance factor. Input variable selection is critical and essential when creating a 3W-LOS model. An excessive number of inputs increases the computation time necessary for building the model. Significant variables are selected to build the accurate 3W-LOS model. The ANFIS model with smallest RMSE with a small number of epochs has greater efficiency of attaining lower RMSE when given more epochs of training. Parameters and membership functions are created then the training begins with division of training of 60% data and 40% testing dataset. In this computational process, instead of learning the complicated functions in one wide input space, it divides the whole space such a way that, by fitting linear function, it gives a good solution. After extracting the ANFIS calculated 3W-LOS value, using linear regression model with perceived 3W-LOS scores, the coefficient of determination for training and testing is found to be 0.8809 and 0.8239 respectively. The result shows a reliable 3W-LOS prediction model over roadway segment facility over Indian context.

References

Amaral, G. (2013) 'Public opinion, traffic performance, the environment,and safetyafter theconstruction of double-lane roundabouts', *Journal of Petrology*, 369(1), pp. 1689–1699.

Chatterjee S., D. (2017) 'Level of Service Criteria on Indian Multilane Highways based on Platoon Characteristics Level of Service Criteria on Indian Multilane Highways based on Platoon Characteristics Department of Civil Engineering Indian Institute of Engineering Science and Tec', (May 2019).

Chen, X. *et al.* (2009) 'Prediction of user perceptions of signalized intersection level of service based on fuzzy neural networks', *Transportation Research Record*, (2130), pp. 7–15. doi: 10.3141/2130-02.

Choocharukul, K., Sinha, K. C. and Mannering, F. L. (2004) 'User perceptions and engineering definitions of highway level of service: An exploratory statistical comparison', *Transportation Research Part A: Policy and Practice*, 38(9–10), pp. 677–689. doi: 10.1016/j.tra.2004.08.001. Das, A. K. and Bhuyan, P. K. (2017) 'Hardcl Method for Defining LOS Criteria of Urban Streets', *International Journal of Civil Engineering*, 15(7), pp. 1077–1086. doi: 10.1007/s40999-017-0207-6.

Deshpande, R., Gartner, N. H. and Zarrillo, M. L. (2010) 'Urban street performance: Level of service and quality of progression analysis', *Transportation Research Record*, (2173), pp. 57–63. doi: 10.3141/2173-07.

Dowling, R. *et al.* (2008) 'Multimodal level of service for urban streets', *Transportation Research Record*, (2071), pp. 1–7. doi: 10.3141/2071-01. Faezi, S. F. *et al.* (2011) 'Level of service model for exclusive motorcycle lane', *Indian Journal of Science and Technology*, 4(4), pp. 387–393. doi: 10.17485/ijst/2011/v4i4/30007.

Flannery, A., Wochinger, K. and Martin, A. (2005) 'Driver assessment of service quality on urban streets', *Transportation Research Record*, (1920), pp. 25–31. doi: 10.3141/1920-03.

HCM (2000) *Highway capacity manual*, *National Research Council, Washington, DC*.

HCM (2010a) 'Highway Capacity Mannual', *Transportation Research Board, Resreach Council, Washington, DC*.

HCM (2010b) *Highway Capacity Manual: Vol.1 Concepts*. Available at: http://hcm.trb.org/?qr=1.

HCM (2016) 'Highway Capacity Mannual', *Transportation Research Board, Resreach Council, Washington, DC*.

Hook, W. and Fabian, B. (2009) 'Regulation and Design of Motorized and non-motorized Two-and-Three-Wheelers in Urban Traffic', p. 50. Jena, S. *et al.* (2017) 'Application of fuzzy inference system to estimate perceived los criteria of urban road segments', *Advances in Intelligent Systems and Computing*, 467, pp. 639–651. doi: 10.1007/978-981-10-1645-5_54.

Maitra, B. (1999) 'T He E Ffect of S Pillovers and C Ongestion on the', *Journal of Transportation Engineering*, 125(6), pp. 508–514. Marwah, B. . and bhuvanesh singh (2000) 'Level of Service Classification for Urban Heterogeneous Traffic : A Case Study of Kanapur Metropolis', *Transportation Research Circular E-C018: 4th International Symposium on Highway Capacity*, (Level I), pp. 271–286.

Mohapatra, S. S., Bhuyan, P. K. and Krishna Rao, K. V. (2012) 'Genetic algorithm fuzzy clustering using GPS data for defining level of service criteria of Urban streets', *European Transport - Trasporti Europei*, (52), pp. 1–18.

Papadimitriou, E. *et al.* (2019) 'Review and ranking of crash risk factors related to the road infrastructure', *Accident Analysis and Prevention*, 125(January), pp. 85–97. doi: 10.1016/j.aap.2019.01.002.

Patnaik, A. K. and Bhuyan, P. K. (2016) 'Application of genetic programming clustering in defining LOS criteria of urban street in Indian context', *Travel Behaviour and Society*, 3, pp. 38–50. doi: 10.1016/j.tbs.2015.08.003.

Singh, A. K. and Abu-Lebdeh, G. (2009) 'A Neural Network-based Approach to Estimating Arterial Level of Service', *Transportation Research Record*, pp. 1–25.

Sriraman, S. *et al.* (2006) 'Competition issues in the road goods transport industry in India with special reference to The Mumbai Metropolitan Region', *Competition Commission of India, New Delhi*, (September).