BICYCLE LEVEL OF SERVICE IN URBAN INDIAN CONTEXT

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CERTIFICATE

This is to certify that project entitled "**Bicycle Level of Service in Urban Indian Context**" submitted by **MINAKSHI SHESHADRI NAYAK** in partial fulfillment of the requirements for the award of **Master Of Technology** Degree in **Civil Engineering** with specialization in **Transportation Engineering** at National Institute of Technology, Rourkela is an authentic work carried out by her under my personal supervision and guidance. To the best of my knowledge the matter embodied in this project review report has not been submitted in any other university /institute for award of any Degree or Diploma.

Prof. P.K Bhuyan

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Abstract

India is a developing country the traffic especially in urban streets is very much heterogeneous consisting various kinds of vehicles having different operational characteristics. Bicycle level of service (BLOS) identifies the quality of service for bicyclists that currently exists within the roadway environment. Because of poor traffic management and un-planned lane space utilization BLOS is decreased. For the safe and convenient traffic flow, it is necessary to measure the Level of Service (LOS) of the bicyclist for urban roads in Indian context. At present BLOS ranges for LOS categories are not well defined for highly heterogeneous traffic flow on urban streets in Indian context. In this study, accordingly, an attempt has been made to arrive at suitable criteria for the BLOS analysis of urban on-streets. In the present study the basic premise of urban streets and BLOS are discussed. Literatures from various sources are collected and an in-depth review on analysis of BLOS is carried out.The video camera was employed to collect the data sets of 35 segments from two cities, Rourkela and Bhubaneswar of Odisha State, India. The average effective width of the outside through lane, motorized vehicle volumes, motorized vehicle speeds, heavy vehicle (truck) volumes, pavement conditionand percentage of on street parking are considered as the influencing factors in defining levels of service criteria of bicyclist in urban street. Emphasis is put on the calibration of BLOS model developed by the Florida Department of Transportation in classifying the levels of service of the bicyclist provided by road infrastructure. The collected data are used to calibrate the BLOS model to find the BLOS score of each road segment. Calibrated model coefficients appropriate in Indian context are determined using multivariate regression analysis. In order to define levels of service provided by urban on-street segments, BLOS scores are classified into six categories (A-F) using k-mean, HAC, fuzzy c-means,Affinity Propagation (AP), Self Organizing Map (SOM) and GA-fuzzy clustering

methods. These clustering methods show different BLOS ranges for service categories. However, to know the most appropriate clustering technique applicable in Indian context, Average Silhouette Width (ASW) is calculated for every clustering method. After a thorough investigation it is induced that *K*-meanclustering method is the most appropriate one to define BLOS categories. The defined BLOS score ranges in this study are observed to be higher than that witnessed by FDOT studies; implies the kind of service the bicyclist perceived in urban Indian context is inferior to that observed by FDOT. From all the factors that affect BLOS score, "effective width of outside through lane" affect the most. The study concludes that bicyclist travel, more often, at the poor quality of service of "D", "E" and "F", than good quality of service of "A", "B" and "C". This may be due to lack of proper attention by the planners and developers towards bicycle facilities in urban Indian context.

Keywords: Urban Street segment, BLOS, BLOS score, *K*-means clustering, Hierarchical agglomerative clustering, Fuzzy *c*-means clustering, Affinity Propagation clustering, Self Organizing Map clustering, GA-fuzzy clustering and Average Silhouette Width.

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Abbreviations

ANN	Artificial Neural Network
AP	Affinity Propagation
ASW	Average Silhouette Width
BCI	Bicycle Compatibility Index
BLOS	Bicycle Level of Service
BSIR	Bicycle Safety Index Rating
FCM	Fuzzy C-Means
FDOT	Florida Department of Transportation
FFS	Free Flow Speed
FHWA	Federal Highway Administration
GIS	Geographic Information System
GPS	Global Positioning System
HAC	Hierarchical Agglomerative Clustering
HCM	Highway Capacity Manual
IHS	Intersection Hazard Score
ISI	Intersection Safety Index
km/hr	kilometer per hour
LOS	Level of Service
QOS	Quality of Service
RCI	Roadway Condition Index
SOM	Self Organizing Map

SW	Silhouette width
TRB	Transportation Research Board

Chapter 1

Introduction

1.1General

In India urban areas are on the edge of bursting , with official data signifying a rapid population explosion, which could touch 530 million in 2021.In 1951, there were only 5 Indian cities with a population greater than 1 million and 41 cities greater than 0.1 million population. Much of Indians are living in 0.56 million villages. In 2011, there are 3 cities with population greater than 10 million and 53 cities with population greater than 1 million. Over 833 million Indians live in 0.64 million villages but 377 million live in about 8,000 urban centers. By 2031, it is projected that there will be 6 cities with a population greater than 10 million. In the decade of 1991–2001, immigration to major cities caused rapid increase in urban population. The percentage of urban Indians population has increased from 27.8 percent in 2001 to 31.16 percent in 2011.

Bicycling and walking are the fundamental form of mobility and are the mode of liberty of transportation for the people who are either too old or too young to drive. Cycles are important mode of transportation in Indian cities, towns and rural areas. Due to renewed interest in the environmental movement cycles have become popular in recent times. For a pollution free environment, it contributes a lot as a cycle makes no noise and emits no pollutants and occupies less space than motorized vehicles. Transportation planners and engineers therefore have the same level of responsibility to provide safety and comfort to the bicyclists as they do for motorists. As the Bicycle level of service (BLOS) is not well defined for highly heterogeneous traffic flow condition on urban corridors in India. For the safe and convenient traffic flow, it is necessary to measure the LOS of the bicyclist for urban roads in Indian context.

The Bicycle Level of Service Models based on the established research documented in Transportation Research Record 1578 published by the Transportation Research Board (TRB) of the National Research Council. BLOS model was developed with a background of over 250,000miles of evaluated urban, suburban, and rural roads and streets across North America. In many urbanized areas, planning agencies and state highway departments are using this established method of evaluating and establishing their roadway networks. Over the past decade, some states in USA including Florida studies have been undertaken in order to develop systematic means of measuring bicyclists experienced LOS (A-F). Even though these studies use various study designs, model development techniques and LOS criteria, the produced models each have a high validity. These studies provided a solid methodological base for this study. Present study emphasized on on-street LOS of bicycle facility.

Botma (1995) proposed LOS methodologies for bicycle paths and bicycle pedestrian paths in terms of events, an event occurs when one user passes another user traveling in the same direction, or when one user encounters another user traveling in the opposite direction. As events become more frequent, the LOS deteriorates from A to F. The Florida Department Of Transportation (FDOT, 2009) and Highway Capacity Manual (HCM, 2010) designates six levels of service from “A” to “F” for BLOS facility, with LOS “A” representing the best operating conditions and LOS “F” the worst. With the “A” through “F” LOS scheme, traffic engineers are much better able to explain to the general public and elected officials operating and design concepts of urban streets.

Science the BLOS is not well defined for Indian context, an in-depth research is carried out to define bicycle level of service in the present study. From various literature BLOS model developed by Florida Department of Transportation is found as the appropriate model. BLOS model is calibrated by using various road segment data and using multivariate regression analysis model co-efficient are determined according to Indian urban road conditions. BLOS score data are calculated from BLOS model for all road segments within the study area and are classified using *k*-mean, HAC, fuzzy c-means, Affinity Propagation (AP), SOM and GA-fuzzy clustering methods. The used clustering methods are compared by using the Average Silhouette Width (ASW) method and the BLOS category ranges provided by the best clustering method (k-means clustering) are compared with the FDOT ranges.

The overall framework of the study is illustrated in fig 1.1

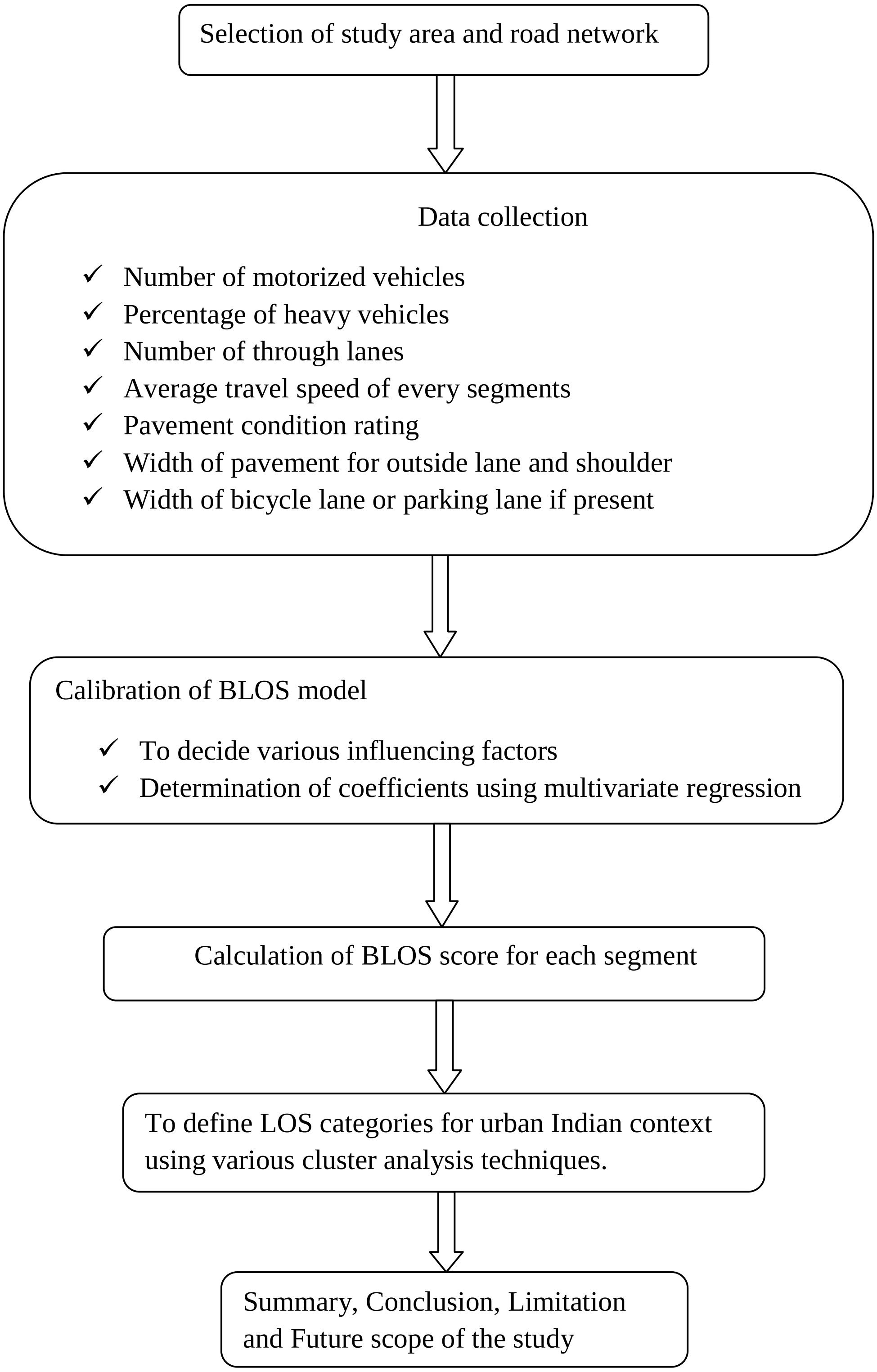


Figure 1.1 Overall framework of the study

1.2Statement of the problem

India is a developing country; the traffic especially in urban streets is very much heterogeneous; consisting various kinds of vehicles having different operational characteristics. The urban road networks in recent times are badly suffering from the problems like decreasing speed, increased congestion, increased travel time and decreased LOS and increase accidental rate. In Indian context researchers neglect the non-motorized mode of transportation (bicycle and pedestrian) effect of the above problems. There is not much more facility for bicycles such as bicycle lanes, zigzag pavement marking at junctions and no specific laws for bicyclist. In the present scenario bicyclists are sometime forced to share the carriageway with motorized modes of transportation. Due to that reason streamline flow interrupted and conflicts of bicyclist with heavy vehicle increased. So, accident rate also increased and the bicycle LOS rate decreased. As the BLOS is not well defined for highly heterogeneous traffic flow condition on urban corridors in India, policy makers cannot include it as a part of the development process. For safe and convenient traffic flow, it is necessary to measure the LOS of the bicyclist for urban roads in Indian context.

1.3Objectives

Based on the above problem statement, the objectives of this study are:

- To develop a methodology for deriving a bicycle level of score that could be used by bicycle coordinators, transportation planners, traffic engineers, and others to evaluate the capability of specific roadways to accommodate both motorists and bicyclists for urban street classes in the context of Indian cities.
- To find the most suitable cluster analysis method in defining BLOS ranges for urban streets.

- To define BLOS scores of the level of service categories for the bicycle mode while traveling on urban roads in Indian context.

1.4Organization of the Report

This report is organized into eight chapters. The first chapter introduces the topic, defines the problem and provides the objectives and scope of the work. In the second chapter a discussion on urban street and bicycle level of service concepts have been presented. The third chapter presents the review of literature on the bicycle level of service analysis of urban streets in various countries. The fourth chapter presents cluster analysis algorithms to classify the bicycle level of service. The fifth chapter presents the study method that is followed to define LOS criteria for bicycle mode while traveling on urban road context. The sixth chapter presents study area and data collection procedure for the present study. In the seventh chapter, results and analysis of the findings have been presented. The eighth chapter presents summery, conclusion and future scope.

Chapter 2

Urban Streets and Bicycle Level of Service Concepts

Bicycle level of service (BLOS) also known as bicycle level of comfort (BLOC), i.e. how much a bicyclist satisfied in the journey period. Bicycle level of service (BLOS) and bicycle level of comfort (BLOC) measure by using rating on the experience of bicycling on the urban road network. The rating ranges from A to F, where A represent the best and F represent the worst scaling of LOS.

There are three basic criteria that contribute to the bicycle level of service:-

1. Stress Levels
2. Roadway Condition Index
3. Capacity-Based Level of Service

1. Stress Levels- Stress level evaluation based upon curb lane vehicle speeds, curb lane vehicle volumes, and curb lane widths. Bicycle stress levels are easy to calculate because of only three input variables, but they do not include other factors hypothesized to affect bicycle suitability.

2. Roadway Condition Index – For roadway condition index variables used are traffic volumes, speed limit, curb lane width, pavement condition factors, and location factors which are mostly used by bicycle planners in urban areas where data can be economically collected for roadways.

3. Capacity-Based Level of Service- Some capacity based study have been adapted in the 2000 Highway Capacity Manual .

Urban Streets

The term “urban street”, refers to urban arterials and collectors, including those in downtown areas. In the hierarchy of street transportation facilities, urban streets are ranked between local streets and multilane suburban and rural highways. The difference is determined principally by street function, control conditions, and the character and intensity of roadside development.

Arterial streets are roads that primarily serve longer through trips. Also an important function of arterials is providing admittance to abutting commercial and residential land uses. Collector streets provide both land admittance and traffic flow within residential, commercial, and industrial areas. Collector streets are more flexible than arterial streets in two ways.Firstly their admittance function is more important than that of arterials, and secondly unlike arterials their operation is not always dominated by traffic signals.

Downtown streets are not only moving through traffic but also provide admittance to local businesses for passenger cars, transit buses and trucks. Turning movements at downtown intersections are often greater than 20 percent of total traffic volume because downtown flow typically involves a significant amount of circulatory traffic. Downtown streets are signalized facilities that often resemble arterials.

Bicycle lanes

There are three types of bicycle lanes

(1) Shared use path: -completely separated present on two sides of the street used by both bicyclist and pedestrians.

(2) On street Bike (bicycle) lane: -A designated lane present on the street separated from other lanes and used by only bicyclist.

(3) Bike rout signed shared roadway : - Bike route sign is provided on the side of the street and used by pedestrian, motorized vehicles and bicyclist as shown in fig 2.1.

Bicycle lane classification:-

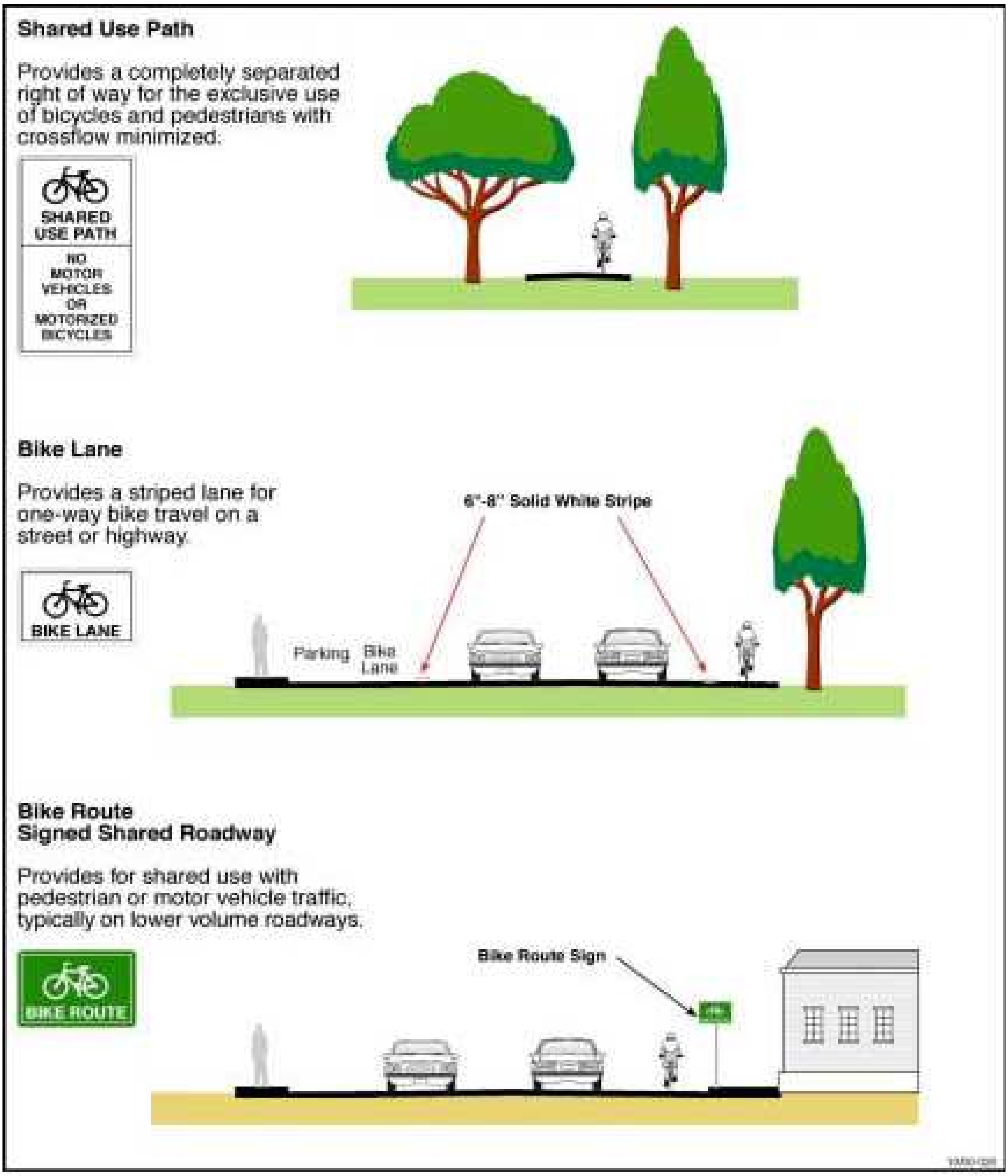


Figure2.1 Representing various types of bicycle lane (Source: -Nevada Bicycle Transportation plan)

On-Street Bicycle Lanes

Designated bicycle lanes are assigned exclusively on a street for the use of bicycles. These lanes detach from motor vehicle traffic by pavement markings as shown in fig2. 2. Bicycle lanes are normally placed on streets where bicycle use is moderate to high. Bicycle lanes are provided for one direction flow, with a lane provided on each side of the street. Some cases shoulders are used by the bicyclist as the same way as they use a designated bicycle lane, where paved shoulders are part of the cross section and not part of the designated traveled way for vehicles and such shoulders may also be shared with pedestrians. In such cases, bicycle traffic is separated from motor vehicle traffic by a right-edge marking.

Figure2.2 Represent the designated bicycle lane with pavement marking (Source Developing a bicycling level of service map for New York state)

Figure2.3 Cycle prohibited (Source IRC-67)

Chapter 3

Review of Literature

3.1 General

Level of service (LOS) is a quantitative stratification of a performance measure or measures that represent quality of service. The LOS concept facilitates the presentation of results, through the use of a familiar A (best) to F (worst) scale. LOS is defined by one or more service measures that both reflect the traveler perspective and are useful to operating agencies. Several models have been developed to relate roadway geometric and operational characteristics of bicyclists perceived levels of comfort and safety (*i.e.*, to measure bicycle compatibility).

3.2 Bicyclist Safety and LOS

Davis (1987) developed the Bicycle Safety Index Rating (BSIR) consists of two sub-models, one for roadway segments and one for intersections . The safety of roadway segments depends on traffic volume, speed limit, outside lane width, pavement condition, and a variety of geometric factors. The safety of intersections is a function of traffic volume, the type of signalization, and several geometric factors. Epperson (1994) modified the BSIR and called the roadway condition index (RCI), in Broward County, Florida. The RCI was further modified by placing less weight on pavement and location factors and by increasing the interaction between curb lane width, speed limit, and traffic volume. Sorton and Walsh (1994) determined bicyclist safety in terms of stress levels as a function of three primary variables peak-hour traffic volume in the curb lane, motor vehicle speeds in the curb lane, and curb lane width. Secondary variables such as the number of commercial driveways were acknowledged but were not included in the analysis because of funding limitations. Landis (1994) developed the Intersection Hazard Score (IHS), which was based on the RCI and other earlier models. The variables in this model included traffic volume, speed limit, outside lane width, pavement condition and the number of driveways.

Hunter et al. (1999) have studied the differences between bike lanes and wide curb lanes. They observed videotapes of almost 4,600 bicyclists and evaluated operational characteristics and interactions between bicyclists and motorists. Overall, they concluded that the type of bicycle facility had much less impact on operations and safety than other site characteristics and recommended that both bike lanes and wide curb lanes be used to improve riding conditions for bicyclists. Torbic et al. (2001) have developed new rumble strip configurations for safety and comfortable riding of the bicyclist. Three primary steps were involved in the development of the new configurations. First, simulation was used to evaluate different configurations for their potential to be bicycle friendly. Second, several configurations that had the greatest potential to be bicycle friendly were installed and field experiments were conducted to further evaluate their effectiveness. Finally, the field data were analyzed and the configurations that were installed were ranked based on their ability to provide a comfortable and controllable ride for bicyclists.

Zolnik and Cromley (2006) have developed a poissioned- multilevel bicycle level of service methodology using the bicycle-motor vehicle collision frequency and severity in the GIS environment. This new methodology complements bicycle level of service methodologies on mental stressors by incorporating the characteristics of cyclists involved in bicycle- motor vehicle collisions as well as the physical stressors where bicycle-motor vehicle collisions occurred to assess bicycle, level of service for regional road network. Carter et al. (2007) have developed a macro-level Bicycle Intersection Safety Index (Bike ISI) by using video data and online ratings surveys, which incorporated both measures of safety. The Bike ISI used data on traffic volume, number of lanes, speed limit, presence of bike lanes, parking, and traffic control to give a rating for an intersection approach according to a six-point scale.

Duthie et al. (2010) have examined the impact of design elements, including the type and width of the bicycle facility, the presence of adjacent motor vehicle traffic, parking turnover rate, land use and the type of motorist bicyclist interface to define the roadway configurations that lead to safe motorist and bicyclist behavior. Kendrick et al. (2011) have attempted to measure and compare simultaneous ultrafine particulate exposure (UFP) for cyclists in a traditional bicycle lane and a cycle track for urban areas. Ultrafine particle exposure concentrations were compared in two settings: (a) a traditional bicycle lane adjacent to the vehicular traffic lanes and (b) a cycle track design with a parking lane separating bicyclists from vehicular traffic lanes. UFP number concentrations were significantly higher in the typical bicycle lane than the cycle track. Authors revealed that a cycle track roadway design may be more protective for cyclists than a traditional bicycle lane in terms of lowering exposure concentrations of UFPs.

3.3 Intersection Bicycle LOS

Crider (2001) has attempted to set up a system of determining “point” level of service for urban intersections. This is a useful concept, because many of the problems that a bicyclist encounters are small, geographically speaking. There may be a narrow road under a bridge or one particularly dangerous intersection, or a bus stop that does not allow bicyclists on board or lack of bicycle parking; all of which will tarnish a bicycling experience for an entire trip. Landis et al. (2003) built upon the segment BLOS to develop an intersection BLOS. Data were obtained from bicyclists who rode through selected intersections and provided comfort and safety ratings on a scale of A through F. In this study roadway traffic volume, total width of the outside through lane, and the intersection crossing distance was found to be the primary factors influencing bicyclists' safety and comfort at intersections whereas the presence of a bike lane or paved shoulder stripe was not as important as it was in the BLOS for segments. Dougald et al. (2012) have defined to assess the effectiveness of the zigzag pavement markings for mid-block. Effectiveness was defined in three ways: (1) an increase in motorist awareness in advance of the crossing locations; (2) a positive change in motorist attitudes; and (3) motorist understanding of the markings. The authors found that motorists have limited understanding of the purpose of the markings and the markings installed in advance of the two crossings heightened the awareness of approaching motorists.

3.4 Shared On-Street LOS

In Highway Capacity Manual (2000), Botma's (1995) LOS methodology for exclusive and shared paths has been adopted. The LOS for on-street bicycle lanes is also dependent on the number of events, which vary according to the bicycle flow rate, mean speed of the bicycle and standard deviation of the speed. For bicycle lanes on urban streets, the LOS depends on average bicyclist speeds. Guttenplan. et. al. (2001) have presented methods of determining the LOS to scheduled fixed-route bus users, pedestrians, and bicyclists on arterials and through vehicles. This was a comprehensive approach for LOS of individual modes conducted for arterial roads in Florida. Dowling et al. (2008) have developed a methodology for the assessment of the quality of service provided by urban streets for the flow of traffic by various modes on the road network at national level. In this research the authors have categorized urban travels into four types (motorized vehicle, transit mode, bicycle rider, and walk mode) and hence developed separate LOS models for each mode of travel. Robertson (2010) developed an empirically supported methodology for determining when shared roadways were not acceptable based upon multimodal Level of Service analysis. The author has used micro simulation to evaluate changes in automobile LOS that result from the bicycle presence in the traveled way.

Transport Research Board (2008) published NCHRP report 616 in which it has been developed and calibrated a method for evaluating the multimodal level of service (MMLOS) provided by different urban street designs and operations. It is designed for evaluating ‘complete streets’, context-sensitive design alternatives and smart growth from the perception of all users of street. The MMLOS method estimates the auto, bus, bicycle, and pedestrian level of service on urban streets. The data requirements of the MMLOS method included geometric cross-section, signal timing, the posted speed limit, bus headways, traffic volumes, transit benefaction and pedestrian volumes. Implementing agencies have been provided with a tool for testing different allocations of scare street right-of-way to the different models. However, according to 2010 version of Highway Capacity Manual (HCM, 2010), there are many ways to measure the performance of a transportation facility or service- and many points of view that can be considered in deciding which measurements to make. The agency operates a roadway, automobile drivers, pedestrians, bicyclists, bus passengers, decision makers, and the community at large all have their own perspectives on how a roadway or service should perform and what constitutes “good” performance. As a result, there is no one right way to measure and interpret performance. In chapter 23 of HCM (2010), it has been described off-Street Bicycle Facilities, and provides capacity and level-of-service estimation procedures for shared-use paths: paths physically separated from highway traffic for the use of pedestrians, bicyclists, runners, inline skaters, and other users of non-motorized modes; and Exclusive off-street bicycle paths: paths physically separated from highway traffic for the exclusive use of bicycles. Elias (2011) investigated both an auto-oriented and a complete street design for four typical right-of-way (ROW) widths and their effects on bicyclists and pedestrians by using new multimodal LOS methodology, which was based on an NCHRP project and was documented in NCHRP Report *616* .The author included a small collector road (60 ft), large collector (80 ft), small arterial (100 ft), and large arterial (120 ft). The results of this research helped in determining cross-section design, to consider when designing a facility with pedestrians or bicyclists in mind.

3.5 Quality of Service using Perception of Bicyclist

Turner et al. (1997) have studied on Bicycle suitability criteria. In that study, fourteen state departments of transportation were contacted to analyze their installation of bicycle suitability criteria. They were picked based on similar geography to Texas and the existence of known statewide suitability criteria by the state department of transportation. Petritsch et.al(2007) have developed Bicycle LOS for arterials model, which was based upon Pearson correlation analyses, stepwise regression and PROBIT modeling of approximately 700 combined real-time perceptions (observations) from bicyclists riding a course along arterial roadways. The study participant represented a cross section of age, gender, riding experience, and residency. The Bicycle LOS for arterials model provides a measure of the bicyclist's perspective on how well an arterial roadway's geometric and operational characteristics meets his/her needs. This model is highly reliable, has a high correlation coefficient (R^2=0. 74) with the average ordinal observations, and is convenient to the huge majority of metropolitan areas in the United States. Jensen (2007) developed methods for objectively quantifying pedestrian and bicyclist stated satisfaction with road sections between intersections. Pedestrian and bicyclist satisfaction models were developed using cumulative logit regression of ratings and variables. The results provided a measure of how well urban and rural roads accommodate Pedestrian and bicycle travel.

Yang et al. (2010) have analyzed of personal factors that affected people's decisions to bicycle for commuting trips included commuter demographic characteristics, perceived benefits, and trip distance. The authors compared between a binomial logit model with the latent variable and a binomial logit model without a latent variable to find the effects of personal factors on bicycle commuting. Monsere et al. (2012) have assessed various user perceptions of two innovative types of separated on-road bicycle facilities such as cycle tracks and buffered bike lanes installed in Portland, to test facilities that were thought to bring higher levels of comfort to bicycle riders through increased separation from motor vehicle traffic. After one year of use, the surveys found improved perceptions of safety and comfort among cyclists, particularly women. Li et al. (2012) have investigated the contributing factors to bicyclists' perception of comfort on physically separated bicycle paths and quantify their impact. The survey was conducted on 29 physically separated bicycle paths in the metropolitan area of Nanjing, China. The factor analysis (FA) and ordered probit (OP) model were used to analyze the data. The results demonstrate that the mean perception of comfort is significantly different between age groups, but not significantly different between gender groups and between electric bicycles and conventional bicycles. The model estimates show that bicyclists' perception of comfort on physically separated bicycle paths are significantly influenced by physical environmental factors, including the width of bicycle lanes, width of shoulder, presence of grade and bus stop, land use, the flow rate of electric and conventional bicycles.

Seiichi and Katia (2012) have presented the results of behavioral and statistical analyses, which focused on the behaviors and attitudes of active cyclists within the Japanese urban context. The analyses were based on the Hokkaido University Transport Survey (HUTS) conducted in April 2011. They highlight characteristics of the transport system and the households, and also individual perceptions that affect students and staff decisions towards cycling. Lowry et al. (2012) have introduced a method to assess the quality of bicycle travel throughout a community by comparing between bicycle suitability and bikeability. The proposed calculation for bikeability builds upon a common accessibility equation and was demonstrated through a case study involving three different capital investment scenarios.

3.6 Modeling and Simulation

Dixon (1996) created a BLOS model as part of the Gainesville Mobility Plan Prototype as an answer to congestion problems in the Gainesville, FL region, USA. This model includes variables, which measure bicycle facility provided, conflicts, speed discrepancy between car and bicycle, motor vehicle LOS, level of maintenance and intermodal links (yes or no). The Gainesville LOS adds up the factors in each realm and determines an established LOS for bicyclists based upon the factors and their associated values. This model is less statistically strong than the Landis model, but is easier to understand and calculate without computing equipment and software. Niemeier (1996) examined composition, weather, and time-of-year count variability for a longitudinal bicycle count program. By using Poisson Bicycle Count model authors proposed a new bicycle functional classification system based on PM peak period composition. Landis et al. (1997) have developed a Bicycle Level of Service (BLOS) model for roadway segments by having bicyclists ride selected roadway segments on a real-life course and provide comfort and safety ratings on a scale of A through F. The presence of a stripe separating the motor vehicle and bicycle areas of an outside travel lane resulted in the perception of a safer condition than an outside travel lane of the same width but without a delineated motor vehicle and bicycle areas. According to the survey results, cycling space and car speed received the greatest weights (30 and 20 out of a possible 100, respectively) in the index.

FDOT (2002) has concluded that the Bicycle LOS Model, developed by Sprinkle Consulting Inc. (SCI), is the best analytical methodology. But according to FDOT (2009) Bicycle LOS Model (Landis, 1997), is the best analytical methodology as it is an operational model. According to FDOT, in the Bicycle LOS Model, bicycle levels of service are based on five variables such as the average effective width of the outside through lane, motorized vehicle volumes, motorized vehicle speeds, heavy vehicle volumes, pavement condition ratings. Sprinkle Consulting Inc. (SCI) (2007) has developed a Bicycle Level of Service Model for segments' having statistically-calibrated mathematical equation is the most accurate method of evaluating the bicycling conditions of shared roadway environments. The Model clearly reflects the effect on bicycling suitability due to factors such as roadway width lane widths, striping combinations, traffic volume, pavement surface conditions, motor vehicles speed and on-street parking.

Harkey et al. (1998) have developed a Bicycle Compatibility Index (BCI) for urban and suburban roadways at midblock locations. The BCI was developed from bicyclists watching a videotape of various roadway segments and providing ratings of how comfortable they would feel riding on each segment. Federal Highway Administration (FHWA, 1998) developed the Bicycle Compatibility Index (BCI) to evaluate the capability of urban and suburban roadway sections (i.e., midblock locations that are exclusive of major intersections) to accommodate both motorists and bicyclists and incorporated those variables that bicyclists typically use to assess the "bicycle friendliness" of a roadway (e.g., curb lane width, traffic volume, and vehicle speeds).

Kidarsa et al. (2006) have developed a model of loop detector–bicycle interaction, verified the model with field measurement, and provided plots documenting the location of bicycle detection zone hot spots adjacent to loop detectors. The authors suggested that when the loops were installed under the pavement, the loop closer to the stop bar be connected to its own individual loop detector to improve its capability to detect bicycles rather than wired in series. Heinen and Maat (2012) have described mode alternation in the Netherlands and compared data from a longitudinal survey with a single-moment survey focusing on bicycle commuting to evaluate the reliability of the latter. Travel data are usually collected at a single moment in time and repeated measures, resulting in longitudinal data. It was found that the error in single-moment surveys cannot be easily corrected. The authors revealed that transport models should include mode variation in their models and it is essential to collect and analyze longitudinal data. LaMondia and Duthie (2012) have studied the impacts that roadway environment, motorist and bicyclist activities have on bicyclist or motorist interactions based on video footage of traffic movements during peak commuting hours at four locations in Austin, Texas. The authors considered this interaction by developing three unique ordered probit regression models describing bicyclist lateral location, bicyclist or motorist interaction movement and bicyclist or motorist distance. Bhuyan and Rao (2010, 2011, 2012) have used Global Positioning System (GPS) and various methods such as Fuzzy-C means (FCM), Hierarchical Agglomerative Clustering (HAC), *k*-means and *k*-medoid clustering to classify urban streets into number of classes and average travel speed on segments into number of LOS categories.

Chapter 4

Cluster Analysis

4.1 Introduction

This chapter presents the details of algorithms used in defining levels of service criteria for bicycle of urban streets.

4.2 Cluster Partitions

Since clusters can formally be seen as subset of the data set, one possible classification of clustering methods can be according to whether the subsets are crisp (hard) or fuzzy. Hard clustering methods are based on classical set theory, and require that an object either does or does not belong to a cluster. Hard clustering in a data set *X* means partitioning the data into a specified number of mutually exclusive subsets of *X*. The number of observations is denoted by *N* and number of subsets (clusters) is denoted by *c*. The structure of the partition matrix $M = [\mu_{ik}]$:

$$M=\begin{bmatrix} \mu_{1,1} & \mu_{1,2} & .. & .. & \mu_{1,c} \\ \mu_{2,1} & \mu_{2,2} & .. & .. & \mu_{2,c} \\ : & : & : & : & : \\ : & : & : & : & : \\ \mu_{N,1} & \mu_{N,2} & .. & .. & \mu_{N,c} \end{bmatrix}$$

Where, μ_{ik} the membership functional value of the ith data point in kth cluster group, c is the number of subsets (clusters), N is the number of data points.

4.2.1 Hard partition

The objective of clustering is to partition the data set X into c clusters. For the time being, assuming that c is known, based on prior knowledge, for instance, or it is a trial value, of which partition results must be validated. Using classical sets, a hard partition can be defined as a family of subsets $\{A_i | 1 \leq i \leq c \subset P(X)\}$; its properties are as follows;

$$U_{i=1}^{c} A_i = X, \tag{4.1a}$$

$$1 \leq i \neq j \leq c, \tag{4.1b}$$

$$\phi \subset A_i \subset X, \ 1 \leq i \leq c. \tag{4.1c}$$

If c=N, each A_i is necessarily a singleton, $A_i = \{x_i\} \forall i$: since this is a trivial case, the range of c is usually $2 \leq c < N$

These conditions mean that the subsets (data points) A_i contain all the data in X, they must be disjoint and none of them is empty nor contains all the data in X. Partition can be represented in a matrix notation.

A $N \times c$ matrix M= [μ_{ik}] represents the hard partition if and only if its elements satisfy:

$$\mu_{ik} \in \{0,1\}, \ 1 \leq i \leq N, \ \ 1 \leq k \leq c, \tag{4.2a}$$

$$\sum_{k=1}^{c} \mu_{ik} = 1, \ 1 \leq i \leq N, \tag{4.2b}$$

$$0 < \sum_{i=1}^{N} \mu_{ik} < N, \ \ 1 \le k \le c. \quad (4.2c)$$

$\sum_{k=1}^{c} \mu_{ik} = 1$ means each x_k is in exactly one of the c subsets; and $0 < \sum_{i=1}^{N} \mu_{ik} < N$ means that no subject is empty, and no subject is of X : in other words, $2 \le c < N$.

4.2.2 Fuzzy partition

Fuzzy partition can be seen as a generalization of hard partition, it allows μ_{ik} attaining real values in [0, 1]. A N×c matix M= [μ_{ik}] represents the fuzzy partitions, its conditions are given by:

$$\mu_{ik} \in [0,1], 1 \le i \le N, \ \ 1 \le k \le c, \quad (4.3a)$$

$$\sum_{k=1}^{c} \mu_{ik} = 1, \ \ 1 \le i \le N, \quad (4.3b)$$

$$0 < \sum_{i=1}^{N} \mu_{ik} < N, \ \ 1 \le k \le c. \quad (4.3c)$$

Equation (4.3b) constrains the sum of each row to 1, and thus the total membership of each object in X equals one where, μ_{ik} expresses a normalized membership value of i^{th} element of X belongs to x^{th} partitions. The distribution of memberships among the c fuzzy subsets is not constrained.

4.3 Methods of Cluster Analysis

The methods to be discussed can be categorized as follows:

- K-mean method, is characterized by a centrally located object called the representative object and each time an object changes clusters the centroids of both its old and new cluster are recalculated.
- Fuzzy C-Means Clustering (FCM), method, where objects are not assigned to a particular cluster but possess a membership function indicating the strength of membership to each cluster.
- Hierarchical Agglomerative Clustering (HAC), starts with all points belonging to their own cluster and then iterates merging the two closest clusters until it gets only one cluster.
- Affinity Propagation (AP), an clustering algorithm that identifies exemplars among data points and forms clusters of data points around these exemplars.
- GA-fuzzy, algorithms are search algorithms that are based on concepts of natural selection and natural genetics.
- Self-organizing map (SOM) is a type of artificial neural network that use unsupervised learning to produce a lower-dimensional (usually 2D) representation of the input space of the training data set samples.

The above mentioned six methods of solving the clustering problem are discusses in the following subsections.

4.3.1 *K*-means Clustering

K-means is one the simplest algorithms that can solve the well known clustering problem. To perform *k*-means cluster analysis on a data set; the following steps are followed:

Step 1: Placing K points into the space represented by the objects that are being clustered. These points represent initial group centroids.

Step 2: Assigning each object to the group whose centroid is closest to the object.

Step 3: Recalculating the positions of the K centroids after assigning all objects

Step 4: Repeating Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups.

Choosing the number of clusters $1 < c < N$ and initializing random cluster centers from the data set, the following steps were followed

Step 1 From a data set of N points, k-means algorithm allocates each data point to one of c clusters to minimize the within-cluster sum of squares:

$$D_{ik}^2 = (x_k - v_i)^T (x_k - v_i), \quad 1 \le i \le c, \quad 1 \le k \le N. \tag{4.4}$$

is a squared inner-product distance norm.

Where, $D^2{}_{ik}$ is the distance matrix between data points and the cluster centers, x_k is the k^{th} data point in cluster i, and v_i is the mean for the data points over cluster i, called the cluster centers. If D_{ik} becomes zero for some x_k, singularity occurs in the algorithms, so the initializing centers are not exactly the random data points, they are just near them. (with a distance of 10^{-10} in each dimension)

Step 2 Selecting points for a cluster with the minimal distances, they belong to that cluster.

Step 3 Calculating cluster centers

$$v_i^{(l)} = \frac{\sum_{j=1}^{N_i} x_i}{N_i} \tag{4.5}$$

$$\max\left|v^{(l)} - v^{(l-1)}\right| \neq 0 \tag{4.6}$$

Where N_i is the number of objects in the cluster *i*, *j* is the j^{th} cluster; *l* is the number of iterations. The main problem of *k*-means algorithm is that the random initialization of centers, because the calculation can run into wrong results, if the centers "have no data points". Hence, it is proposed to run *k*-means several times to achieve the correct result. To avoid the problem described above, the cluster centers are initialized with randomly chosen data points.

Advantages of *k*-means clustering:

The main advantages of this algorithm are its simplicity and speed which allows it to run on large datasets.

Disadvantages of *k*-means clustering:

Its disadvantage is that it does not yield the same result with each run, since the resulting clusters depend on the initial random assignments. It minimizes intra-cluster variance, but does not ensure that the result has a global minimum of variance.

4.3.2 Fuzzy *c*-means clustering

Fuzzy *C*-Means (FCM) clustering algorithm introduced by Bezdek (1981) is adopted in the present study, which is considered one of most popular and accurate algorithms in cluster analysis/pattern recognition (Fukunaga, 1990; Jain and Dubes, 1988; Sayed et al., 1995; Wang, 1997). Based on concepts, centers are as similar as possible to each other within a cluster and as different as possible from elements in other clusters. Bezdek et al. (1999) have presented successful application of Euclidian distance to a wide variety of clustering problems. Hence, though the fuzzy c-means algorithm is able to handle different distance measures, the Euclidian distance between two data points was employed in this study.

The Fuzzy *c*-means clustering algorithm is based on the minimization of an objective function called *c*-means functional. It is defined by Dunn as:

$$J(X;M,V)=\sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m\left\|X_k-V_i\right\|_A{}^2 \tag{4.7}$$

Where

$$V=[V_1,V_2,V_3,\ldots\ldots\ldots\ldots.,V_c],V_i\in R^n \tag{4.8}$$

is a vector of cluster prototypes (centers), which have to be determined, and

$$D_{ikA}^2=\left\|X_k-V_i\right\|_A^2=(X_k-V_i)^T A(X_k-V_i) \tag{4.9}$$

is a squared inner-product distance norm.

Where, X is the data set, U is the partition matrix; V is the vector of cluster centers; V_i is the mean for those data points over cluster i; m is the weight exponent which determines the fuzziness of the clusters (default value is 2); n is the number of observations; $D^2{}_{ik}$ is the distance matrix between data points (X_k) and the cluster centers (V_i); A_i is a set of data points in the i^th cluster;

Statistically, (4.7) can be seen as a measure of the total variance of X_k from V_i .The minimization of the *c*-means functional (4.7) represents a nonlinear optimization problem that can be solved by using a variety of variable methods, ranging from grouped coordinate minimization, over simulated annealing to genetic algorithm. The most popular method, however, is a simple Picard iteration through the first-order conditions for stationary points of (4.7), known as the fuzzy *c*-means algorithm.

The stationary points of the objective function (4.7) can be found by adjoining the constraint (4.3b) to *J* by means of Lagrange multipliers:

$$\bar{J}(X;M,V,\lambda) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m D^2{}_{ikA} + \sum_{k=1}^{N}\lambda_k\left(\sum_{i=1}^{c}\mu_{ik} - 1\right) \tag{4.10}$$

and by setting the gradients of ($\bar{J}$) with respect to *M, V* and λ to zero. If $D^2_{ikA} > 0, \forall_{i,} k$ and m>1, then *(M, V)* may minimize (4.11) only if

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(D_{ikA}/D_{jkA}\right)^{2/m-1}}, \quad 1 \le i \le c, \quad 1 \le k \le N \tag{4.11}$$

and

$$V_i = \frac{\sum_{k=1}^{N}\mu_{ik}^m X_k}{\sum_{k=1}^{N}\mu^m{}_{i,k}}, \; 1 \le i \le c, \tag{4.12}$$

This solution also satisfies the constraints (4.3a) and (4.3c). It is to be noted that equation (4.12) gives V_i as the weighted mean of the data items that belong to a cluster, where the weights are the membership degrees. That is why the algorithm is called *c*-means. It can be seen that the FCM algorithm is a simple iteration through (4.11) and (4.12). The FCM algorithm computes with the standard Euclidian distance norm. Hence it can only detect clusters with the same shape and orientation because the common choice of norm inducing matrix is; A=I

or A is defined as the inverse of the $n \times n$ covariance matrix; $A = F^{-1}$, with

$$F = \frac{1}{N}\sum_{k=1}^{N}\left(X_k - \overline{X}\right)\left(X_k - \overline{X}\right)^T \tag{4.13}$$

Here $\overline{X}$ denotes the sample mean of the data. Given the data set X, choose the number of clusters $1<c<N$. Take the weight exponent $m>1$, the termination tolerance $\varepsilon>0$ and the norm-inducing matrix as A.

After initializing the partition matrix randomly, the algorithm repeats for each iteration of l=1, 2…

Step 1: computing the cluster prototypes (means)

$$v_i^{(l)} = \frac{\sum_{k=1}^{N}(\mu_{ik}^{(l-1)})^m x_k}{\sum_{k=1}^{N}(\mu_{i,k}^{(l-1)})^m}, \quad 1 \le i \le c \tag{4.14}$$

Steps 2: computing the distances

$$D_{ikA}^2 = (x_k - v_i)^T A (x_k - v_i),\ 1 \le i \le c,\ 1 \le k \le N \tag{4.15}$$

Step 3: updating the partition matrix

$$\mu_{i,k}^{(l)} = \frac{1}{\sum_{j=1}^{c}\left(\frac{D_{ikA}}{D_{jkA}}\right)^{2/(m-1)}} \tag{4.16}$$

$$\text{until } \left\| M^{(l)} - M^{(l-1)} \right\| \langle \, \varepsilon$$

Where, v_i is the calculated cluster center which is the mean of the data points in cluster *i;*

Changing the weight exponent *m* of the memberships in this fuzzy *c*-means algorithm has some influence on the allocation of the objects in the clustering. What is certain is that decreasing the weight exponent will yield higher values of the largest membership coefficients, i.e., the clusters will appear less fuzzy. However, because the aim of fuzzy clustering is to use the particular features of fuzziness, we should not go too far in that direction. Hence the correct choice of weight exponent is important: as *m* approaches one, the partition becomes hard. The partition becomes maximally fuzzy, (i.e. $\mu_{ik} = 1/c$), when *m* approaches infinity. A value of 2 for the weight exponent, however, seems to be a reasonable choice, and is applied for the clustering problem of this study as a default value.

Advantages of fuzzy c-means clustering

It has the advantage that it does not force every object into a specific cluster. Fuzzy clustering has two main advantages over other methods:

Firstly, memberships can be combined with other information. In particular, in the special case where memberships are probabilities, results can be combined from different sources using Bayes' theorem. Secondly, the memberships for any given object indicate whether there is a second best cluster that is almost as good as the best cluster, a phenomenon which is often hidden when using other clustering techniques.

Disadvantage of fuzzy c- means clustering

It has the disadvantage that there is massive output and much more information to be interpreted. Unfortunately, the computations are rather complex and therefore neither transparent nor intuitive.

4.3.3 Hierarchical agglomerative clustering

Basic procedure

To perform Hierarchical Agglomerative Clustering (HAC) on a data set, the following procedure is followed:

Step 1:

Find the similarity or dissimilarity between every pair of objects in the data set. In this step, we calculate the distance between objects using the distance function. The distance function supports many different ways to compute this measurement.

Step 2:

Group the objects into a binary, hierarchical cluster tree. In this step, we link together pairs of objects that are in close proximity using the linkage function. The linkage function uses the distance information generated in step 1 to determine the proximity of objects to each other. As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed.

Step 3:

Determine where to divide the hierarchical tree into clusters. In this step, we divide the objects in the hierarchical tree into clusters using the cluster function. The cluster function can create clusters by detecting natural groupings in the hierarchical tree or by cutting off the hierarchical tree at an arbitrary point.

Finding the similarities between objects

The distance function is used to calculate the distance between every pair of objects in a data set. For a data set made up of *m* objects, there are *m (m-1)/2* pairs in the data set. The result of this computation is commonly known as a distance or dissimilarity matrix. There are many ways to calculate this distance information. By default, for *p*-dimentional data objects $i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jp})$, the distance function calculates distance for each pair of objects *i* and *j* by the most popular choice, the Euclidean distance

$$d(i,j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \ldots\ldots\ldots + (x_{ip} - x_{jp})^2} \tag{4.17}$$

However, we can specify one of several other options like

City block distance or Manhattan distance, defined by

$$d(i,j) = \left|x_{i1} - x_{j1}\right| + \left|x_{i2} - x_{j2}\right| + \ldots\ldots\ldots\ldots + \left|x_{ip} - x_{jp}\right| \tag{4.18}$$

A generalization of both the Euclidean and the Manhattan metric is the Minkowski distance given by:

$$d(i,j) = \left(\left|x_{i1} - x_{j1}\right|^q + \left|x_{i2} - x_{j2}\right|^q + \ldots\ldots\ldots\ldots + \left|x_{ip} - x_{jp}\right|^q\right)^{\frac{1}{q}} \tag{4.19}$$

Where, q is any real number larger than or equal to 1. For the special case of q = 1, the Minkowski distance gives the City Block distance, and for the special case of q = 2, the Minkowski distance gives the Euclidean distance. And other options are like Cosine distance, Correlation distance, Hamming distance, Jaccard distance.

Defining the links between objects

Once the proximity between objects in the data set has been computed, we can determine which objects in the data set should be grouped together into clusters, using the linkage function. The linkage function takes the distance information generated by distance function and links pairs of objects that are close together into binary clusters (clusters made up of two objects). The linkage function then links these newly formed clusters to other objects to create bigger clusters until all the objects in the original data set are linked together in a hierarchical tree.

Single linkage, also called nearest neighbor, uses the smallest distance between objects in the two groups.

Complete linkage, also called furthest neighbor, uses the largest distance between objects in the two groups.

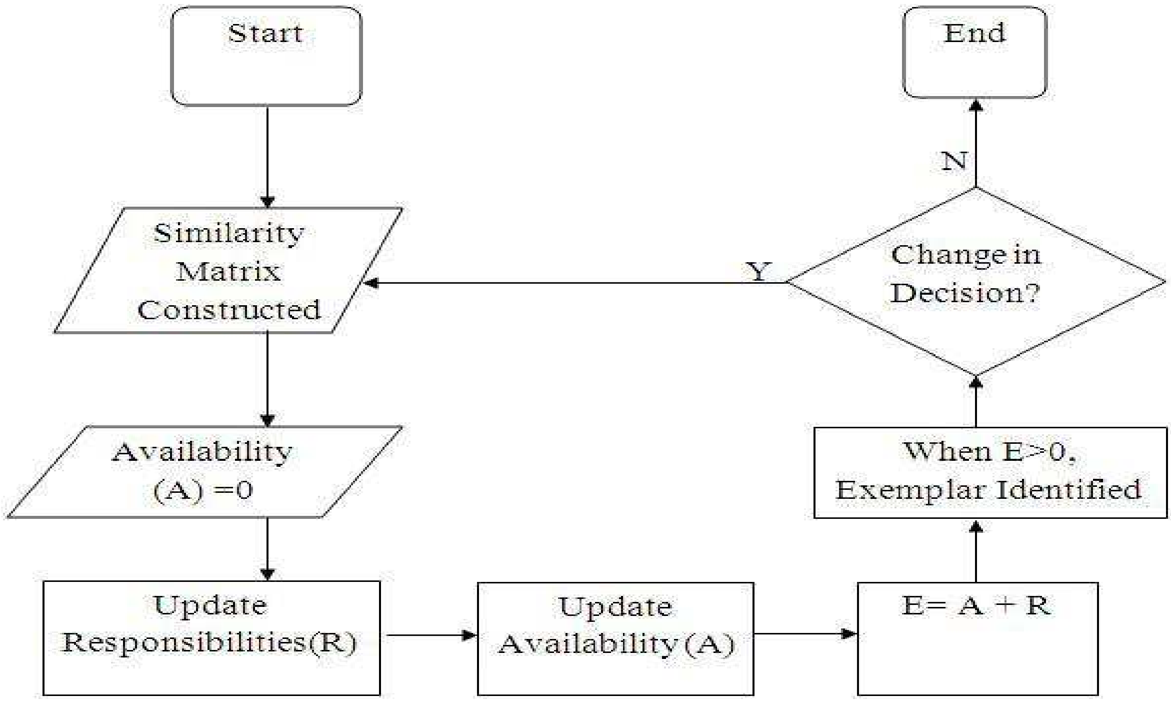
Average linkage, uses the distance between average points of the objects in the two groups.

Centroid linkage, uses the distance between the centroids of the two groups.

Ward linkage uses the incremental sum of squares; that is, the increase in the total within-group sum of squares as a result of joining two groups.

4.3.4 Affinity Propagation (AP) clustering

Affinity propagation (AP) is a relatively new clustering algorithm that has been introduced by Brendan J. Frey and Delbert Dueck. AP is used to classify the BLOS score for the different street segment for urban street. AP an algorithm that identifies exemplars among data points and forms clusters of data points around these exemplars. It operates by simultaneously considering all data points as potential exemplars and exchanging messages between data points until a good set of exemplars and clusters emerges. Different Street segments were analyzed in this research to get the BLOS score value and the values were clustered using AP.



4.1 Flowchart of AP Clustering

Steps:

1. Input similarity matrix *s(i,k)*: the similarity of point *i* to point *k.*

2. Initialize the availabilities $a(i, k)$ to zero: $a(i, k)=0$.

3. Updating all responsibilities $r(i,k)$:

$$r(i,k) \leftarrow s(i,k) - \max_{k' \neq k} \left\{ a(i,k') + s(i,k') \right\} \tag{4.20}$$

4. Updating all availabilities *a (i,k):*

$$a(i,k) \leftarrow \min\left\{0, r(k,k) + \sum_{i' : i' \notin \{i,k\}} \max\left\{0, r(i',k)\right\}\right\} \text{ for } k \neq i \tag{4.21}$$

5. Availabilities and responsibilities matrix were added to monitor the exemplar decisions. For a particular data point *i ;* $a(i,k) + r(i,k) > 0$ for identification exemplars.

6. If decisions made in step 3 did not change for a certain times of iteration or a fixed number of iteration reaches, go to step 5. Otherwise, go to step 1.

7. Assign other data points to the exemplars using the nearest assign rule that is to assign each data point to an exemplar which it is most similar to.

4.3.5 GA-Fuzzy Algorithm

The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GA operates on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation.

Genetic algorithms (GAs) based on the mechanism of natural selection and genetics have been widely used for various optimization problems**.** Because GAs use population-wide search instead of a point search, and the transition rules of GAs are stochastic instead of deterministic, the probability of reaching a false peak in GAs is much less than one in other conventional optimiztion methods. Although GAs can not guarantee to attain the global optimum in theory, but non-inferior solutions can be obtained at least and sometimes it is possible to attain the global optimum.

- **Genetic algorithm**

The quality of cluster result is determined by the sum of distances from objects to the centers of clusters with the corresponding membership values: $J=\sum_{k=1}^{m}\sum_{i=1}^{c}(\mu_{ki})^m d(v_k,x_i)$ where $d(v_i,x_j)$ is the Euclidean distances between the object $x_j=(x_{j1},x_{j2},...,x_{jn})\frac{\pi}{3}$ and the center of cluster $v_i=(v_{k1},v_{k2},...,v_{kn}),m\in(1,\infty)$ is the exponential weight determining the fuzziness of clusters.

The local minimum obtained with the fuzzy *c*-means algorithm often differs from the global minimum. Due to large volume of calculation realizing the search of global minimum of function *J* is difficult. GA which uses the survival of fittest gives good results for optimization problem. GA doesn't guarantee if the global solution will be ever found but they are efficient in finding a "Sufficiently good" solution within a "sufficient short" time.

- **FCM clustering**

Step 1. Set Algorithm Parameters: c - the number of clusters; m - exponential weight; ε- Stop setting algorithm.

Step 2. Randomly generate a fuzzy partition matrix F satisfying the following conditions

$$F = [\mu_{ki}], \mu_{ki} \in [0,1], k = \overline{1, M}, i = \overline{1, C} \tag{4.22}$$

$$\sum_{i=\overline{1,C}} \mu_{ki} = 1, k = \overline{1, M} \tag{4.23}$$

$$0 < \sum_{k=\overline{1,M}} \mu_{ki} < N, i = \overline{1, C} \tag{4.24}$$

Step 3. Calculate the centers of clusters: $V_i = \frac{\sum_{k=\overline{1,N}} (\mu_{ki})^m \cdot X_k}{\sum_{k=\overline{1,N}} (\mu_{ki})^m}, i = \overline{1, c}$

(4.25)

Step 4. Calculate the distance between the objects of the X and the centers of clusters:

$$D_{ki} = \sqrt{\left\| X_k - V_i \right\|^2}, k = \overline{1, M}, i = \overline{1, c} \tag{4.26}$$

Here X is the observation matrix

Step 5. Calculate the elements of a fuzzy partition $(i = \overline{1, c}, k = \overline{1, M})$:

$$\text{If } D_{ki} > 0: \quad \mu_{ki} = \frac{1}{\left(D_{ik}{}^2 \cdot \sum_{j=\overline{1,c}} \frac{1}{D_{jk}{}^2}\right)^{1/(m-1)}} \tag{4.27}$$

$$\text{If } D_{ki} = 0: \quad \mu_{kj} = \begin{cases} 1, j = i \\ 0, j \neq i, j = \overline{1, c} \end{cases} \tag{4.28}$$

Step 6. Check the condition $\left\|F - F^*\right\|^2 < \varepsilon$ Where F^* is the matrix of fuzzy partition on the previous iteration of the algorithm. If "yes", then go to step 7, otherwise - to Step 3.

Step 7. End.

4.3.6 Self-organizing map (SOM) clustering

Self-organizing map (SOM) is a type of artificial neural network that use unsupervised learning (in the learning process) to produce a lower-dimensional (usually 2D) representation of the input space of the training data set samples. This input space are called as a map (grid,random or hexagonal). In this research hexagonal input space is used. Self-organizing maps are different from other artificial neural networks. SOM uses a neighbourhood function to preserve the topological properties of the input space.

The clustering using SOM algorithm was done in two steps.

1. The input data are compared with all the input weight vectors $m_i(t)$ and the Best Matching Unit (BMU) on the map is identified. The BMU is the node having the lowest Euclidean distance with respect to the input pattern $x(t)$. The final topological organization of the map is heavily influenced by this distance. BMU $m_c(t)$ is identified by:

For all $\quad i, \|x(t)-m_c(t)\| \leq \| x(t)-m_i(t)$ (4.29)

2. Weight vectors of BMU are updated as

$$m_i(t+1) = m_i(t) + \alpha h_{b(x)i}(x(t) - m_i(t)) \quad (4.30)$$

Here $h_{b(x)}$ is the neighbourhood function. Which is

$$h_{b(x)} = \alpha(t) e^{\left(\frac{\|r_i - r_{b(x)}\|^2}{2\sigma^2(t)}\right)} \quad (4.31)$$

Where 0< $\alpha(t)$<1 is the learning rate factor which decreases with each iteration . r_i and $r_{b(x)}$ are the locations of neurons in the input lattic. $\alpha(t)$ defines the width of the neighbourhood function. The above two steps were repeated iteratively till the pattern in input was processed.

4.4 Cluster Validation Measure: Silhouettes

Cluster validity is concerned with checking the quality of clustering results. The graphical representation of each clustering is provided by displaying the silhouettes introduced by Rousseeuw (1987). A wide silhouette indicates large silhouette values and hence a pronounced cluster. The other dimension of a silhouette is its height, which simply equals the number of objects within a category. The average of the silhouettes for all objects in a cluster is called the average silhouette width of that cluster. For application purpose the maximum value of average silhouette width for the entire data set is called the silhouette coefficient. The silhouette coefficient is a dimensionless quantity which is at most equal to 1.

4.5 Average silhouette width

Average silhouette width ASW (Kaufman & Roosseeuw 1990: Chapter 2) coefficient assesses the optimal ratio of the intra-cluster dissimilarity of the objects within their clusters and the dissimilarity between elements of objects between clusters.

- ASW measures the global goodness of clustering
- ASW = (Qi SWi) / n
- 0 < ASW < 1
- The larger ASW the better the split

Silhouette width (SW)

SW is a way to assess the strength of clusters

- SW of a point measures how well the individual was clustered
- SWi = (bi-ai) / max(ai,bi)
- Where a is the average distance from point ai i to all other points in i‘ s cluster, and bi is is the minimum average distance from point i to all points in another cluster -1 < SWi < 1

Chapter 5

Methodology

5.1 Bicycle Level of Service (BLOS) Model

There are various models used in previous studies in different countries to determine BLOS. Among all these models**,** FDOT (2009) concluded that Bicycle LOS Model developed by Landis (1997), is the best analytical methodology as it is an operational model. The BLOS Model is an evaluation of bicyclist perceived safety and comfort with respect to motor vehicle traffic while travelling in a roadway corridor. It identifies the factors that affect the quality of service for bicyclists that currently exists within the roadway environment. In the BLOS Model, bicycle LOS are based on five variables with relative importance ordered in the following list:

- Average effective width of the outside through lane
- Motorized vehicle volumes
- Motorized vehicle speeds
- Heavy vehicle volumes
- Pavement condition

These influencing attributes have developed certain relationships with BLOS is represented in the Figure 5.1.

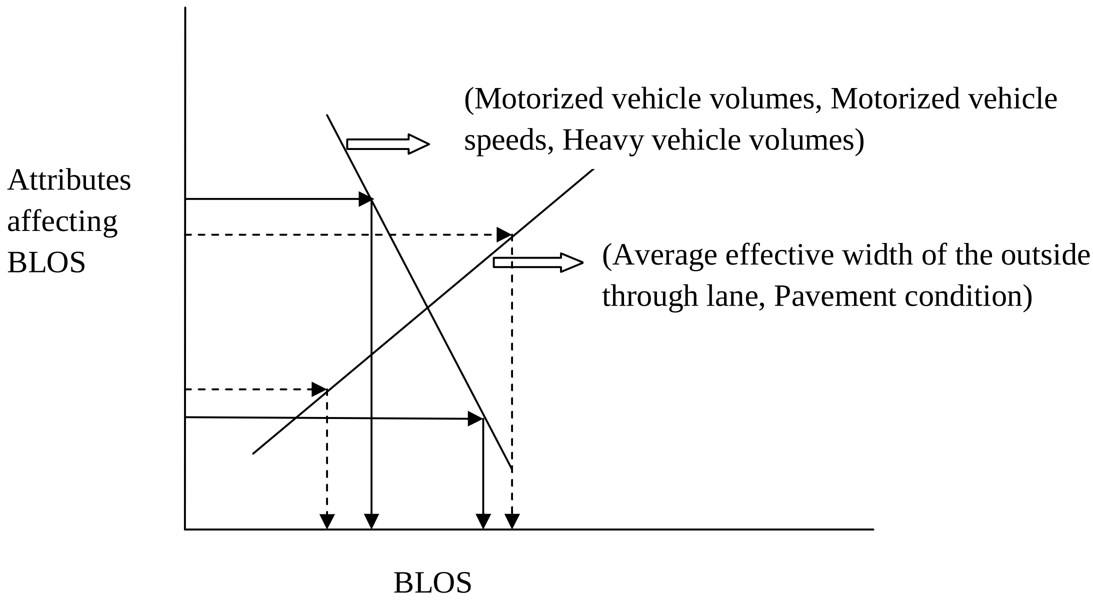


Figure 5.1 Co-relationship between influencing attributes and BLOS

Although, FDOT (2009) have considered above variables and different factors such as volume of directional motorized vehicles in the peak 15 minute time period, total number of directional thru lanes, posted speed limit, total width of outside lane (and shoulder) pavement, percentage of segment with occupied on-street parking, width of paving between the outside lane stripe and the edge of pavement, width of pavement striped for on-street parking, effective width as a function of traffic volume, effective speed factor and average annual daily traffic(AADT) to calculate BLOS score.

$$\text{BLOS}= 0.507 ln\left({VoL_{15}}/{L}\right) + 0.199 SP_t(1 + 10.38HV)^2 + 7.066({1}/{PR_5})^2 - 0.005(We)^2 + 0.760$$

Source: 2009 FDOT quality/level of service handbook

According to FDOT bicycle LOS Categories are represented by the following table

Table 5.1 Bicycle LOS Categories

BLOS	SCORE
A	≤ 1.5
B	> 1.5 and ≤ 2.5
C	> 2.5 and ≤ 3.5
D	> 3.5 and ≤ 4.5
E	> 4.5 and ≤ 5.5
F	> 5.5

(Source 2009 FDOT quality/level of service handbook)

An in-depth analysis is carried out in this study based on the BLOS model and by using various cluster analysis methods BLOS score are classified in Indian context. According to Indian urban traffic condition, roadway factors and speed factors BLOS score are calculated by using the following equation:

$$\text{BLOS}=0.478ln\left({}^{VoL_{15}}/_{L}\right)+0.193SP_t(1+10.38HV)^2+2.95({}^{1}/_{PR_5})^2-0.074(We)^2+1.729$$

This BLOS model is represented by the following forms of a multi-variable regression analysis

$$\text{y}=a1.x1+a2.x2+a3.x3-a4.x4+c$$

Where the coefficients are calculated for Indian context by using multivariate regression analysis as, $a1$=0. 478 $a2$=0. 193 $a3$=2. 95 $a4$= -0.074 c=1. 729

Where:

$BLOS$ = Bicycle level of service score

Ln = Natural log

VoL_{15} = Volume of directional motorized vehicles in the peak 15 minute time period

L = Total number of directional thru lanes

SP_t = Effective speed factor = 1.1199 In (SP_p – 32.18) + 0.8103

SP_p = Posted speed limit (a surrogate for average running speed)

HV = percentage of heavy vehicles

PR_5 = FHWA's five point pavement surface condition rating

We = Average effective width of the outside thru lane

(Which incorporates the existence of a paved shoulder or

Bicycle lane if present)

Where:

W_e = WV - (10ft x %OSP) Where W*l*= 0

W_e = WV + W*l* (1 - 2x %OSP) Where W*l*> 0 &Wps = 0

W_e = WV + W*l*- 2 (10 x %OSP) Where W*l*> 0 &Wps> 0

and a bicycle lane exists

Where:

Wt = total width of the outside lane (and shoulder) pavement

%OSP = percentage of segment with occupied on-street parking

W*l* = width of paving between the outside lane stripe and

the edge of pavement

Wps = width of pavement striped for on-street parking

WV = Effective width as a function of traffic volume

Where:

WV = Wt if ADT > 4,000 veh/day

WV = Wt (2-(0.00025 x ADT)) if ADT < 4,000 veh/day,

And if the street/road is undivided and unstriped

5.2 Terms used in BLOS model

Width of pavement for the outside lane and shoulder (Wt)

- Wt measurement is taken from the center of the road (yellow stripe) to the gutter pan of the curb (or to the curb if there is no gutter present).
- In the case of a multilane configuration, it is measured from the outside lane stripe to the edge of pavement. Wt does not include the gutter pan.
- When there is angled parking adjacent to the outside lane, Wt is measured to the traffic-side end of the parking stall stripes.
- The presence of unstriped on-street parking does not change the measurement; the measurement should still be taken from the center of the road to the gutter pan.

Figure 5.2 Width of pavement for the outside lane and shoulder (Wt) (two lane undivided)

Bisra chowk to Bandhamunda chowk, Rourkela

Figure 5.3 Width of pavement for the outside lane and shoulder (Wt) (For multilane road)

AG chowk to Rajmahal chowk

Width of paving between the shoulder stripe and the edge of pavement (Wl)

- This measurement is taken when there is additional pavement to the right of an edge stripe, such as when striped shoulders, bike lanes, or parking lanes are present. It is measured from the shoulder/edge stripe to the edge of pavement, or to the gutter pan of the curb. Wl does not include the gutter pan.
- When there is angled parking adjacent to the outside lane, Wl is measured to the traffic-side end of the parking stall stripes.

Width of pavement striped for on-street parking (Wps)

Measurement is taken only if there is parking to the right of a striped bike lane. If there is parking on two sides on a one-way, single-lane street, the combined width of striped parking is reported.

Chapter 6

Study Area and Data Collection

6.1 Introduction

In this chapter, details of study area and data collection procedure are described. To achieve the objectives of this research, data sets of road segment attributes and traffic flow parameters are collected from two cities in the State of Odisha, India. The data used in this research are collected limited to two cities only because of time and budget constraints. The following section presents the detail description about study area and data collection procedure. The Roadway attributes collected for BLOS model are also discussed in detail.

6.2 Study Corridors and Data Collection

6.2.1 Study corridors

Steel city Rourkela and capital city of Odisha State, Bhubaneswar are considered as the study areas for this research. Fifteen segments of the Rourkela road network and twenty segments of the Bhubaneswar road network are observed in the present study. The road segments on these two cities are preferred because of variation observed in road geometry and traffic behavior. Rourkela City is located in the north western part of Odisha State. It is situated about 340 kilometers north of the state capital Bhubaneswar. As perceived in other parts of India, the traffic flow on these two cities are highly heterogeneous. In Rourkela, the road segments taken into considerations are mostly two lane un-divided carriageways and few segments are four lane divided carriageways. Whereas, in Bhubaneswar city roads segments are typically four lanes divided carriageways, some segments are six lane divided and few segments are two lane un-divided. There are significant percentages of two wheelers and three wheelers in the total composition of vehicles. The design speed limit for these segments is 40km/h. Some segments included in this study, however, are having very good flow characteristics with wide roads, footpath/ shoulder, access facilities but there is no facility of separate bicycle lanes which is more often observed in Indian context. Therefore, the methodology developed in this study for defining levels of service criteria for on-street bicycle facilities could be applied to the urban streets of Indian cities in general.

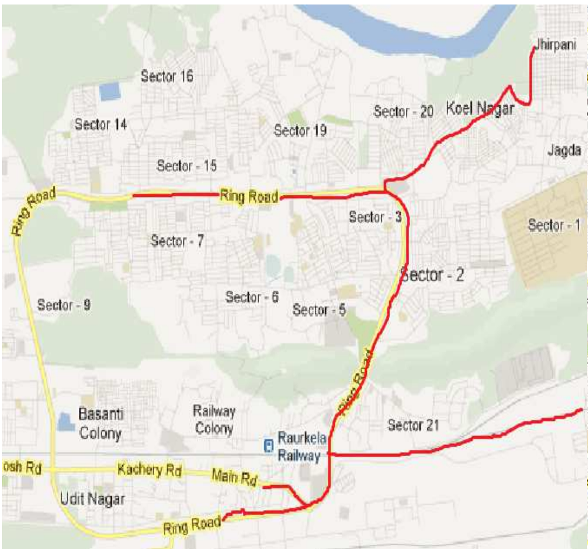


Figure 6.1 Map showing the road segments of data collection for Rourkela

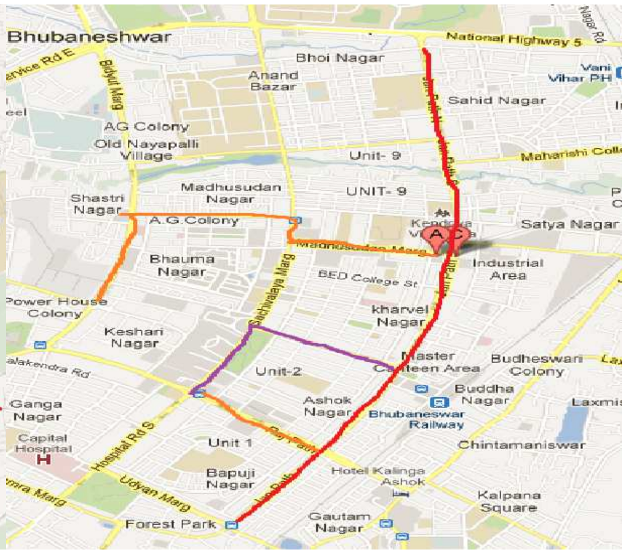


Figure 6.2 Map showing the road segments of data collection for Bhubaneswar city

Fig.6.3 D –block(Koel Nager) to Police station ,Jhirpani, Rourkela

Fig.6.4 Jan path road, Bhubaneswar

Fig6.5 Ring Road, Rourkela

Fig6.6 AG chowk to PMG chowk, Bhubaneswar

6.2.2 Data Collection

Data were collected by using Handycam fitted on a tripod stand and video shooting was carried out for two to three hours during both morning and evening peak hours for every segment. Using running average method peak 15 minute data are taken into considerations in this research. Basically seven types of data sets were collected such as number of motorized vehicles, the percentage of heavy vehicles, number of through lanes , average travel speed on each segment , width of bicycle lane (if present), pavement condition rating and percentage of segments occupied by on-street parking. Roadway attributes of street segments collected during inventory survey is shown in the Table 6.1.

Fig 6.7 Handycam fitted on a tripod stand

Table 6.1 Roadway attributes of street segments collected during inventory survey

Segment No. ………………………………………………………………………							
Segment Name ……………………………………………………………………							
Attributes							
No. of lanes	No. of vehicles in peak 15minutes	Percentage of heavy vehicles	No. of through lanes	Average travel speed on street segments	Bicycle lane (Yes/No)	Pavement condition rating (Excellent-5……Bad-1)	On Street Parking (%)
Six Lane Divided	540	1	1	40	No	5	0%
Four Lane Divided	280	5	1	40	No	4	1%
Two Lane Undivided	700	7	1	40	No	3	2%
Two Lane Undivided	800	9	1	40	No	-	3%

Chapter 7

Results of Cluster Analysis for LOS Criteria

7.1. Introduction

This chapter presents the result that derived from various clustering methods. Cluster analysis groups objects based on the information found in the data describing their relationships. The goal is that the objects in a group will be similar to one another and different from the objects in other groups. Objects in a cluster are closer to the "center" of a cluster, then the center of any other cluster. A good clustering method will produce clusters with the property that their intra-cluster distance is small and their inter-cluster distance is large (Kaufman and Rousseeuw, 1990). BLOS score was calculated for each segment by using BLOS model. Six cluster analysis methods (*k*-means, FCM, HAC, AP, GA-Fuzzy and SOM) were applied to classify the LOS category and Average Silhouette Width (ASW) for each method were calculated to determine the effective methods of classification for Indian conditions. Results found from applying these six methods show different BLOS categories for urban street segments in Indian context.

7.1.1 *K*-means Clustering

K-means clustering of BLOS scores of street segments of these two cities having different bicycle flow characteristics are classified into six LOS categories are shown in Figure 7.1. In this figure, both X and Y axes represent the BLOS scores and BLOS categories "A" to "F" are shown by different colours and symbols. From this figure it has been observed that BLOS score (≤4. 55) represents the LOS A and BLOS score (≥6) represent the LOS F. From the cluster analysis it is found that more BLOS score data are under the LOS categories C, D, E and F than A, B. This signifies that bicyclists travel at average and lesser to it levels of service more often. To provide better service quality (A, B) few factors affecting the BLOS need to be addressed. The silhouettes plot of BLOS scores of urban street segments categorized into six levels of service "A" to "F" based on *k*-means clustering is shown in Figure 7.2.

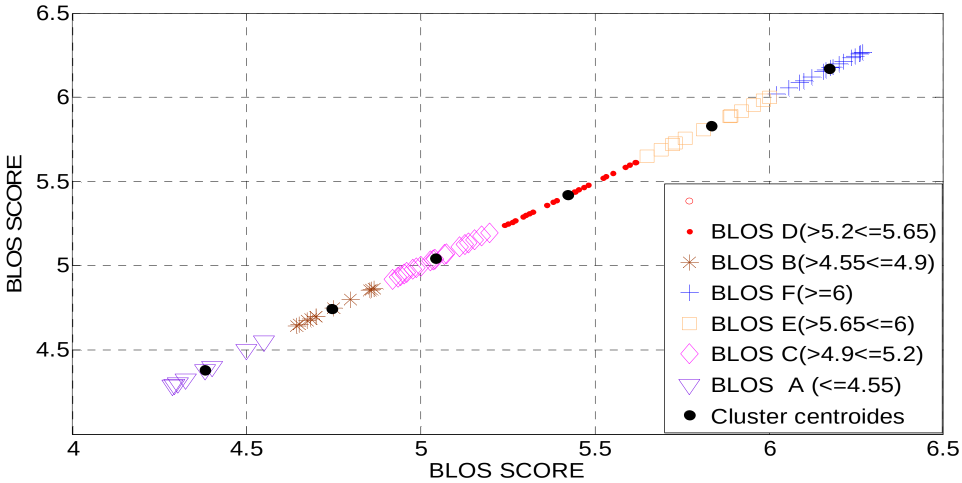


Figure 7.1 *K*-Means clustering of BLOS Scores

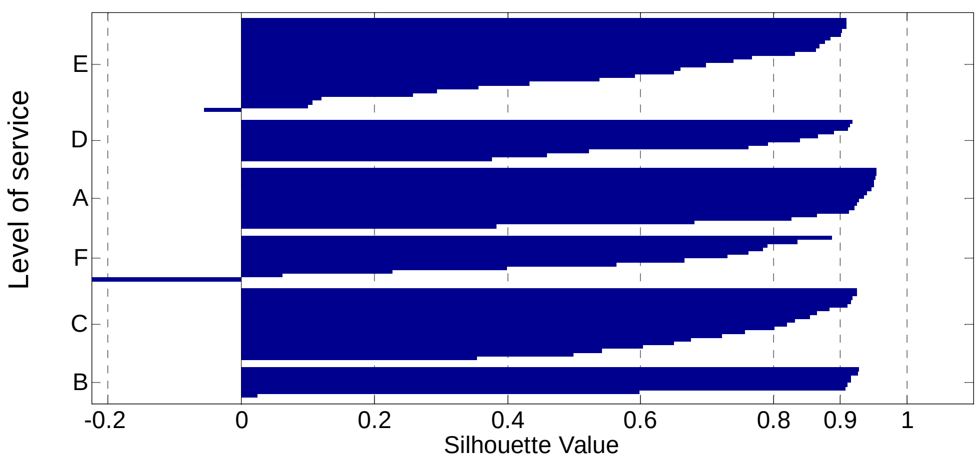


Figure 7.2 Silhouettes Plot of BLOS Scores using *K*-Means Clustering

From this figure it has been observed that Silhouette values lie between 0.9 and 1.0 for BLOS categories A and B. Based on this plot, it has been observed that BLOS data of group A and B are strongly bonded, although data are less in comparison to group C and E. This suggests that segments providing good quality of services are having very good geometry features (pavement in good condition, bicyclist get good percentage of shared space) and traffic flow of motorised vehicles are well managed within the available width of roadways. There lies an average bonding between the data of group C and D; which indicate that pavement condition of some segments are good and some segments are below average. Similarly, on some segments traffic movement is well organized and on some segments traffic move in a very haphazard manner. Bonding among data sets for LOS E and F are comparatively poor. This is because of large diversity lies among road segments in terms of road geometry and general operational characteristics of traffic flow. Also large numbers of road segments are within BLOS categories E and F; which indicate that a major share of the road network are not bicycle user friendly and need substantial improvement in this regard.

7.1.2 Hierarchical Agglomerative Clustering (HAC)

Another hard partitioning method such as Hierarchical Agglomerative Clustering (HAC) is used to classify BLOS scores to find the LOS categories for different urban street segments surveyed are shown in Figure 7.3. In this method, hierarchical tree of binary clusters was divided into larger clusters using the cluster function and desired number of groups formed. In this figure, BLOS scores for six categories “A” to “F” for urban street segments are shown by different colours and shapes. From this figure it has been observed that BLOS score (≤4. 5) represents the LOS A and BLOS score (≥5. 85) represent the LOS F. Figure indicate more dense group C, D, E and F than A, B. Also, data sets under BLOS categories A and B follow shorter ranges compared to others. Traffic on these two better service categories mostly follows more homogeneous flow with better roadway geometry features. Whereas, traffic flow for other categories are heterogeneous with varying roadway features makes it more congested to flow by vehicles and bicyclists. The silhouettes plot for the bicycle score of LOS categories “A” to “F” for urban street segments based on HAC clustering is shown in Figure 7.4.

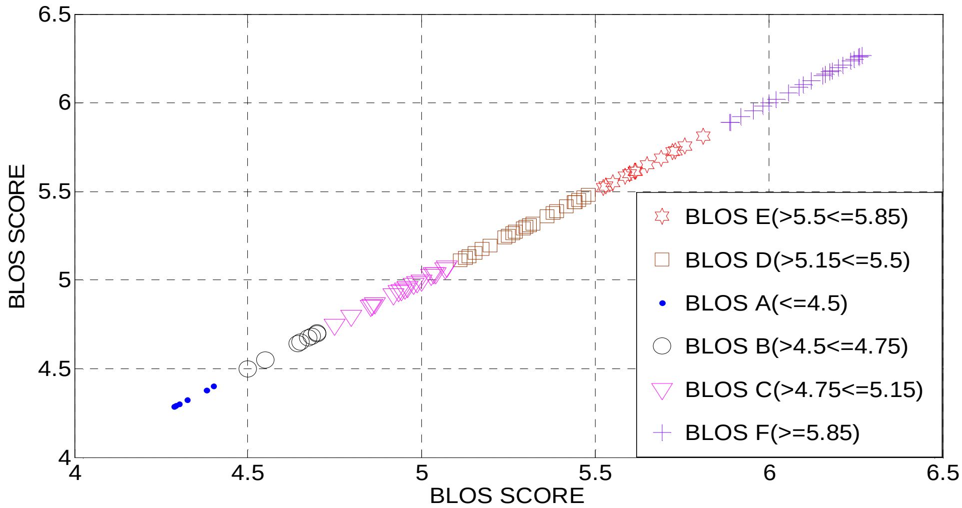


Figure 7.3 HAC of BLOS Scores

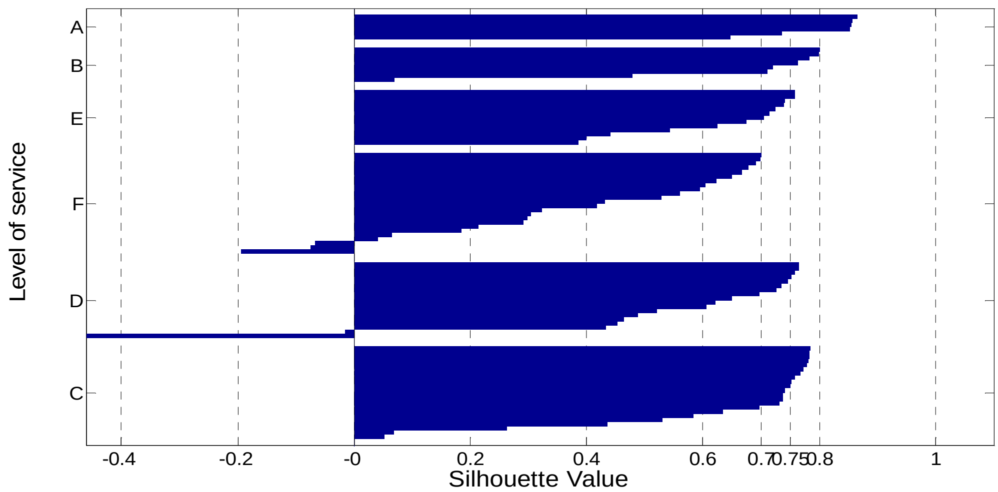


Figure 7.4 Silhouettes Plot of BLOS Scores using HAC

From this figure it has been observed that silhouette values lie between 0.8 and 1.0 for few street segments of BLOS category A and in maximum cases silhouette values lies between 0.60 and 0.75, indicated by BLOS categories (B-E) and silhouette values lies between 0.4 and 0.70, indicated by BLOS category F. For the group A, B and C data are well bonded within the same group than the other groups of data.

Hierarchical tree of binary clusters was divided into larger clusters using the cluster function. The dendogram formed out of bicycle score data was cut off at a level where it formed six clusters as shown in Figure 7.5; the dendogram is shown starting from a level where it will have only 30 leaf nodes. Therefore, in Figure 7.5, some of the leaf nodes among these 30 nodes will have multiple data points.

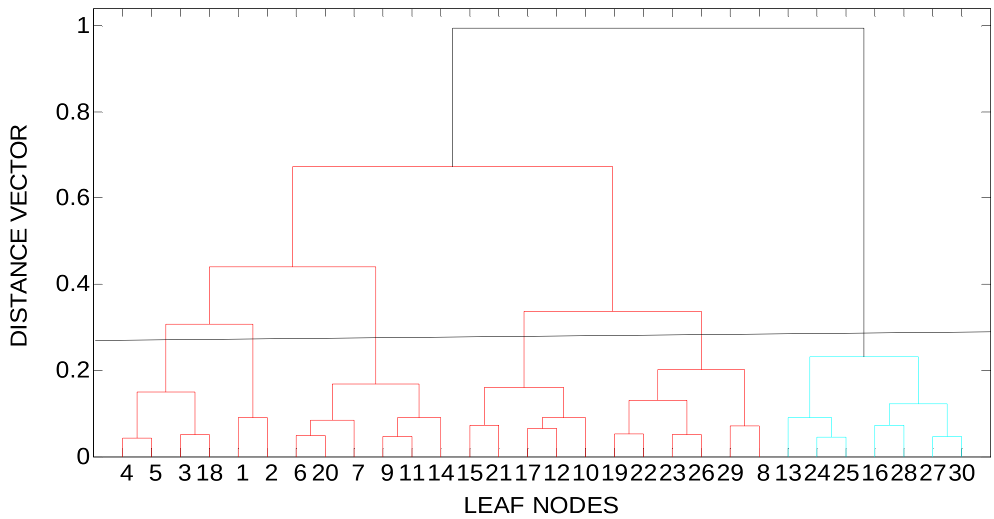


Figure 7.5 Dendogram using HAC on bicycle score data

7.1.3 Fuzzy C-Means (FCM) Clustering

Fuzzy clustering generalizes partition clustering methods (such as *k*-means) by allowing an individual to be partially classified into more than one cluster. In partition clustering, each individual is a member of only one cluster. Where as in fuzzy clustering objects are not assigned to a particular cluster: they possess a membership coefficient indicating the strength of membership in all or some of the clusters. This is called fuzzification of the cluster configuration. In a fuzzy cluster analysis, the number of subsets is assumed to be known, and the membership coefficient of each object in each cluster is estimated using an iterative method, usually a standard optimization technique based on a heuristic objective function. The concept of a membership coefficient derives from fuzzy logic but the connection between fuzzy logic and fuzzy cluster analysis is usually only through the application of membership coefficient, and not the more comprehensive theory.

Fuzzy C-Means (FCM) Clustering is also used for the classification of BLOS scores into categories. BLOS scores found using BLOS model developed in Indian context are used as the input values in Fuzzy C-Means (FCM) Clustering for the classification of the service measure into six categories are shown in Figure 7.6. In this figure, bicycle scores of LOS categories “A” to “F” for urban street segments are shown by different colours and symbols. From this figure it has been observed that BLOS score (≤4. 5) represents the LOS A and BLOS score (≥6) represent the LOS F. The silhouettes plot for the BLOS scores of service categories “A” to “F” of urban street segments based on Fuzzy C-Means (FCM) clustering is shown in Figure 7.7. From this figure it has been observed that Silhouette values lie between 0.90 and 1.0 for street segments under BLOS categories A and B, which indicates that data are well bonded because of similarity in road features and traffic characteristics. The same characteristics for BLOS categories C, D, E and F are somewhat varying.

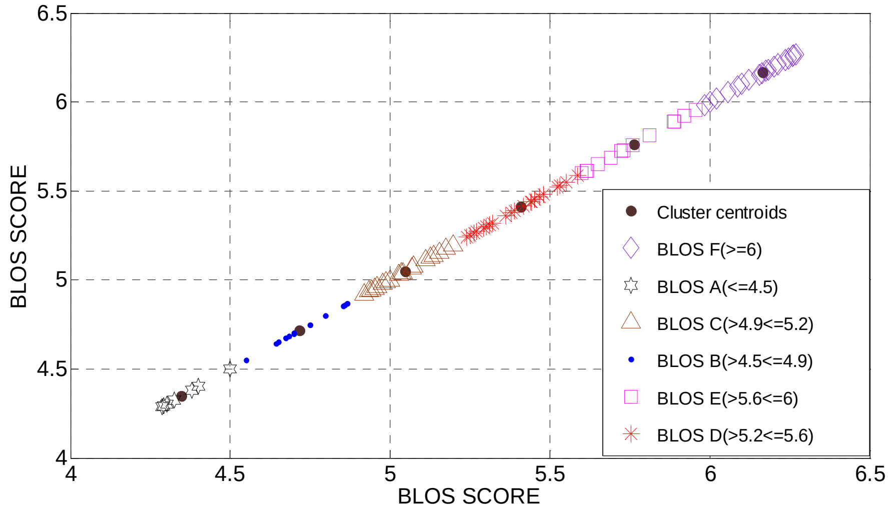


Figure 7.6 FCM Clustering of BLOS Scores

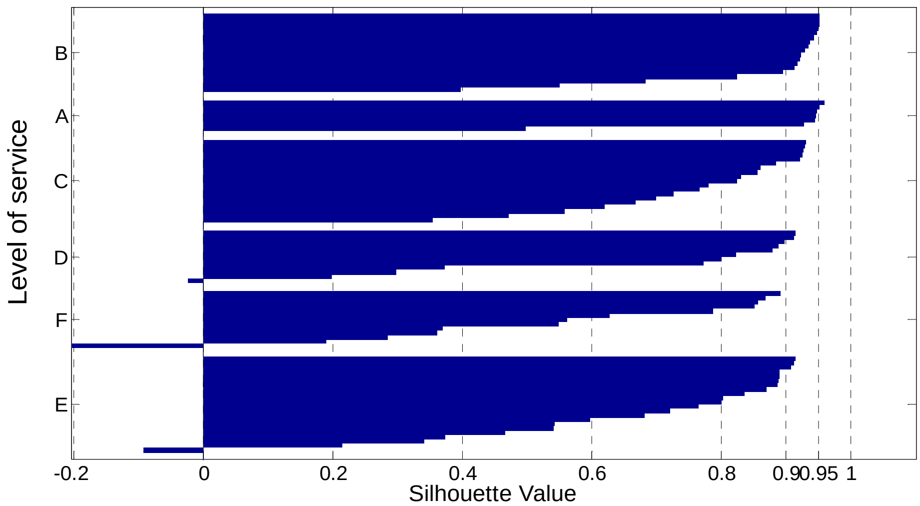


Figure 7.7 Silhouettes Plot of BLOS Scores using FCM Clustering

7.1.4 Affinity Propagation (AP) clustering

AP which is a new clustering tool developed in the recent past is used to classify the BLOS score for different urban street to find the ranges of LOS categories. Every algorithm has its natural way of classification of the data set into number of groups. When a data set is clustered into its optimal number of clusters the quality of the cluster is best as the variation between the data points belonging to a particular cluster is minimal. The user selects initial “self similarity” values from a set derived from the data itself, such that lower self similarity values give rise to a smaller number of clusters.

BLOS scores of various street segments found by the calibration of BLOS model are given to the algorithm in the form of similar matrix. The distribution of data after AP clustering is shown in fig 7.8. The different cluster group represents different LOS categories for urban streets. Where LOS A represent the best (<=4. 5) and LOS F represent the worst (>=5. 85). From the categories ranges it is observed that more data are in the LOS categories C,D,E and F than A, B i.e. number of street segments having more BLOS score are higher. Also level of service ranges are higher than the ranges provided by FDOT. It indicates that the bicycle level of service in Indian cities is poorer than the Florida due to scarcity of facility for bicyclists in the roadway environment in Indian urban context.

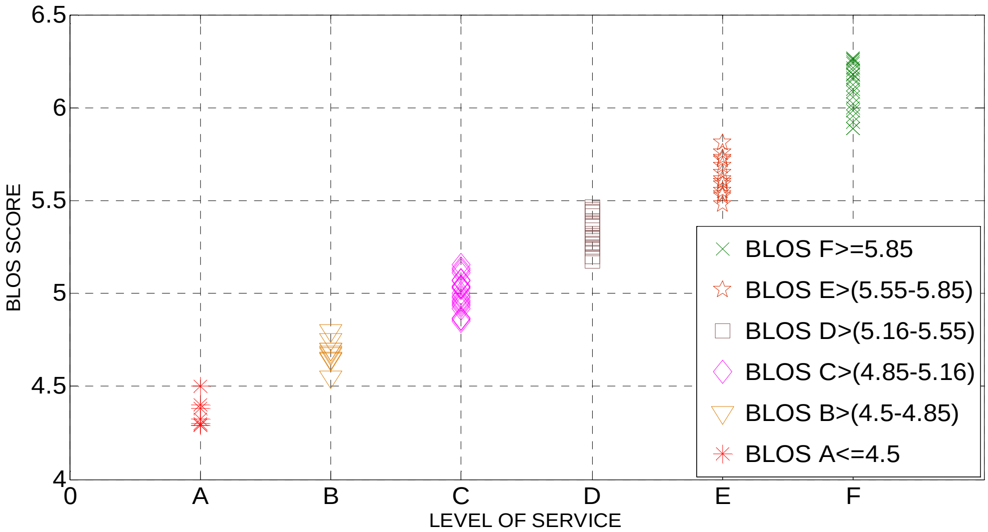


Figure 7.8 Plot for bicycle LOS for Urban Street segments using Affinity Propagation (AP) clustering

7.1.5 GA-Fuzzy

Like the previous algorithms input data (BLOS score) to GA-Fuzzy clustering and its output (cluster centers) found from the cluster analysis are used in computing the values to classify the input data. In this study data collected from 35 road segments were analyzed using BLOS model and BLOS score for each segment are classified using GA-Fuzzy algorithm. GA-Fuzzy algorithm classified BLOS score data of each segment for each direction into six clusters to find the LOS ranges of different urban street segments. The result of clustering is shown in figure 7.9. Each LOS class represented in the figure with a different symbol and colour. Legend of the figure illustrated the ranges of LOS classes (A-F), where LOS A represent the best (<=4. 5) and LOS F represent the worst (>=6). From the figure it is observed that more data are in LOS group C, D, E and F (poor) than A, B (good) quality level of service. Because of unplanned lane space utilization and poor management of traffic in urban Indian context.

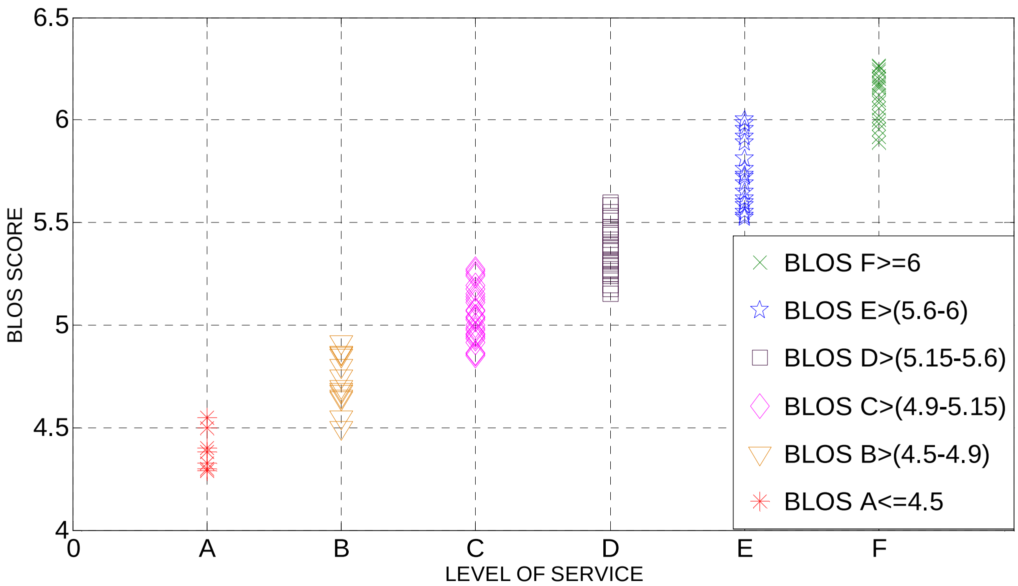


Figure 7.9 Plot for bicycle LOS for Urban Street segments using GA-Fuzzy clustering

7.1.6 SOM in ANN

Similarly SOM algorithm of ANN is also used to classify BLOS score found from BLOS model for the categorization of LOS ranges. The result of clustering is shown in figure 7.10. Each LOS class represented in the figure with a different symbol and colour and ranges (A-F), where LOS A represent the best (<=4. 85) and LOS F represent the worst (>=6). In this clustering method data points of group A are more than the other clustering methods which indicates SOM method consider relatively more number of good qualities of street segments than the other methods, but like the other methods the figure represents more data points in group D, E and F than A,B and the separation between the data points of group A are higher than the other group indicates not properly bonded.

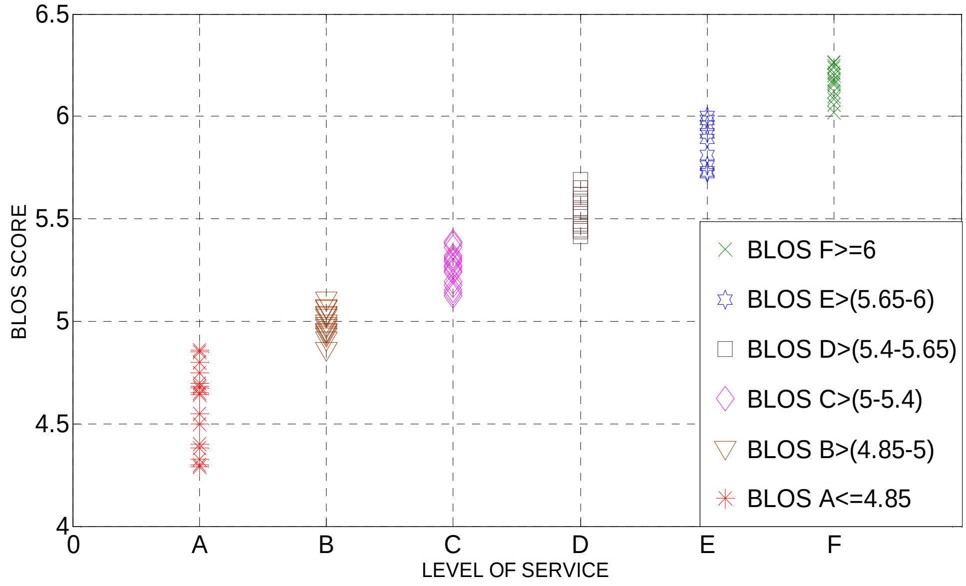


Figure 7.10 Plot for bicycle LOS for Urban Street segments using SOM clustering

K-means, HAC, FCM, AP, GA-Fuzzy and SOM clustering methods are used to classify BLOS scores to find LOS ranges. Values of LOS ranges of six methods are different from one to another as represented in Table 3. The lowest value represents BLOS A, i.e. the compatibility level is extremely high and the highest value represents BLOS F, i.e. the compatibility level is extremely low. From different plots of various clustering methods it is interpreted that poor service quality (D, E, and F) follow the road segments more often than good quality of service (A, B, C). To full fill the objective of the study i.e. to know the best clustering method suitable to define BLOS criteria in Indian context, Average Silhouettes Width (ASW) for all these six clustering methods are calculated. From the calculated ASW, it is observed that *K*-means, HAC, FCM, AP, GA-Fuzzy and SOM clustering methods have ASW values 0.7263, 0.604, 0.7167, 0.571, 0.564 and 0.465 respectively. Table 7.1 represents various BLOS ranges derived from various clustering method and ASW of these used methods.

Table 7.1 Classification of scores to define BLOS categories in Indian context

BLOS	*K*-means Clustering	Hierarchical Agglomerative Clustering (HAC)	Fuzzy C-Means (FCM) Clustering	Affinity Propagation (AP) clustering	GA-Fuzzy	Self Organizing Map (SOM)
A	≤4.55	≤4.5	≤4.5	≤4.5	≤4.5	≤4.85
B	>4.55≤4.9	>4.5≤4.75	>4.5≤4.9	>4.5≤4.85	>4.5≤4.9	>4.85≤5
C	>4.9≤5.2	>4.75≤5.15	>4.9≤5.2	>4.85≤5.16	>4.9≤5.16	>5≤5.4
D	>5.2≤5.65	>5.15≤5.5	>5.2≤5.6	>5.16≤5.55	>5.16≤5.6	>5.4≤5.65
E	>5.65≤6	>5.5≤5.85	>5.6≤6	>5.55≤5.85	>5.6≤6	>5.65≤6
F	≥6	≥5.85	≥6	≥5.85	≥6	≥6
Average Silhouette Width ASW	0.7263	0.604	0.7167	0.571	0.564	0.465

Various ranges of Average Silhouette Width are presented in table 7.2 indicate the strength and weakness of the structure.

Table 7.2 Ranges of ASW (Source: Kaufman & Roosseeuw 1990, chapter 2, pp. 88)

I	0.71-1.00	A strong structure has been found
II	0.51-0.70	A reasonable structure has been found
III	0.26-0.50	The structure is weak and could be artificial
IV	≤ 0.25	No substantial structure has been found

ASW of various used clustering methods is different from one to another and compared as shown in figure 7.11.

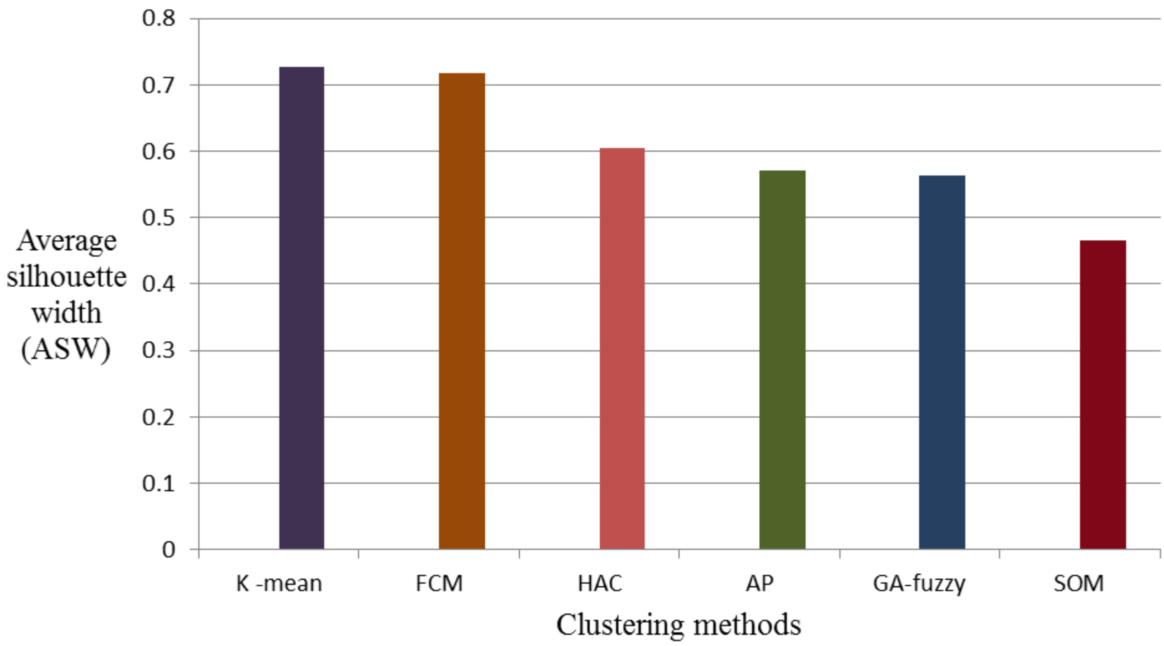


Figure 7.11 Comparison of ASW values of various clustering methods

According to Kaufman & Roosseeuw (1990) more the ASW value represents a strong structure. *K*-means and FCM have the ASW ranges in between 0.71-1.0 (strong structure), HAC, AP and GA-fuzzy have the ASW ranges in between 0.51-0.70 (reasonable structure) and SOM has the ASW ranges in between 0.26-0.50 (weak structure). Science *K*-means clustering has the highest average silhouette width than the other five clustering methods, *K*-means is a more suitable method to classify BLOS score of urban on street road segments in Indian context. BLOS score ranges of each individual level of service category using *K*-means clustering are elaborated in Table 7.3. From the table it can be outlined that level of service ranges are higher than the ranges provided by FDOT.

Table 7.3 Comparison of BLOS ranges in Indian context with FDOT BLOS ranges

BLOS	K-MEAN CLUSTERING BLOS RANGES	FDOT BLOS RANGES
A	≤4.55	≤ 1.5
B	>4.55≤4.9	> 1.5 and ≤ 2.5
C	>4.9≤5.2	> 2.5 and ≤ 3.5
D	>5.2≤5.65	> 3.5 and ≤ 4.5
E	>5.65≤6	> 4.5 and ≤ 5.5
F	≥6	> 5.5

Chapter 8

Summary, Conclusions and Future Scope

8.1 Summary

In this study, an attempt has been made to define bicycle LOS criteria for urban on-streets in the context of Indian cities. Handycam was used to collect data from different street segments. Various methods of bicycle LOS analysis are discussed in the literature review. From literatures it is observed that BLOS model developed by FDOT is in a very generic form, the coefficients of which can be easily calibrated in Indian context. BLOS model associate with several factors from which average effective width of the outside through lane, motorized vehicle volumes, motorized vehicle speeds, percentage of heavy vehicles (truck) and pavement condition rating have significant effect whereas bicycle volumes and pedestrian volumes have insignificant effect on BLOS. From all these factors “effective width of outside through lane” affect the most to BLOS score. Many researchers have adopted this model to define LOS in different countries and some have adopted Bicycle Compatibility Index (BCI) model. Based on safety point of view various models were developed such as Bicycle Safety Index Rating (BSIR), roadway condition index (RCI), Intersection Hazard Score (IHS), and Intersection Safety Index (ISI).

Defining BLOS is basically a classification problem and cluster analysis is found to be the most suitable technique for solving this classification problem. Cluster analysis groups objects based on the information found in the data describing their relationships. *K*-means, hierarchical agglomerative, fuzzy *c*-means, Affinity Propagation (AP), SOM and GA-fuzzy clustering are the six methods, those are employed to define LOS criteria in this study. The validation parameter, “silhouette” is used to evaluate and compare partitions resulting from different clustering algorithms and resulting from the same algorithms under different parameters. ASW is calculated for every clustering method to compare between the clustering methods and to find the best clustering method. *K*-mean cluster analysis is found to be the most suitable method in defining BLOS ranges for level of service categories of urban streets in Indian context.

8.2Conclusion

Following are the important conclusions that are drawn from the present study in defining Bicycle level of service criteria for urban streets in Indian context.

- The BLOS model which is calibrated for Indian context having lower coefficient values for a1, a2, a3 and higher value for a4 than BLOS model developed by FDOT 2009.
- It is observed that the numbers of motorized vehicles, vehicular speed and percentage of heavy vehicles have a negative impact and width of outside through lane, pavement condition rating have a positive impact on bicycle LOS.
- Bicycle LOS on urban on-streets are defined based on BLOS scores used by six cluster analysis methods. Defined BLOS scores for LOS categories are found to be different for all six clustering methods. BLOS score ranges for LOS categories (A-F) in the present study are found to be higher (implies lower in BLOS) than the ranges provided by FDOT (2009). The poor in service quality are due to the absence of separate bicycle lane, highly heterogeneous traffic flow on urban road corridors with varying geometry in India.
- Due to higher in Average Silhouettes Width (ASW) *K*-means is perceived to be better to classify BLOS score data than the other five clustering methods applied in this study.

- Also, it was found that bicycle traveled, more often, at the poor quality of service of “D”, “E” and “F”, than good quality of service of “A”, “B” and “C”.

8.3 Contributions

Bicycle level of service ranges for level of service categories of urban streets are defined using cluster analysis methods and BLOS model is calibrated and co-efficients are changed considering the local conditions of road segments for the first time in Indian context.

8.4Applications

BLOS assessment may be functional in several ways:

The bicycle level of service categories (A-F) defined in this study can be used in general in the bicycle level of service analysis of urban streets in Indian context which will help to the transportation planner and designer for a bicycle friendly environment. A bicycle map can be produced to attract bicyclist and a pollution free environment can be predicted.

8.5 Limitations and Future Scope

There are opportunities for further improvement to this study. Some of them are given below:

The study area for the present study was confined to two cities in India due to time and budget constraints. Similar study needs to be carried out in a number of cities in India. As one calibrated model and six clustering methods, are used for this study, there are opportunities for calibration of various models such as BCI, BSIR and ISI using the field data and use of various clustering methods for defining LOS criteria of bicycle in urban Indian context. In this study BLOS scores are calculated only for on street segments, similar research needs to be carried out for signalized intersections and off-street bicycle facilities.

The model is not applicable to off-street bicycle facilities, such as shared use paths or sidewalks. This study is a quantitative analysis of bicycle level of service but bicyclist perception of existing facility should be paid due consideration while defining bicycle level of service criteria of urban streets. In true sense to make the methodology on bicycle level of service analysis more realistic stated preference survey of bicyclist needs to be conducted and analyzed. However, the structure of the combined methodology on bicycle level of service analysis using quantitative and qualitative methods needs a thorough research.

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List of Publications

Journals:

published

1. Bhuyan, P. K, Nayak, M. S. A Review on Level of Service Analysis of Urban Streets. *Transport reviews,* Vol. 33, No. 2, 2013, 219–238.

Submitted

2. Nayak, M. S., Bhuyan, P.K. Bicycle Level of Service in Urban Indian Context. *Transport policy,* 2013.

Under Preparation

3. Nayak, M. S., Bhuyan, P.K. Defining BLOS Criteria of Urban on Street Road Segments Using SOM, GA-Fuzzy and AP Clustering in Indian Context. *Transportation,* 2013.