LEVEL OF SERVICE CRITERIA OF URBAN WALKING ENVIRONMENT IN INDIAN CONTEXT USING CLUSTER ANALYSIS

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CERTIFICATE

This is to certify that project entitled, "**level of service criteria of urban walking environment in Indian context using cluster analysis"** submitted by **RIMA SAHANI** in partial fulfillment of the requirement 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 supervision and guidance. To the best of my knowledge, the matter embodied in this Project review report has not been submitted to any other university/ institute for award of any Degree.

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ABSTRACT

Pedestrians form the largest single road user group and also are the most vulnerable road users. Pedestrians' movements are not restricted to lanes or specific routes however they are restricted by the physical boundaries around them such as the presence of walkways or pedestrian ways. To know how well roadways accommodate pedestrian travel or how they are pedestrian friendly it becomes necessary to assess the walking conditions. It would also help evaluating and prioritizing the needs of existing roadways for sidewalk construction. Estimation of Pedestrian Level of Service (PLOS) is the most common approach to assess the quality of operations of pedestrian facilities. The focus of this study is to identify and access the suitable methodology to evaluate PLOS for off-street pedestrian facilities in Indian context. Defining the level of service criteria for urban off-streets pedestrian facilities are basically classification problems. Cluster analysis is found to be the most suitable technique for solving these classification problems. Cluster analysis groups object based on the information found in the data describing their relationships. *K*-means, Hierarchical Agglomerative Clustering (HAC), Fuzzy *c*-means (FCM), Self Organizing MAP (SOM) in Artificial Neural Network (ANN), Affinity Propagation (AP) and Genetic Algorithm Fuzzy (GA Fuzzy) clustering are the six methods are those employed to define PLOS criteria in this study. Four parameters such as pedestrian space, flow rate, speed and volume to capacity (v/c) ratio are considered to classify PLOS categories of off-street pedestrian facilities. And from the analysis six LOS categories i.e. A, B, C, D, E and F which are having different ranges of the four parameters are defined. From the study it found that pedestrian faces a good level of service of "A", "B" and "C"are more often than at poor levels of service of "D", "E" and "F". From all the six clustering methods *K*-means is found to be the most suitable one to

classify PLOS in Indian context. The PLOS ranges defined in this study are significantly different from that mentioned in HCM (2010) because of highly heterogeneous traffic flow on main carriageway, poor enforcement of traffic laws, varying road geometry, unauthorized vendors' activities, unwanted obstructions from utilities, and illegal parking in off-street facilities etc.

Key words: Pedestrian Level of service, Pedestrian Facilities, video data collection, average pedestrian space, flow rate, speed, volume to capacity ratio, clustering technique

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Abbreviations and Symboles

ANN	Artificial Neural Network
AP	Affinity propagation
A_P	Pedestrian space
FCM	Fuzzy C-Means
GA Fuzzy	Genetic Algorithm Fuzzy
HAC	Hierarchical Agglomerative Clustering
HCM	Highway Capacity Manual
LOS	Level of Service
m	Meter
p	Pedestrian
PHF	Peak hour factor
PLOS	Pedestrian Level of Service
sec	Second
SOM	Self Organizing Map
S_p	Pedestrian speed
Sw	Silhouette width
v/c	Volume to capacity ratio
V_{15}	Pedestrian flow rate during peak 15 min

V_h	Pedestrian demand during analysis hour
V_P	Pedestrian flow per unit width
W_E	Effective walkway width,
W_o	Sum of fixed-object effective widths and linear feature
W_T	Total walkway width at a given point along walkway, and

Chapter-1

Introduction

1.1. General

Cities play a vital role in generating economic growth and prosperity. Keeping with the global trend economic growth has ushered India to go under tremendous urbanization in last century which become more significant after the independence. The sustainable development of cities largely depends upon their physical, social and institutional infrastructure. In this context, the importance of transport infrastructure is paramount. To facilitate this, what is required is a sound urban transport policy. The urban population in India has increased significantly from 62 million in 1951 to 285 million in 2001 and is estimated to grow to around 540 million by the year 2021. In terms of percentage of total population, the urban population has gone up from 17% in 1951 to 29% in 2001 and is expected to increase up to around 37% by the year 2021. Consequently, the number and size of cities have also increased considerably. Urban areas in India, which includes wide ranges of mega cities, cities, towns are not all that lucky in terms of intra & inter city transportation. Transport in this context has been a victim of ignorance, neglect and confusion all these at once. In 2002, 58.8 million vehicles were plying on Indian roads. According to statistics provided by the Ministry of Road Transport & Highways, Government of India, the annual rate of growth of motor vehicle population in India has been about 10 percent during the last decade. The basic thing is that transportation is the most important factor for developing urbanization and a significant proportion of every modal trip is made by walking. Therefore the needs of the pedestrian, like the needs of motor vehicles, should be considered in the design of the urban environment and transportation facilities. Efforts should be directed toward the safe, accessible, and convenient mobility for pedestrians. Walking provides mobility to a large percentage of people in many cities, especially the poor who often do not have other alternatives. It is also essential in supporting public transport facilities, improving the overall livability of cities, providing accessibility within built areas, and providing an alternative to private vehicles for short-distance trips.

Indian cities have traditionally been cities of walkers, and many urban dwellers rely on walking, cycling and public transport for their daily travel. However, with the exponential increase in motorization, limited attention has been paid to pedestrian and public transport facilities. A change in focus is required which will allow people, not vehicles, to reclaim the urban environment. Growing motorization has also lead to a dramatic increase in the number of pedestrian fatalities and accidents, and high levels of air pollution—particularly exposing pedestrians who walk to work or access public transport to reach their destinations. There are few initiatives to promote the improvement of walking in Indian cities. The few civil society organizations and nongovernment organizations working in this area can play key roles in promoting improvements on walkability and pedestrian facilities in their cities.

India being a developing country the traffic especially in urban street is very much heterogeneous consisting various kind of vehicles having different operational characteristics. There is a pressing need to overhaul the existing pedestrian guidelines or develop appropriate guidelines for Asian cities; particularly for Indian cities. The available guidelines are often ambiguous or inequitable and rarely enforced in cities. Traffic experts still rely on speed as the basis of performance measurement in urban areas, as found in the United States Highway

Capacity Manual (HCM). This antiquated view emphasizes the improvement of speed rather than planning for streets that promote accessibility for all users.

At present no proper methodology is available to evaluate Pedestrian Level of Service (PLOS) provided by urban streets in India. It is important to develop suitable methodologies for level of service analysis of urban streets. Defining PLOS criteria is a module of level of service analysis procedure for urban streets. These methodologies affect the planning, design, and operational aspects of transportation projects as well as the allocation of limited financial resources among competing transportation projects. This envisages the importance of suitable methods that should be adopted while defining pedestrian level of service criteria of urban streets in the context of cities in India. As pedestrian level of service is not well defined for highly heterogeneous traffic flow condition on urban corridors in India, an attempt has been made in this regard to define pedestrian level of service criteria in this study.

Level of Service (LOS) concept germinated from the concept of "practical capacity" presented in the 1950 HCM. In the 1965 HCM, LOS was stated as "qualitative measure of the effect of numerous factors, which include speed and travel time, traffic interruptions, freedom to maneuver, safety, driving comfort and convenience, and operating cost." In the 1985 HCM the statement of 1965 HCM was clarified by incorporating two significant factors i.e. "Qualitative major of operational factors" and "Perception of motorist and passengers" however "Operation Cost" was dropped. In 1965 and 1985 HCM the LOS was described by the six classes from "A" to "F" defined, based on the combination of travel time and the ratio of traffic flow rate to the capacity, because travel time was recognized as a dominant factor of the service quality. Highway capacity as well as LOS is dynamic, ever-changing and evolving phenomenon. The number of vehicles on the road, the amount of congestion, vehicle performance characteristics and geometric standards has significantly changed the environment in which a driver has to drive (Kittelson, 2000). Highway Capacity Manual (HCM, 2000) defined LOS as “a quality measure describing operational conditions within a traffic stream, generally in terms of such service measures as speed and travel time, freedom to maneuver, traffic interruptions, and comfort and convenience.”. The HCM designates six levels of service, A-F; describe operations from best to worst for each type of facility. In course of time the definition of LOS went in an evolution process and what is being followed is the LOS defined in 2010 HCM (HCM, 2010).

Highly heterogeneous traffic flow on main carriageway, poor enforcement of traffic laws, varying road geometry, unauthorized vendors activities, unwanted obstructions from utilities and illegal parking on footpaths etc. are the major factors affecting the PLOS of urban off-streets facilities. In simple language defining LOS can be called as a classification problem which can be solved using the various clustering tool available. Prassas et al. (1996) applied the cluster analysis tools to a set of traffic engineering data on which deterministic modeling and regression analysis have been applied before. From this study the authors have concluded that cluster analysis is a powerful exploratory technique and helps in identifying several distinct modalities within the traffic data. For this study six clustering methods such as *K*-Means, Fuzzy *C* means, Hierarchical Agglomerative Clustering, SOM, Affinity propagation and GA Fuzzy are considered to define the PLOS criteria. Considering the importance of level of service analysis for urban off-streets pedestrian facilities in Indian context, an in-depth research is carried out in the present study. Video camera is used for data collection, and average pedestrian space, flow rate, speed of pedestrian and volume to capacity ratio data are used as input for defining level of service categories for the present context.

The overall framework of this study is illustrated in Figure 1.1

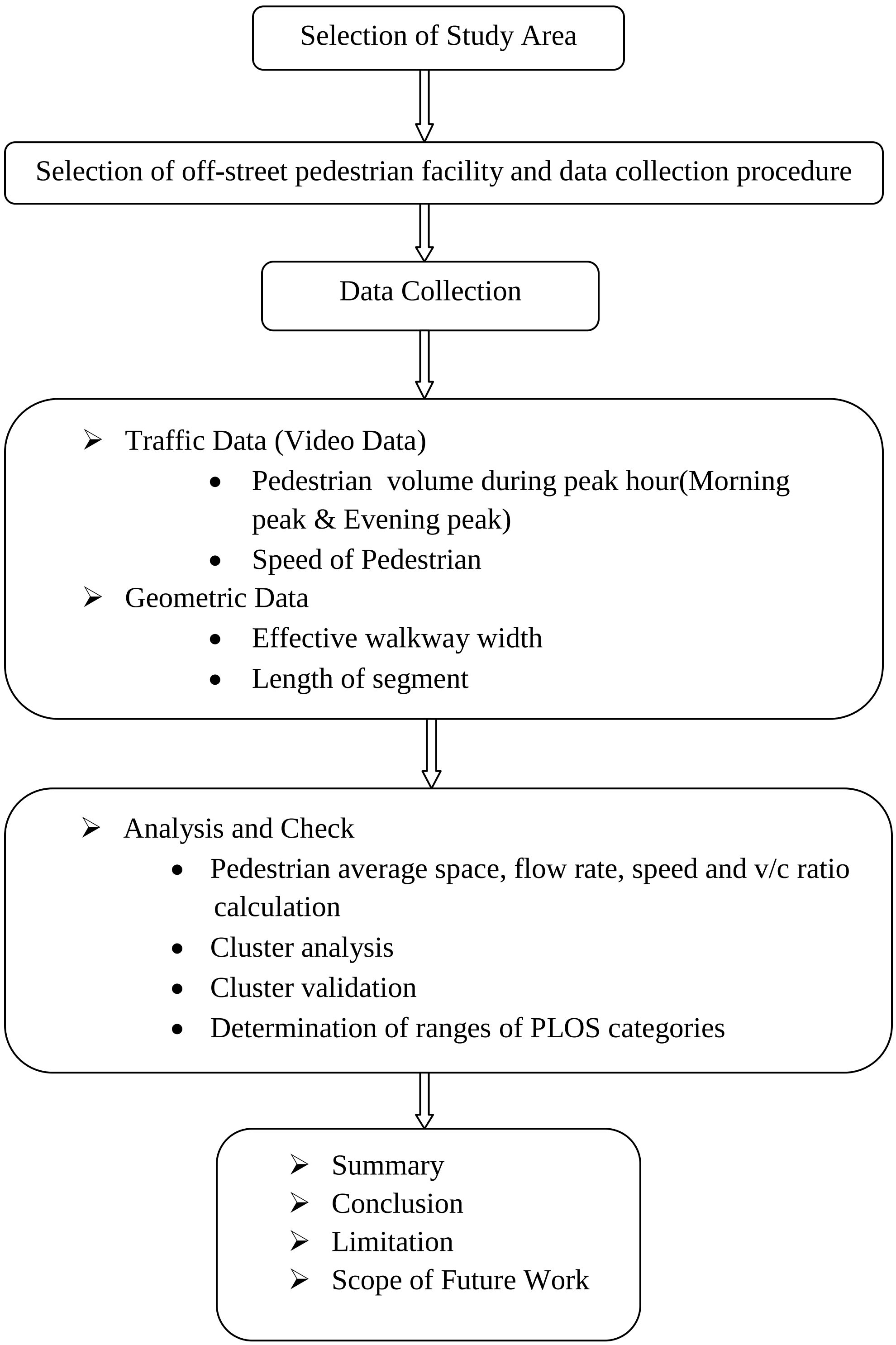


Figure 1.1 Overall framework of the study

1.2. Statement of the Problem

Like every coin have two sides the urbanization also showing the consequences by taking toll on the urban infrastructures. Urban pedestrian facilities are not spared from the ill effect of urbanization. As a result of which the operating condition of road available to the commuter decreasing day by day. Today, the urban road networks are suffering from the problems like decreasing speeds, increased congestion, increased travel time, and decreased level of service and increase in accident rates. The needs of the pedestrian, like the needs of motor vehicles, should be considered in the design of the urban environment and transportation facilities. A national review has shown that nearly 60 per cent of deaths and injuries on national highways are among pedestrians and hospital-based studies indicate pedestrian deaths to vary from 22% to 35%, and population based studies reveal that 1/3rd to 1/4th of road deaths are among pedestrians. The precise number of pedestrians injured and killed is difficult to ascertain and could be approximately 40,000 deaths annually in India. Collision with heavy vehicles like buses/trucks and medium sized vehicles like cars/jeeps resulted in higher deaths.

PLOS analysis is an important concept in defining the operating condition of a pedestrian facility. A common application of the level of service analysis is to compute the LOS of a current or changed facility for the near term or distance future. An important use of this analysis is to address growth management. Also, operational efficiency of urban road infrastructures can be very well judged by PLOS criteria. The proper PLOS categories in Indian context will help in LOS analysis of urban pedestrian facilities. Unlike United States, there is no proper methodology and suitable criterion to define LOS of pedestrian facilities in Indian context. Moreover, in Indian context, where, the traffic, roadway and environmental characteristics are completely different from those in the context of developed countries, modified criteria for LOS need to be arrived at. So there is a bare need of determining the PLOS criteria in Indian context.

1.3. Objectives and Scope of the Study

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

- To develop procedures for the collection of pedestrian data that is required in applications like defining pedestrian level of service criteria of urban off-streets.
- To outline a suitable criteria, which will be most appropriate for Indian context to evaluate pedestrian level of service
- To define pedestrian average space, speed, flow rate and volume to capacity ratio ranges of urban off-street pedestrian facilities of PLOS categories using advanced clustering algorithms.
- To find the most suitable cluster analysis algorithm in defining PLOS ranges.

1.4. Organization of Report

This report comprises of seven chapters. The first chapter provides an introduction to this research and also describes the objective and scope of this study. Second chapter gives an insight into the two major components of this research work i.e. urban off-street pedestrian facility and methodology to define pedestrian level of service (PLOS). In third chapter a thorough discussion on various literatures related to pedestrian level of service, and clustering techniques are presented. The fourth chapter a detailed description on the cluster techniques is presented for clear understanding of this research. Fifth chapter provides idea about the study area of this work and methodology of data collection. Result and analysis of the findings are illustrated in sixth chapter. The seventh chapter gives a summary of this work and conclusion of the research.

Limitations in the current study and scope for future work are highlighted.

References and Appendix are given at the end of this report.

Chapter-2

Pedestrian Level of Service Concepts

2.1 Introduction

The measures used to determine LOS for transportation system elements are called service measures. The HCM defines six levels of service, ranging from A to F, for each service measure, or for the output from a mathematical model based on multiple performance measures. LOS A represents the best operating conditions from the traveler's perspective and LOS F the worst. For cost, environmental impact, and other reasons, roadways are not typically designed to provide LOS A conditions during peak periods, but rather some lower LOS that reflects a balance between individual travelers' desires and society's desires and financial resources. Nevertheless, during low-volume periods of the day, a system element may operate at LOS A.

The LOS criteria for pedestrian flow are based on subjective measures, which can be imprecise. However, it is possible to define ranges of space per pedestrian, flow rates, and speeds, which can be used to develop quality-of-flow criteria. Speed is an important LOS criterion because it can be observed and measured easily, and because it is a descriptor of the service pedestrians perceive. There are other significant indicators of service levels. For example, a pedestrian's streams ability to cross a pedestrian stream is impaired at space values less than 3.5 m^2/pedestrian (p). Above that level, the probability of stopping or breaking the, normal walking gait is reduced to zero. Below 1.5 m^2/p, virtually every crossing movement encounters a conflict. Similarly, the ability to pass slower pedestrians is unimpaired above 3.5 m^2/p, but becomes progressively more difficult as space allocations drop to 1.8 m^2/p, the point at which passing becomes virtually impossible. Another LOS indicator is the ability to maintain flow in the minor direction when opposed by a major pedestrian flow. For pedestrian streams of roughly equal flow in each direction, there is little reduction in the capacity of the walkway compared with one-way flow, because the directional streams tend to separate and occupy a proportional share of the walkway.

Photographic studies show that pedestrian movement on sidewalks is affected by other pedestrians, even when space is more than 4 m^2/p . At 6 m^2/p, pedestrians have been observed walking in a checkerboard pattern, rather than directly behind or alongside each other. These LOS criteria are based on average flow and do not consider platoon flow. The concept of using the average space available to pedestrians as a walkway LOS measure also can be applied to queuing or waiting areas. In these areas, the pedestrian stands temporarily, waiting to be served. The LOS of the waiting area is related to the average space available to each pedestrian and the degree of mobility allowed. In dense, standing crowds, there is little room to move, but limited circulation is possible as the average space per pedestrian increases. LOS descriptions for queuing areas (with standing pedestrians) are based on average pedestrian space, personal comfort, and degrees of internal mobility. Standing areas in the LOS E category are encountered only in the most crowded elevators or transit vehicles. LOS D, also typically describes crowding, but with some internal maneuverability. This commonly occurs on sidewalks when groups of pedestrians wait to cross at street corners. Waiting areas that require more space for circulation, such as theater lobbies and transit platforms, must meet a higher LOS.

2.2 Pedestrian Facilities

2.2.1 Uninterrupted-flow Pedestrian Facilities

Uninterrupted pedestrian facilities include both exclusive and shared pedestrian paths (both indoor and outdoor) designated for pedestrian use. These pedestrian facilities are unique because pedestrians do not experience any disruption except the interaction with other pedestrians and, on shared paths, with other non-motorized modes of transportation. These procedures use pedestrian walking speed, pedestrian start-up time, and pedestrian space requirements.

Walkways and Sidewalks

Walkway and sidewalk paths are separated from motor vehicle traffic and typically do not allow bicycles or users other than pedestrians. These facilities are often constructed to serve pedestrians on city streets, at airports, in subways, and at bus terminals. These pedestrian facilities include straight sections of sidewalk, terminals, stairs, and cross-flow areas where streams of pedestrians cross. Such facilities accommodate the highest volumes of pedestrians of the three uninterrupted types of facility. They also provide the best levels of service, because pedestrians do not share the facility with other modes traveling at higher speeds.

Cross Flows

A cross flow is a pedestrian flow that is approximately perpendicular to and crosses another pedestrian stream. In general, the smaller of the two flows is referred to as the cross-flow condition.

Queuing Areas

The average space available to pedestrians also can apply as the walkway service measure for queuing or waiting areas. The pedestrian stands temporarily in these areas, waiting to be served. In dense standing crowds, there is little room to move, but limited circulation is possible as the average space per pedestrian increases.

Pedestrian Platoons

Short-term fluctuations are present in most unregulated pedestrian traffic flows because of the random arrivals of pedestrians. On sidewalks, these random fluctuations are exaggerated by the interruption of flow and queue formation caused by traffic signals. Transit facilities can create added surges in demand by releasing large groups of pedestrians in short time intervals, followed by intervals during which no flow occurs. Until they disperse, pedestrians in these types of groups move together as a platoon. Platoons also can form if passing is impeded because of insufficient space, and faster pedestrians must slowdown behind slow walkers.

2.2.2 Interrupted-flow Pedestrian Facilities

These facilities consider about impact of motor vehicles on pedestrian flow.

Signalized Intersections

For a signalized intersection LOS procedure has a pedestrian crossing on at least one approach. The signalized intersection crossing is more complicated to analyze than a midblock crossing, because it involves intersecting sidewalk flows, pedestrians crossing the street, and others queued waiting for the signal to change. The service measure is the average delay experienced by a pedestrian.

Un-signalized Intersections

LOS can also be determined for an un-signalized intersection with a pedestrian crossing against a free-flowing traffic stream or an approach not controlled by a stop sign. However, if there are zebra-striped crossings at an un-signalized intersection, this procedure does not apply, because pedestrians have the right-of-way; instead, pedestrian delay can be estimated using the method for two-way stop-controlled (TWSC) intersections.

Pedestrian Sidewalks on Urban Streets

This section focuses on the analysis of extended pedestrian facilities with both un-interrupted and interrupted flows. Average pedestrian travel speed, including stops, is the service measure. This average speed is based on the distance between two points and the average amount of time required including stops to traverse that distance

This study is based on pedestrian flow on uninterrupted walkway facilities of urban streets and the methodology of level of service analysis is described below.

2.3 Methodology

Off-street pedestrian facility serves only non-motorized traffic and is separated from motor vehicle traffic to the extent that such traffic does not affect their quality of service. There are three general categories of exclusive pedestrian facilities: walkways, cross-flow areas, and stairways. The LOS thresholds for each category are different, but all are based on the concept of space per pedestrian, which is a measure of pedestrian comfort and mobility. Following are the steps in Figure 2.1 followed to determine the LOS of exclusive off-street walkways pedestrian facilities.

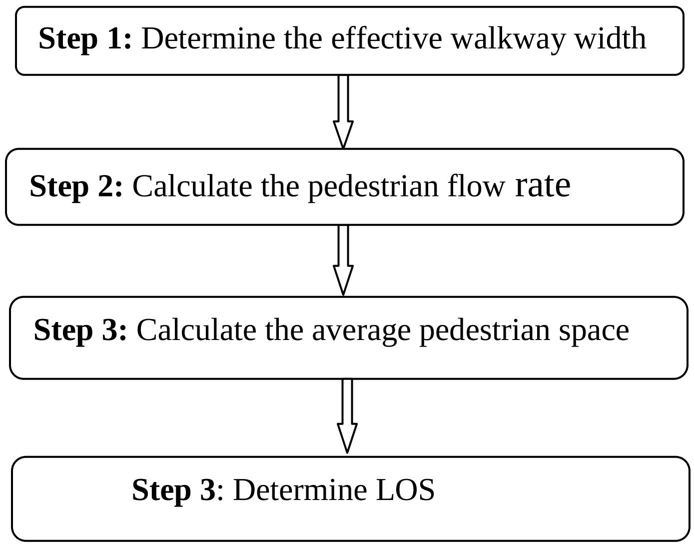


Figure 2.1: LOS methodology for off-street walkways in HCM 2010

Step 1: Determination of Effective Walkway Width

Effective walkway width is the portion of a walkway that can be used effectively by pedestrians. Various types of obstructions and linear features, discussed below, reduce the walkway area that can be effectively used by pedestrians. The effective walkway width at a given point along the walkway is computed as follows:

$$W_E = W_T - W_O \tag{1}$$

Where

W_E= effective walkway width,

W_T= total walkway width at a given point along walkway, and

W_o= sum of fixed-object effective widths and linear feature shy distances at a given point along walkway.

Step 2: Calculation of Pedestrian Flow Rate

An hourly pedestrian demand is used as an input to the analysis. Consistent with the general analysis procedures used throughout the HCM, hourly demand is usually converted into peak 15min flows, so that LOS is based on the busiest 15 consecutive minutes during an hour:

$$V_{15} = \frac{V_h}{4 * PHF} \tag{2}$$

Where,

V_{15}= pedestrian flow rate during peak 15 min (p/h),

V_h= pedestrian demand during analysis hour (p/h), and

PHF = peak hour factor.

However, if peak-15min pedestrian volumes are available, the highest 15-min volume can be used directly without the application of a peak hour factor. Next, the peak 15-min flow is converted into a unit flow rate (pedestrians per second per meter of effective path width):

$$V_P = \frac{V_{15}}{15 \times W_E} \tag{3}$$

Where,

V_P is pedestrian flow per unit width (p/m/sec) and all other variables are as previously defined.

Step 3: Calculation of Average Pedestrian Space

The service measure for walkways is pedestrian space, the inverse of density. Pedestrian space can be directly observed in the field by measuring a sample area of the facility and determining the maximum number of pedestrians at a given time in that area. The pedestrian unit flow rate is related to pedestrian space and speed:

$$A_P = \frac{S_P}{V_P} \tag{4}$$

Where,

A_P= pedestrian space (m^2/p),

S_p= pedestrian speed (m/sec), and

V_p= pedestrian flow per unit width (p/m/sec).

Volume by Capacity ratio Calculation

For determination of PLOS category of off-street pedestrian facility volume to capacity *(v/c)* ratio is one of the most important factor. For this study pedestrian hourly volume can be found out from video data collection and capacity of side-walks has been taken from IRC: 103-1988. Here width of side-walk for 1.5m, 2m, 2.5m, 3m and 4m capacities in number of persons per hour in both directions are 800, 1600, 2400, 3200 and 4000 respectively.

Step 4: Determine LOS

PLOS categories are to be resolute on the basis of average pedestrian space (A_p) , speed of pedestrian(S_p), flow rate (V_p) and volume by capacity (*v/c*) ratio. Six no of PLOS designated as “A” to “F” has to determine for off-street pedestrian facilities. The PLOS categories defined by HCM 2010 is as described in Table 2.1

Table 2.1: PLOS categories in HCM 2010

LOS	Average Space (ft^2/p)	Related Measures			Comments
		Flow Rate (p/min/ft)	Average Speed(ft/s)	v/c ratio	
A	>60	≤5	>4.25	≤0.21	Ability to move in desired path, no need to alter movements
B	>40-60	>5-7	>4.17-4.25	>0.21-0.31	Occasional need to adjust path to avoid conflicts
C	>24-40	>7-10	>4.00-4.17	>0.31-0.44	Frequent need to adjust path to avoid conflicts
D	>15-24	>10-15	>3.75-4.00	>0.44-0.55	Speed and ability to pass slower pedestrians restricted
E	>8-15	>15-23	>2.50-3.75	>0.65-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤8	variable	≤2.50	variable	Speed severely restricted, frequent contact with other users

Summary

This chapter gives a brief understanding on urban pedestrian facilities and Level of Service analysis. Various nomenclature used in this study are described in lucid manner. The PLOS analysis procedure given in HCM-2010 which is followed in this study is described. Average space, speed, flow rate and volume to capacity ratio ranges of PLOS categories of urban off-street classes mentioned in HCM 2010 are also shown in the Table 2.1. The next chapter describes various literatures that give an insight for this study.

Chapter-3

Review of Literature

3.1 General

For the first time the level-of-service concept was introduced in the 1965 HCM as a convenient way to describe the general quality of operations on a facility with defined traffic, roadway, and control conditions. HCM 2000 defined pedestrian LOS by dividing it into two segments that is uninterrupted pedestrian facility and interrupted pedestrian facility. The HCM 2010 methods for analyzing pedestrian LOS are based on the measurement of pedestrian flow rate and sidewalk space. The Pedestrian flow rate incorporates pedestrian speed, density, and volume, which is equivalent to vehicular flow. According to the HCM "As volume and density increase, pedestrian speed declines. As density increases and pedestrian space decreases, the degree of mobility afforded to the individual pedestrian declines, as does the average speed of the pedestrian stream."

Miller et al. (2000) had taken a step to use visualization as a simulation tool to validate and calibrate pedestrian LOS in suburban areas, which is a unique application of this technology. The animations were produced in a short time, and respondents were able to understand from the visualizations what types of improvements were being considered. According to Transit Capacity and Quality of Service Manual, the average area occupied by the pedestrian can be computed by dividing the square area of the effective walk way width with the peak hour pedestrian volume. Jaskiewicz (2000) stated that in order to encourage walking as a viable alternate form of transportation, it is essential that careful attention be paid to pedestrian comfort and safety in addition to traditional volume and capacity factors. Petritsch et al. (2005) incorporated perceived safety and comfort (i.e., perceived exposure and conflicts) and operations (i.e., delay and signalization) and the resulting model provides a measure of the pedestrian's perspective on how well an intersection's geometric and operational characteristics meets his or her needs.

Kim et. al. (2006) suggested that street performers have a negative impact on pedestrian LOS as they create congestion, limit access, and interfere with pedestrian flows. Although street performers have freedom of expression rights, there are serious questions about their rights to the use of public property. Muraleetharan and Hagiwara(2007) focused on examining the influence of overall LOS of sidewalks and crosswalks on pedestrian route choice behavior and attributes affecting overall LOS of sidewalks and crosswalks were defined and weighted by relative importance through the stated preference survey. Jianhong et. al. (2008) analyzed the pedestrian flow characteristics on basis of one-way passageways, two-way passageways, descending stairways, and ascending stairways in Shanghai metro stations and revealed that consistent rules for traffic flow, density, and speed could be applied to both pedestrian flows and vehicle flows from the view of macroscopic statistics. Schneider et. al. (2009) demonstrated how pedestrian volumes can be routinely integrated into transportation safety and planning projects and how data from automated counters can be used to extrapolate total weekly pedestrian intersection crossing counts from manual counts. Smith (2009) suggested that perceptions as well as objective assessment of the environment are significant in different ways in predicting walking behavior. Marshall and Garrick (2012) suggest that all three of the fundamental measures of a street network-street connectivity, street network density, and street patterns are highly significant and associated with influencing the choice to drive, walk, bike, or take transit. Ullman and Trout (2009) established preliminary message design guidelines for the development of audio messages to assist visually impaired pedestrians with navigation in work zones and the authors have noted that the visually impaired pedestrians strongly desire accurate and credible guidance information when they experience unexpected path conditions. Aultman-Hall et al. (2009) suggested that season and weather have an effect on levels of pedestrian volume in downtown Montpelier, Vermont. Precipitation reduces the average hourly volume level by approximately 13% and the winter months reduce it by 16% and also it was noted that at best a combination of weather variables accounts for 30% of the variance measured in hourly volumes.

3.2 Level of Service Analysis for Pedestrian Facilities

3.2.1 Sidewalk

Petritsch et al.(2006) incorporated traffic volumes on the adjacent roadway and exposure (i.e., crossing widths) at conflict points with intersections and driveway and the study reveals that traffic volumes on the adjacent roadway and the density of conflict points along the facility are the primary factors in the LOS model for pedestrians traveling along urban arterials with sidewalks. Sisiopiku et al. (2007) compared the various pedestrian sidewalk assessments and shown that the same sidewalk segment may receive multiple LOS ratings when different assessment methods are considered and the fact applies to sidewalks located on both urban and campus-like environments. Houten et al. (2007) stated that because pedestrian signal violations at mid-block crosswalks are associated with pedestrian crashes, it is important to improve pedestrian signal compliance at these locations. One way to improve compliance is to decrease pedestrian delay by reducing minimum green time. Miller et al. (2008) investigated the approach speed and passing clearance that Seg-way devices exhibit on encountering a variety of obstacles on the sidewalk.

3.2.2 Crosswalk

Golani et al. (2007) developed a model which includes all the elements affecting the crossing time of a pedestrian platoon: start-up time, walking speed and pedestrian headways (lag) as a function of the size of the dominant platoon, and the opposite platoon separately and the proposed model was calibrated according to data extracted from a video survey of crosswalks in three major metropolitan areas in Israel. Montufar et al. (2007) found that in all cases the normal walking speed is lower than the crossing walking speed. It also found that younger pedestrians walk faster than older pedestrians, regardless of season and gender, and females walk slower than males regardless of season and age. Furthermore, both younger and older pedestrians have a greater normal walking speed in summer than in winter but lower crossing speed in winter than in summer. Mitman et al. (2008) stated that crosswalks at uncontrolled intersections are numerous and widespread. Although engineering countermeasures offer significant potential for reducing pedestrian crash risk, not every intersection is in need of an engineering treatment. Lu and Noyce (2009) provided a quantitative comparison among several existing options for signalizing midblock crosswalk (MBC) at varied geometries.

Schroeder and Rouphail (2010) demonstrated the application of a framework on the basis of pedestrian and driver behavioral parameters to develop a mixed priority delay model for pedestrian crossings at single-lane roundabouts. “Mixed priority” refers to crosswalk operations where drivers sometimes yield to create crossing opportunities, but where pedestrians sometimes have to rely on their judgment of gaps in traffic to cross the street. Ma et al. (2011) on the basis of detailed modeling of key operational characteristics, such as pedestrian delays and the area of the central refuge island, presented a multi-objective optimization model and its solution algorithm for optimal control of a two-stage midblock crosswalk that consists of different traffic modes (i.e., walking and driving). Ren et al. (2011) shown that most of the pedestrians evaluated walk normally when they cross the street. More than 80% of pedestrians completely use the crosswalks. However, only 73.6% cross the street during the green time. The total pedestrian compliance rate is 62.8%. Hagiwara et al. (2012) investigated the communication capability of a dedicated short-range communications (DSRC) system (5.8GHz) between right-turning vehicles and pedestrians in the crosswalk.

3.2.3 Intersection

Muraleetharan et al. (2005) revealed that the factor ‘turning vehicle’ has greater influence on pedestrian LOS than other factors and when the number of turning vehicles increases, a corresponding decrease in the perceived safety to the pedestrian. Therefore the authors have recommended that at intersections the signal systems must be designed to minimize the pedestrian-vehicle interaction because pedestrians feel discomfort due to the conflicts with vehicles. Pulugurtha and Repaka (2008) indicated that population, total employment, urban residential area, and the number of transit stops are critical independent variables to model or estimate pedestrian activity at signalized intersections. The positive coefficient for these critical independent variables indicates that pedestrian activity is high at signalized intersections in densely populated neighborhoods and with transit stops. Hagiwara et. al. (2008) investigated conflicts between the right-turning vehicle and the pedestrian coming from the right in the crosswalk in Japan and found that the time lag is constantly reevaluated during the right turn by the driver, and the driver slows and enters the crosswalk behind the pedestrian, if the time lag at the conflict point is less than 2 s. Also, the braking location of drivers who braked to avoid conflict with the pedestrian after starting was 10.3 m before the conflict point. Chen et. al. (2008) have shown that pedestrians have a strong impact on the right-turn capacities at low pedestrian volumes and that the effects of additional pedestrians decrease as the pedestrian volumes increase. Hubbard et al.(2008) described how to use existing traffic signal equipment to develop pedestrian performance measures that provide accurate, relevant information with little investment.

Bian et. al. (2009) revealed that the factors significantly influence pedestrian LOS at signalized intersections included right turning vehicle and bicycle volume from the street parallel to the crosswalk during pedestrian green time, permissive left-turning vehicles and bicycles approaching from the street parallel to the crosswalk, through bicycle volume on the street parallel to the crosswalk, and pedestrians' delay. Wang and Tian (2010) indicated that pedestrian platooning significantly influences the average pedestrian delay compared with random arrivals, when pedestrians are going through several pedestrian signals. Dougald et. al. (2012) in his study about effectiveness of the zig-zag pavement had defined in three ways: (1) an increase in motorist awareness in advances of the crossing locations; (2) a positive change in motorist attitudes; and (3) motorist understanding of the markings. And the authors found that the markings installed in advance of the two crossings heightened the awareness of approaching motorists. This was evidenced by reduced mean vehicle speeds within the marking zones.

3.2.4 Modeling and Simulation

Landis et. al. (2001) stated that the Pedestrian LOS Model provides a measure of a roadway segment's performance with respect to pedestrians' primary perception of safety or comfort; as such it serves as the basis for the Florida Department of Transportation's state-wide multimodal (particularly for the pedestrian mode) level of service evaluation techniques. Dandan et al.

(2007) quantificationally analyzed the correlation between the pedestrian LOS and the affected factors; then on the basis of the analysis of urban roads with typical road transect form it interpreted that the factors which significantly affected the pedestrian LOS were the bicycle volume, the vehicle volume, the pedestrian volume, driveway access frequency and the distance between sidewalk and vehicle lane and also a pedestrian LOS model has been developed with the significant variables.

Petritsch et. al. (2008) represented a progressive shift in evaluating the quality of service from a provider-based measure how many vehicles or pedestrians can be moved and how fast to a user-based measure how well do drivers and pedestrians believe the facility meets their needs. The proposed model consists of a pedestrian density LOS and a pedestrian non-density LOS. Gangi and Velonà (2009) did a comparison between experimental data and simulation and found that the use of appropriate simulation models can realistically reproduce user behavior and then shows how such models can be used as a support for creating effective evacuation plans**.** Abdelghany et. al. (2010) presented a modeling framework for evaluating the performance of large-scale crowded pedestrian facilities during emergency evacuation. Chen et al. (2010) focused on the relationships and characteristics of pedestrian traffic flow in confined passageways. A level passageway, ascending stairway, descending stairway, and two-way stairway in Shanghai Metro stations were selected as observation sites for the collection of pedestrian flow data and the quantitative relationships for speed–density and volume–density were calibrated for all passageways observed.

Miranda-Moreno and Fernandes (2011) have shown the important link between land use and urban form patterns and pedestrian activity, which is consistent with the findings of previous work and also shows that pedestrian activity reacts to weather conditions, in particular, humidity and extreme temperature and the importance of the spatial and temporal trends in pedestrian flows. Rudloff et. al. (2011) revealed that the quality of the data had a strong effect on the suitability of different calibration strategies and that the information content in the scene under investigation limited the transferability of the results to other scenarios and the results suggest that several data sets with different characteristics do not need to be included in the calibration process to achieve a model that performs well in a wider variety of settings. Galiza and Ferreira (2011) introduced the concept of standard pedestrian equivalency (SPE) factors in order to convert heterogeneous pedestrian flow into a uniform commuter flow and this approach used simulation modeling to develop the time occupancy versus flow relationships adapted from PCE methodologies. Schneider et. al. (2012) stated that San Francisco Pedestrian Volume Model has a good overall fit, and it incorporates several variables that have not been included in previous intersection-based pedestrian volume models. Specifically, significantly higher pedestrian volumes are associated with intersections in high activity zones with metered on-street parking, in areas with fewer hills, near university campuses, and controlled by traffic signals.

3.2.5 Sustainable Pedestrian Facilities

Savolainen et. al. (2011) demonstrated that targeted enforcement can be effectively used to reduce the rate of pedestrian violations and that these improvements can be sustained for some period after enforcement has been completed. However, for such benefits to be realized, appropriate infrastructure is required to facilitate pedestrian compliance. Saunier et. al. (2011) proposed a simple method to extract frequency and length of pedestrian stride automatically from video data collected non-intrusively in outdoor urban environments. The walking speed of a pedestrian oscillates during each stride; the oscillation can be identified through the frequency analysis of the speed signal. Montufar and Foord (2011) presented the results of an analysis of the performance of three commercially available curbside automatic pedestrian detectors (APD)- a passive infrared and stereovision curbside detector, a passive infrared curbside detector, and a microwave detector in the field as a function of weather, temperature, and temporal variations at signalized intersections during the winter months at temperatures ranging from −34℃ (−29℉) to 0℃ (32℉).

Li et.al. (2012) demonstrated that accurate pedestrian counts and tracking can be performed using computer vision techniques which can expand the possibilities for pedestrian data collection significantly. This automation of pedestrian data collection can widen the range of feasible data both geographically (different locations) and temporally (for longer periods of time). Zielstra and Hochmair (2012) show that the combined use of network datasets significantly reduces shortest path distances compared to the use of single datasets, leading to the conclusion that data integration leads to an increased value for users of pedestrian routing applications. Schneider and Pande (2012) provided a more complete picture of pedestrian activity than is commonly shown by national and regional household survey summaries. Analyses of only the primary mode used on trips omit pedestrian movements connecting to parking and transit stops. Tal and Handy (2012) demonstrated that suburban areas with lower housing density and a pedestrian network based on pathways, parks, and greenbelts, as found in parts of Davis, California, USA, can have a higher level of connectivity and accessibility than measured in a more traditional grid network with four-way intersections and small blocks. Accounting for actual pedestrian connectivity, particularly the connections to schools and other public facilities, can lead to both better planning and more accurate research with respect to the conditions that promote walking.

3.3 Methods of Cluster Analysis

Formation of groups of objects based on the information found in the data which describes their relationships is known as clustering. In simple words, it can be defined as a way to form groups from a large data set. This powerful exploratory technique helps in identifying several distinct modalities within the data used in transportation studies. Various cluster analysis approaches have been applied on different kind of classification problems. Based on the previous successful applications, an attempt has been made to apply *k*-means, fuzzy *c*-means, hierarchical agglomerative clustering, SOM in ANN, affinity propagation and GA Fuzzy cluster analysis methods for classification of off-street pedestrian level of service categories. A brief description of the algorithms and application of such methods is presented in the following sections.

3.3.1 *K*-means clustering

One of the most well-known hard partitioning methods is *k*-means clustering. It is most useful for forming a small number of clusters from a large number of observations. It requires variables that are continuous with no outliers. The function *k*-means partitions the observed data into *k* mutually exclusive clusters, and returns a vector of indices indicating to which of the *k* clusters it has assigned each observation. *K*-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid. This algorithm moves objects between clusters until the sum cannot be decreased further. However, *k*-means does not guarantee unique clustering because different results are shown with randomly chosen initial clusters. The *k*-means algorithm gives better results only when the initial partitions are close to the final solutions (Jain and Dubes, 1988). Several attempts have been reported to solve the cluster initialization problem. Penã et al. (1999) presented a comparative study for different initialization methods for the *k*-means algorithms. The result of their experiments illustrate that Kaufman initialization method outperforms the rest of the compared methods. Khan and Ahmad (2004) proposed an algorithm to compute initial cluster centers for *k*-means clustering. The initial cluster centers computed using this methodology were found to be very close to the desired cluster centers, for iterative clustering algorithms.

Kim and Yamashita (2005) used *k*-means clustering technique for analyzing pedestrian crash pattern. The authors have described how *k*-means clustering technique can be used to analyze the locations and patterns of traffic accidents. The authors have found that for pedestrian safety analysis *k*-means is the most appropriate method to locate compact, localized clusters. They have mentioned that k-means is not just a useful exploratory data analysis tool, but it could also be applied to the evaluation of effectiveness in the reduction of injuries and fatalities and incidents across time and space.

3.3.2 Fuzzy *c*-means 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 regular clustering, each individual is a member of only one cluster. Suppose we have *k* clusters and we define a set of variables that represent the probability that object *i* is classified into cluster *k* in partition clustering algorithms, one of these values will be one and the rest will be zero. This represents the fact that these algorithms classify an individual into one and only one cluster. However, in fuzzy clustering, objects are not assigned to a particular cluster: they possess a membership function indicating the strength of membership in all or some of the clusters. This is called fuzzification of the cluster configuration. The concept of a membership function derives from fuzzy logic, an extension of Boolean logic in which the concepts of true and false are replaced by that of partial truth. Boolean logic can be represented by set theory, and in an analogous manner fuzzy logic is represented by fuzzy set theory.

Fuzzy set theory was introduced by Zadeh (1965) as a general approach to express the different types of uncertainty in human systems. The connection between fuzzy logic and fuzzy cluster analysis is usually only through the application of membership functions, and not the more comprehensive theory. Laviolette et al. (1995) along with a number of discussants compare fuzzy and probabilistic approaches in general, and among these contributions is a discussion of fuzzy cluster analysis. However, an example in which the principles of fuzzy logic are used to derive a clustering algorithm is given by Zhang et al. (1998) in an application to a small data set concerned with monitoring mechanical equipment.

Chakroborthy and Kikuchi (1990) have discussed the application of fuzzy set theory to the analysis of highway capacity and level of service. The authors have shown the limitations of the current procedure to determine highway capacity and service level. In this study, fuzzy numbers were used to represent the values of input variables and output variables which were involved in calculating capacity and service level. In this study it has been shown that it is much better if the levels of service categories are defined as fuzzy sets. Ndoh and Ashford (1994) developed a model to evaluate airport passenger services using fuzzy set techniques. In their words, “The literature on transportation level of service evaluation indicates a strong impetus to move away from a strictly capacity/volume or time/space based measure to one that directly incorporates the perception of passengers".

To meet the user requirements of advanced traffic management and information system Cheol and Stephen (2002) have demonstrated a technique for the development of real-time intersection level of service criteria. In this study the authors have used a new measure of effectiveness, which they called Reidentification Delay (RD) at signalized intersections. The authors have applied several cluster analysis methods including *k*-means, fuzzy and self-organizing map (SOM) in ANN for the derivation of LOS categories. The procedures used in this study were readily transferable to other signalized intersections for the derivation of real-time LOS.

3.3.3 Hierarchical agglomerative clustering

Hierarchical clustering is a way to investigate grouping in data, simultaneously over a variety of scales, by creating a cluster tree. The tree is not a single set of clusters, but rather a multi-level hierarchy, where clusters at one level are joined as clusters at the next higher level. This allows us to decide what level or scale of clustering is most appropriate in our application.

Lingra (1995) compared grouping of traffic pattern using the Hierarchical Agglomerative Clustering and the Kohonen Neural Network methods in classifying traffic patterns. It has been mentioned that the Kohonen neural network integrates the hierarchical grouping of complete patterns and the least-mean-square approach for classifying incomplete patterns. It is advantageous to use hierarchical grouping on a small subset of typical traffic patterns to determine the appropriate number of groups and change its parameters to reflect the changing traffic patterns. Such an approach is useful in using hour-to-hour and day-to-day traffic variations in addition to the monthly traffic-volume variation in classifying highway sections. The same author, Lingra (2001) applied Hierarchical Agglomerative Clustering technique and an evolutionary Genetic Algorithms approach for classifying highway sections. It has been pointed out that hierarchical approach tends to move farther away from the optimal solution for smaller number of groups, however Genetic Algorithms based approach provides better results when the number of groups is relatively small.

3.3.4 Self-Organizing Map (SOM) Clustering

Self-Organizing Map (SOM) is one of the Artificial Neural Network (ANN) having the inherent capability to learn the pattern of input and to detect regularities and correlations in their input and responses in future accordingly. The application this particular problem to define the LOS of urban street artificial neural network (ANN) is used for clustering of speed data. Levy et al. (1994) compared the ability of supervised and unsupervised learning method for classification and clustering. Lingra (1995) compared grouping of traffic pattern using the Hierarchical Agglomerative Clustering and the Kohonen Neural Network methods in classifying traffic patterns. It is advantageous to use hierarchical grouping on a small subset of typical traffic patterns to determine the appropriate number of groups and change its parameters to reflect the changing traffic patterns. Such an approach is useful in using hour-to-hour and day-to-day traffic variations in addition to the monthly traffic-volume variation in classifying highway sections. Garni and Abdennour (2008) developed a technique using the ANN neural network to detect and count the vehicles plying on road from the video graph data. Sanchez et al. (2002) proposed a back propagation neural network to discriminate zones of high mineral potential in the

Rodalquilar gold field, south-east Spain, using remote sensing and mineral exploration data stored in a GIS database. A neural network model with three hidden units was selected by means of the k-fold cross-validation method. The trained network estimated a gold potential map efficiently, indicating that both previously known and unknown potentially mineralized areas can be detected. Yang and Qiao (1998) used neural network to classify traffic flow state. Author applied a self-organizing neural network pattern recognition method to classify highway traffic states into some distinctive cluster centers.

Jian-ming (2010) developed a combined ANN and Genetic Algorithm method for the prediction of traffic volume in Sanghai Metropolitan Area. The accuracy of prediction of traffic volume of future traffic improved significantly with this combined algorithm. Cetiner et. al. (2010) developed a back propagation Neural Network traffic flow model for prediction of traffic volume of Istanbul City. The model uses the historical data at major junctions of the city for prediction of future traffic volume. Florio and Mussone (1995) have taken the advantage of application of ANN in classification problem to develop the flow-density relationship of a motorway. The author defined the stability and instability of spacing of vehicle in traffic stream. Murat and Basken (2006) used ANN for determination of non-uniform delay which is part of total vehicular delay at signalized intersections. Sharma et al. (1994) studied and compared the learning ability of both supervised and unsupervised type of learning method for clustering.

3.3.5 Affinity Propagation (AP) Clustering

Affinity propagation is a theoretic clustering method recently developed by Frey and Dueck (2007). This algorithm simultaneously considers all of data points as possible exemplar (center point) where each message is sent to reflect the latest interest which is owned by each data point to be able to select another data points as their exemplar. In recent past researchers have used this efficient and accurate algorithm in solving various clustering problems. Frey and Deuck (2007) used AP algorithm to cluster images of faces and genes in microarray data. The authors found AP to cluster data with much lower error than other methods, and it did the clustering in less than one-hundredth the amount of time. Conroy and Xi (2009) developed a semi-supervised AP algorithm for face-image clustering and functional Magnetic Resonance Imaging (fMRI) volumetric pixel clustering. Xia et.al. (2008) presents two variants of AP for grouping large scale data with a dense similarity matrix. The local approach was Partition Affinity Propagation (PAP) and the global method was landmark affinity propagation (LAP). Refianti et.al. (2012) compared accuracy and effectiveness of AP and K-Means algorithm. The authors have found that AP to be more effective than *K*-Means by implementing these algorithms on the relationship between two variables i.e Grade Point Average (GPA) and duration of Bachelor-Thesis completion at Gunadarma University. Zhang and Zhuang (2008) presented a modified AP algorithm called voting partition affinity propagation (voting-PAP) which is a method of clustering using evidence accumulation. Yang and Bruzzone (2010) used AP for classifying large amount of remote sensing images data quite accurately. Authors found the algorithm to be very much efficient for clustering of data for which training data is not available. Yang et.al. (2010) used this newly developed AP clustering algorithm in traffic engineering. The authors have proposed a model-based temporal association scheme and novel pre-processing and post-processing operations which together with affinity propagation make a quite successful method for vehicle detection and on road traffic surveillance. Zhang et.al. (2012) proposed an instant traffic clustering algorithm using AP to find points on road having similar traffic pattern. Authors found the algorithm to be suitable in predicting the traffic pattern and for finding the influence of traffic pattern at one point to that at another point. These are some of researches carried out at different locations under different traffic conditions which give a strong back ground for further research carried out in this study in defining PLOS criteria in Indian Context.

3.3.6 GA-Fuzzy Clustering

Many researchers have utilized Genetic Algorithm in optimizing the clustering problems. Zhou et al. (2010) developed a Genetic Fuzzy Clustering Algorithm combining FCM clustering and Genetic Algorithm (GA). Fuzzy clustering is a process in which a data point is not assigned to a single cluster rather each data points possess a membership function. This membership function indicates the strength of the data point. Alata et al. (2008) optimized the FCM clustering algorithm using GA. The researcher used the subtractive clustering algorithm to provide the optimal number of clusters needed by FCM algorithm by optimizing the parameters of the subtractive clustering algorithm by an iterative search approach and then to find an optimal weighting exponent (m) for the FCM algorithm. Wei et al. (2010) found FCM clustering has inherent problem being very time consuming and having poor clustering result. The authors exploited the search capability of GA by enhancing the global search process. GA is used in traffic engineering field by various researchers to solve traffic engineering problems. Lingras et. al (2004) utilized Genetic Algorithm to estimate the missing traffic count. 50% of permanent traffic counts have missing data. The researchers designed a genetically designed regression model having very high precision. Kidwai et. al (2005) presented an optimized model for bus scheduling. The bus scheduling problem was solved in two levels. First level minimum bus in a route with a guarantee of load feasibility was determined. In second level fleet size in first step was taken as upper bound and fleet size was again minimized using GA.

3.4 Summary

A thorough literature review is discussed in this chapter related to LOS analysis and six clustering methods used in this study. From literature review it was found that there is lot of scope to carry out further research on the current PLOS methodology shown in HCM. Video data collection method was found to be an efficient and accurate technique for collection of pedestrian data. Cluster analysis was found to be suitable for grouping data in order to define PLOS categories. Chapter-4 discusses about the study area and data collection technique applied for this study.

Chapter 4

Cluster Analysis

4.1 Introduction

This chapter presents the details of algorithms used in defining off-street Pedestrian level of service criteria of urban areas. Six cluster analysis methods are used for this purpose. From Highway capacity manual it is clear that it is quite convenient to derive off-street pedestrian LOS by using video data.

4.2 Methods of Cluster Analysis

4.2.1 *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.

The steps mentioned above are expressed mathematically as flows after 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:

$$D_{ik}^2 = (x_k - v_i)^T (x_k - v_i), \quad 1 \le i \le c, \quad 1 \le k \le N. \tag{4.1}$$

Where, $D^2{}_{ik}$ is the distance matrix between data points and the cluster centers, x_k is the kth data point in cluster i, and v_i is the mean for the data points over cluster i, called the cluster centers.

Step 2 Selecting points for a cluster which are having the minimal distances from the centroid.

Step 3 Calculating cluster centers

$$v_i^{(l)} = \frac{\sum_{j=1}^{N_i} x_i}{N_i} \tag{4.2}$$

$$\max \left| v^{(l)} - v^{(l-1)} \right| \neq 0 \tag{4.3}$$

Where N_i is the number of objects in the cluster i, j is the jth cluster; l is the number of iterations. It is to be noted that for the above equation (4.2) $1 \le i \ne j \le c$.

The flowchart in Figure 4.1 shows the way the algorithm functions for finding speed clusters.

Following two points need to be noted while using the k-means algorithm:

1. The numbers of groups or partitions need to be known beforehand.

2. The initial values of the centroids have to be picked judiciously, or else a program should be used that picks random data points as the initial centroids.

The detail process of *K* Means clustering is given below in Figure 4.1.

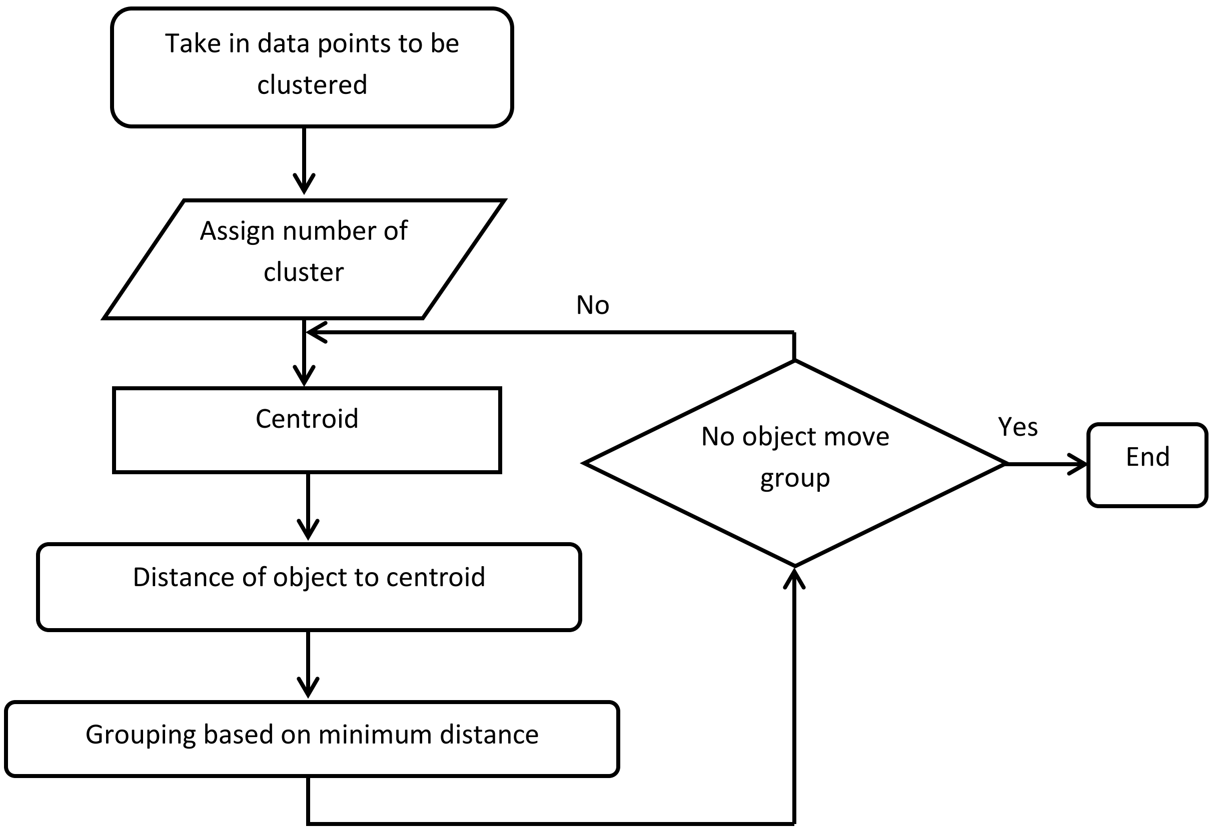


Figure 4.1 Flowcharts of *K*-Means Clustering

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.

4.2.2 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. 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:

$$J(X;M,V)=\sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^{m}\left\|X_{k}-V_{i}\right\|_{A}^{2} \tag{4.4}$$

Where

$$V=[V_1,V_2,V_3,..............,V_c],V_i\in R^n \tag{4.5}$$

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

$$D_{ikA}^{2} = \|X_k - V_i\|_A^2 = (X_k - V_i)^T A (X_k - V_i) \tag{4.6}$$

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 ith cluster;

Statistically, (4.4) can be seen as a measure of the total variance of X_k from V_i .The minimization of the *c*-means functional (4.4) 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 (4.4), known as the fuzzy *c*-means algorithm.

The stationary points of the objective function (4.4) can be found by adjoining the constraint to J by means of Lagrange multipliers:

$$\bar{J}(X;M,V,\lambda) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m D^2{}_{ikA} + \sum_{k=1}^{N}\lambda_k\left(\sum_{i=1}^{c}\mu_{ik} - 1\right) \tag{4.7}$$

and by setting the gradients of ($\bar{J}$) with respect to *M, V* and λ to zero. If $D_{ikA}^2 > 0, \forall_{i,} k$ and m>1, then *(M, V)* may minimize (4.8) only if

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(D_{ikA} / D_{jkA} \right)^{2/m-1}}, \quad 1 \le i \le c, \quad 1 \le k \le N \tag{4.8}$$

and

$$V_i = \frac{\sum_{k=1}^{N} \mu_{ik}^m X_k}{\sum_{k=1}^{N} \mu^m{}_{i,k}}, \; 1 \le i \le c, \tag{4.9}$$

It is to be noted that equation (4.9) 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 (4.8) and (4.9). 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

$$F = \frac{1}{N} \sum_{k=1}^{N} \left(X_k - \overline{X} \right) \left(X_k - \overline{X} \right)^T \tag{4.10}$$

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)

$$v_i^{(l)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m x_k}{\sum_{k=1}^{N} (\mu_{i,k}^{(l-1)})^m}, \quad 1 \le i \le c \tag{4.11}$$

Steps 2: computing the distances

$$D_{ikA}^2 = (x_k - v_i)^T A(x_k - v_i),\ 1 \le i \le c,\ 1 \le k \le N \tag{4.12}$$

Step 3: updating the partition matrix

$$\mu_{i,k}^{(l)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ikA}}{D_{jkA}} \right)^{2/(m-1)}} \tag{4.13}$$

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

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.

4.2.3 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-dimensional 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

$$d(i,j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \ldots\ldots\ldots + (x_{ip} - x_{jp})^2} \tag{4.14}$$

However, we can specify one of several other options like

City block distance or Manhattan distance, defined by

$$d(i,j) = \left|x_{i1} - x_{j1}\right| + \left|x_{i2} - x_{j2}\right| + \ldots\ldots\ldots\ldots + \left|x_{ip} - x_{jp}\right| \tag{4.15}$$

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

$$d(i,j) = \left(\left|x_{i1} - x_{j1}\right|^q + \left|x_{i2} - x_{j2}\right|^q + \ldots\ldots\ldots\ldots + \left|x_{ip} - x_{jp}\right|^q\right)^{\frac{1}{q}} \tag{4.16}$$

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.

Plotting the cluster tree

HAC computes hierarchical trees of clusters called dendograms. A typical dendogram is shown in the Figure 4.2. A clustering of the data objects can be obtained by cutting the dendogram at the d

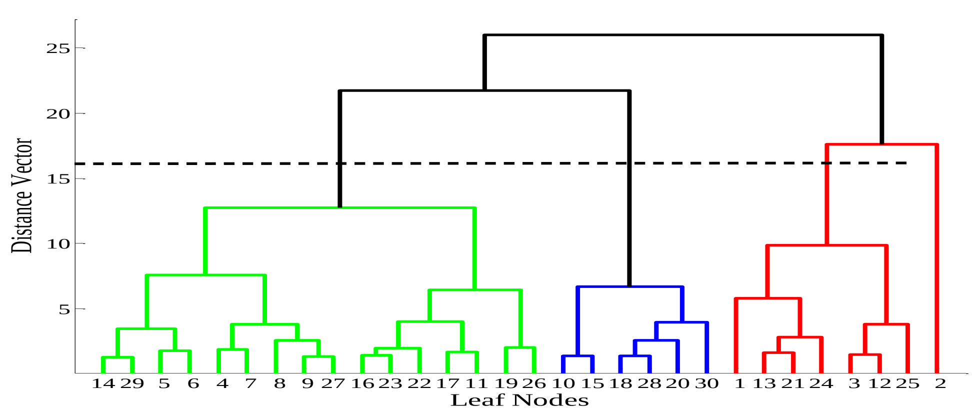


Figure 4.2 Typical Dengogram

Advantage and disadvantage of hierarchical agglomerative clustering

A hierarchical method suffers from the defect that it can never repair what was done in previous steps. Indeed, once an agglomerative algorithm has joined two objects, they cannot be separated any more. This rigidity of hierarchical method is both the key to its success (because it leads to small computation times) and its main disadvantage (the inability to correct erroneous decisions).

4.2.4 SOM Algorithm

Among various types of ANN algorithms, in this study Self-Organizing Map is used for clustering of speed data because of its inherent capability to learn the pattern of input. SOM is trained iteratively being inspired by neural networks in the brain. Self-Organization Map (SOM) uses a competition and cooperation mechanism to achieve unsupervised learning. In SOM, a set of nodes is arranged in a geometric pattern which is typically a 2-dimensional lattice. This arrangement of neuron may be grid, hexagonal or random topology. In this research Hexagonal topology is used. Each node is associated with a weight vector with the same dimension as the input space. The purpose of the SOM is to find a good mapping. During training, each node is presented to the map so also the input data associated with it. An input weight vector of same dimension as that of input data dimension was given to the ANN. The clustering using SOM algorithm was done in two steps.

Step: 1

The input data is 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 $i, \| x(t) - m_c(t) \| \leq \| x(t) - m_i(t)$ (4.17)

Step: 2

Weight vectors of BMU are updated as

$$m_i(t+1) = m_i(t) + \alpha h_{b(x)i}(x(t) - m_i(t)) \tag{4.18}$$

Here $h_{b(x)}$ is the neighborhood function, which is

$$h_{b(x)} = \alpha(t) e^{\left(-\frac{\left\| r_i - r_{b(x)} \right\|^2}{2\sigma^2(t)}\right)} \tag{4.19}$$

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 neuron in the input lattice. $\alpha(t)$ defines the width of the neighborhood function. The above two steps were repeated iteratively till the pattern in input was processed.

4.2.5 Affinity Propagation (AP)

Affinity propagation is a low error, high speed, flexible, and remarkably simple clustering algorithm that may be used in forming teams of participants for business simulations and experiential exercises, and in organizing participants' preferences for the parameters of simulations. The four-equation algorithm is easy to encode into a computer program. Affinity propagation is a graph theoretic clustering method recently developed by Frey and Dueck (2007), who have tested it against *k*-centers clustering, an iterative partitioning method similar to the popular *k*-means procedure that is available on SPSS 15, differing in that *k*-means clusters items around a computed central values whereas *k*-centers clusters them around exemplars, each one being the most central item of its cluster. When applied to a large database of human faces and a large database of mouse DNA segments, Frey and Dueck found that affinity propagation gave rise to smaller errors and arrived at its solution at least two orders of magnitude faster, an important consideration because clustering data is inherently a computationally intensive problem. Moreover, unlike *k*-centers and *k*-means, affinity propagation is more flexible in two ways. First, it does not require the user to specify the number of clusters in advance. Rather, 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.

Mézard (2007) points out that affinity propagation is known in computer science as a message-passing algorithm, and suggests that the algorithm can be understood by taking an anthropomorphic viewpoint. Thus, imagine that each item being clustered sends messages to all other items informing its targets of each target's relative attractiveness to the sender. Each target then responds to all senders with a reply informing each sender of its availability to associate with the sender, given the attractiveness messages that it has received from all other senders. Senders absorb the information, and reply to the targets with messages informing each target of the target's revised relative attractiveness to the sender, given the availability messages it has received from all targets. The message-passing procedure proceeds until a consensus is reached on the best associate for each item, considering relative attractiveness and availability. The best associate for each item is that item's exemplar, and all items sharing the same exemplar are in the same cluster. Essentially, the algorithm simulates conversation in a gathering of people, where each in conversation with all others seeks to identify his or her best representative for some function. Figure 4.3 shows the steps those are performed during AP clustering.

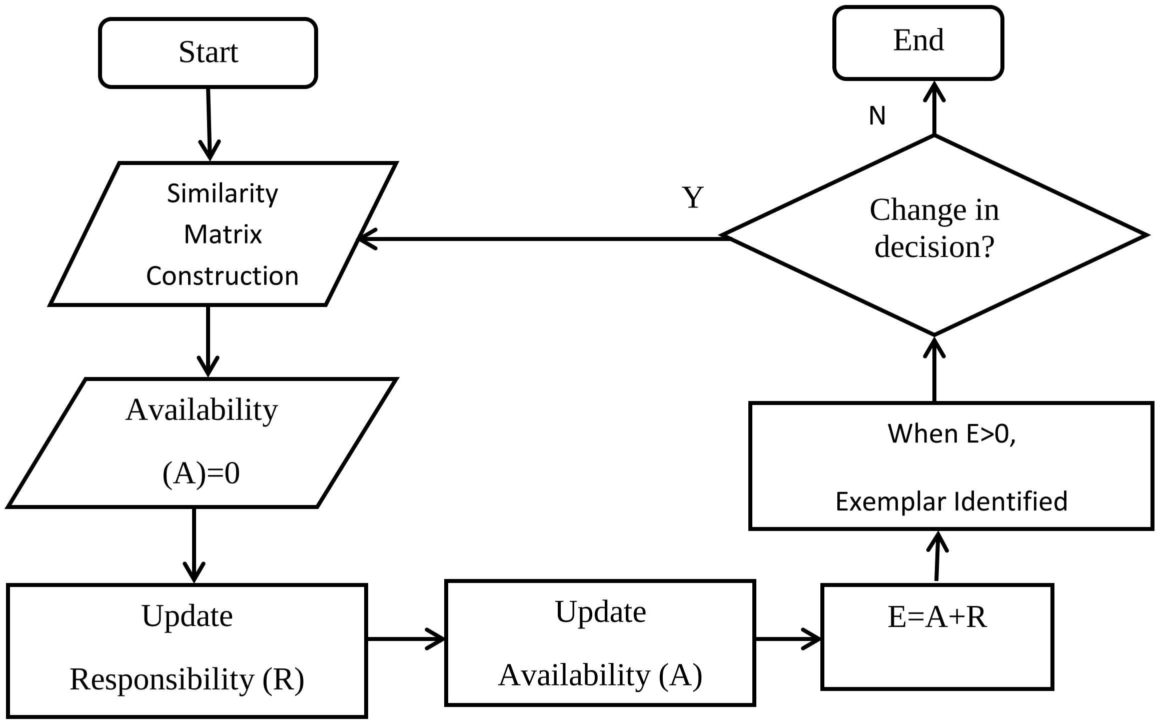


Figure 4.3 Flowchart of AP Clustering

Procedurally, the algorithm operates on three matrices: a similarity (s) matrix, a responsibility (r) matrix, and availability (a) matrix. Results are contained in a criterion (c) matrix. These matrices are iteratively updated by four equations, where *i* and *k* refer, respectively, to the rows and columns of the associated matrix.

The algorithm is processed in the following seven steps to find out the exemplar which is the cluster centre.

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):*

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

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.

4.2.6 GA-Fuzzy Algorithms (GA)

Genetic Algorithms are search algorithms that are based on concepts of natural selection and natural genetics. Genetic algorithm was developed to simulate some of the processes observed in natural evolution, a process that operates on chromosomes (organic devices for encoding the structure of living being). The genetic algorithm differs from other search methods in that it searches among a population of points, and works with a coding of parameter set, rather than the parameter values themselves. It also uses objective function information without any gradient information. The transition scheme of the genetic algorithm is probabilistic, whereas traditional methods use gradient information because of these features of genetic algorithm; they are used as general purpose optimization algorithm. They also provide means to search irregular space and hence are applied to a variety of function optimization, parameter estimation and machine learning applications.

The evolutionary process of a GA is a highly simplified and stylized simulation of the biological version. It starts from a population of individuals randomly generated according to some probability distribution, usually uniform and updates this population in steps called generations. Each generation, multiple individuals are randomly selected from the current population based upon some application of fitness, bred using crossover and modified through mutation to form a new population.

• **Crossover** – exchange of genetic material (substrings) denoting rules, structural components, features of a machine learning, search, or optimization problem

• **Selection** – the application of the fitness criterion to choose which individuals from a population will go on to reproduce

• **Replication** – the propagation of individuals from one generation to the next

• **Mutation** – the modification of chromosomes for single individuals

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.

4.3 Selection of the best Cluster Method

From the above six clustering methods, the best method which will be relevant for Indian context has to be determined. It can be evaluated by the help of Silhouette Width Index.

➢ **Silhouette Width Index**

This index was proposed by Rousseeuw (1987) to evaluate clustering results. Silhouette width (Sw) is a composite index which reflects the compactness and separation of the clusters. For each data point i the Silhouette width is calculated as follows:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{4.22}$$

Where $a(i)$ is the average distance of a data point i to other data point in the same cluster, $b(i)$ is the average distance of the that particular data point to all the data points belonging to the nearest cluster. The average $s(i)$ of all data points reflects the quality of clustering result. Larger silhouette value signifies good cluster.

4.4 Summary

In this chapter the methodology of six clustering techniques used for the present study are discussed. Details of the six clustering algorithms i.e. *K*-Means, FCM, HAC, SOM, AP and GA-Fuzzy used in this study is elaborated step by step. These clustering methods are used to find the ranges of four parameters used in defining PLOS categories of off-street pedestrian facilities in

Indian context. And out of these six clustering methods the most appropriate one for Indian context is selected by using cluster validation index (Silhouette).

Chapter 5

Study Area and Data Collection

5.1 Introduction

In this chapter details of study area, map preparation and data collection are described. The study area for this research work is taken as Bhubaneswar and Rourkela City of Odisha state, India. The required data of the study area are obtained using video data cameras. Type and timing of data collection, data smoothing and data compilation are also discussed in detail. Observations of the characteristics and walking speeds of pedestrians were collected on sidewalks. A survey was used to build a pedestrian database, to aid in understanding the relationship between pedestrian characteristics. Using a digital video camera, the data recorded sidewalks at various locations in 15-minute segments. The video clips were then used to observe pedestrian walking behavior, including pedestrian interactions with street furniture or with other pedestrians. Pedestrians were counted and their walking speeds and relevant characteristics were recorded at different sidewalk locations. These data were used to build a pedestrian database, which is the core data source for this study. The survey data helped in finding out how pedestrian characteristics are affecting, and are affected by, the sidewalk environment.

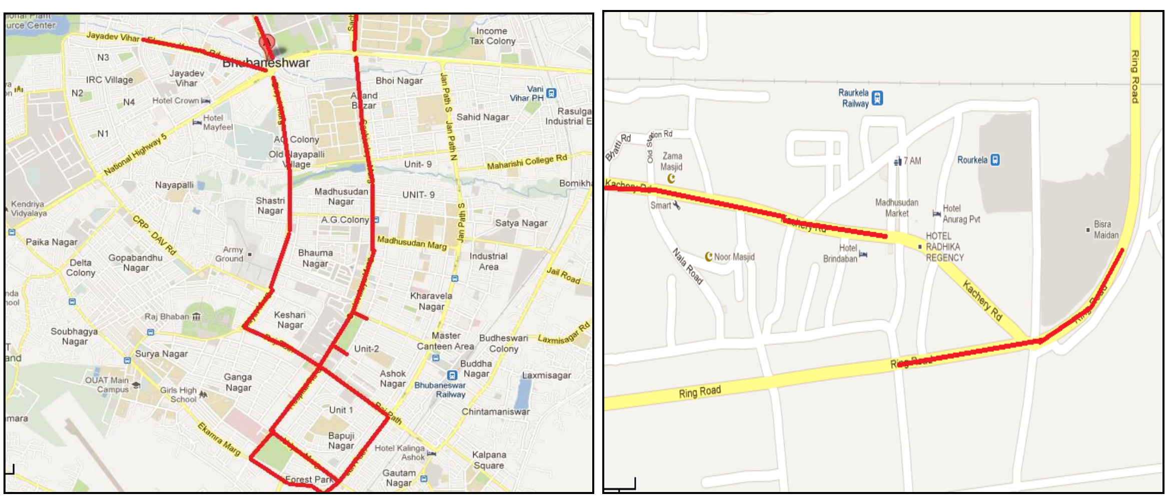
5.2 Study Corridors and Data Collection

5.2.1 Map preparation

A detailed roadway map is prepared from Google map which helps in the inventory study records of off-street pedestrian facility before capturing video of the road segments.

5.2.2 Study Corridors

A century of industrialization and technical advancement has brought forth rapid urbanization in India. The statistics of the census of 2001 reveals that about 285 million or 27.8% of the total population of 1.02 billion of India lives in urban areas. Odisha is one of the least urbanized states in India. As per urbanization trend of 2001 census, Odisha state is 24th most urbanized and 5th least urbanized state in India with about 14.97 percent of urban population. The urbanization trend in the state is much lower in comparison to the national average of 27.82 percent as per the 2001 census. However the urban decadal growth during the last decade (1991-2001) has been enormous with a growth rate of about 30.28 percent, almost matching that of country, which had an urban decadal growth rate of 32.60 percent. It is noteworthy that the state's population during the last decade has grown by about 14 percent while that of the urban population has grown at almost at double this rate. Study corridors for the study area are presented in Figure 5.1.



Bhubaneswar Study Corridors

Rourkela Study Corridors

Figure 5.1: Map showing the road corridors of the study areas

Two important cities Bhubaneswar and Rourkela of Odisha state, India are taken up in the present study. Bhubaneswar, the temple city enjoys excellent connectivity with other adjoining regions of strategic importance - however, the passenger transit option needs improvement of greater interaction. Bhubaneswar is primarily an administrative city and a tourism city. Bhubaneswar has emerged as a fast-growing, important trading and commercial hub in the state and eastern India. Tourism is a major industry, attracting about 1.5 million tourists in 2011. Bhubaneswar was designed to be a largely residential city with outlying industrial areas. The economy had few major players until the 1990s and was dominated by retail and small-scale manufacturing. There exists a significant level of disparity within this region in terms of accessibility to major urban centres. At intra urban level, capacity of the existing traffic and transportation network will create a serious constraint to its future growth. The traffic demand management will play a key role as the role of supply management is near exhaustion. On the other hand Bhubaneswar enjoys a variable level of mobility at different parts of the city. Rourkela, the site for this study is commonly known as the steel city in all over world is one of the largest city located at northern west of the Odisha state. It is situated at the heart of mineral belt .The correct selection of sample sites is an important issue in designing the field survey. In reality, selection of a proper site is not an easy task because different routes need to appear in different LOS conditions to examine the influence of LOS on pedestrian route choice. Sampled area sees heavy foot traffic, because of sidewalks on the streets and transit points. Riders of public transportation (subway, bus, train) usually walk from transit points to their destinations. Another feature of the selected area is the great variety of land uses: residential, commercial, office and institutional (e.g., school, hospital). Often, commuters need to walk at least a short distance to reach their final destinations. Figure 5.2 shows some photos of off-pedestrian facilities during data collection.

Figure5.2: Photos showing off-street Pedestrian flow in the study area

Bhubaneswar and Rourkela has straight, wide streets, unlike the narrow, winding, ancient streets found in most Indian cities. Almost all the streets have sidewalks that are separated from the carriageway by small trees and curbs. Since bicycle lanes have not been established in cities cyclists also use these sidewalks. Streets are arranged in a grid, meeting at signalized/unsignalized intersections that are installed with pedestrian crosswalks. In the surveyed area, almost all the streets have sidewalks on both sides and crosswalks at intersections.

5.2.3 Data collection

From extensive literature survey it was found that the measure aspects for the survey are effective walkway width, pedestrian speed and hourly volume of pedestrian. Effective walkway width is the portion of a walkway that can be used effectively by pedestrians. Various types of obstructions and linear features, discussed below, reduce the walkway area that could be effectively used by pedestrians. It is calculated manually by following HCM 2010 procedure. Linear features such as the street curb, the low wall, and the building face each have associated shy distances. The shy distance is the buffer that pedestrians give themselves to avoid accidentally stepping off the curb, brushing against a building face, or getting too close to other pedestrians standing under awnings or window shopping. Fixed objects, such as the tree, have effective widths associated with them. The fixed object effective width includes the object's physical width, any functionally unusable space, and the buffer given the object by pedestrians. Effective walkway width is shown in Figure 5.3.

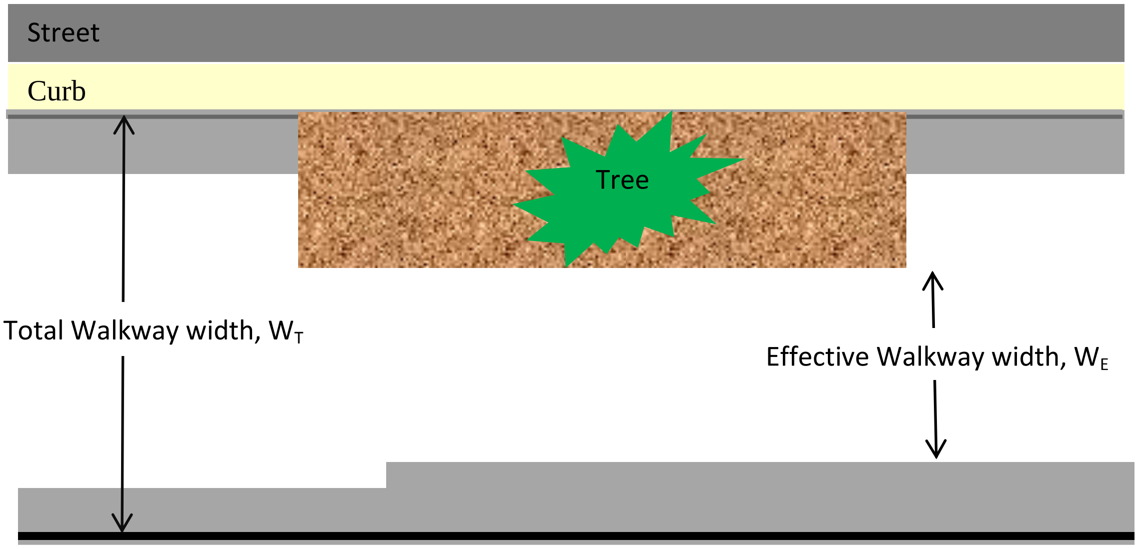


Figure 5.3: Typical diagram of Walkway Width

Typically, a walkway operational analysis evaluates the portion of the walkway with the narrowest effective width, since this section forms the constraint on pedestrian flow. A design analysis identifies the minimum effective width that must be maintained along the length of the walkway to avoid pedestrian queuing or spillover.

Speed and attributes on road features data were collected on a sample of 3,764 pedestrians observed at various sidewalk locations in both of the cities about 62 days in both peak and off-peak hours of working and non-working days. In the same locations, over the same time period, all pedestrians were counted in order to determine sidewalk flow rates, and basic information about each of the 31 station points was recorded. Then video clips were loaded in office computer to analyze the recorded videos. The pedestrian peak flow rates were calculated from video data at office. The speed of each pedestrian recorded is calculated and average speed of pedestrians for each segment is also considered. Based on these sets of data, two databases were built: a database containing speed and an aggregate database of each of the study locations.

This aggregated locational database includes the calculated flow rate based on the count at the location, the effective width of the sidewalk, and land use proportions based on two cities. Various types of obstructions such as trees, electric poles, information sign boards, projections of road side shops and linear features, reduce the walkway area that could have effectively used by pedestrians.

5.3 Summary

This chapter provided the details of the study area, map preparation and data collection procedure. The detail of two study corridors on which video data was collected is discussed briefly. The next chapter describes details about result and findings of the research work.

Chapter 6

Result and Analysis for Defining PLOS

6.1 Introduction

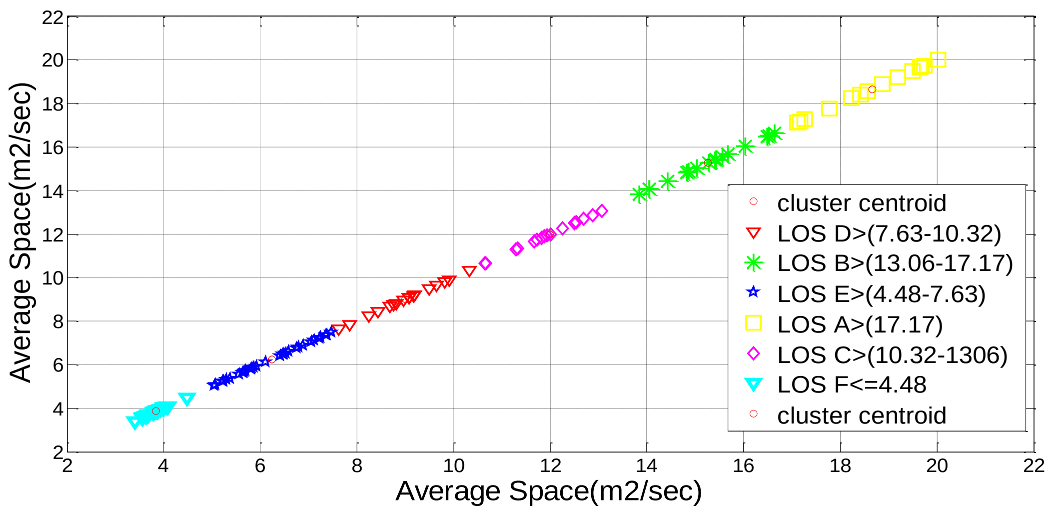
Result of cluster analysis is discussed in this chapter. In clustering the *K*-Means, FCM, HAC, SOM, AP and GA Fuzzy algorithms were used. The basic idea about the algorithm used is described. Using the above six cluster algorithms the average pedestrian space, speed, flow rate and volume to capacity ratio data collected from off-street pedestrian facilities are classified into six levels of service categories (A-F).

6.2 Application of Cluster Analysis Methods in Defining PLOS Criteria of Urban Off-street Facilities

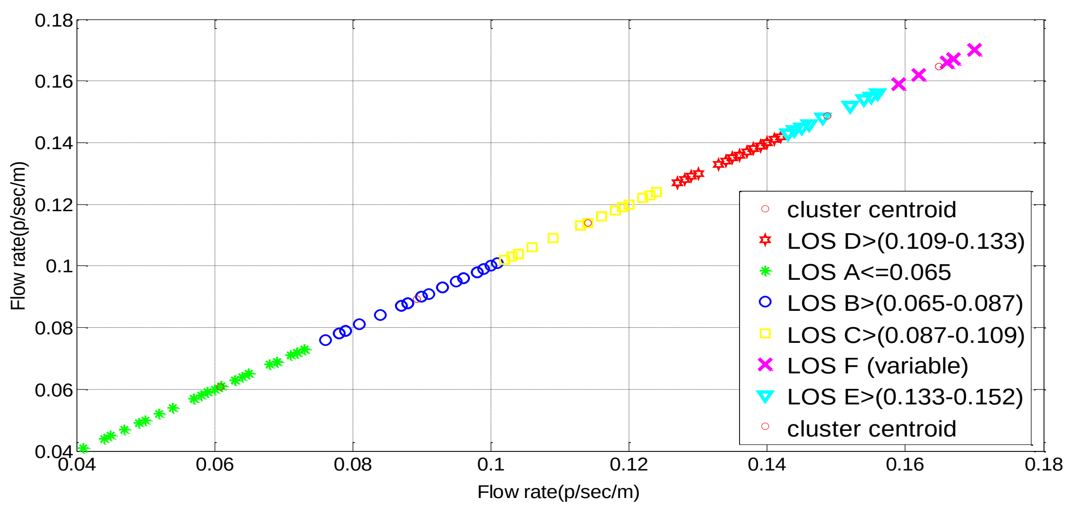
All the parameters like average pedestrian space, flow rate, speed and volume to capacity ratio are calculated for each segment. Six advanced cluster analysis techniques (*K*-Means, FCM, HAC, SOM, AP and GA Fuzzy) are applied on these parameters. By the application of clustering methods all these four parameters gives different ranges of PLOS categories. Six PLOS categories that is “A” to “F” are defined on the basis of this classification in Indian context.

6.2.1 *K*- means clustering

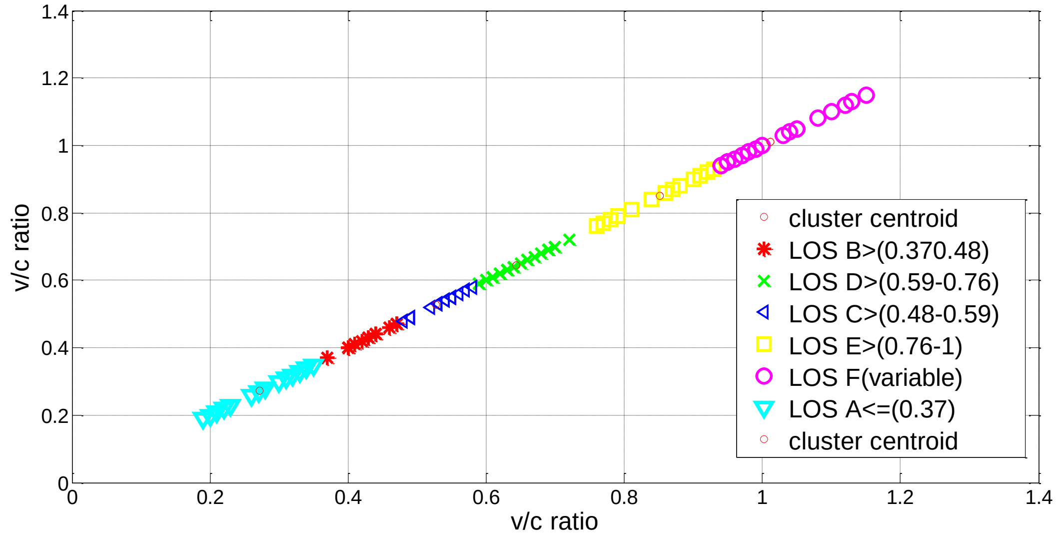
Average pedestrian space values for all the road segments were calculated from data collected from the video survey. Average pedestrian speeds were calculated by taking the average of all second-wise collected speed data on each segment. Flow rates and volume to capacity ratio for each segment were also calculated. *K*-means cluster analysis was applied on all these four parameters to classify the data into six number of cluster in defining level of service of urban off-street pedestrian facilities. The different ranges of LOS categories by using *K*-Means clustering method are shown in Figure 6.1 (A-D) and Table 6.1.



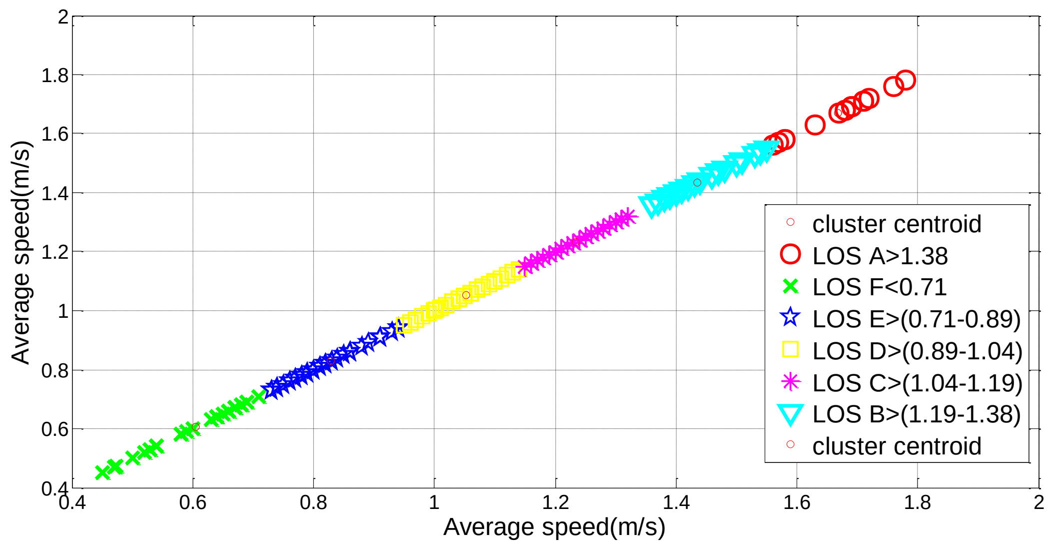
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) *v/c* ratio of PLOS categories

Figure 6.1: PLOS Categories of Urban off-Street Pedestrian Facilities using *K*-Means Clustering on Various Parameters

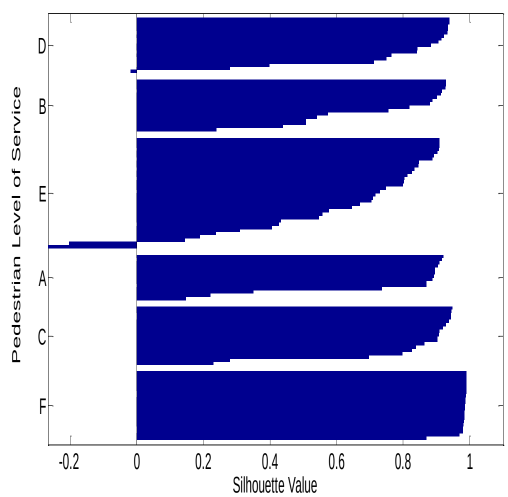
In this figure, average space, flow rate, speed, volume to capacity ratio ranges for PLOS categories "A" to "F" for urban off-street pedestrian facilities are shown by different colours and symbols. The different ranges of PLOS categories are also shown in the legends of this figure.

Table 6.1: PLOS Categories for Urban Off-Street Pedestrian Facilities using *K*-Means Clustering

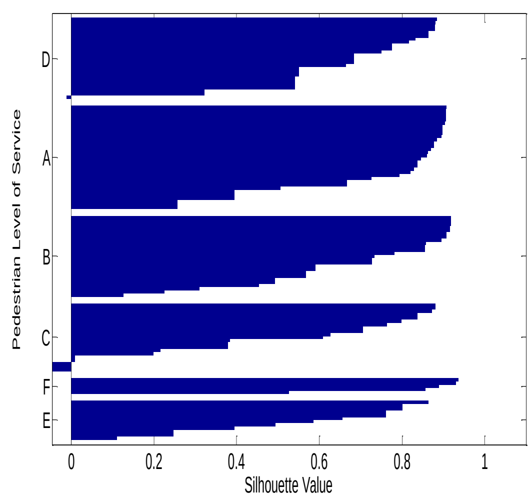
LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>17.17	≤0.065	>1.38	≤0.37	Ability to move in desired path, no need to alter movements
B	>13.06-17.17	>0.065-0.087	>1.19-1.38	>0.37-0.48	Occasional need to adjust path to avoid conflicts
C	>10.32-13.06	>0.087-0.109	>1.04-1.19	>0.48-0.59	Frequent need to adjust path to avoid conflicts
D	>7.63-10.32	>0.109-0.133	>0.89-1.04	>0.59-0.76	Speed and ability to pass slower pedestrians restricted
E	>4.48-7.63	>0.133-0.152	>0.71-0.89	>0.76-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤4.48	>0.152	≤0.71	>1.00	Speed severely restricted, frequent contact with other users

From *k*-means cluster analysis it is found that the pedestrian average space of PLOS "A" is greater than 17.17m^2/pedestrian, where pedestrians have the ability to move in desired path and there is no need to alter the movement. This is also known as the free flow condition because here users can move freely without facing any problem. In this level of service flow rate is less than 0.065p/sec/m and volume to capacity ratio is less than 0.37. Here pedestrians can move with a speed of greater than 1.38m/sec. In case of level of service B pedestrians can move easily but occasionally need to change their path. When volume to capacity ratio became greater than 1, then speeds of pedestrian severely restricted. This condition occurs in level of service "F", which is the worst state for pedestrian movement. Using *k*-means clustering it is found that the average pedestrian space for LOS “F” is less than 4.48m^2/p.

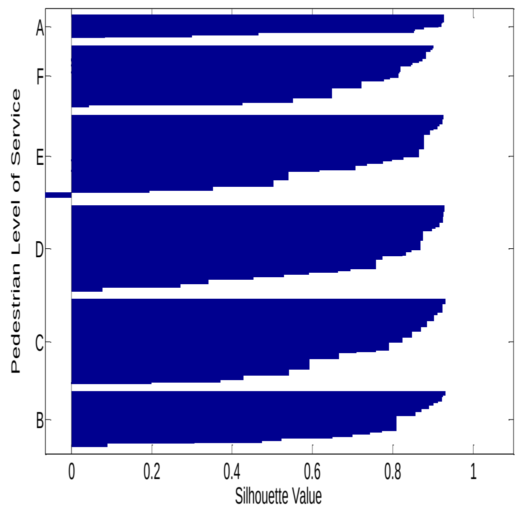
Silhouettes plot of urban off-street pedestrian facilities for six level of service categories based on k-means clustering is shown in Figure 6.2 In this figure, silhouette of urban PLOS is the plot of the silhouette values ranked in decreasing order. In order to obtain an overview, the silhouettes of all six PLOS are printed below each other. This way the entire clustering was displayed by means of a single plot, which enabled us to distinguish clear-cut clusters from weak ones. A wide silhouette indicates large silhouette values and hence a pronounced cluster. In this figure, pedestrian space, speed, flow rate and volume to capacity ratio points that lie well within their clusters (urban street classes) and the ones which are merely somewhere in between clusters can be seen. The other dimension of silhouette is its height, which simply equals the number of objects in that cluster.



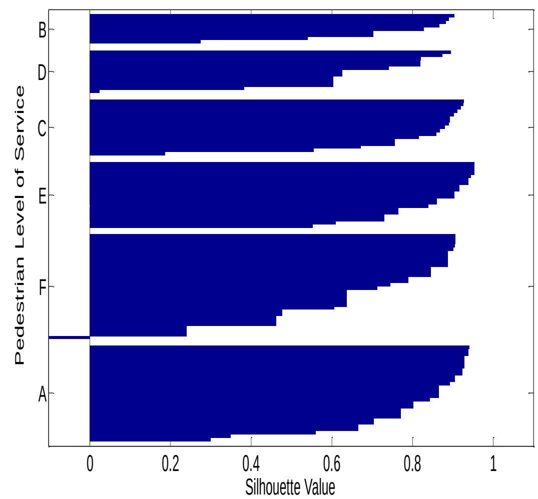
A: Silhouettes Plot for PLOS Categories of Average space



B: Silhouettes Plot for PLOS Categories of Flow rate



C: Silhouettes Plot for PLOS Categories of Speed

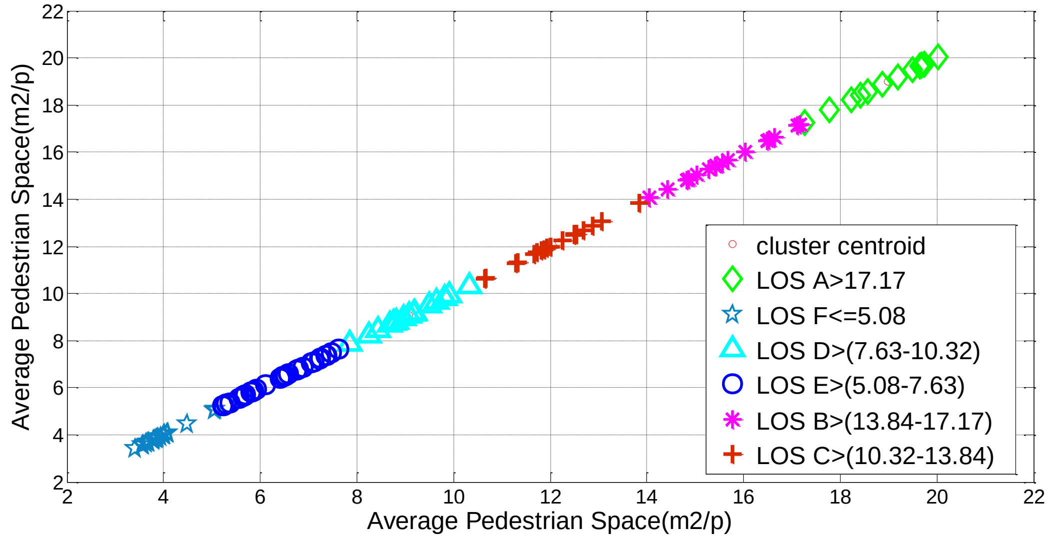


D: Silhouettes Plot for PLOS Categories of Flow rate

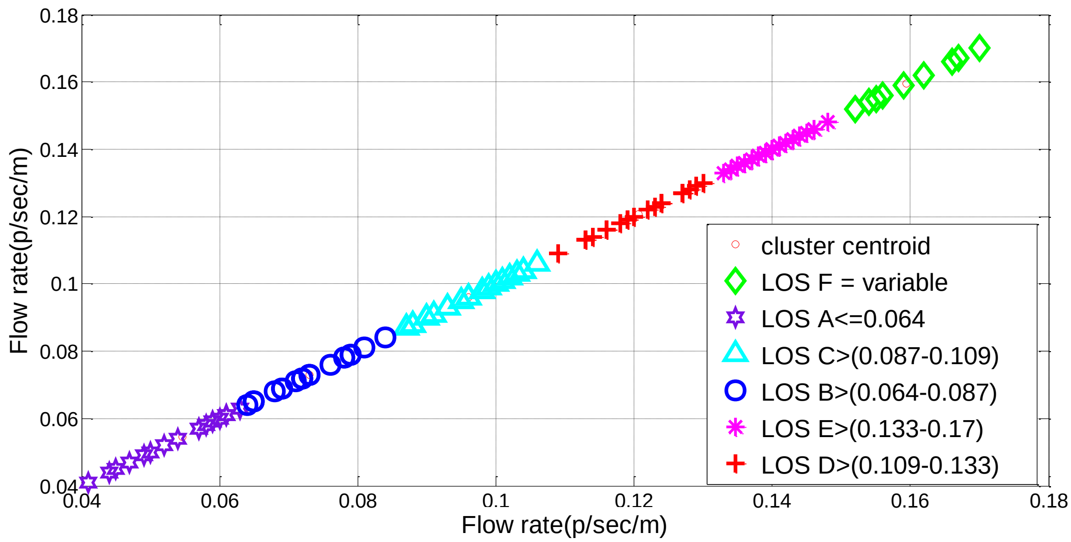
Figure 6.2: Silhouettes Plot of PLOS Categories using *K*-Means Clustering on four parameters

6.2.2 Fuzzy *c*-means clustering

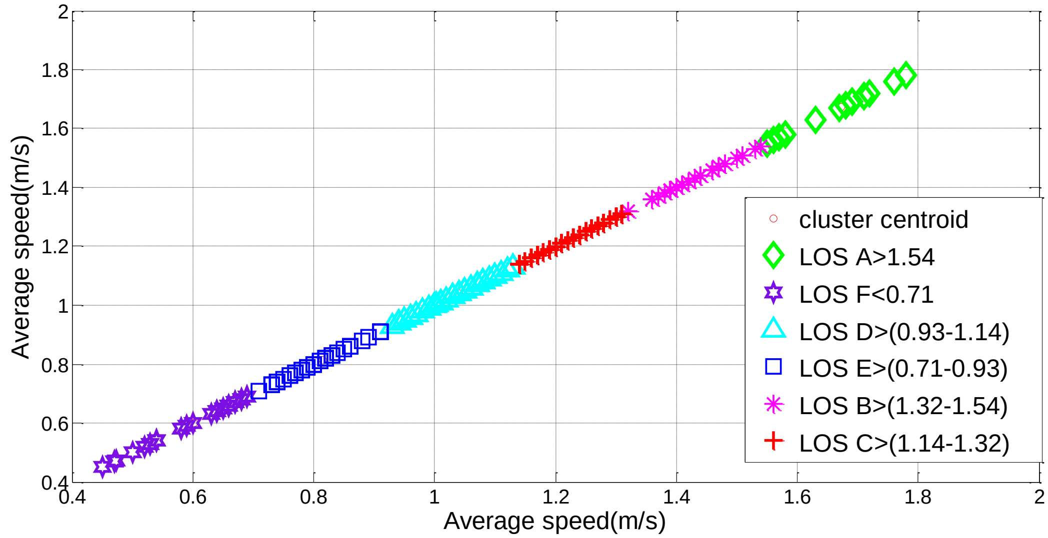
The previous method was on hard partitioning. The most popular method in fuzzy classification called Fuzzy *C*-Means (FCM) clustering was discussed in the Chapter-4. The fuzzy *c*-means algorithm was applied on average pedestrian space, flow rate, speed and volume to capacity ratio and the different ranges are shown in Figure 6.3 and Table 6.2 Fuzzy *c*-means cluster analysis was applied on all the four parameters to classify the data into six number of cluster in defining level of service of urban off-street pedestrian facilities.



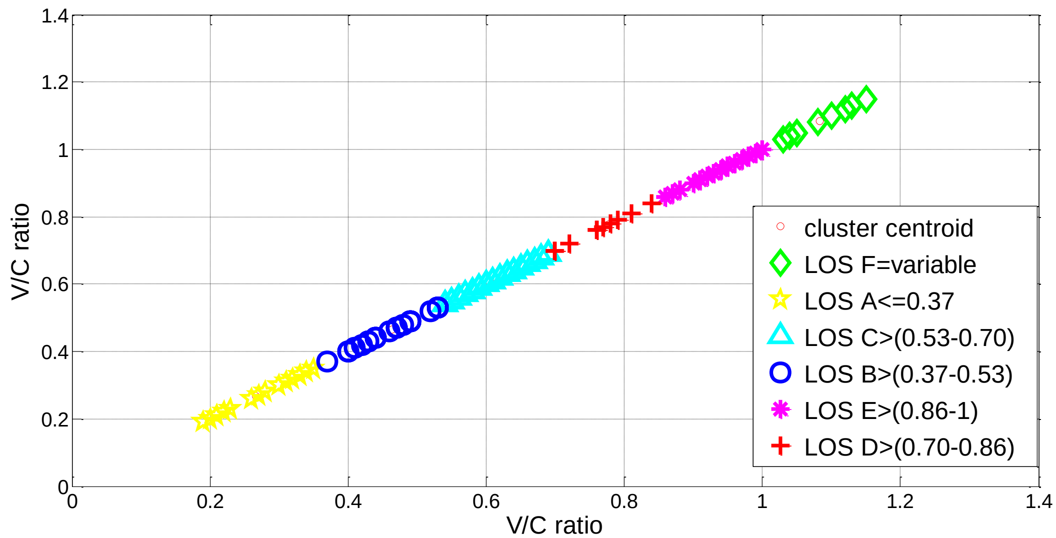
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) *v/c* ratio of PLOS categories

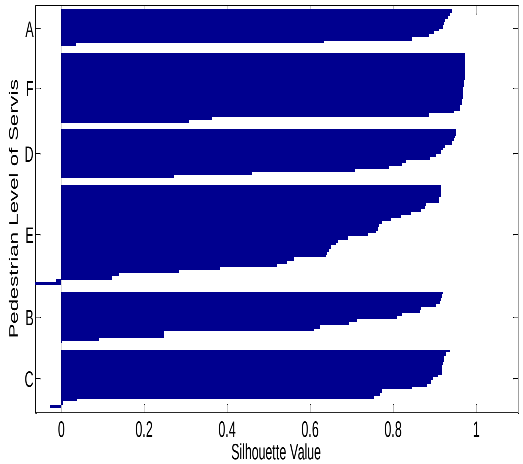
Figure 6.3: PLOS Categories of Urban Off-Street Pedestrian Facilities using FCM Clustering on Various Parameters

Table 6.2: PLOS Categories for Urban Off-Street Pedestrian Facilities using FCM Clustering

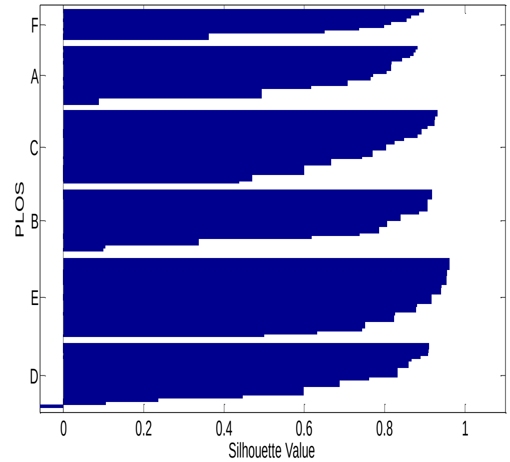
LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>17.17	≤0.064	>1.54	≤0.37	Ability to move in desired path, no need to alter movements
B	>13.84-17.17	>0.064-0.087	>1.32-1.54	>0.37-0.53	Occasional need to adjust path to avoid conflicts
C	>10.32-13.84	>0.087-0.109	>1.14-1.32	>0.53-0.70	Frequent need to adjust path to avoid conflicts
D	>7.63-10.32	>0.109-0.133	>0.93-1.14	>0.70-0.86	Speed and ability to pass slower pedestrians restricted
E	>5.08-7.63	>0.133-0.17	>0.71-0.93	>0.86-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤5.08	>0.17	≤0.71	>1	Speed severely restricted, frequent contact with other users

From FCM cluster analysis it is found that for PLOS "A" average pedestrian space is greater than 17.17m^2/p and for PLOS "F" it is less than 5.08m^2/p. As per the FCM values pedestrians will face frequent contact with other users when flow rate is greater than 0.17p/sec/m and at that time volume to capacity ratio is at extreme level i.e. near about 1. Whereas pedestrians can move at their desired speed at less than 0.064 p/sec/m flow rate and less than 0.37 volume to capacity ratio. This occurs in PLOS "A" condition and here pedestrians move at near about 1.54m/sec speed.

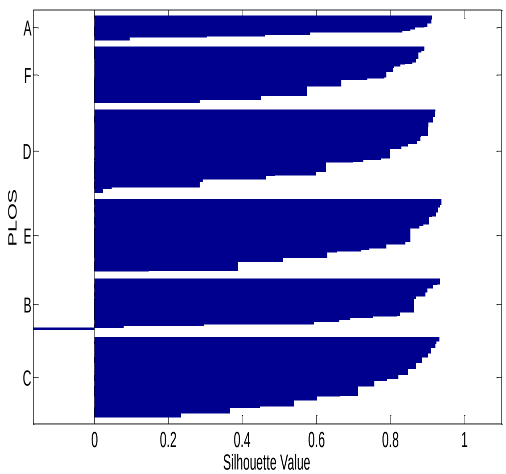
Figure 6.4 shows Silhouettes plot for urban off-street pedestrian facilities by using FCM clustering. Height of the Silhouettes represents the number of data points available in each cluster. The silhouettes of all the four parameters are given bellow figure.



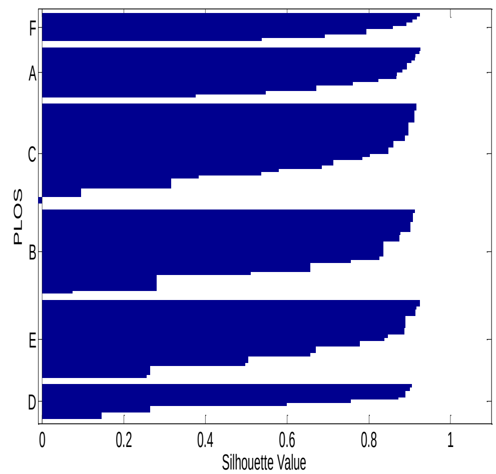
A: Silhouettes Plot for PLOS Categories of Average space



B: Silhouettes Plot for PLOS Categories of Flow rate



C: Silhouettes Plot for PLOS Categories of Speed

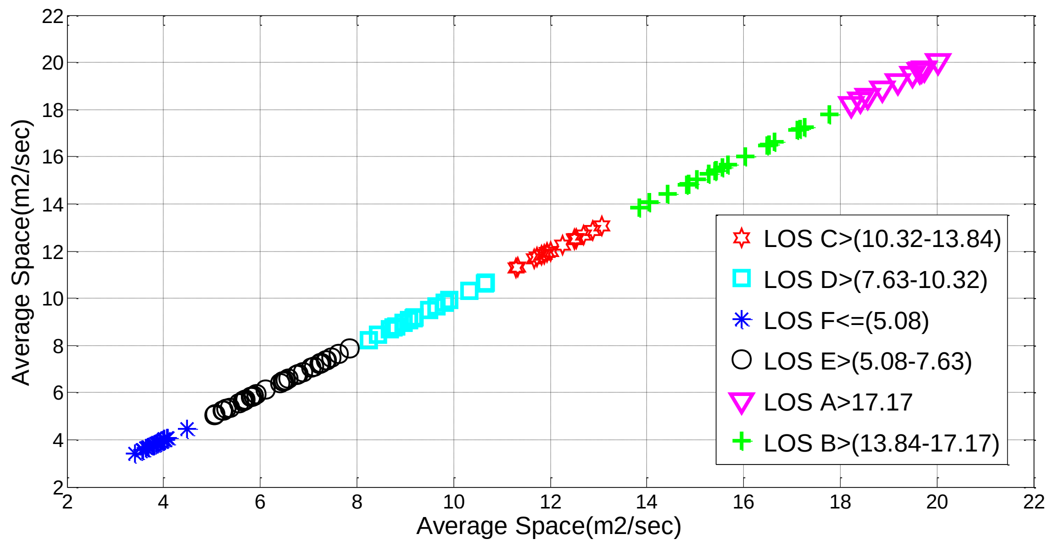


D: Silhouettes Plot for PLOS Categories of Flow rate

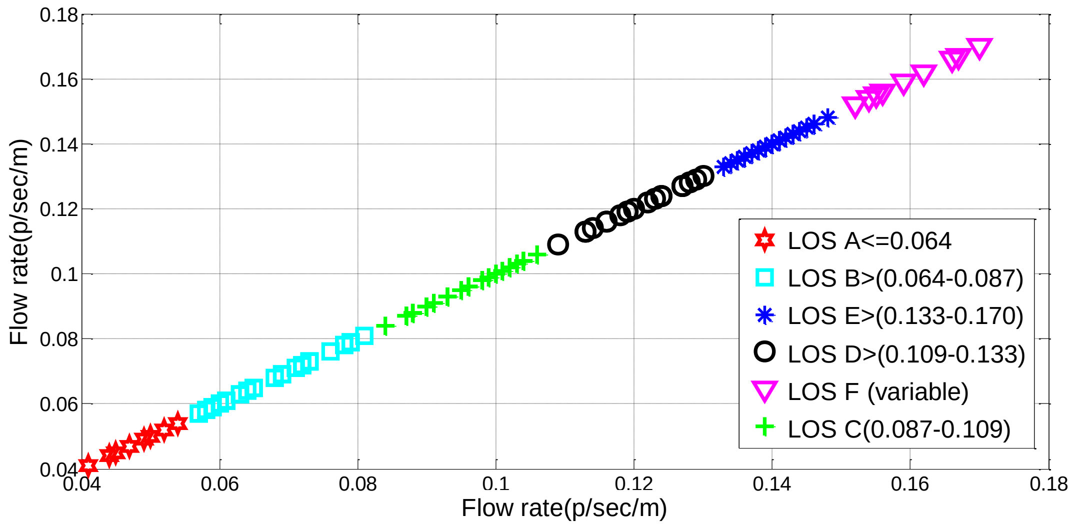
Figure 6.4: Silhouettes Plot for PLOS Categories of Urban off-Street categories using FCM Clustering

6.2.3 Hierarchical agglomerative clustering

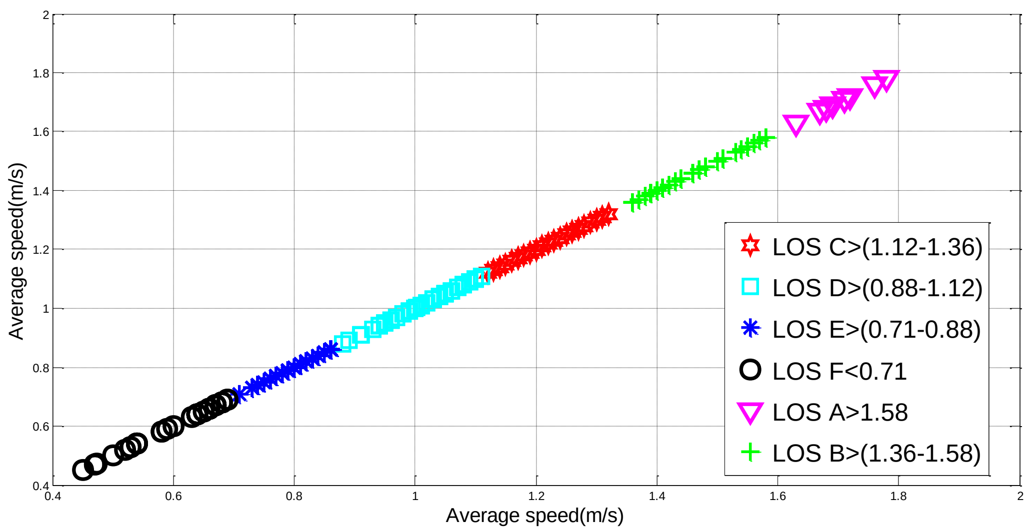
The Hierarchical Agglomerative Clustering (HAC) algorithm was applied on average pedestrian space, speed, flow rate and volume to capacity ratio and corresponding range of PLOS were found for urban off-street pedestrian facilities. The PLOS categories of all four parameters by using HAC clustering technique are shown in Figure 6.5and Table 6.3.



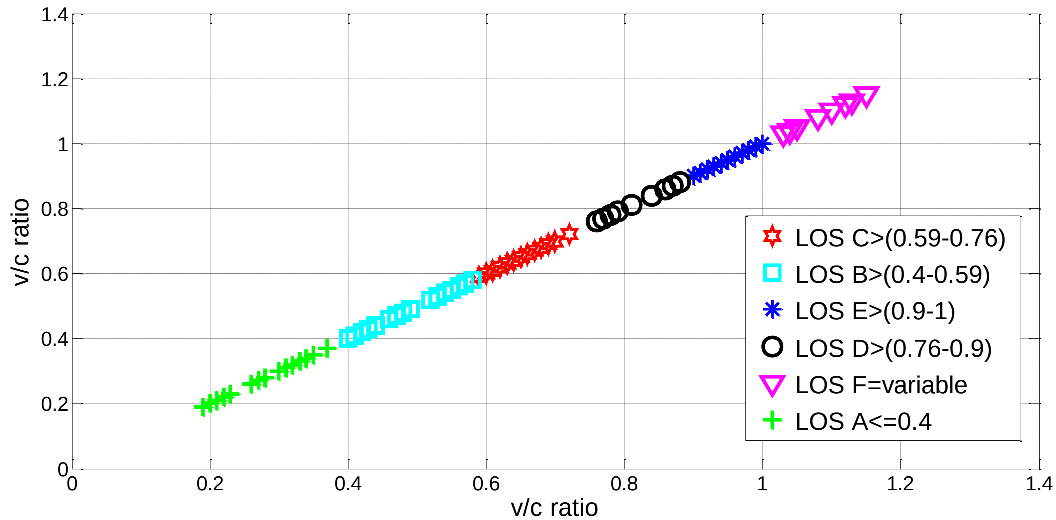
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) *v/c* ratio of PLOS categories

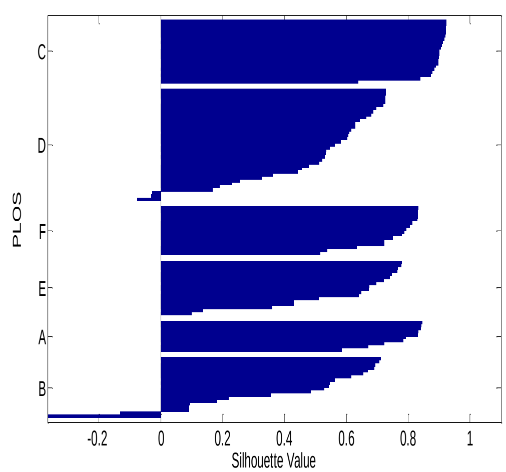
Figure 6.5: PLOS Categories of Urban off-Street Pedestrian Facilities using HAC Clustering on Various Parameters

Table 6.3: PLOS Categories for Urban off-Street Pedestrian Facilities using HAC Clustering

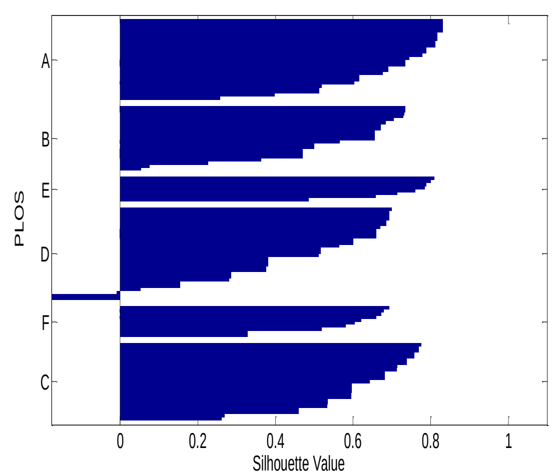
LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>17.17	≤0.064	>1.58	≤0.4	Ability to move in desired path, no need to alter movements
B	>13.84-17.17	>0.064-0.087	>1.36-1.58	>0.4-0.59	Occasional need to adjust path to avoid conflicts
C	>10.32-13.84	>0.087-0.109	>1.12-1.36	>0.59-0.76	Frequent need to adjust path to avoid conflicts
D	>7.63-10.32	>0.109-0.133	>0.88-1.12	>0.76-0.9	Speed and ability to pass slower pedestrians restricted
E	>5.08-7.63	>0.133-0.17	>0.71-0.88	>0.9-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤5.08	>0.17	≤0.71	>1	Speed severely restricted, frequent contact with other users

The PLOS ranges of average pedestrian space and flow rate found from HAC cluster analysis are similar to FCM clustering, but the speed and volume to capacity ratio ranges are different. From HAC cluster analysis it is found that for PLOS "A" average pedestrian space is greater than $17.17m^2/p$ and for PLOS "F" it is less than $5.08m^2/p$. Pedestrians will face frequent contact with other users when flow rate is greater than 0.17p/sec/m and at that time volume to capacity ratio is at extreme level i.e. near about 1. Whereas pedestrians can move at their desired speed at less than 0.064 p/sec/m flow rate and less than 0.4 volume to capacity ratio. This occurs in PLOS "A" condition and here pedestrians move at near about 1.58m/sec speed.

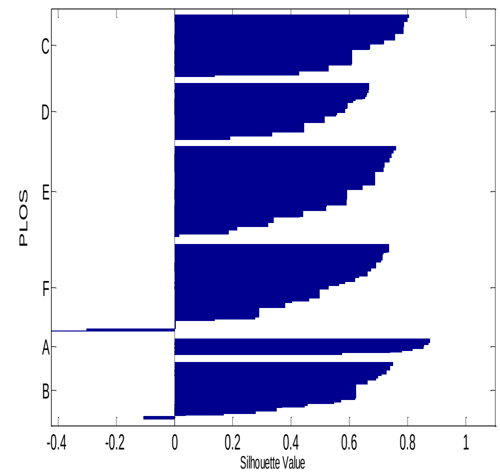
Figure 6.6 shows Silhouettes plot for urban off-street pedestrian facilities by using HAC clustering. Height of the Silhouettes represents the number of data points available in each cluster. The silhouettes of all the four parameters are given bellow figure.



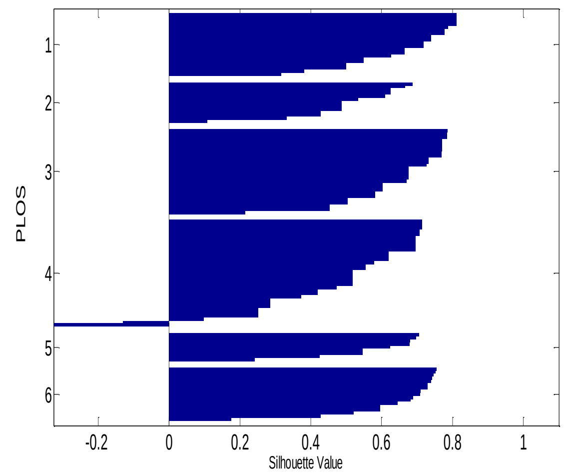
A: Silhouettes Plot for PLOS Categories of Average space



B: Silhouettes Plot for PLOS Categories of Flow rate



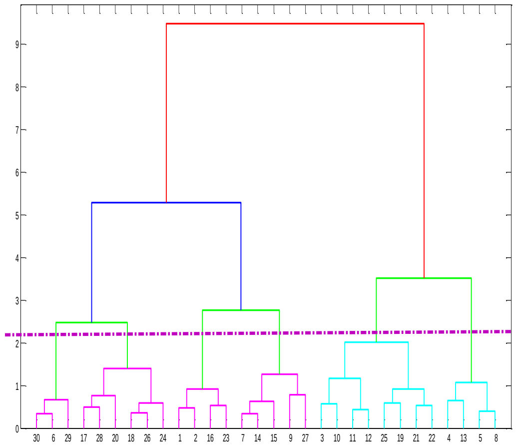
C: Silhouettes Plot for PLOS Categories of Speed



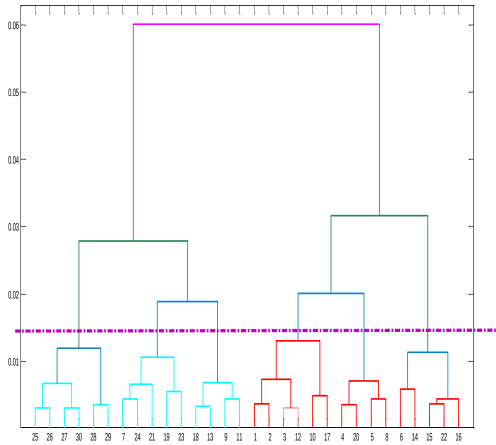
D: Silhouettes Plot for PLOS Categories of Flow rate

Figure 6.6: Silhouettes Plot for PLOS Categories of Urban off-Street categories using HAC Clustering

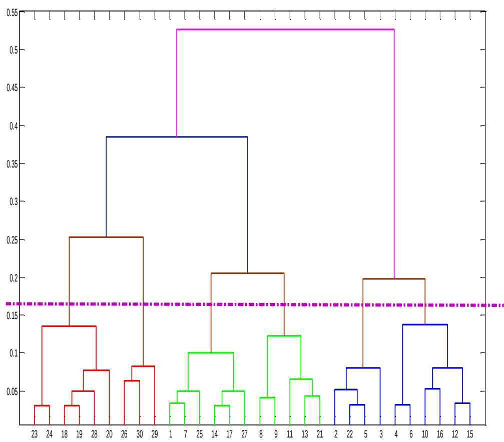
Hierarchical tree of binary clusters was divided into larger clusters using the cluster function. The dendogram formed out of all four parameters data was cut off at a level where it formed five clusters as shown in Figure 6.7 In this figure the free flow speed corresponding to leaf node “2” (on the horizontal axis) is considered as an outlier point, hence in reality four clusters are formed whose PLOS ranges are used in urban off-street pedestrian facilities classification. For the purpose of clarity, in Figure 6.7, the dendogram is shown starting from a level where it will have only 30 leaf nodes. Therefore, in Figure 6.7, some of the leaf nodes among these 30 nodes will have multiple data points.



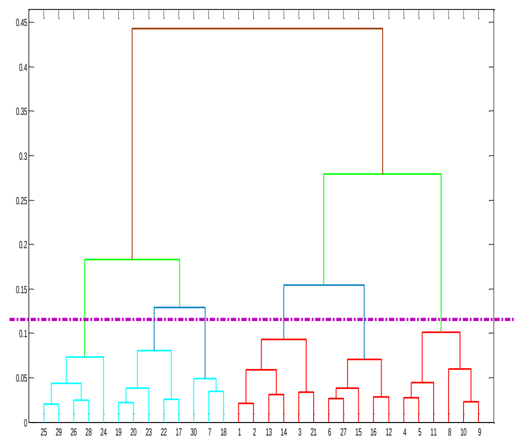
A: Dendogram for PLOS
Categories of Average space



B: Dendogram for PLOS
Categories of Flow rate



C: Dendogram for PLOS
Categories of Speed

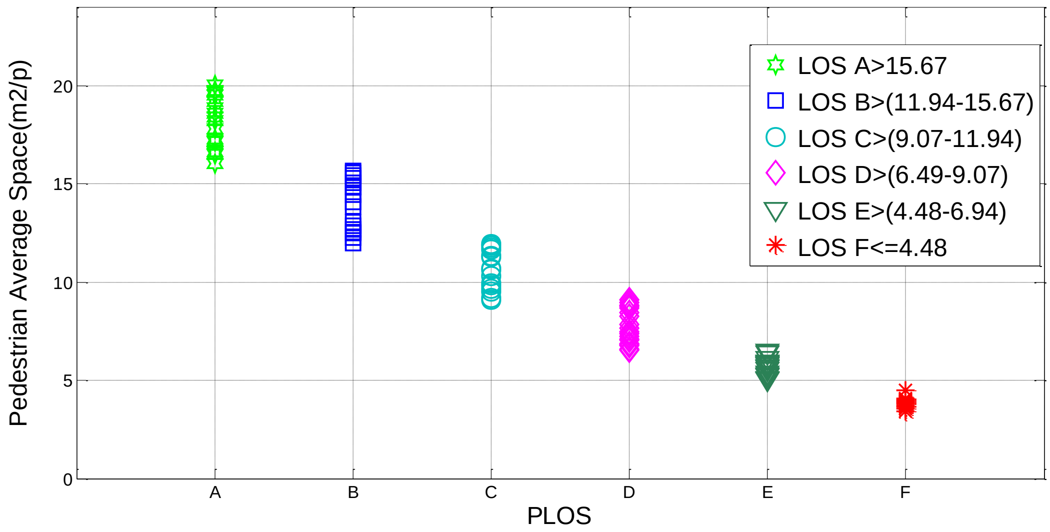


D: Dendogram for PLOS
Categories of v/c ratio

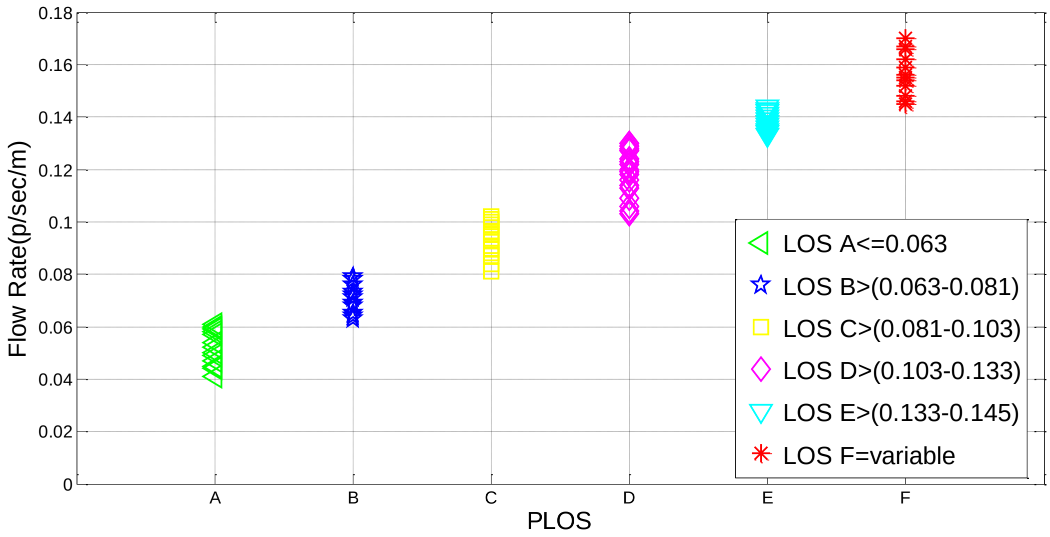
Figure 6.7: Dendogram using HAC on Four Parameters

6.2.4 SOM Clustering

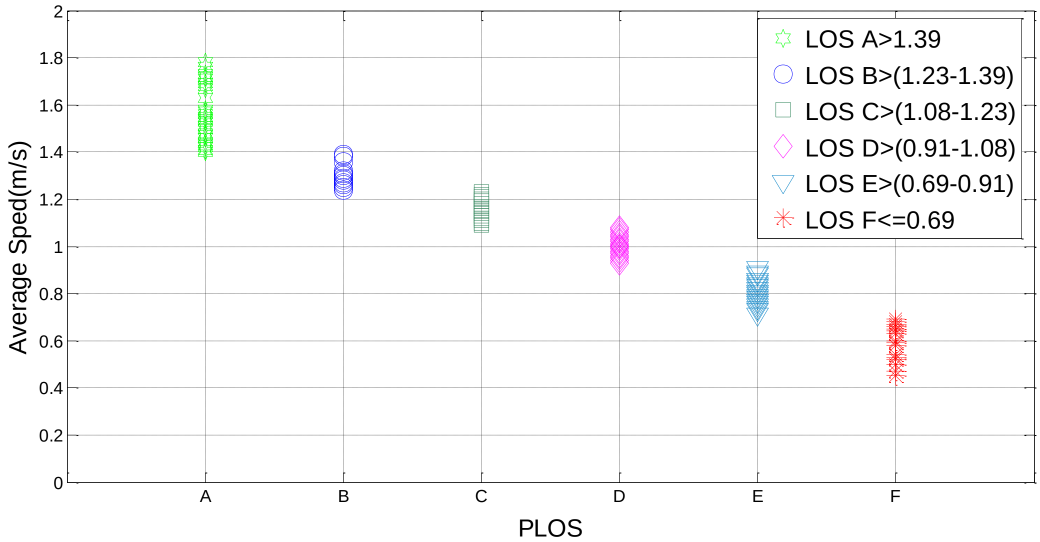
The average pedestrian space, speed, flow rate and v/c ratio data acquired through video data collection was clustered using the SOM algorithm of ANN. Figure 6.8 shows the different pedestrian level of service ranges of urban off-street pedestrian facilities. Different symbol in the plot used for different PLOS categories. The ranges of the parameters are also shown in Table 6.4



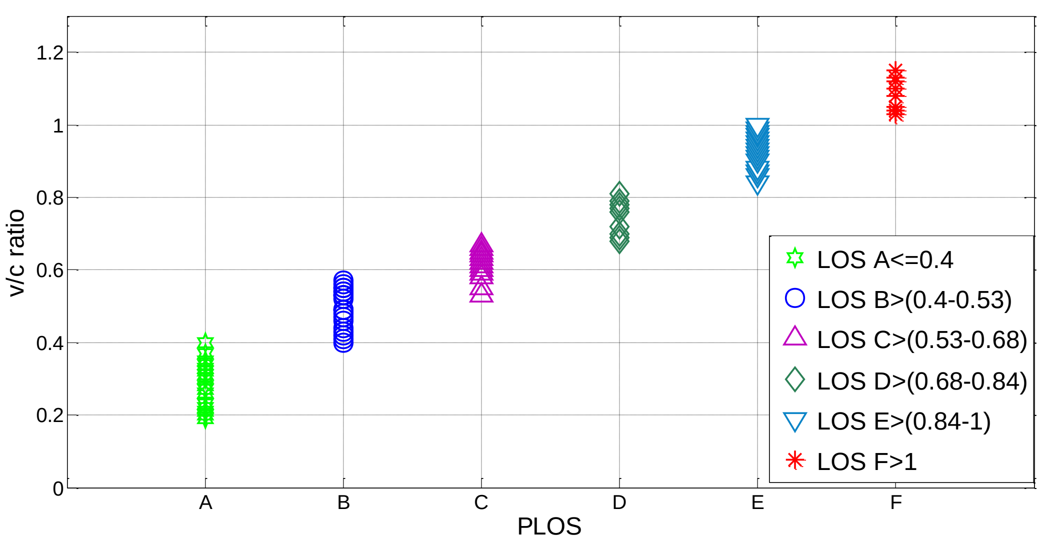
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) *v/c* ratio of PLOS categories

Figure 6.8: PLOS Categories of Urban Off-Street Pedestrian Facilities using SOM Clustering on Various Parameters

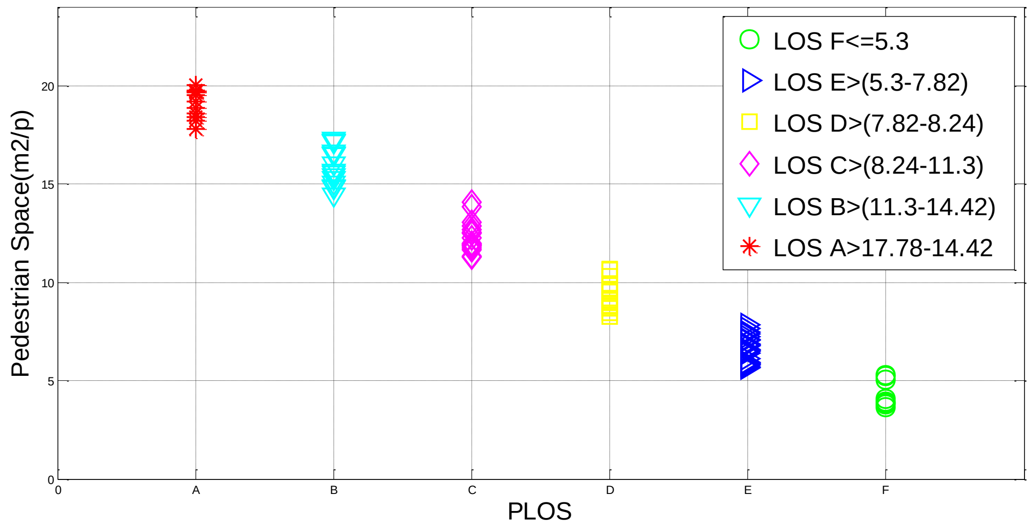
Table 6.4: PLOS Categories for Urban Off-Street Pedestrian Facilities using SOM Clustering

LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>15.67	≤0.063	>1.39	≤0.4	Ability to move in desired path, no need to alter movements
B	>11.94-15.67	>0.063-0.081	>1.23-1.39	>0.4-0.53	Occasional need to adjust path to avoid conflicts
C	>9.07-11.94	>0.081-0.103	>1.08-1.23	>0.53-0.68	Frequent need to adjust path to avoid conflicts
D	>6.49-9.07	>0.103-0.133	>0.91-1.08	>0.68-0.84	Speed and ability to pass slower pedestrians restricted
E	>4.48-6.49	>0.133-0.145	>0.69-0.91	>0.84-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤4.48	>0.145	≤0.69	>1	Speed severely restricted, frequent contact with other users

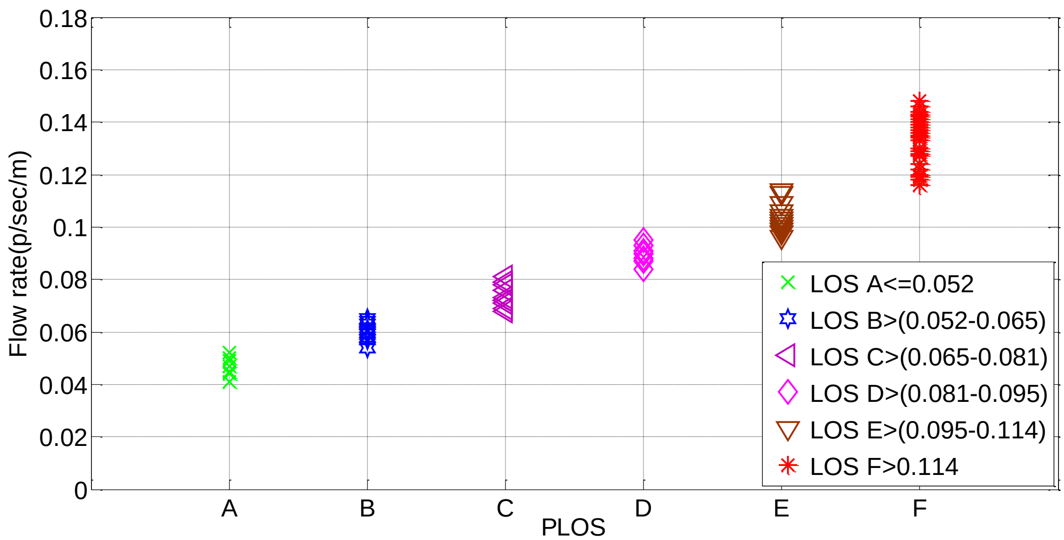
From SOM cluster analysis it is found that for PLOS "A" average pedestrian space is greater than 15.67m^2/p and for PLOS "F" it is less than 4.48m^2/p. Pedestrians will face frequent contact with other users and speed is restricted when flow rate is greater than 0.145p/sec/m and at that time volume to capacity ratio is at extreme level i.e. near about 1. Whereas pedestrians can move at their desired speed at less than 0.064 p/sec/m flow rate and less than 0.4 volume to capacity ratio. This occurs in PLOS "A" condition and here pedestrians move at near about 1.39m/sec speed.

6.2.5 Affinity Propagation (AP) clustering

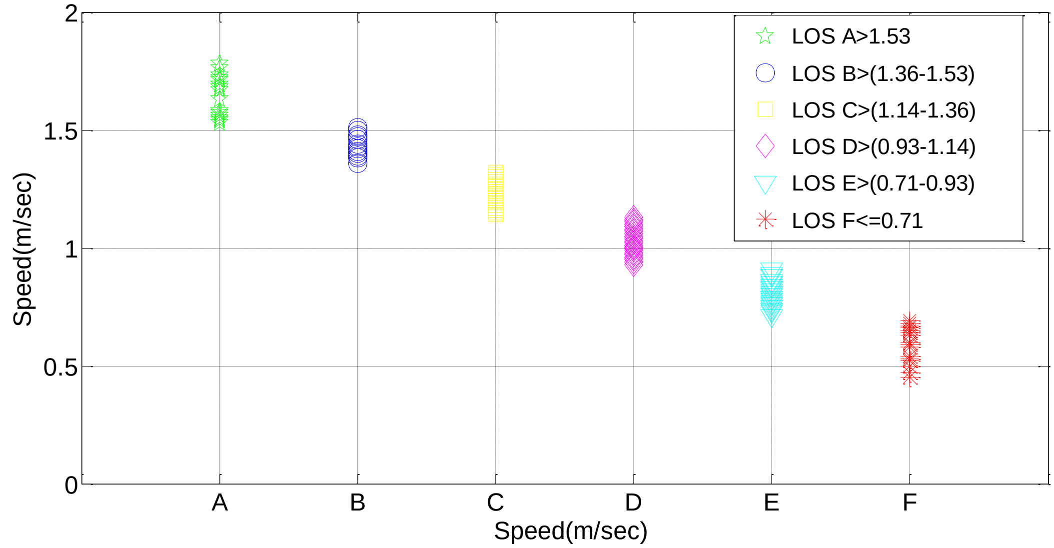
AP which is a very much new clustering tool developed in the recent past is used to get the PLOS ranges. For determination of the PLOS criteria for off-street pedestrian facility, pedestrian space, speed, f low rate and v/c ratio data acquired through video data are taken as input parameter. Figure 6.9 and Table 6.5 shows the different ranges of four parameters for PLOS categories.



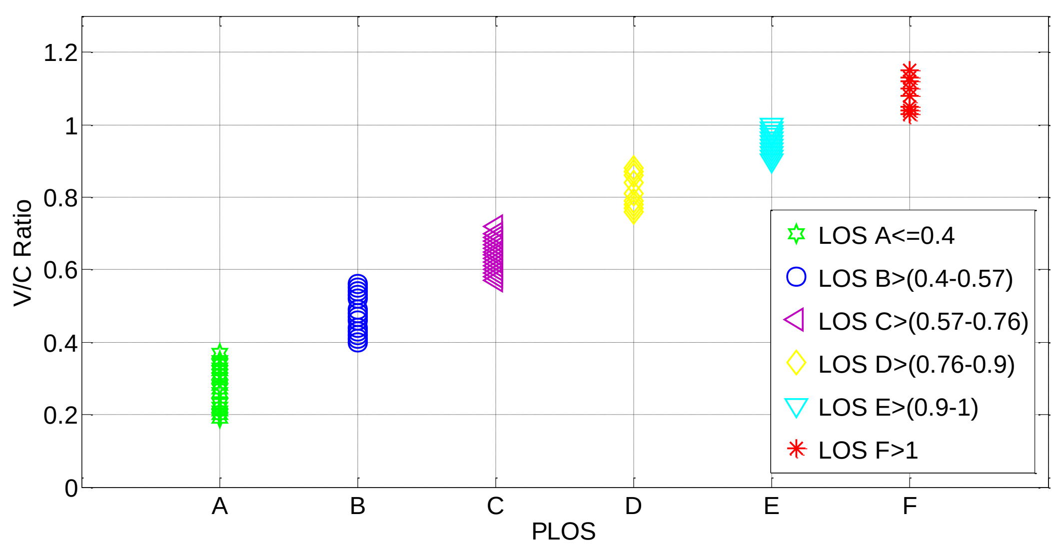
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) *v/c* ratio of PLOS categories

Figure 6.9: PLOS Categories of Urban off-Street Pedestrian Facilities using AP Clustering on Various Parameters

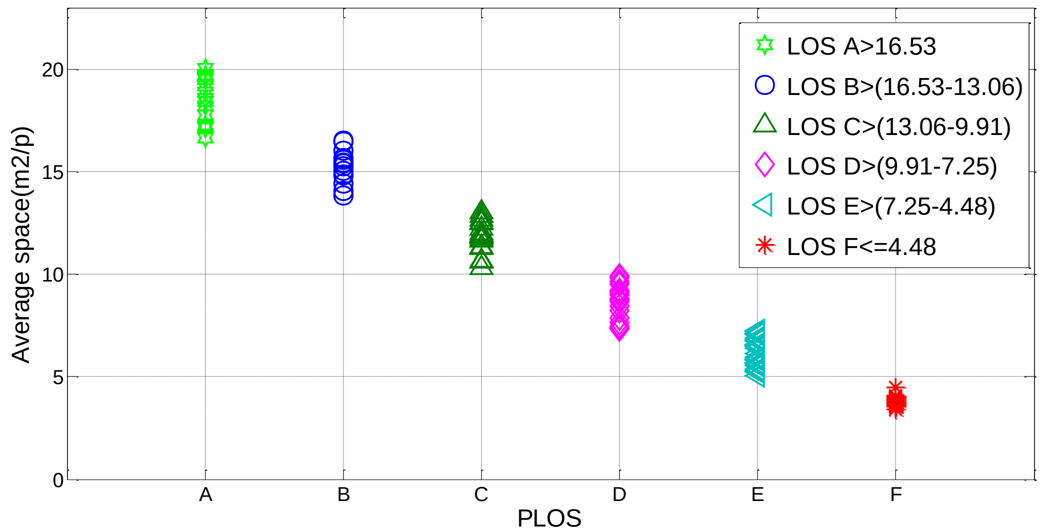
Table 6.5: PLOS Categories for Urban off-Street Pedestrian Facilities using AP Clustering

LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>14.42	≤0.052	>1.53	≤0.4	Ability to move in desired path, no need to alter movements
B	>11.3-14.42	>0.052-0.065	>1.36-1.53	>0.4-0.57	Occasional need to adjust path to avoid conflicts
C	>8.42-11.3	>0.065-0.081	>1.14-1.36	>0.57-0.76	Frequent need to adjust path to avoid conflicts
D	>7.82-8.24	>0.081-0.095	>0.93-1.14	>0.76-0.9	Speed and ability to pass slower pedestrians restricted
E	>5.3-8.24	>0.095-0.114	>0.71-0.93	>0.9-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤5.3	>0.114	≤0.71	>1	Speed severely restricted, frequent contact with other users

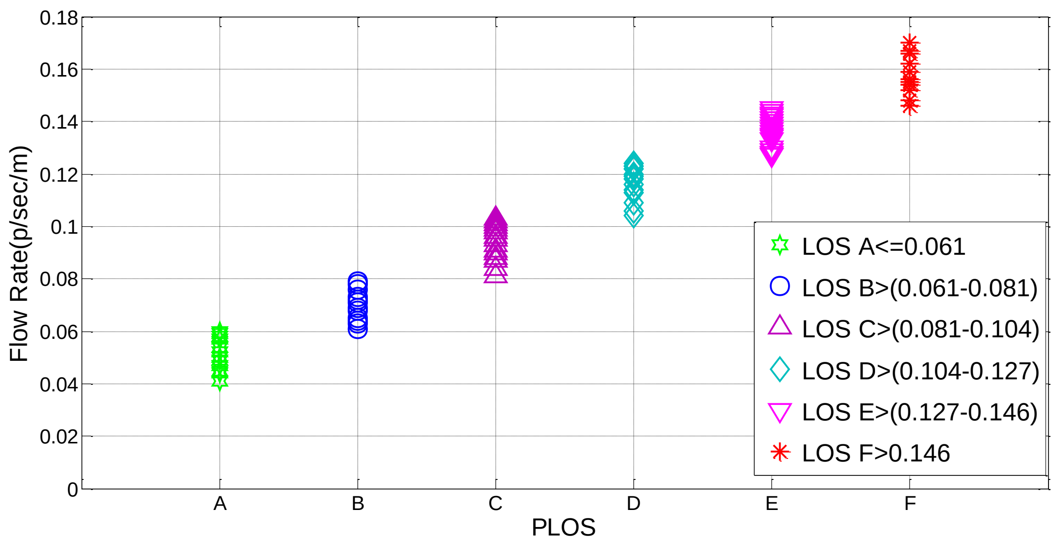
From AP cluster analysis it is found that for PLOS "A" average pedestrian space is greater than $14.42m^2/p$ and for PLOS "F" it is less than $5.3m^2/p$. Pedestrians will face frequent contact with other users and speed is restricted when flow rate is greater than 0.114p/sec/m and at that time volume to capacity ratio is at extreme level i.e. near about 1. Whereas pedestrians can move at their desired speed at less than 0.052 p/sec/m flow rate and less than 0.4 volume to capacity ratio. This occurs in PLOS "A" condition and here pedestrians move at near about 1.53m/sec speed.

6.2.6 GA-Fuzzy clustering

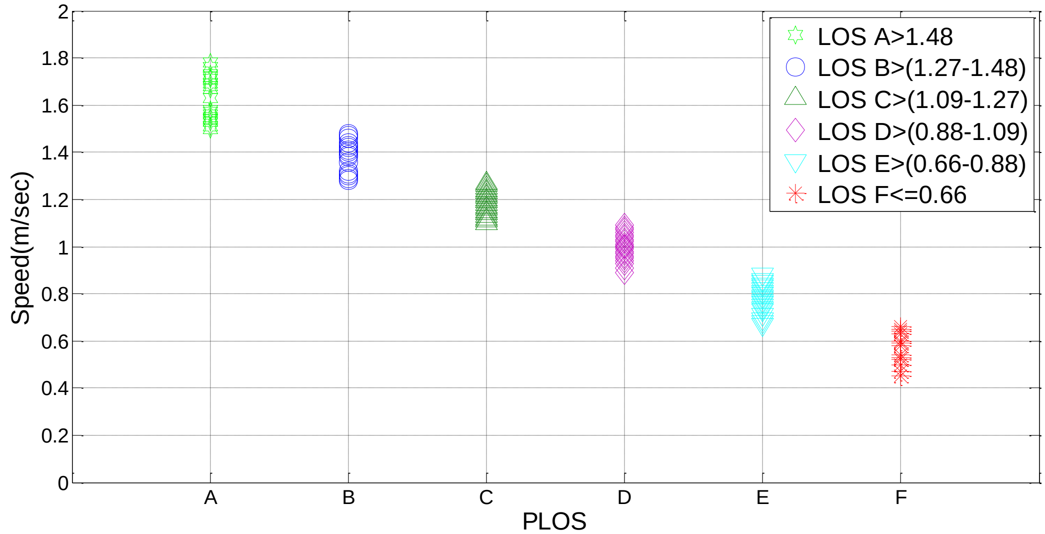
The most popular method in fuzzy classification called Genetic Algorithm Fuzzy is used for defining PLOS criteria of off-street pedestrian facilities. GA is used for optimization of search, to get the local minima which differ from global minima. The search for the global minimum can't be realized due to a large volume of calculations, but GA is used to get a sufficiently good solution. For determination of the PLOS criteria for off-street pedestrian facility, pedestrian space, speed, f low rate and v/c ratio data acquired through video data are used. Figure 6.10 and Table 6.6 describes about the PLOS ranges of off-street pedestrian facilities found from GA Fuzzy clustering.



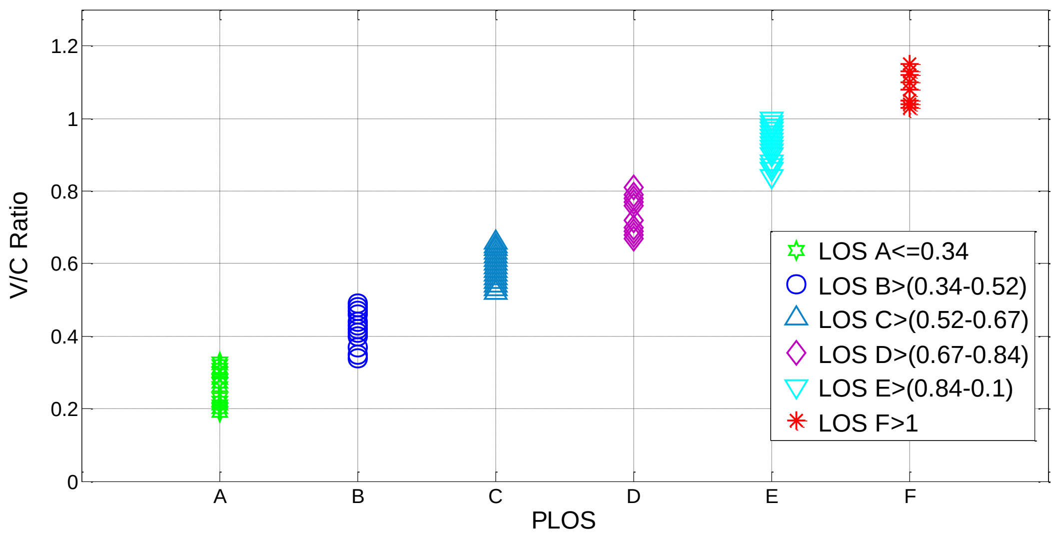
(A)Average Pedestrian Space of PLOS Categories



(B) Flow rate of PLOS Categories



(C) Average Travel Speed of PLOS Categories



(D) Volume to capacity ratio of PLOS Categories

Figure 6.10: PLOS Categories of Urban off-Street Pedestrian Facilities using GA Fuzzy Clustering on Various Parameters

Table 6.5: PLOS Categories for Urban off-Street Pedestrian Facilities using GA Fuzzy Clustering

LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>16.53	≤0.061	>1.48	≤0.34	Ability to move in desired path, no need to alter movements
B	>13.06-16.53	>0.061-0.081	>1.27-1.48	>0.34-0.52	Occasional need to adjust path to avoid conflicts
C	>9.91-13.06	>0.081-0.104	>1.09-1.27	>0.52-0.67	Frequent need to adjust path to avoid conflicts
D	>7.25-9.91	>0.104-0.127	>0.88-1.09	>0.67-0.84	Speed and ability to pass slower pedestrians restricted
E	>4.48-7.25	>0.127-0.146	>0.66-0.88	>0.84-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤4.48	>0.146	≤0.66	>1	Speed severely restricted, frequent contact with other users

From GA Fuzzy cluster analysis it is found that for PLOS “A” average pedestrian space is greater than 16.53m^2/p and for PLOS “F” it is less than 4.48m^2/p. Pedestrians will face frequent contact with other users and speed is restricted when flow rate is greater than 0.146p/sec/m and at that time volume to capacity ratio is at extreme level i.e. near about 1. Whereas pedestrians can move at their desired speed at less than 0.061 p/sec/m flow rate and less than 0.34 volume to capacity ratio. This occurs in PLOS “A” condition and here pedestrians move at near about 1.48m/sec speed.

6.3 Selecting the Best Clustering Method in Defining PLOS Criteria of Urban off-Streets Facilities

In this study six advance clustering methods are used in to get the ranges of different parameters and to define PLOS categories but to select the most suitable method for this purpose one validity index (silhouette) is used in this study. Silhouette index value of level of service categories (A-F) is calculated for six algorithms. Different colors and symbols are used for each algorithm to illustrate the result clearly.

In Figure 6.11 Silhouette width of PLOS categories (A-F) of six clustering methods are plotted. The method having highest Silhouette width index for PLOS categories is considered to be the most suitable one in this context. From figure it can be seen that *k*-means is having highest index value hence selected. Table 6.7 also gives the silhouette values of all clustering methods.

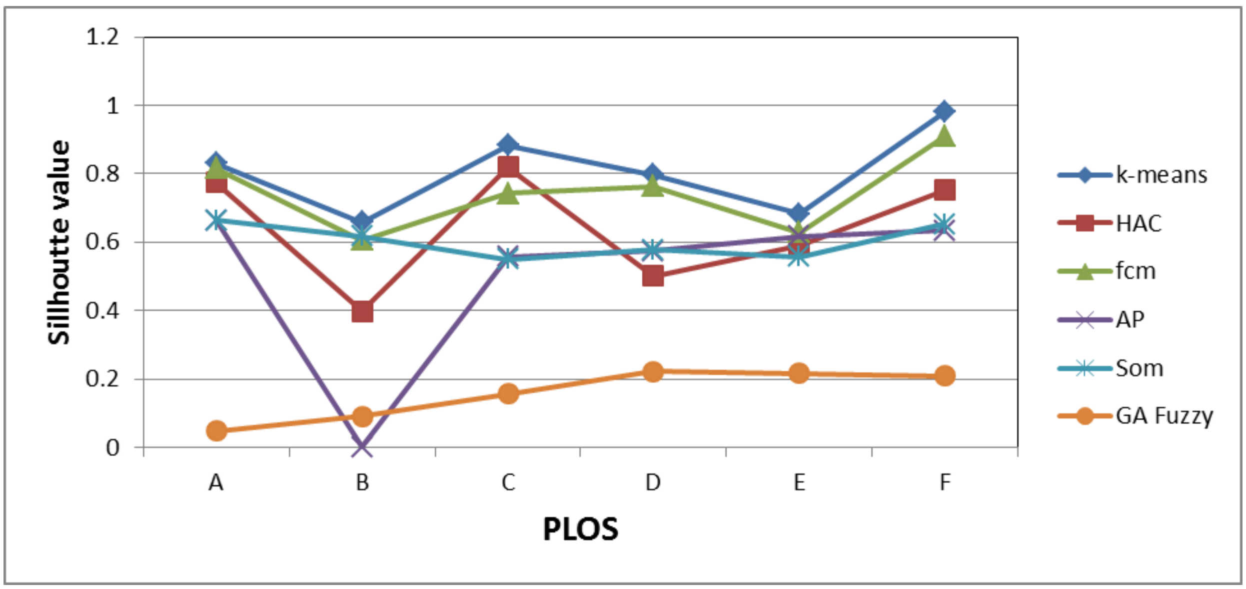


Figure 6.11 Silhouette widths vs. PLOS Plot for different clustering methods

Table 6.7 Silhouette width of PLOS categories for different clustering methods

Cluster Method	PLOS					
	A	B	C	D	E	F
K-means	0.8299	0.6584	0.8827	0.7973	0.6826	0.9801
HAC	0.7748	0.397	0.8192	0.5003	0.5885	0.751
FCM	0.8147	0.6057	0.7421	0.7626	0.6287	0.9083
AP	0.66352	o.61771	0.556653	0.57432	0.61668	0.63441
SOM	0.66352	0.61769	0.55006	0.57739	0.55647	0.65268
GA Fuzzy	0.0476	0.0902	0.1554	0.2216	0.2161	0.2096

6.4 Summary

The average pedestrian space, flow rate, speed, volume to capacity (v/c) ratio data collected using video survey are clustered using six clustering algorithm namely *K*-means, FCM, HAC, SOM, AP and GA Fuzzy algorithms. After getting the cluster result the parameter ranges were given in tabular form for all six clustering methods. From this study by considering silhouette validation index for PLOS categories of all six clustering methods, it is observed *k*-means is the most suitable one that can be applied to define the ranges of PLOS categories in Indian context. The next chapter elaborates on summary, conclusion, limitation and future work possible.

Chapter 7

Summary, Conclusions and Future Scope

7.1 Summary

In this study, existing pedestrian level of service analysis method is discussed and its theoretical underpinnings and performance are appraised. The discussion is restricted only to approaches that have been successfully applied to assess pedestrian level of service (PLOS). The review undertaken illustrates that, over the years, PLOS methods have been developed in a variety of ways however the analysis of the methods discussed suggests the need for substantial improvements in analysis procedures. In Indian context no suitable methodology is developed to access the pedestrian level of service (PLOS). Various models available are suitable for homogenous traffic flow condition as seen in developed countries. From the available source it is found that HCM (2010) methodology for the prediction of PLOS can be used for Indian context after due modifications. Hence the PLOS methodology developed in HCM (2010) is adopted in this study. The majority of these methods and models have been developed by combining models that have been applied to other choice contexts and, as a result, are not suited to universal applications. Currently available methodologies of assessing service levels for pedestrians are unable to analyze the entire spectrum of the walking experience. About study area and video data collection from off-street pedestrian facilities from different segments are described briefly. Literature on six clustering methods such as k-means, FCM, HAC, SOM, AP and GA fuzzy clustering with their advantages, disadvantages and applicability on the kind of classification problems have been elaborated. On the basis of these six cluster analysis six level of service criteria that is from “A” to “F” are defined for pedestrian LOS for off-street pedestrian facility in Indian context. By taking four parameters (average pedestrian space, flow rate, speed and volume to capacity (v/c) ratio), the classification of PLOS is defined. All the six cluster analysis was applied on each parameter and different ranges of different level of service are found. As the six clusters method gives different level of service values, the most suitable clustering algorithm which is appropriate for Indian condition is elected by using silhouette index.

7.2 Conclusion

Over the years, PLOS methods have been developed in a variety of ways for different walking environments and it has been suggested for substantial improvements in the analysis procedures. Six clustering methods such as *k*-means, HAC, FCM, SOM, AP and GA Fuzzy are used to define PLOS criteria. Different LOS values based on pedestrian space, flow rate, speed of pedestrian and volume to capacity (v/c) ratio are defined from each clustering analysis method which gives numeric ranges for LOS categories. From this study it is observed that pedestrian data collection using video cameras is a very simple and accurate procedure. Also, by using silhouette index it is found *K*-Means clustering is most suitable in Indian context and highly efficient in terms of time saving and provides a very accurate solution to this kind of classification problem. By using cluster analysis ranges of parameters for six pedestrian level of service categories i.e. A, B, C, D, E and F are defined for off-street walking facility in Indian context; where LOS “A” represents the best operating conditions and LOS “F” the worst.

The following PLOS criteria for urban off-streets facilities in Indian context are suggested based on the results found using k-means clustering:

LOS	Average Space (m^2/p)	Related Measures			Comments
		Flow Rate (p/sec/m)	Average Speed (m/sec)	v/c ratio	
A	>17.17	≤0.065	>1.38	≤0.37	Ability to move in desired path, no need to alter movements
B	>13.06-17.17	>0.065-0.087	>1.19-1.38	>0.37-0.48	Occasional need to adjust path to avoid conflicts
C	>10.32-13.06	>0.087-0.109	>1.04-1.19	>0.48-0.59	Frequent need to adjust path to avoid conflicts
D	>7.63-10.32	>0.109-0.133	>0.89-1.04	>0.59-0.76	Speed and ability to pass slower pedestrians restricted
E	>4.48-7.63	>0.133-0.152	>0.71-0.89	>0.76-1.00	Speed restricted, very limited ability to pass slower pedestrians
F	≤4.48	>0.152	≤0.71	>1.00	Speed severely restricted, frequent contact with other users

The PLOS ranges for urban off-street pedestrian facilities found from this study are significantly different from those values mentioned in HCM 2010. In this study, these two cities are having less than a million populations, for which pedestrian movement is comparatively low than the highly populated metropolitan cities. In Indian cities highly heterogeneous traffic flow on the main carriageway occasionally influence the pedestrian’s movement on off-street facilities. Due to poor enforcement of laws for traffic on main carriageways as well as the off-street pedestrian facilities, a haphazard movement is perceived. Also it has been observed that inadequate road infrastructures lead to varying geometry conditions creates unwanted confusion to the users. Besides, some of the pedestrian facilities are unauthorized occupied by vendors for their commercial use and installation of advertisements boards. In some cases unplanned utilities such as electric and telephone poles become a natural obstruction to the pedestrian movements on the path. Illegal parking on off-street facilities becomes a common phenomenon for which the pedestrian has to forcefully reduce its speed and divert the direction of movement. For these reasons PLOS ranges in Indian cities are different from other developed countries. In India, social and cultural inheritance is also different as people love to move in platoons, which has a broad effect on off-street movements. Also the physical size of Indian population is another contributing factor for which the PLOS categories in this study are different from the values described in HCM. Considering the local condition, data collection method using video cameras and *K*-Means clustering techniques can be applied in other countries to define the PLOS categories. One limitation to the application of *k*-means cluster analysis is that it require large amount of data set for which is cumbersome. This study is carried out for two cities having population size less than a million each; hence similar studies can be carried out for other bigger cities having population size more than a million to develop comprehensive PLOS criteria.

7.3 Applications

- **Operational Analysis**

A common application of operational analysis is to compute the LOS of a facility under existing or future demand.

- **Periodization**

Pedestrian level of service evaluation of the infrastructures provided to the pedestrians helps in prioritizing the development activity with the limited resource available. Infrastructures having poor LOS has to be given more emphasis for immediate development.

- **Traffic management**

Pedestrian shares a major percentage of local trips of urban mobility in India. To streamline pedestrian movement with the highly heterogeneous motorized vehicular movement realistic PLOS assessment helps in managing the traffic in the urban confinement.

- **Planning and Preliminary Engineering Analyses**

Planning and preliminary engineering analyses use estimates, default values, or local default values as inputs and determine LOS.

7.4 Limitations and Future Scope

These are some limitations in this study and opportunities lie in future studies to eliminate these limitation.

- This study is conducted for the city of Bhubaneswar and Rourkela of Odisha state, India. Similar studies can be carried out in other cities of India, as it is having significant diversities among pedestrians and their characteristics.
- For this research only off-street pedestrian facility is used for data collection purpose. All though off-street pedestrian facility has significance presence in urban pedestrian facility of India but to get complete picture of pedestrian movements further studies can be exicuted using more pedestrian facilities like cross walk, stair way, platoon flow, queuing area etc.
- In defining PLOS criteria user perception should be given due consideration. Along with quantitative analysis qualitative analysis from stated preference survey needed to be given due consideration. The relation between the qualitative and quantitative study need to be established.

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Appendix-I

The table below illustrates complied data used for this research work.

Table AI: Data used for the analysis of this research work

Segment No	Effective walkway width (W_E)	Average space (S_p)	Volume during Analysis hour (V_h)	Peak 15 min Volume (V_{15})	Capacity	Flow rate (V_P)	Average pedestrian space (A_P)	Volume to capacity ratio (V/C)
1	1.5	0.9	388	97	800	0.072	12.53	0.49
2	1.5	0.9	372	93	800	0.069	13.06	0.47
3	1.5	1.2	424	106	800	0.079	15.28	0.53
4	1.5	0.9	264	66	800	0.049	18.41	0.33
5	1.5	0.89	240	60	800	0.044	20.03	0.30
6	1.5	1.22	512	128	800	0.095	12.87	0.64
7	2	1.1	864	216	1600	0.120	9.17	0.54
8	1.5	0.8	220	55	800	0.041	19.64	0.28
9	2	0.72	528	132	1600	0.073	9.82	0.33
10	3	0.9	656	164	3200	0.061	14.82	0.21
11	1.5	1	384	96	800	0.071	14.06	0.48
12	1.5	1.01	436	109	800	0.081	12.51	0.55
13	1.5	0.81	316	79	800	0.059	13.84	0.40
14	3	0.92	1128	282	3200	0.104	8.81	0.35
15	1.5	1.1	468	117	800	0.087	12.69	0.59
16	1.5	1.02	556	139	800	0.103	9.91	0.70
17	2	0.76	732	183	1600	0.102	7.48	0.46
18	2	0.81	1024	256	1600	0.142	5.70	0.64
19	1.5	0.83	608	152	800	0.113	7.37	0.76
20	1.5	0.76	624	156	800	0.116	6.58	0.78
21	2	0.83	932	233	1600	0.129	6.41	0.58
22	1.5	0.76	692	173	800	0.128	5.93	0.87
23	2	0.8	852	213	1600	0.118	6.76	0.53
24	2	0.91	892	223	1600	0.124	7.35	0.56
25	2	0.97	408	102	1600	0.057	17.12	0.26
26	1.5	1.1	616	154	800	0.114	9.64	0.77
27	1.5	1.02	516	129	800	0.096	10.67	0.65
28	1.5	0.78	552	138	800	0.102	7.63	0.69
29	2	0.69	856	214	1600	0.119	5.80	0.54
30	1.5	0.54	772	193	800	0.143	3.78	0.97

31	2	0.88	972	243	1600	0.135	6.52	0.61
32	2	0.91	1012	253	1600	0.141	6.47	0.63
33	2	0.99	984	246	1600	0.137	7.24	0.62
34	1.5	0.53	800	200	800	0.148	3.58	1.00
35	2	0.79	976	244	1600	0.136	5.83	0.61
36	1.5	0.53	780	195	800	0.144	3.67	0.98
37	1.5	1.12	484	121	800	0.090	12.50	0.61
38	1.5	1.1	412	103	800	0.076	14.42	0.52
39	1.5	1.2	420	105	800	0.078	15.43	0.53
40	1.5	1.3	372	93	800	0.069	18.87	0.47
41	1.5	1.31	388	97	800	0.072	18.23	0.49
42	1.5	1.1	756	189	800	0.140	7.86	0.95
43	1.5	0.55	772	193	800	0.143	3.85	0.97
44	1.5	1.07	608	152	800	0.113	9.50	0.76
45	1.5	1.1	704	176	800	0.130	8.44	0.88
46	1.5	0.55	764	191	800	0.141	3.89	0.96
47	1.5	0.92	540	135	800	0.100	9.20	0.68
48	1.5	0.54	752	188	800	0.139	3.88	0.94
49	1.5	1.03	492	123	800	0.091	11.30	0.62
50	3	1.22	676	169	3200	0.063	19.49	0.21
51	3	1.21	704	176	3200	0.065	18.56	0.22
52	2	0.9	436	109	1600	0.061	14.86	0.27
53	2	1.02	372	93	1600	0.052	19.74	0.23
54	2	0.8	324	81	1600	0.045	17.78	0.20
55	3	0.71	612	153	3200	0.057	12.53	0.19
56	1.5	0.9	292	73	800	0.054	16.64	0.37
57	1.5	0.87	272	68	800	0.050	17.27	0.34
58	1.5	0.76	256	64	800	0.047	16.03	0.32
59	2	0.83	488	122	1600	0.068	12.25	0.31
60	1.5	0.55	756	189	800	0.140	3.93	0.95
61	1.5	0.53	788	197	800	0.146	3.63	0.99
62	1.5	0.54	756	189	800	0.140	3.86	0.95
63	2	1.03	632	158	1600	0.088	11.73	0.40
64	1.5	1.2	572	143	800	0.106	11.33	0.72
65	1.5	1.04	528	132	800	0.098	10.64	0.66
66	1.5	1.01	388	97	800	0.072	14.06	0.49
67	1.5	0.97	340	85	800	0.063	15.41	0.43
68	1.5	0.88	316	79	800	0.059	15.04	0.40
69	1.5	0.76	352	88	800	0.065	11.66	0.44
70	2	0.73	1004	251	1600	0.139	5.24	0.63

71	2	0.69	876	219	1600	0.122	5.67	0.55
72	1.5	0.61	456	114	800	0.084	7.22	0.57
73	1.5	0.8	668	167	800	0.124	6.47	0.84
74	1.5	0.9	684	171	800	0.127	7.11	0.86
75	1.5	0.66	672	168	800	0.124	5.30	0.84
76	1.5	0.68	684	171	800	0.127	5.37	0.86
77	1.5	0.55	728	182	800	0.135	4.08	0.91
78	1.5	0.53	788	197	800	0.146	3.63	0.99
79	1.5	0.67	716	179	800	0.133	5.05	0.90
80	2	0.71	752	188	1600	0.104	6.80	0.47
81	2	0.67	788	197	1600	0.109	6.12	0.49
82	1.5	0.8	744	186	800	0.138	5.81	0.93
83	1.5	0.7	724	181	800	0.134	5.22	0.91
84	1.5	0.9	688	172	800	0.127	7.06	0.86
85	1.5	0.8	628	157	800	0.116	6.88	0.79
86	1.5	1.2	392	98	800	0.073	16.53	0.49
87	2	1.12	420	105	800	0.058	19.20	0.53
88	1.5	1.21	332	83	800	0.061	19.68	0.42
89	2	1.2	524	131	800	0.073	16.49	0.66
90	2	1.21	560	140	800	0.078	15.56	0.70
91	1.5	1.01	348	87	800	0.064	15.67	0.44
92	1.5	1.03	324	81	800	0.060	17.17	0.41
93	1.5	1.12	504	126	800	0.093	12.00	0.63
94	1.5	1.2	548	137	800	0.101	11.82	0.69
95	1.5	1.07	484	121	800	0.090	11.94	0.61
96	1.5	1.03	468	117	800	0.087	11.88	0.59
97	1.5	0.8	476	119	800	0.088	9.08	0.60
98	2	0.81	708	177	1600	0.098	8.24	0.44
99	2	0.83	688	172	1600	0.096	8.69	0.43
100	1.5	0.81	500	125	800	0.093	8.75	0.63
101	1.5	0.79	476	119	800	0.088	8.96	0.60
102	1.5	0.9	536	134	800	0.099	9.07	0.67
103	1.5	0.7	644	161	800	0.119	5.87	0.81
104	1.5	0.81	424	106	800	0.079	10.32	0.53
105	1.5	0.62	840	210	800	0.156	3.99	1.05
106	1.5	0.61	820	205	800	0.152	4.02	1.03
107	1.5	0.59	836	209	800	0.155	3.81	1.05
108	1.5	0.64	860	215	800	0.159	4.02	1.08
109	1.5	0.63	920	230	800	0.170	3.70	1.15
110	1.5	0.57	904	226	800	0.167	3.40	1.13

111	1.5	0.59	896	224	800	0.166	3.56	1.12
112	2	0.61	1096	274	1600	0.152	4.01	0.69
113	1.5	0.7	744	186	800	0.138	5.08	0.93
114	1.5	0.69	832	208	800	0.154	4.48	1.04
115	1.5	0.66	876	219	800	0.162	4.07	1.10
116	1.5	0.77	748	187	800	0.139	5.56	0.94
117	1.5	0.79	756	189	800	0.140	5.64	0.95
118	1.5	0.82	784	196	800	0.145	5.65	0.98
119	1.5	0.88	732	183	800	0.136	6.49	0.92
120	2	0.89	884	221	1600	0.123	7.25	0.55

List of Publication

Journals:

1. Amol R. Patil, P K Bhuyan, Rima Sahani, "Estimation of Cordon Based Marginal Congestion Cost for Greater Mumbai Road Network", European Transport (Status: Comment received and manuscript revised)
2. Rima Sahani, P K Bhuyan, "Evaluation Criteria of Off-Street Pedestrian Facilities in Urban Indian Context", Transportmetrica, Taylor and Francis (Status: Manuscript Communicated)
3. Rima Sahani, P K Bhuyan, "Affinity Propagation, SOM and GA Fuzzy Clustering in Defining Urban Pedestrian Level of Service Criteria in Indian Context", *Transport*, Taylor and Francis (Status:Manuscript under preparation)

Conference:

1. Rima Sahani and P K Bhuyan, "Level of Service Criteria for Urban Walking Environment in Indian Context", Symposium on Sustainable Infrastructure Development (SID) 8th-9th February 2013, IIT Bhubaneswar, Bhubaneswar, Odisha, India(Status: Published)
2. Rima Sahani and P K Bhuyan, "Level of Service Criteria of Off-street Pedestrian Facilities in Indian Context using Affinity Propagation Clustering", Transportation Research Group of India", Agra, India (Status: Abstract Accepted)