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Original Article

Unraveling Mixed Traffic Complexity: A Fuzzy Clustering Approach to Establish the Level of Service Classifications

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Abstract - *Urban roads suffer from significant traffic congestion problems due to the rapid rise in vehicles, especially under mixed traffic conditions. A wide variety of vehicles' speeds and sizes in the same lane makes it more challenging to establish Level of Service (LOS) classifications. An approach for determining Level of Service (LOS) classifications, ranging from 'A' to 'F' introduced by the Highway Capacity Manual (HCM), is very helpful for homogenous traffic. The Indo HCM developed LOS classifications that have been established by examining speed data for mixed traffic. However, there has been limited research to identify distinct categories of determining the LOS for roads in urban areas carrying mixed traffic. This study aims to offer useful information on determining the "Level of Service" categories for urban road segments in Ahmedabad city. Furthermore, it also attempts to address the current lack of research on this topic and provide a valuable basis to improve traffic management strategies by applying three variables, namely speed, flow, and density. The FCM results clearly represent clusters of input data collected for the road segments according to specific characteristics. This enables the recognition of patterns and observations that are relevant to the research.*

Keywords - *Fuzzy c-means, Mixed traffic, MATLAB, Level of Service.*

1. Introduction

In recent years, the exponential urbanization and growth in population have resulted in an enormous rise in vehicles plying on urban roads. Significant issues such as severe traffic congestion have arisen as a result of this enormous rise in mixed traffic. Also, vehicles with different speeds and sizes using the same lanes intensify the complexities. These circumstances make it challenging to ascertain precise categories of LOS when faced with a scenario involving mixed traffic. The Highway Capacity Manual (2000) defines the "level of service" as a metric that evaluates the operating conditions within a traffic stream, specifically using performance indicators like travel time, speed, mobility, congestion, ease of movement, accessibility, and convenience of entry. Furthermore, Highway Capacity Manual 2000 classifies all facilities into six unique service levels. LOS 'A' represents the most favorable operating conditions, while LOS 'F' represents the least favorable. The IRC:1990 guidelines suggest that the Level of Service (LOS) on highways in metropolitan areas is badly affected by factors like traffic diversity, speed limits, frequency of intersections, bus stops, on-street parking, roadside commercial activities, etc. [1]. Although the Indo HCM (2017) has given LOS categories based on speed data in mixed traffic to establish LOS categories explicitly for urban-roads handling mixed types of traffic.

Several researchers have presented various methodologies to analyze LOS. However, very few have considered more than one parameter, such as speed and volume-to-capacity ratio, to arrive at LOS classification. Also, in mixed traffic, the scenario is different due to the presence of vehicles involving different characteristics. This disparity makes it extremely difficult to evaluate and control traffic flow in urban areas. Past studies have observed that speed alone offers acceptable LOS classification. However, flow along with relevant density also affects LOS, so it becomes significant to include both parameters. Considering this aspect, we used three parameters: "speed," "flow," and "density" to acquire a different approach that offers a valuable outcome for obtaining LOS for urban roads handling mixed traffic. The main goal of this research is to address the gap mentioned above in research by conducting a comprehensive traffic survey on important road segments in Ahmedabad, India. Using one of the cutting-edge analytical tools, more precisely, MATLAB's fuzzy c-means clustering analysis, the study seeks to identify several LOS category classifications using speed data, flow data, and density data. This analytical method offers an improved and context-specific framework for LOS measurement by providing a detailed understanding of particular traffic flow carried by urban road segments. This work is significant as it suggests a distinct evaluation method to assess LOS categories for urban-roads. The findings obtained from this research can assist urban planners, transportation engineers, and policymakers in implementing more efficient strategies for reducing traffic congestion and improving the overall effectiveness of road networks in urban areas.

2. Literature Review

The HCM (1965, 1985, 2000, 2010) definition of LOS is the one that is currently in use. LOS is a measure explaining operational conditions for a concerned traffic stream, usually involving measures of service such as freedom of maneuver, speed, travel time, traffic interruptions, comfort, and convenience [3-6]. Indo-HCM has established six categories for Levels of Service (LOS) to be used in situations with a mixed type of traffic [2]. Patel and Joshi (2012) studied the complexity of speed and flow within mixed traffic on access controlled urban roads in Surat (India) [7]. Microsimulation was created by Arasan, V. T., and Vedagiri, P. (2010) to investigate the effect caused by designated bus lanes' heterogeneous traffic on Indian metropolitan roadways [8]. The study aimed at achieving dedicated bus lanes to improve bus transportation's LOS in terms of dependability, safety, and other factors, including speed. Bhuyan and Nayak. (2013) emphasized soft computing approaches for the LOS analysis of urban roads [9].

The authors determined that the limitations for these LOS standards appropriate for India are lower than those recommended by HCM when classifying LOS for streets in urban areas. Lee and Lam (2003) studied LOS rating considering users' perceptions of the stairways of Hong Kong, MTR-stations being a main cause for concern [10]. Azimi and Zhang, (2010) have classified motorway conditions based on flow characteristics by utilizing three-pattern recognition techniques: FCM, K-means, and Clustering Large Applications (CLARA) [11]. The HCM was considered for comparing the classification outcomes out of the three clustering techniques. In their book "Level of Service 2010 and Beyond", Roess et al. (2010) made an effort to discuss the LOS idea with its applications in transportation planning [12]. Chen et al. (2009) have implemented fuzzy neural networks to establish a way to get the LOS perceived by drivers at signalized crossings [13]. The study combined perceived qualities for determining LOS by applying a neural network that contained fuzzy reasoning experiences. To study the variables affecting the perceived LOS, Cao et al. (2009) conducted a thorough analysis. They suggested criteria for LOS pertaining to urban rail-transit platforms applied for designing a transit system [14]. According to their study, the significant element influencing the platform's LOS was congestion, which was followed by waiting times, information signs, air quality, and passenger orders. Fuzzy sets were used by Kikuchi and Chakraborty (2006) to identify uncertainty levels pertaining to the LOS categories [15]. The authors suggested six frameworks to ascertain the degree of uncertainty related to each LOS category. The author concluded that the six categories listed in HCM for LOS differentiation are adequate. However, they also suggested creating a new set of six service levels by combining LOS A and B and dividing LOS F into two categories. Using statistical modeling, Semeida et al. (2021) determined the connection between heavy trucks and road geometry features [16]. Becher (2011) created a process to assess traffic light-controlled intersections, accounting for the impact of mean delays on road user's assessment of quality [17]. Boora et al. (2016) investigated LOS ranges for an intercity highway with two-lanes that was established by doing cluster analysis using NFPC and FD, which yielded various threshold values [18]. Marisamynathan and Dadagiri (2017) validated two models for predicting PLOS [19]. They applied K-means and FCM to classify PLOS. Sharma and Pandit (2021) demonstrated a method for establishing service level benchmarks of fixed-route shared para-transit systems in developing nations [20]. The established LOS thresholds by Bari et al. (2021) are highly valuable for engineers and practitioners to assess the current performance of tollbooths and subsequently implement suitable strategies for efficiently managing toll plaza operations [21]. Bhuyan and Rao (2010) have applied FCM clustering to obtain LOS classification considering speed values for urban roads handling heterogeneous traffic. Considering the previous studies, it became necessary to include three parameters, as discussed earlier, for defining the LOS classifications in the Indian environment [22].

3. Materials and Methods

3.1. Study Area and Roadway Geometry

3.1.1. Study Area

The study emphasizes key road segments characterized by diverse conditions of traffic in Ahmedabad, India. Ahmedabad is densely populated and one of the largest cities in India, presenting a significant challenge concerning traffic congestion because of the increasing numbers of various vehicles. The chosen road segments, namely, Kalupur Road (Kalupur Circle- Kalupur Rly. Station segment) and Ring Road (also called 120 ft. Ring Road) (IIMA- GMDC segment), capture the mixed traffic complexity due to different vehicles along with varying sizes and speeds.

3.1.2. Road Geometry and Pavement Condition

For the Kalupur road segment, a length of 350 m was considered, with a carriageway width of 11.50 m and 3 lanes. While, a length of 900 m was considered for the ring-road segment, which had a total carriageway width of 19.0 m and 4 lanes. The selected road segments were straight, without any gradients. The pavement conditions of both road segments were excellent.

3.2. Data Collection

3.2.1. Traffic Survey

A traffic survey was carried out to gather relevant data for analysis. The survey included:

Traffic Flow Measurements

Statistics on the vehicles moving on the road mentioned above segments were collected during a specific period. The data was gathered at every 5-minute interval and thereafter converted into the "number of vehicles for an hour".

Vehicle Speed Measurements

Calculation of the speed of vehicles using a general equation given below:

$$V = \frac{d}{t}$$

Where V= speed of the i^{th} vehicle in km/h,
d= distance traveled by i^{th} vehicle in km,
t= time required for traveling the distance in an hour.

3.2.2. Data Variables and Measurements

In traffic engineering, the traffic-stream parameters are categorized into two main types: macroscopic parameters and microscopic parameters. Macroscopic parameters pertain to the overall traffic flow and its characteristics, while microscopic parameters pertain to the functioning of individual vehicles or pairs of vehicles within the traffic stream. Flow, speed, and density are the three principal macroscopic parameters that describe a traffic stream. In this work the gathered data comprises vehicles' flow and speed values. Generally, density cannot be extracted directly in the field, so the same was obtained using a fundamental relationship given below:

$$D = \frac{Flow\ (v/h)}{Speed\ (km/h)}$$

Where, D= density (v/km/carriageway).

3.3. Statistical Analysis and Clustering Task

3.3.1. Statistical Analysis

Statistics is a powerful technique that assures a degree of trust in the results. It plays a key role in reaching a meaningful conclusion that supports the output obtained through the results. It includes standard techniques such as f-test, t-test, z-test, ANOVA, and many others for the output. In clustering tasks, the structural analyses include mathematical and computational approaches for identifying the classification of objects within a particular dataset. For validating clustering results, clustering indices are employed as discussed in Section 3.5

3.3.2. Clustering Task

To obtain the LOS value, the data should be categorized systematically. Clustering is considered the best option for classifying the data set comprehensible. Clustering is an unsupervised machine-learning approach which categorizes related data points into groups according to their properties." Each cluster comprises data that presents, but as a collective, the cluster is distinct from other data points.

Clustering methods enable us to present hidden structures, patterns, and correlations within given data. Cluster analysis categorizes the data so that objects that exist in the same group are similar rather than objects in different groups. Clustering is used in market segmentation, result grouping, medical imaging, social network analysis, anomaly detection, and picture segmentation.

3.4. Fuzzy c-means Cluster Analysis

3.4.1. Overview of Fuzzy c-means Algorithm

Fuzzy logic principles are found to be efficient in categorizing multidimensional data. Compared to usual hard-threshold clustering, this technique is considerably stronger as it assigns each point a precise and accurate label.

It provides greater flexibility compared to the k-means technique. It allows the data to be a part of more than one cluster simultaneously. The FCM clustering technique can be applied to analyze the gathered data and also to arrive at a clear classification of LOS. It is very appropriate for the inherent uncertainties and complexities associated with traffic data analysis.

3.4.2. FCM Algorithm

The FCM algorithm assigns membership values to each data point according to the distance between the cluster centre and the data point. The data nearest to the cluster centre indicates stronger membership towards the cluster centre.

Of course, the total of the membership of every data must be equivalent to one. After each repetition, the membership and cluster centres are modified considering the equations given below:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij}/d_{ik})^{\left(\frac{2}{m}-1\right)}} \quad (1)$$

$$v_j = \left(\sum_{i=1}^{n} (\mu_{ij})^m x_i \right) / \left(\sum_{i=1}^{n} (\mu_{ij})^m \right),$$

$$\forall j = 1,2,\cdots\cdots C \quad (2)$$

Where 'n' is the number of variables. The j^{th} cluster-centre is represented by "v_j", and" m" represents the fuzziness number, which is between 1 and ∞. The number "c" refers to the cluster centre. "μ_{ij}" states that the ith data is part of the j^{th} cluster centre. The Euclidean distance between the i^{th} data point and the j^{th} cluster centre is denoted by "d_{ij}."

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} \left(\mu_{i_j}\right)^m \left\|\chi_i - v_j\right\|^2 \qquad (3)$$

Where, $\left\|\chi_i - v_j\right\|^2$ is the Euclidean distance between the data point i^{th} and cluster centre j^{th}.

3.5. Cluster Validity Indices

These are the measures used to validate the clustering algorithms. They identify cluster numbers, compactness, and the separation of the clusters. The partition coefficient, partition entropy coefficient, and silhouette index are such indices; they are described below:

3.5.1. Partition Coefficient (PC)

It is a crucial tool that quantifies the degree of separation or cohesiveness. It provides significant guidance in assessing the clusters that are well defined. It is beneficial when applied to clustering algorithms like FCM. It performs cluster validation that assists in choosing cluster numbers. Bezdek (1973) has defined PC by the Equation (4) [23]:

$$PC_v = \frac{1}{\eta} \sum_{j=1}^{k} \sum_{i=1}^{n} u_{j,i}^2 \qquad (4)$$

Where, PC_v = Partition Coefficient,
n = number of given data points,
k = clusters,
$u_{j,i}$ = membership degree

3.5.2. Partition Entropy Coefficient (PEC)

It quantifies the fuzziness degree or overlap of the clusters. Like the Partition Coefficient, PEC is also considered to assess the usefulness of fuzzy clustering techniques, providing information on how the membership values are distributed. As discussed earlier, Bezdek has defined the PCE, which can be given by Equation (5):

$$PEC_V = \sum_{i=1}^{n} \sum_{i=1}^{n} u_{j,i} \log_a(u_{j,i}) \qquad (5)$$

Where PEC_v= Partition Entropy Coefficient,

3.5.3. Silhouette Analysis

The Silhouette index examines the degree to which each data point fits with its designated cluster and the distinction between clusters. It offers a means to assess the clustering -accuracy without knowing the actual labels of that data. Thus, it indicates the matching of a particular data point to its allocated cluster, along with the uniqueness of clusters from each other.

Algorithm of Silhouette Index

If a_{is} represents the average distance or dissimilarity of i_s^{th} point with respect to other points within that particular cluster, indicating cohesiveness. Similarly, b_{is} represents the mean distance or dissimilarity of i_s^{th} point to all other points of the closest or neighboring cluster. Thus, b_{is} indicates separation. Usually, the Silhouette Index (SI) can be calculated by Equation (6) given below:

$$SI = \frac{(b_{is} - a_{is})}{\max(a_{is}, b_{is})} \qquad (6)$$

Interpretation of Silhouette Index

SI values are useful in performing cluster validity analysis. The values of SI $range\ from\ -1\ to\ 1$. Here, -1 indicates poor clustering, 0 indicates a point between two given clusters, whereas 1 indicates very good clustering.

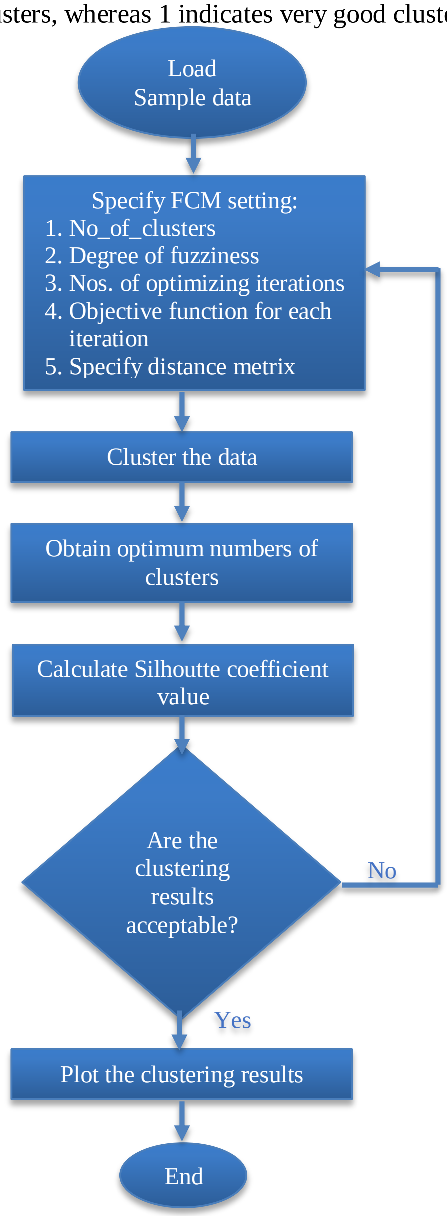

Fig. 1 Flow chart showing the general steps of FCM in MATLAB

3.6. Application of FCM in Traffic Data Analysis

The Fuzzy c-means algorithm was executed using the versatile MATLAB programming language, which offers various tools for analyzing data. Applying fuzzy membership values for categorizing similar traffic conditions will lead to distinct LOS classifications for urban streets. Considering the variations in vehicle sizes and speeds for road segments, this technique presents information on traffic conditions. As discussed in section 3.2.2, three principal macroscopic-parameters that describe a particular traffic stream, and they are:

- Volume (or rate of flow),
- Speed, and
- Density.

Out of the three, density is defined as "the number of vehicles occupying a specific length of highway or road". It is typically stated by "veh/mile (or km)". Measuring density is difficult since it necessitates an elevated vantage point, allowing observation of the highway portion being studied. It is commonly established using measurements of speed value and flow-rate. Density is significant to the three basic traffic stream parameters as it has the closest relationship to traffic demand. Several land uses produce traffic, forcing many vehicles into congested road areas. This process yields a vehicle density. Density, an important indicator of traffic-flow quality, represents the closeness of other vehicles, which influences the freedom to maneuver and the psychological comfort of drivers. Figure 1 shows the flowchart stating the general steps of FCM clustering in MATLAB.

4. Results and Discussion

4.1. Clustering Results and LOS Categories

FCM clustering technique was performed in MATLAB to obtain precise classifications of LOS using speed data, flow data, and density data. The findings revealed multiple groups that represent distinct conditions of traffic for the selected road segments. Six clusters were assigned to six LOS categories ("A" to "F"), offering a detailed viewpoint of city road segments. We have employed cluster validity indices like Partition Coefficient (PC), Partition Entropy Coefficient (PEC), and Silhouette Index (SI) values to determine the number of clusters obtained, and their cohesiveness and separation. Moreover, the correlation between the sum-of-square error and the number of clusters is illustrated by visual representation using the elbow technique. These indices help to reduce errors, identify discrepancies, and confirm the authenticity of the outcomes. Partition coefficient and partition entropy coefficient values are computed and tabulated in Table 1. A higher value of PC indicates a smaller degree of overlap and separation between the given clusters. Contrarily, a larger value of PEC implies a greater degree of fuzziness, and the overlapping of clusters is also greater. The tabular representation of both these values clearly demonstrates that there is a minor change in the values after six clusters. Simply this confirms the optimal number of clusters.

Table 1. PC and PEC values for different clusters

Name of the Road Segment	Numbers of Clusters	Partition Coefficient (PC)	Partition Entropy Coefficient (PEC)
Kalupur Road Segment	2	0.88362	0.19516
	4	0.79591	0.39925
	6	0.73342	0.53014
	8	0.75281	0.52190
	10	0.73461	0.57898
Ring Road Segment	2	0.87794	0.20373
	4	0.82853	0.34201
	6	0.76181	0.47968
	8	0.74187	0.53396
	10	0.72947	0.57806

Silhouette value provides an approach to examine the distance of separation for the clusters that are formed. The plot of silhouette graphically represents the closeness of every point within a particular cluster to points covered by neighboring clusters, which enables assessment of cluster output. As discussed earlier, the range of Silhouette Coefficient (SC) values is from -1 to 1, with a higher number indicating better performance for a chosen algorithm for clustering. As the Silhouette values are significant, they are utilised to assess outcomes obtained through the Fuzzy c means clustering approach.

In Figures 2 and 3, relevant silhouette coefficient values are shown graphically. Moreover, an elbow method was applied to calculate optimal values of clusters. It involves the simple steps mentioned below for calculating the optimal value of clusters:

- Set the starting value of cluster k.
- Increment value of cluster k.
- Sum of Squared Errors (SSE) is calculated by summing the squared differences between each value of k.
- A sum of square error results from the k value has significantly dropped, indicating a positive trend in the analysis.
- Identify and establish the k value corresponding to the elbow-shaped point.

Figures 4 and 5 display the SSE values against the number of clusters. The Output acquired from the analysis of SC values and the Elbow technique is deemed appropriate for the FCM results.

As mentioned previously, the specific attributes of the dataset decide the justification of an optimal number of given clusters (k). PC, PEC, elbow technique, and silhouette score have been utilized to determine an ideal value for k. Each figure graphically represents the clustered data points.

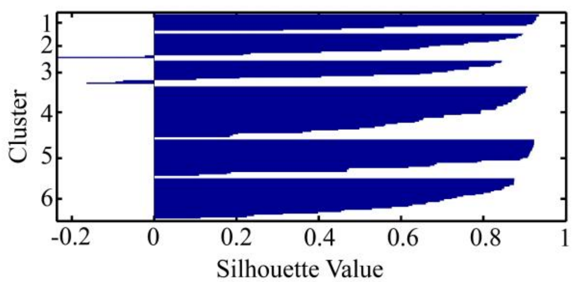

Fig. 2 Silhouette value for kalupur road segment

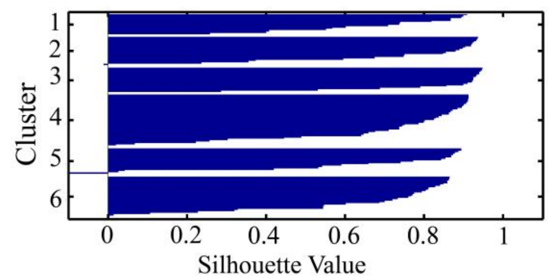

Fig. 3 Silhouette value for ring road segment

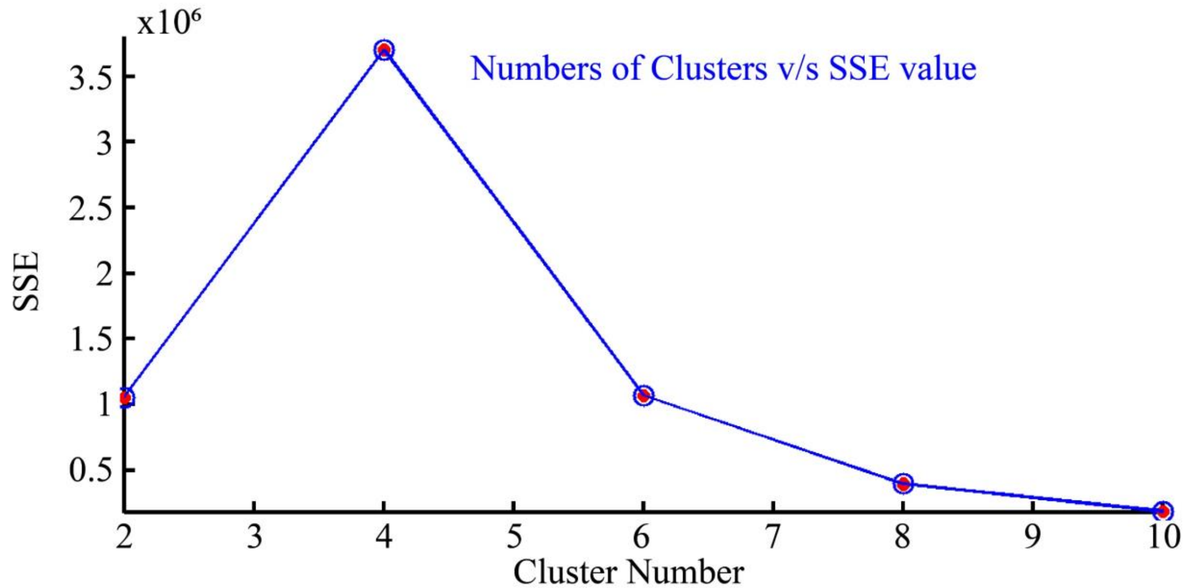

Fig. 4 Plot showing cluster- numbers and SSE values for the kalupur road segment

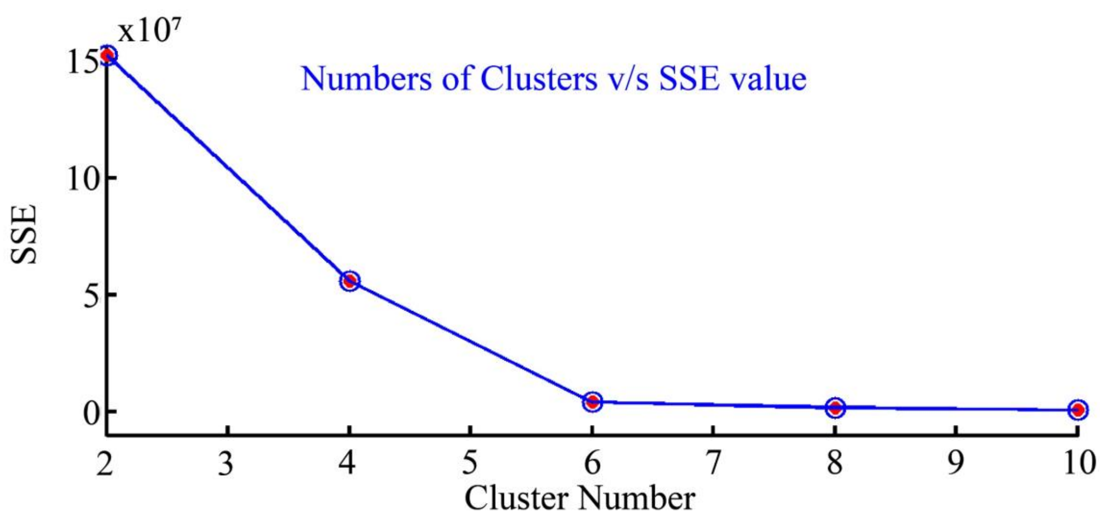

Fig. 5 Plot showing cluster- numbers and SSE values for the ring road segment

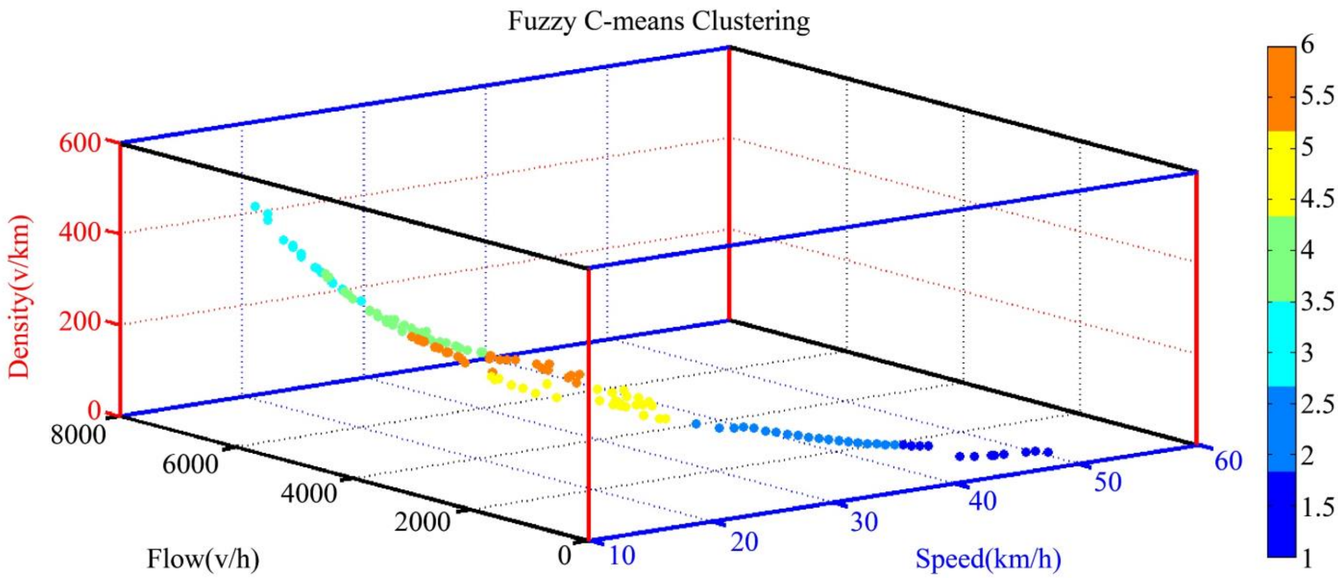

Fig. 6 3D plot of fuzzy-C-means clustering for the kalupur road segment

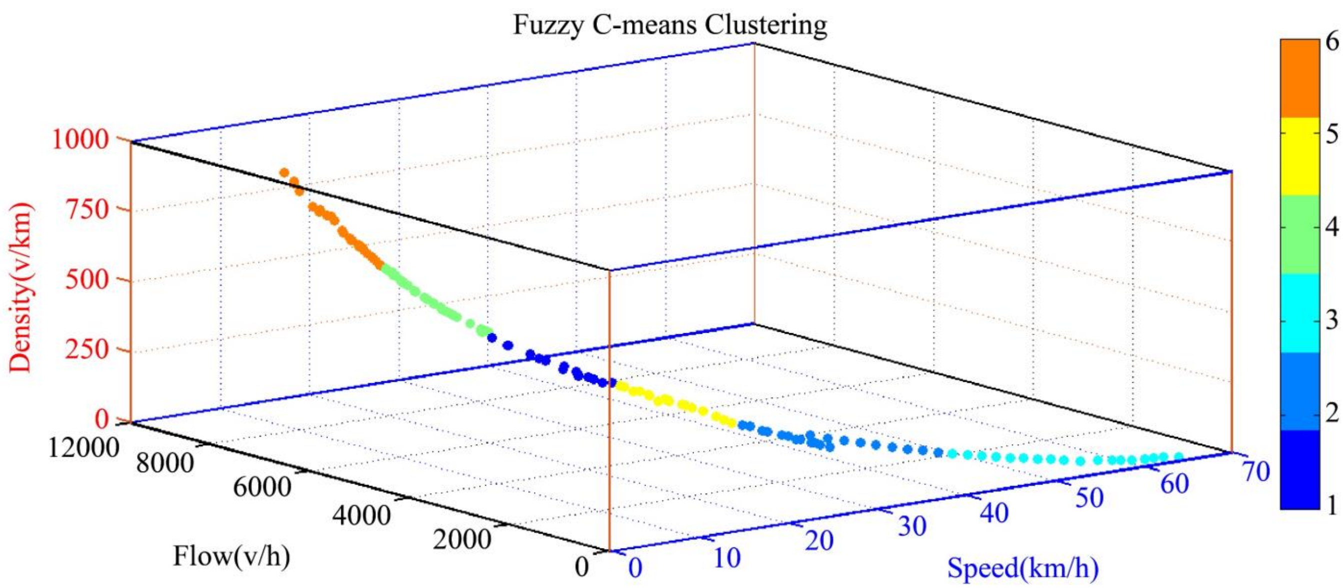

Fig. 7 3D plot of fuzzy-C-means clustering for the ring road segment

As the classification involves three key parameters of the traffic stream, the 3D visualization of the FCM results, depicted in Figures 6 and 7, offers a distinct depiction of clusters of road segments determined by certain qualities. This facilitates an identification of patterns and insights that are pertinent to the investigation.

4.2. Interpretation of Fuzzy-C-Means Results

4.2.1. Differentiated LOS Categories

The clustering analysis of fuzzy c-means identified differentiated LOS categories that reflect the varying traffic conditions in Ahmedabad's urban roads. Unlike traditional categorizations, the fuzzy nature of the clusters allowed a more accurate representation of the mixed traffic dynamics, considering the uncertainties in vehicle speeds and sizes.

4.2.2. Comparison with Existing LOS Categories

The HCM-2010 mentioned standards for evaluating the effectiveness of derived LOS categories considering speed data. So, the LOS categories obtained through cluster analysis are compared with HCM-2010.

The comparison is tabulated in Table 2. The proposed categories, tailored for urban road segments using fuzzy clustering, offered a more realistic and context-specific representation of traffic conditions.

Table 2. Comparison of existing LOS value with HCM (2010)

LOS	%FFS (HCM-2010)	%FFS Range (Kalupur Segment)	%FFS Range (Ring Road Segment)
A	>85	76-100	72-100
B	>67-85	62-73	51-71
C	>50-67	40-61	44-51
D	>40-50	34-58	32-43
E	>30-40	24-47	24-35
F	<=30	22-34	20-25

5. Conclusion

Some important conclusions have been identified by carrying out a thorough examination and combining current literature with empirical study. Vehicles of varying sizes and speeds badly affected traffic flow behavior under the situation of mixed-traffic situations. The level of service combines many operational characteristics at varying levels of traffic flow, like flow, stream speed, concentration, travel time, etc.

This study involves three variables, namely (i) speed, (ii) flow, and (iii) density, for assessing 'LOS' categories. The results offer valuable insights to implement targeted interventions depending on specific characteristics of every LOS category for similar roads. The findings suggest that LOS classifications for urban roadways deviate from the levels given in HCM (2010), particularly for categories D, E, and F, where the values are significantly low. These differences arise from the diverse characteristics of mixed traffic. This study requires a substantial quantity of speed data and flow data points to achieve more accurate outcomes, which may be a limitation of work.

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