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Development of Congestion Severity Index for Speed Humps Utilizing Fundamental Parameters and Clustering Techniques – A Case Study in India

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ABSTRACT: Traffic congestion has widespread negative impacts on the environment, urban development, and road safety, leading to increased commute times and heightened incidents of road rage and accidents. Evaluating congestion, particularly in relation to speed humps, becomes crucial due to their complex impact on traffic flow. Although few studies have explored delay estimation and lane-changing behaviour at speed humps, the larger issue of traffic congestion has received less attention. Recognizing and measuring congestion levels at these humps can be pivotal in devising specified strategies to alleviate the challenge. The present investigation focused on adapting travel time reliability metrics, specifically the Planning Time Index (PTI) and Travel Time Index (TTI), to consider the influence of speed humps. These adjusted metrics have been used to assess congestion in two critical zones: the area before the speed humps where vehicles slow down and the sections covering the humps. The study took a comprehensive approach by using video analysis to gather data on various vehicles operating on the road. Subsequently, the PTI and TTI were analyzed for their relationships with different speed percentiles (98th, 85th, and 15th). The findings revealed compelling correlations allying PTI, TTI, the 15th and 85th percentile speeds, surpassing the relation with the 98th percentile speed. This analysis formed the basis for a congestion severity index, outlining distinct congestion levels. The study employed K-means clustering, ensuring a logical and data-driven categorization of congestion severity at speed humps. To sum up, this research not only enhances our understanding of traffic congestion at speed humps but also lays the groundwork for implementing targeted measures to effectively mitigate these issues.

KEYWORDS: Speed humps; Traffic congestion; Travel time index; Planning time index; Clustering

1. INTRODUCTION

Traffic congestion is a pervasive issue with profound implications for urban life, impacting the environment, economic growth, and the well-being of city dwellers. It extends commute times, fosters frustration among road users, increases the likelihood of accidents, and exacerbates road rage (Reed and Kidd, 2019). Researchers have provided various technical definitions for traffic congestion. According to some authors (Aftabuzzaman 2007; Afrin and Yodo 2020; Samal et al., 2020; Kumar et al 2020) traffic congestion arises when the volume of travel exceeds capacity or when there are more volumes than it was originally planned to accommodate.

Among the various traffic management elements, speed humps are often perceived as a solution to enforce reduced speeds, enhance road safety, and minimize traffic-related problems in residential and commercial areas (Samal et al., 2022a; Samal et al., 2022b). Speed humps are engineered to be crossed comfortably at a specific speed (Jain et al., 2012). In India, IRC 99-2018 contains guideline for the design of traffic calming devices such as speed humps. It stipulates that vehicles should not be forced to decelerate below 20 kmph while traversing these humps. Numerous researchers (Wortman and Fox, 1994; Bennett and Dunn, 1995; Akçelik and Besley, 2001; Wang et al., 2005) have documented the substantial deceleration rates experienced at speed humps, contributing to the transition of the traffic flow into a congested state. Several other researchers (Pau, 2002; Jain et al., 2012; Antic et al., 2013) have also highlighted that the significant reduction in vehicle speeds when traversing speed bumps plays a role in exacerbating congestion. However, the presence of speed humps introduces complex dynamics into traffic flow, raising questions about their impact on congestion (Mohanty et al., 2021; Samal et al., 2022a, Samal et al., 2024). While previous studies have explored aspects like delay estimation and lane-changing behaviors related to speed humps, there remains a dearth of studies that comprehensively investigate traffic congestion at these road features. Understanding the congestion dynamics at speed humps is essential for effective traffic management, as this information can guide location-specific measures to alleviate congestion, improving overall road safety and traffic flow.

The use of TTI and PTI is widespread globally for evaluating traffic congestion on any road (Lyman and Bertini, 2008; Rao and Rao, 2012; He et al., 2016; Samal et al 2020; Samal et al 2021; Samal et al 2022b). While modern approaches like fuzzy logic, VISSIM software simulations, artificial neural networks (ANN), queuing analysis, and others are employed for congestion assessment, congestion indices remain a preferred choice due to their capacity to directly represent real-world conditions (Padiath et al., 2009; Mohanty et al., 2023; Samal et al., 2023). Nevertheless, despite its fundamental importance, speed has not been directly incorporated into the calculation of these congestion indices. Even though speed influences travel times, which are integral to congestion index determinations, the conventional approach relies on mean and off-peak travel times as well as the 95th percentile, while overlooking the 15th percentile speed. The 15th percentile speed stands out as a critical indicator of congestion as it

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gauges the speeds of the slowest vehicles in the traffic flow. It's worth noting that the congestion indices are typically designed for midblock segments and are not tailored for assessing congestion specifically at speed humps. Therefore, in this study, we have attempted to design a congestion severity level at speed humps where the initial step involves adapting the existing congestion indices to accommodate the unique characteristics of speed humps. Minor adjustments were made to the conventional definitions to align with the peculiarities of speed humps. Subsequently, speed, including its various aspects such as the 98th, 85th, and 15th percentile speeds, was incorporated and analyzed in conjunction with the congestion indices. This comprehensive approach aimed to enhance the assessment of congestion specifically at speed humps. Lastly, a clustering technique was applied to classify the severity levels of congestion systematically. Crucially, the applicability of the present findings extends to 6-lane divided roads with speed humps. However, the underlying methodology can be adapted for use in other road typologies. These proposed congestion levels offer a more nuanced and insightful approach to evaluating congestion at speed humps in comparison to a sole reliance on congestion index values. Ultimately, this study plays a pivotal role in identifying congestion levels and categorizing traffic congestion at speed humps, thus serving as a valuable resource for formulating location-specific strategies to mitigate this issue.

2. DATA COLLECTION AND EXTRACTION

To assess traffic congestion caused by speed humps, data was collected from various speed humps located on urban roads divided into 6 lanes in Bhubaneswar, India. Bhubaneswar, categorized as a smart city of tier-II, has a population of approximately 1.5 million. The classification of Indian cities is a ranking system used by the Government of India for various purposes like knowing the population range, the amenities available, along with prices of commodities which helps in assessing the various allowances that are given to government employees. Based on population, as developed by Reserve Bank of India (RBI), there are 6-tiered classification of cities where population greater than 1,00,000 (in 2011 census) is classified as tier-1 city. Similarly, a population of 50,000 to 99,999 (in 2011) is placed in Tier – 2 city. Bhubaneswar is placed in tier – 2 city based on the 2011 census. Tier – 2 cities are the cities where infrastructure and investments are steadily increasing but haven't hit the peak levels yet. Real estate prices usually rise in these markets with sustained development. Presently the population of Bhubaneswar has exceeded 10 lakhs but as per the 2011 census the tiering is classified. Similarly, Government of India has introduced the Smart city concept in 2015 with an aim to promote sustainable and inclusive cities that provide core infrastructure and give a decent quality of life to its citizens, a clean and sustainable environment along with application of 'Smart' Solutions. Based on a competition/selection, various cities were declared as smart cities in 2018, and Bhubaneswar is one of them. The selection of this city was based on its representation of tier-II cities across India, sharing similar demographics. To analyze congestion using congestion indices, details was gathered from the initiation of the slow-down section (the area upstream of speed humps where vehicles begin to decelerate/Start applying brakes) situated about 20 meters ahead of the speed hump, extending to the end of the speed hump. Field data was collected along a 60-kilometer stretch of main roads within an Indian smart city, stemming from NH 16. For this study, the emphasis was placed on selecting the most significant roads. The road surfaces were primarily bituminous pavements, and the data recording periods were characterized by predominantly sunny weather, occasionally featuring partial cloud cover.

Speed data was derived from traffic data that was gathered in the field. The process involved the utilization of two cameras for the purpose of data recording. The configuration of the camera arrangement employed for the data collection is visually depicted in Figure 1 as presented below.

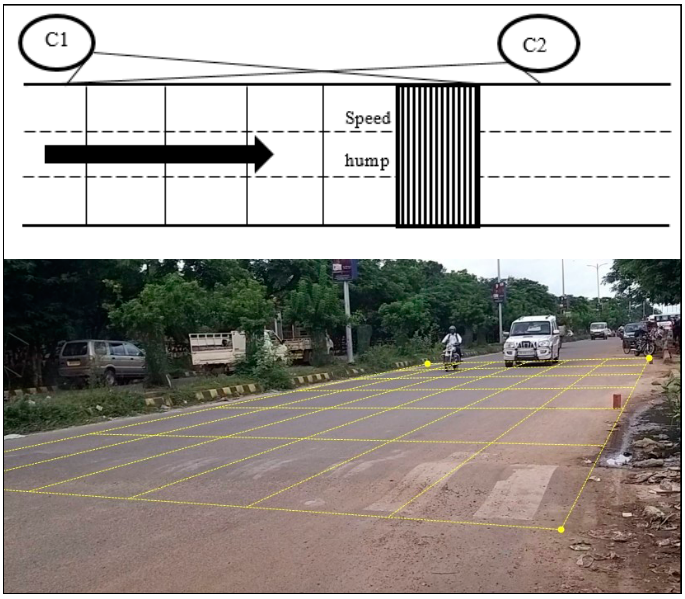

Fig. 1 Arrangement of cameras for the collection of data along with an image capture from one of the specific locations

Four sections, each spanning 5 meters, were designated upstream of the speed humps. Data collection was conducted at various times of the day. The duration for vehicles to traverse these 5-meter segments was recorded, enabling the calculation of speeds for each vehicle. The captured videos were displayed on a monitor using Kinovea, a freely accessible video editing software (Samal et al 2022a; Mohanty et al 2023).

3. CONGESTION INDICES AND METHODOLOGY

The key congestion indices, as outlined in different literature sources (Lyman and Bertini, 2008; Samal et al., 2022b; Mohanty et al., 2023; Samal et al., 2023), are presented below along with their default formulas or expressions.

(1) $Planning\ Time\ Index\ (PTI) = \frac{95th\ Percentile\ Travel\ Time}{Off-Peak\ Travel\ Time}$

(2) $Travel\ Time\ Index\ (TTI) = \frac{Mean\ Travel\ Time}{Off-Peak\ Travel\ Time}$

(3) $Buffer\ Index\ (BI) = \frac{95th\ Percentile\ Travel\ Time - Mean\ Travel\ Time}{Mean\ Travel\ Time}$

However, this study was conducted specifically at speed humps, which required modifying the definitions of congestion indices to align with speed hump characteristics. In this research, average travel times for both the slowdown stretches and the zone within the speed hump were recorded. Additionally, the 95th percentile travel time was computed from the gathered travel time data. The steady and unaffected speed observed beyond 20 meters from the commencement of the speed hump in the upstream route (where the influence of the speed hump is minimal or nonexistent) was applied to determine off-peak travel time. Using the collected data, various congestion indices were computed. The obtained results were then compared with various percentile speeds and a model was formulated to directly obtain the congestion index values without needing travel times. Finally, a range of the indices for various congestion severity levels were identified using clustering technique. Travel times were extracted and computed to ascertain different congestion indices. Subsequently, an array of quantitative and descriptive analyses was utilized to investigate congestion at the speed humps. The study employed two congestion indices, specifically the PTI and TTI, for the assessment of congestion. The Buffer Index (BI) was excluded from consideration in this study since initial calculations indicated that it does not adequately accommodate the variations in 95th and 15th percentile speeds or travel times under extremely excessive and moderate volumes. This discrepancy may arise from the fact that PTI and TTI compare travel times to off-peak or Uninfluenced conditions, in contrast BI compares travel times to the average travel time, potentially leading to bias if there's a significant presence of vehicles moving at slow or high speeds.

It is worth noting that many derived traffic parameters stem from fundamental traffic measures such as speed, flow and density. Traffic congestion indices are deduced from travel time, which indirectly reflects speed. Operating speeds, a crucial metric for assessing traffic flow, have well-documented practical applications in real-world scenarios. Therefore, it is more straightforward to analyze traffic congestion in terms of speed rather than travel time.

Standard speed calculations like 98th, 85th, or 15th percentile values for any given road are imperative for determining lower speed limits, safe speed limits and design speed. Thus, it is logical to associate various congestion indices using percentile speeds. This correlation not only enhances the evaluation of traffic congestion on speed humps but also directly ties it to a fundamental traffic parameter. Notably, the15th percentile speed represents the lower speed limit and the 85th percentile speed signifies the upper speed limit. Around 70% of road users typically adhere to speeds within these percentile ranges. Therefore, if two roads with the same 85th percentile speed exhibit different 15th percentile speeds, or other way around, that exhibit distinct traffic flow conditions. For instance, if road 1 and road 2 have the same 85th percentile speed but 15th percentile speeds of 25 kmph and 20 kmph, respectively, it indicates that road 2 has more vehicles operating at lower speeds, rendering it more susceptible to traffic congestion. Thus, these percentile speeds play a crucial role in congestion assessment.

In this study, clustering techniques were used to classify congestion levels based on percentile speeds. Clustering is a prevalent method for sorting data into a predetermined number of groups, relying on the Euclidean distances between data points (Mohapatra et al., 2012; Mohanty and Dey, 2019; Monteserin., 2018); Boora et al., 2017). Among the clustering techniques, K-means is frequently utilized when dealing with large datasets featuring normally distributed data points. Cluster analysis involves grouping objects based on the data describing their relationships. The goal of clustering is to organize data such that points within the same group are like each other, while being different from points in other groups. In a well-defined cluster, data points are closer to the center of their own group compared to the centers of other groups. An effective clustering method yields clusters where the distance within each cluster (intra-cluster distance) is small, and the distance between different clusters (inter-cluster distance) is large (Jain and Dubes; 1988). Commonly used clustering in traffic engineering includes K-means, K-medoid, and hierarchical agglomerative methods. In this study, K-means clustering was employed to group data points. SPSS software was utilized for both cluster analysis and validation. K-means clustering is an unsupervised hard partitioning method used to address classification problems (Mohapatra and Dey; 2015). The K-means method uses within-cluster variation to form homogeneous clusters. Specifically, it aims to segment data such that the variation within each cluster is minimized. The clustering process begins by randomly assigning objects to different clusters. These objects are then repeatedly reassigned to other clusters to minimize within-cluster variation, measured as the squared distance from each observation to the center of its associated cluster. If reassigning an object to a different cluster reduces the within-cluster variation, the object is moved to that cluster (Sarstedt and Mooi; 2014). In K-means clustering, the number of clusters must be predetermined by the researcher, or it can be determined using hierarchical clustering methods. However, K-means generally outperforms hierarchical methods as it is less sensitive to outliers and irrelevant clustering variables. Additionally, K-means is well-suited for very large datasets following a normal distribution, as it is computationally less demanding than hierarchical methods (Sarstedt and Mooi, 2014; Kanungo et al., 2002). They also recommend using the K-means clustering process for datasets larger than 500. Silhouette could be used to define the number of clusters (K) for clustering analysis (Rousseeuw, 1987). Several studies [Arbelaitz et al., 2013; Pollard and Van der Laan, 2002] have found that the silhouette width index performs well in numerous comparative experiments. Boora et al., (2017) state that an average silhouette value between 0.71 and 1.00 indicates a strong cluster. Additionally, it is important to ensure that the means or centers of these clusters are significantly different from each other at the 5% significance level. Additionally, the clustering process continues until a predetermined number of iterations is reached or convergence is achieved (Sarstedt and Mooi, 201; Jain et al., 1999). Convergence is a crucial aspect of the k-means clustering technique. It occurs when the cluster affiliations no longer change (Jain et al., 1999). Convergence is attained through iterative steps. Initially, SPSS computes the cluster centers based on the predefined number of clusters. Lloyd's algorithm is a well-known heuristic used for k-means clustering (Kanungo et al., 2002; Jain, 2010; Berkhin, 2006]. According to Yadav and Sharma (2013), Loyd's algorithm can be succinctly described in two phases. In the first phase, K centroids are initially chosen randomly, where K represents the number of predefined clusters. In the second phase, each data point in the set is assigned to the nearest centroid based on Euclidean distance. If a data point is closer to another centroid than its initially assigned centroid, the assignment is updated until all data points within a cluster are closest to their cluster's centroid.

A meticulously crafted research methodology is essential for producing dependable and valid outcomes, guaranteeing that research discoveries make a substantial contribution to the existing knowledge within a specific domain. The present investigation employed the research approach outlined in Figure 2.

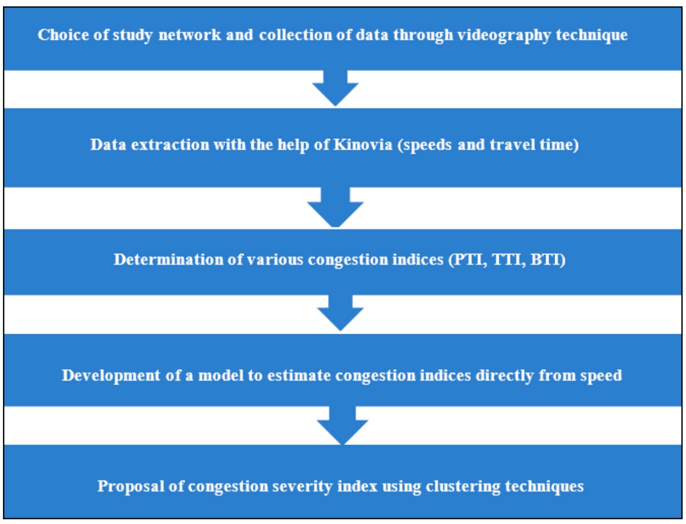

Fig. 2 Flowchart depicting the methodology.

4. RESULTS AND ANALYSIS

Each speed hump on both sides of traffic flow was measured using a measuring tape and leveling staff. The chord length, height, and arc length of each speed hump were recorded. Figure 3 illustrates the definitions of chord length, height, and arc length of speed humps in the context of this study. According to Indian Road congress (IRC) specifications, humps are typically either trapezoidal or circular. However, in the study area, all the speed humps were designed as circular.

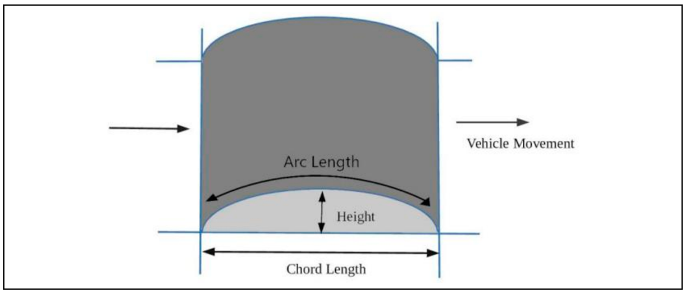

Fig. 3 Speed hump technical specifications

A total of 12 speed humps were identified on the studied road network. The chord lengths and heights of these speed humps are detailed in Table 1 below.

Sl. No.	Chord length (m)	Height (m)
1	1.70	0.07
2	1.97	0.08
3	2.20	0.08
4	1.27	0.08
5	0.98	0.07
6	2.04	0.07
7	2.23	0.10
8	2.25	0.08
9	2.25	0.07
10	1.88	0.08
11	2.15	0.06
12	1.60	0.07
Average	1.88	0.08

Table 1. Geometrical measurement of speed humps

Table 1 shows that the chord length of speed humps ranges from 0.98 m to 2.25 m, with an average chord length of 1.88 m. Similarly, the height of the speed humps varies from 0.06 m to 0.10 m, with an average height of 0.08 m. According to IRC specifications, the minimum chord length for installing speed humps is 3 meters. However, data from Table 1 indicates that the speed humps on the arterial roads are improperly constructed. On average, the chord lengths of all the speed humps are 40 percent shorter than the minimum prescribed length according to IRC 99-2018. For smooth traversal over speed humps, the chord length should be at least 3 meters, which is not the case under current traffic conditions. This discrepancy forces vehicles to decelerate more abruptly, reducing their speed to almost a rolling state, leading to congestion and increased wear and tear on the vehicles and a higher likelihood of rear-end collisions when approaching the speed humps.

Travel times and speed were derived from the captured videos spanning across 12 distinct speed humps. As explained in the 'Data Collection and Extraction' and 'Methodology' sections, the study procured speed and travel time data for analysis. The speed data has been acquired in three separate stages.

1. Uninfluenced speed beyond 20 meters on the upstream of speed hump.
2. Mean, 98th, 85th, and 15th percentile speeds from beginning of slowdown stretches to the commencement of speed hump.
3. Mean,15th, 85th, and 98th cumulative percentile speeds on the speed hump.

Cumulative curves were used to determine the15th, 85th, and 95th, percentile travel times. The time required for vehicles to cover each 5-meter segment in the slowdown section upstream of speed humps is measured, specifically for the distances of 20-15 meters, 15-10 meters, and so on up to the speed hump. For each vehicle approaching the speed hump, travel times for these segments are recorded, tabulated, and sorted in ascending order to identify the minimum and maximum times required to traverse each 5-meter stretch. Next, these travel times are grouped into specific intervals. For example, the travel times for the 20-15 meter segment range from 0.4 to 1.2 seconds, so the time intervals for plotting the cumulative curves are 0.4-0.5 seconds, 0.5-0.6 seconds, 0.6-0.7 seconds, 0.7-0.8 seconds, and so on, up to 1.1-1.2 seconds. The frequency and cumula tive frequency of these occurrences are recorded and used to plot cumulative travel time curves. The data points on the plot represent the midpoints of each time interval group; for instance, the midpoint for the 0.4-0.5 seconds interval is 0.45 seconds, and for the 0.5-0.6 seconds interval, it is 0.55 seconds.

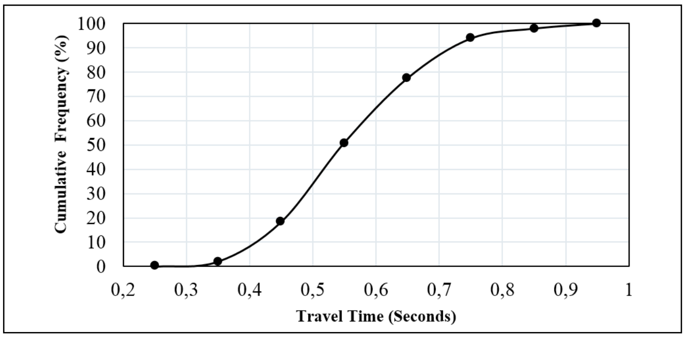

Fig. 4 Cumulative travel time curves at 20-15 m from the upstream of the speed humps

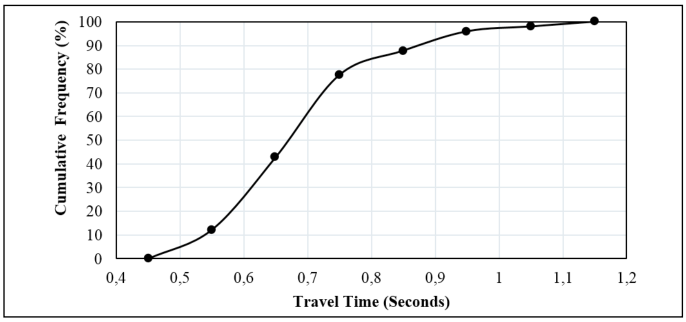

Fig. 5 Cumulative travel time curves at 15-10m from the upstream of the speed humps

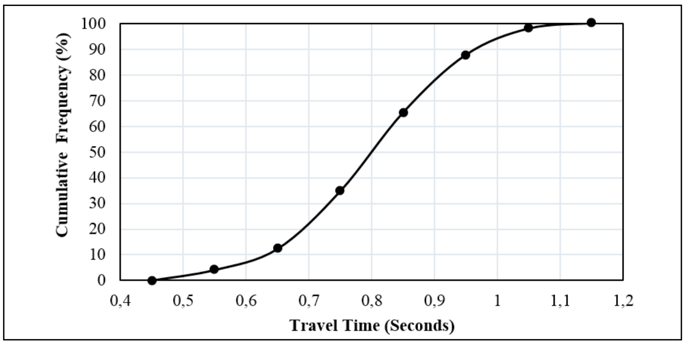

Fig. 6 Cumulative travel time curves at 10-5m from the upstream of the speed humps

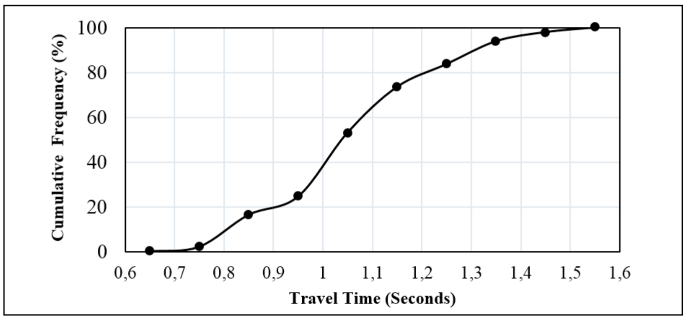

Fig. 7 Cumulative travel time curves at 5m-start of speed humps

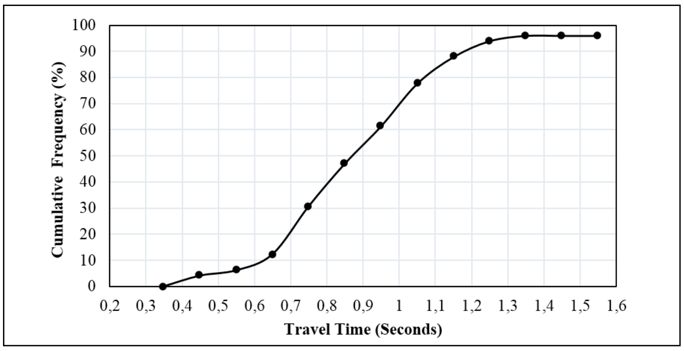

Fig. 8 Cumulative travel time curves on speed humps

In the case of speed humps, it's commonly noticed that vehicles slow down as they approach them. The degree of this deceleration varies based on changes in traffic volume. Irrespective of the volume, a substantial decline in speed occurs even during less busy periods/off-peak periods, mainly due to challenging geometric design. The methodology employed offers a precise and reliable approach to determining traffic congestion index values, as it considers real-world traffic flow parameters at speed humps. The summarized table in Table 2 presents the different travel time indices computed using field data from the commencement of the slowdown section to the onset of the speed humps, as well as on the speed humps themselves.

Distance of the road stretch on the upstream of speed hump	PTI (%)	TTI (%)	BTI (%)
(20-15) m	138	100	38.64
(15-10) m	168.76	123.87	36.23
(10-5) m	179.53	143.62	25
(5m - start of speed humps)	249.55	188.50	32.38
On the speed humps	461	311.6	95.88

Table 2. Travel time indices at speed humps

From Table 2, it is apparent that both congestion indices (PTI and TTI) escalate as vehicles approach the speed humps, experiencing a significant surge in their values while traversing the speed humps. Nevertheless, the degree of increase near the onset of speed humps and on the speed humps may potentially exaggerate congestion compared to the congestion observed upstream of the slowdown section. In this study, speeds were recorded from 70m to start of the speed humps. The data revealed that the vehicles started slowing down from 20 m on the upstream of speed humps. Therefore, the 98th, 85th, and 15th cumulative percentile speed curves are calculated and are presented for various road segments leading up to speed humps, including the unaffected region (road stretch before the deceleration zone), from the beginning of the deceleration zone to the commencement of the speed humps, and on the speed humps themselves. Prior to that, Figure 9 shows the speed variation from 70 m to the start of speed humps. A sudden drop in speed can be observed approximately 20 meters upstream of the speed hump. Subsequently, the identified congestion indices are compared with these speeds to evaluate the extent to which percentile speeds are adequately considered in the existing congestion indices. Figures 10-14 and Table 3 illustrate the diverse cumulative percentile speed curves covering different road segments.

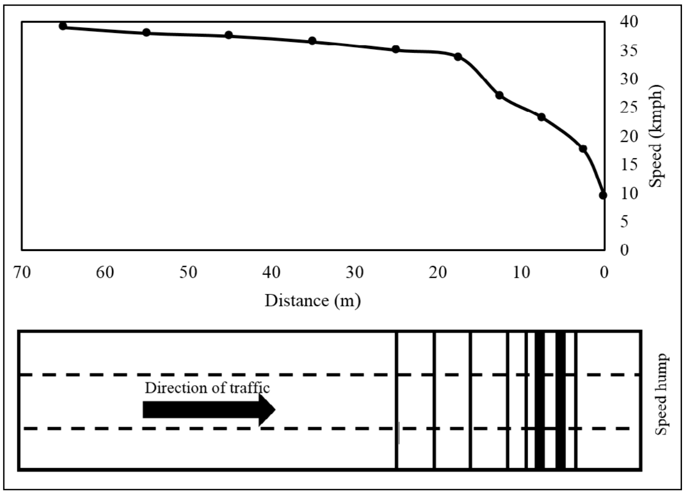

Fig. 9 Speed variation as vehicles approach speed humps

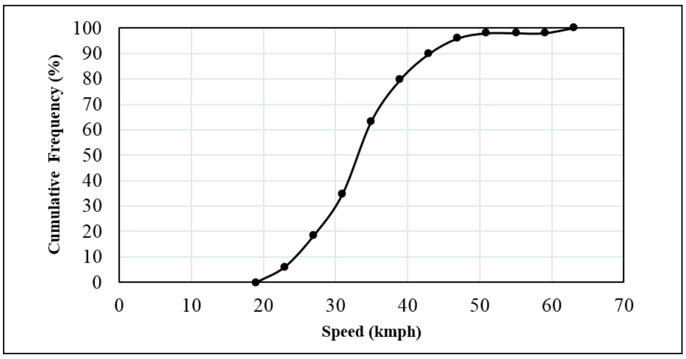

Fig. 10 Cumulative percentile speed curves at 20-15 m from the upstream of the speed humps

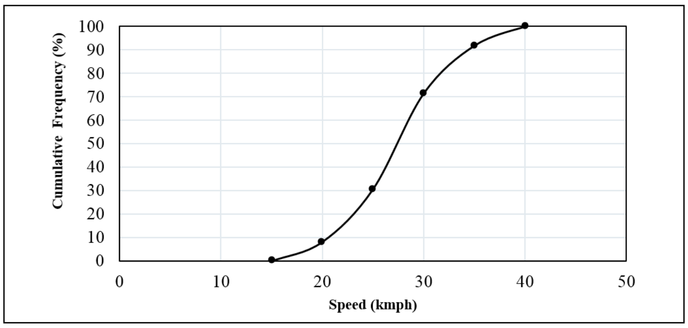

Fig. 11 Cumulative percentile speed at 15-10m from the upstream of the speed humps

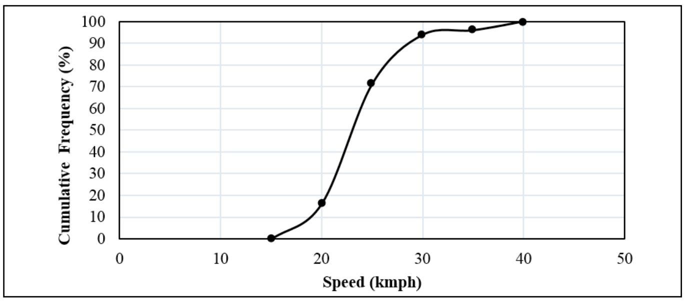

Fig. 12 Cumulative percentile speed at 10-5m from the upstream of the speed humps

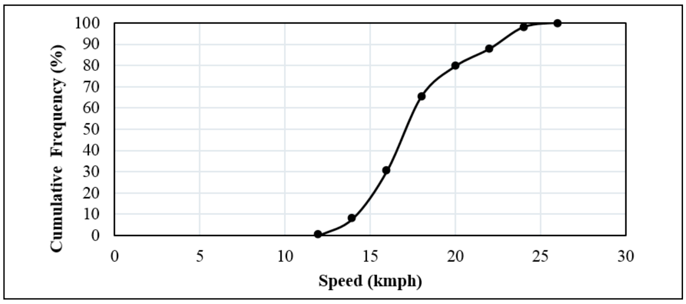

Fig. 13 Cumulative percentile speed at 5m-start of speed humps

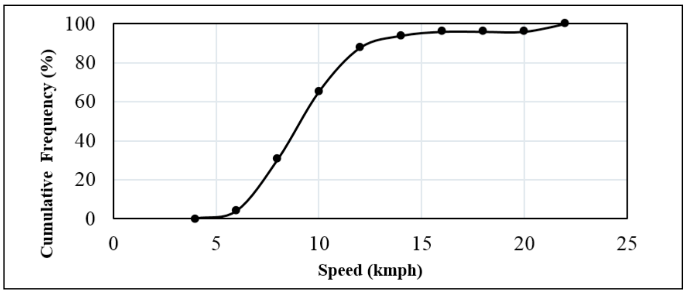

Fig. 14 Cumulative percentile speed on speed humps

Location/Segments	98^{h} Per. Speed	85^{th} Per. Speed	15^{th} Per. Speed
(20-15) m	51	41.3	25.5
(15-10) m	38.1	32.2	21.5
(10-5) m	37	27.2	18.1
(5-Start of speed humps)	24	21.2	15.5
On the speed humps	21	11	6.2

Table 3. Stretch wise 98^{th}, 85^{th}, and 15^{th} Percentile Speeds

The different percentile speeds show a consistent decreasing pattern as vehicles approach the speed humps. These patterns align with the trends observed in the established congestion indices. To investigate if there is any correlation between the PTI, TTI, and the 98th, 85th, and 15th percentile speeds, a Pearson correlation analysis was conducted. The results of this analysis are presented in Table 4.

		98th Per. Speed	85th Per. Speed	15th Per. Speed	PTI (%)	TTI (%)
98th Per. Speed	Pearson Correlation	1	.965**	.913*	-.821*	-.862*
	Sig. (1-tailed)		.004	.015	.044	.030
85th Per. Speed	Pearson Correlation	.965**	1	.986**	-.913*	-.945**
	Sig. (1-tailed)	.004		.001	.015	.008
15th Per. Speed	Pearson Correlation	.913*	.986**	1	-.962**	-.982**
	Sig. (1-tailed)	.015	.001		.004	.001
PTI (%)	Pearson Correlation	-.821*	-.913*	-.962**	1	.996**
	Sig. (1-tailed)	.044	.015	.004		.000
TTI (%)	Pearson Correlation	-.862*	-.945**	-.982**	.996**	1
	Sig. (1-tailed)	.030	.008	.001	.000	

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

Table 4. Pearson correlation among congestion indices and percentile speeds

The results from the Pearson correlation are quite surprising. Interestingly, the PTI and TTI results show a more robust relationship with the 15th and 85th percentile speeds in contrast to the 98th percentile speeds. This suggests that TTI and PTI can be accurately derived straightway from any one of the percentile speeds.

Generalized linear regression equations for estimating the TTI and PTI directly from the percentile speeds are provided below. The table below also includes p-values and R-squared values for the independent parameters. As observed from the equations and their corresponding p-values, the entire established equations are statistically significant at a 95% confidence interval or a 5% significance level. This is because the p-values are below 0.05 in all instances, except for the equation developed for TTI and PTI with the 98th percentile speed. The R-squared values are all more than 0.65 for these equations.

Formulated model	R-Square	p-value
PTI = 542.844 – 8.868*(98^{th} Per. Speed)	0.67	0.088>0.05
PTI = 516.947 – 10.443*(85^{th} Per. Speed)	0.83	0.030<0.05
PTI = 538.657 – 17.240*(15^{th} Per. Speed)	0.93	0.009<0.05
TTI = 378.048 – 5.977*(98^{th} Per. Speed)	0.74	0.060>0.05
TTI = 358.013 – 6.941*(85^{th} Per. Speed)	0.89	0.015<0.05
TTI =369.678 – 11.300*(15^{th} Per. Speed)	0.97	0.003<0.05

Table 5. Utilizing linear regression models for PTI and TTI determination

While average and 95th percentile travel times are typically used to evaluate congestion indices, it's noteworthy that stronger R-squared values are observed when these indices are calculated from 85th and 15th percentile speeds. This emphasizes the capacity to derive congestion indices from speed alone, foregoing the need to calculate travel times. However, it's essential to understand that congestion indices alone might not be sufficient for highly congested scenarios. Therefore, a comprehensive congestion assessment should consider both percentile speeds and congestion indices. The values of the 98th, 85th, and 15th percentile speeds offer insights into the real traffic flow condition at speed hump locations, and the results indicate that these percentile speeds correlate well with congestion indices. In this regard, a congestion severity index can be established based on the values of the 98th, 85th, and 15th percentile speeds, rendering congestion index calculations unnecessary. It's essential to note that this study pertains to 6-lane divided roads, and if applied to other types of roads, a similar methodology should be employed.

In the current study, clustering techniques have been employed to classify levels of congestion according to percentile speeds. In this research, a two-step clustering process is initially executed to determine the optimal number of clusters. Silhouette values, as depicted in Figure 15, are used for this purpose. The obtained silhouette value of 0.9 corresponds to a very strong membership for 4 clusters, which is considered the ideal choice in this context.

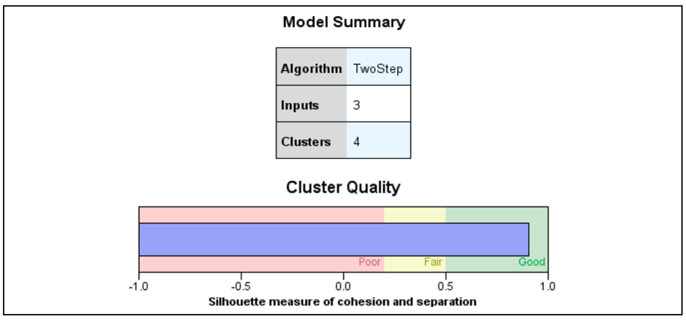

Fig. 15 Silhouette measure for four clusters

Final Cluster Centers				
	Cluster			
	1	2	3	4
98th Per. Speed	51.00	37.55	21.00	24.00
85th Per. Speed	41.30	29.70	11.00	21.20
15th Per. Speed	25.50	19.80	6.20	15.50

Table 6. Ultimate cluster centers obtained from K-means clustering

As depicted in Table 7, when the average speeds for the 98th, 85th, and 15th percentiles in the slowdown section (20-15 meters from the start of the speed humps) exceed 44.23 kmph, 35.5 kmph, and 22.65 kmph, respectively, the flow of traffic can be described as smooth, indicating no congestion. This is categorized as Congestion Level 0. Likewise, if the average 98th percentile speed falls within the range of 30.78-44.23 kmph, the 85th percentile speed is within 25.45-35.50 kmph, and the 15th percentile speed is within 17.65-22.65 kmph, this signifies mildly congested traffic or the initiation of congestion, denoted as Congestion Level 1. Other congestion levels have also been established in accordance with the values of different percentile speeds.

However, in real-world scenarios, it's not always the case that the same speed ranges specified in the proposed congestion severity index will be consistently maintained. These suggested levels are applicable to the speed humps under heterogeneous traffic environment and provide a more comprehensive approach to assessing congestion compared to solely determining congestion index values.

5. CONCLUDING REMARKS

This study aimed to comprehensively assess traffic congestion because of the existence of speed humps on arterial roads in Bhubaneswar, India. The study utilized several congestion indices, including the PTI and TTI, to evaluate congestion at speed humps. To ensure the relevance of these indices for speed humps, the definitions were modified to align with speed hump characteristics. Significantly, the research revealed that traffic congestion is not solely dependent on these indices. The study introduced a novel perspective by emphasizing the role of percentile speeds (98th, 85th, and 15th percentiles) in assessing congestion. It was observed that these percentile speeds exhibit a strong correlation with congestion indices, and they can even be used to predict congestion directly. The study employed clustering techniques to classify levels of congestion according to percentile speeds. Four distinct congestion levels were proposed, each associated with specific speed ranges. This approach provides a more comprehensive assessment of congestion, especially when different percentile speeds fall into different congestion levels.

In the present study, data collection involved video surveys encompassing all vehicle categories. Various speed parameters, including the 98th, 85th, and 15th percentile speeds, were computed. The assessment of traffic congestion at speed humps was carried out by modifying and applying travel time reliability metrics, namely the PTI and the TTI. The obtained PTI and TTI were correlated with the 98th, 85th, and 15th percentile speeds. It was observed from developed linear regression equations that the congestion indices showed more closeness with the 15th and 85th percentile speeds (R-square values of 0.97, 0.93, 0.89, 0.84) as compared to 98th percentile speeds (0.74, 0.67), based on their R-square values. Even the equations had better R-square with 15th percentile speed (0.97, 0.93) as compared to 85th percentile speeds (0.89, 0.84) showcasing the sensitivity of congestion more towards 15th percentile speeds. This correlation facilitated the development of a congestion severity index with distinct ranges. To categorize these congestion levels, the study employed the K-means clustering technique. The congestion severity index was developed in accordance with the values of the 15th, 85th and 98th and percentile speeds. This index allows for the easy determination of congestion on any speed humps without the necessity of using traditional congestion indices. The clustering analysis resulted in the establishment of values and ranges for all clusters, which pertain to different percentile speeds. The study proposed four congestion severity levels, designated as Level 0 (representing No Congestion), Level 1 (indicating Mild Congestion), Level 2 (signifying Moderate Congestion), and Level 3 (representing Severe Congestion), all based on the 98th, 85th, and 15th percentile speeds. These proposed congestion levels are intended to be applicable to all 6-lane divided roads with speed humps, offering an improved approach to congestion assessment compared to merely calculating congestion index values. This study aids in identifying and classifying traffic congestion at speed humps, which, in turn, can assist in devising location-specific strategies to alleviate the issue. It is important to note that while this study focused on 6-lane divided roads, the methodology and findings can be adapted for application on other types of roads, providing a versatile approach to assessing congestion and improving road infrastructure. The results of this study contribute to the body of knowledge on traffic congestion and offer a valuable framework for future research and practical application in urban road planning and management. The proposed congestion severity index offers a more detailed understanding of congestion levels, allowing for better-informed decision-making in traffic management and road design. Further, the study also reveals that the root cause for congestion is due to the geometrically faulty speed humps. Therefore, the study can inspire the traffic engineers and practitioners to adopt more stringent guidelines for constructing speed humps. Various technological advancements can also be utilized like the sensors to measure the average speed and then warn road users about congestion ahead due to speed humps.

98th Per. Speed (kmph)	85th Per. Speed (kmph)	15th Per. Speed (kmph)	Congestion severity level	Remarks
> 44.23	>35.50	>22.65	0	No Congestion
30.78-44.23	25.45-35.50	17.65-22.65	1	Mild Congestion (Drivers not able to maneuver on speed humps at desired speed)
22.50-30.77	16.10-25.44	10.85-17.64	2	Moderate Congestion (Discomfort with reduced speeds while maneuvering over speed humps)
<22.50	<16.10	<10.85	3	Severe Congestion (Vehicles moving at excessively less speeds near and over speed humps)

Table 7. Congestion Index according to clustering approach

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