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DEVELOPING A SPEED-BASED CONGESTION SEVERITY INDEX USING THE CLUSTERING TECHNIQUE FOR DEVELOPING COUNTRIES

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Resume

A novel approach for traffic congestion assessment has been presented using percentile speeds as key indicators, focusing on urban roads. By evaluating the 98th, 85th, and 15th percentile speeds, authors of the research developed a congestion severity index, offering a more precise and intuitive method for analyzing traffic flow compared to traditional travel time-based indices. Key congestion indices, such as the Planning Time Index (PTI) and Travel Time Index (TTI) were compared to percentile speeds, revealing a significant association with the 15th and 85th percentile speeds. The K-means clustering technique was applied to classify congestion severity into three levels, validated by a high silhouette value indicating the robust clustering. The study's speed-based congestion severity index provides a practical and efficient framework for real-time congestion management, particularly in heterogeneous traffic environments.

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1 Introduction

Traffic congestion is a growing concern globally, affecting both developed and developing countries. The rapid increase in vehicular traffic, coupled with insufficient infrastructure, has led to excessive delays for road users, negatively impacting economic productivity, environmental sustainability, and public health. The development of any country, particularly a nation like India, heavily relies on its transportation infrastructure. With the rapid rise in vehicle numbers, the current road infrastructure is struggling to handle the increased traffic demand, resulting in widespread congestion [1-5]. In developing countries, traffic congestion has become a major challenge for road users. Typically, congestion occurs when current traffic demand surpasses the capacity of existing roadways. This not only extends the travel time, but also negatively impacts human health, contributing to a deteriorating traffic environment [6-8]. The rise in population, the increasing number of vehicles, and the migration of people from rural to urban areas are the primary factors contributing to traffic congestion [9]. Traffic congestion increases driver stress, which can lead to road accidents [10]. Faulty traffic infrastructure, especially in developing countries, such as poorly designed speed humps, an abundance of three-wheelers, and reckless driving behavior, all contribute to prolonged congestion [11-17]. Due to congestion, the Level of Service (LOS) of the road decreases drastically during the peak hours [18]. Understanding the congestion dynamics is crucial for effective traffic management, as it helps implement targeted measures to reduce congestion, enhancing both road safety and traffic flow.

Traditional methods of assessing congestion, such as the Planning Time Index (PTI) and Travel Time Index (TTI), primarily focus on travel times. While these indices provide useful insights, they may not fully capture the complexities of urban traffic, particularly in heterogeneous environments like those found in many Indian cities. Congestion indices, such as TTI and PTI, are widely used around the world to evaluate traffic congestion [19-23]. Despite its fundamental importance, speed has not been directly factored into the

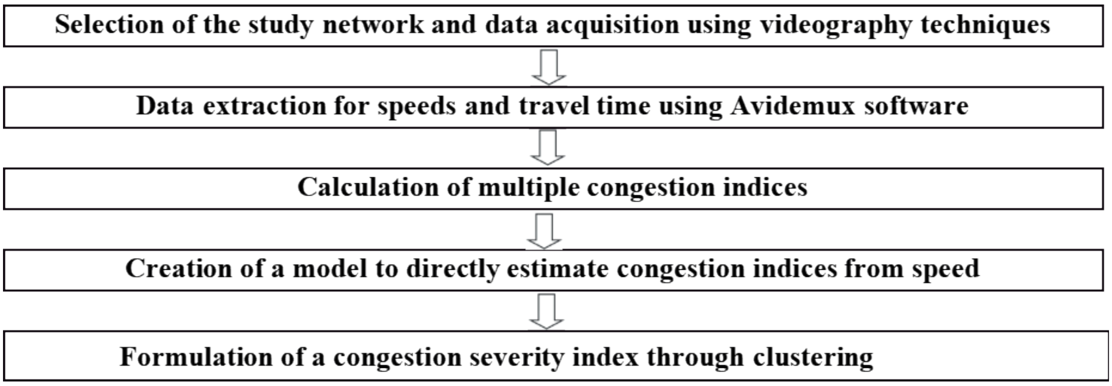

Figure 1 *Flowchart illustrating the research framework*

calculation of congestion indices, while the speed affects travel times, essential for determining these indices. The traditional method relies on average and off-peak travel times, as well as the 95th percentile travel time, neglecting the 15th percentile speed. This 15th percentile speed is particularly significant as it reflects the speeds of the slowest vehicles in the traffic flow, making it a vital indicator of congestion. In this study, clustering techniques were utilized to categorize levels of congestion based on percentile speeds. Clustering techniques were extensively employed to categorize the severity congestion intensity. Clustering is a common technique used to organize specified data into groups, depends on the Euclidean distances between the input information [24-29].

In this study is introduced an alternative approach to evaluating traffic congestion by leveraging percentile speeds, specifically the 98th, 85th, and 15th percentiles, as more direct indicators of congestion severity. By analyzing the speed data, the research aim was to develop a congestion severity index that provides a more intuitive and accurate reflection of traffic flow conditions. In the study are also compared the traditional congestion indices to the speed-based metrics, finding that the 15th and 85th percentile speeds have a stronger correlation with congestion than the 98th percentile. Additionally, K-means clustering is employed to classify congestion into distinct levels, further enhancing the practicality of this speed-based approach for real-time congestion management. This novel methodology offers an enhanced ideas of urban traffic dynamics and serves as a valuable strategy for alleviating congestion in cities with complex traffic patterns.

2 Study framework

The framework is a critical component of any research for achieving the desired results. The current study follows the approach outlined below, as illustrated in Figure 1.

3 Selection of the road network and data collection

To evaluate the traffic congestion, data was collected from various arterial roads. Bhubaneswar, recognized as a tier-II smart city featuring a population of approximately 1.5 million, was chosen for its representation of tier-II cities across India, sharing similar demographic characteristics. The study was focused on selecting the most critical roads for analysis. The road surfaces were mainly bituminous pavements, and the data collection took place during mostly sunny weather, with occasional partial cloud cover.

The speed data and travel time data were obtained from field-recorded videos. Cameras were used for recording data at different times of the day. The time it took for vehicles to cross specific road segments was tracked, allowing for the calculation of their travel time and speeds. The recorded videos were reviewed on a monitor using Avidemux, a free video editing software, and the necessary data, such as the 15th, 85th, and 98th percentile speeds, along with average, 95th percentile, and off-peak travel times, were calculated during this process to meet the study's objectives.

4 Congestion indices

The primary congestion indices, as highlighted in several literature sources are listed below along with their standard formulas or expressions.

Planning Time Index = 95^{th} Percentile Travel Time/Off-Peak Travel Time (1)

Travel Time Index (TTI) = Mean Travel Time/Off-Peak Travel Time (2)

Buffer Time Index (BTI) = (95^{th} Percentile - Mean Travel Time)/Mean Travel Time (3)

This study was conducted specifically at mid-block sections under a heterogeneous traffic environment, necessitating modifications to the definitions of congestion indices to suit the study's characteristics. In this research, average travel time, 95th percentile travel time, and off-peak travel time were calculated from the collected travel time data. Based on this data, various congestion indices were computed, and the results were compared to different percentile speeds. A model was then developed to directly estimate congestion index values without relying on travel time data. Finally, a range of congestion index values corresponding to different severity levels was identified using a clustering technique.

5 Results and discussions

Travel times and speeds were derived from the captured videos. As detailed in the "Data Collection and Research Framework" sections, speed and travel time data were gathered for analysis. Key metrics such as the 15th, 85th, and 98th percentile speeds, as well as average, 95th percentile, and off-peak travel times, were estimated and used for further analysis.

These travel times were extracted and analyzed to determine various congestion indices. A combination of quantitative and descriptive analyses was then applied to investigate the traffic congestion. The study focused on three key congestion indices: the Planning Time Index (PTI), the Travel Time Index (TTI), and the Buffer Time Index (BTI), to assess the level of congestion.

The methodology used provides an accurate and dependable means of assessing the traffic congestion by considering real-world traffic flow parameters. The summarized data in Table 1 outlines the various congestion indices calculated using the field data.

The study utilized two congestion indices, namely the PTI and TTI, for assessing congestion levels. The Buffer Time Index (BTI) was omitted from this analysis because initial calculations revealed that it does not sufficiently account for variations in the 95th and 15th percentile travel times throughout both extremely high and moderate traffic volumes. This limitation may stem from the fact that the PTI and TTI relate travel times to off-peak or-free flowing conditions, while the BTI compares travel times to the average travel time. This could introduce bias, particularly in scenarios where there is a significant number of vehicles traveling at either slow or high speeds.

It is important to recognize that many traffic metrics are derived from fundamental parameters like speed, flow, and density. Congestion indices, for instance, are typically based on travel time, which serves as an indirect indicator of speed. Among these factors, operating speed is a critical measure for evaluating the traffic flow and has well-established practical applications in real-world traffic analysis. Given the direct relationship between the speed and congestion, it becomes simpler and more intuitive to assess and analyze traffic congestion using speed data rather than relying on travel time. This is because speed offers a more immediate reflection of traffic conditions, enabling a clearer and more efficient evaluation of congestion levels.

Standard speed calculations, such as the 15th, 85th, and 98th percentile values for a given road, are essential for establishing lower and upper speed limits, as well as determining the design speed. These percentile values serve as benchmarks for safe driving speeds and help guide speed limit policies. Therefore, it is logical to correlate various congestion indices with percentile speeds, as this enhances the overall evaluation of traffic congestion, particularly in areas more susceptible to congestion, by linking it directly to fundamental traffic parameters. For example, the 15th percentile speed is typically used to define the lower speed limit, while the 85th percentile speed represents the upper limit. This range is crucial because around 70% of road users generally drive within these speeds, making them a reliable indicator of traffic behavior. When the two roads have similar 85th percentile speeds but differ in their 15th percentile speeds, this discrepancy reveals differences in traffic flow conditions. Consider two roads, Road 1 and Road 2, both of which have an 85th percentile speed of 38 km/h. However, Road 1 has a 15th percentile speed of 22 km/h, whereas Road 2 has a 15th percentile speed of 11 km/h. This difference suggests that a larger proportion of vehicles on Road 2 travel at lower speeds, indicating heavier congestion or more variability in vehicle speeds. Thus, despite having the same 85th percentile speed, Road 2 is more prone to congestion because more vehicles are operating at reduced speeds. Percentile speeds, particularly the 15th and 85th, are therefore essential in congestion assessment. They not only highlight the variability in traffic flow across different road segments, but also help to identify areas where congestion is more likely to occur. Roads with significant gaps between these two percentile values may exhibit greater congestion issues, as they suggest a broader range of vehicle operating speeds and, potentially, a higher number of slower-

Table 1 *Congestion indices for the selected road network*

Stretch	PTI (%)	TTI (%)	BTI(%)
Stretch 1	200.10	171.50	34.29
Stretch 2	182.23	147.81	26.30
Stretch 3	170.00	126.89	37.66
Stretch 4	140.09	102.91	40.01

***Table 2** Percentile speeds (98th, 85th, and 15th) for different road stretches, [km/h]*

Stretch	98th	85th	15th
Stretch 1	23.9	21.1	15.05
Stretch 2	36.8	27.1	17.90
Stretch 3	38	31.90	21
Stretch 4	50.90	40.80	25.40

***Table 3** Pearson correlation between percentile speeds and congestion indices*

		98th Per. Speed	85th Per. Speed	15th Per. Speed	TTI (%)	PTI (%)
98th Per. Speed	Pearson Correlation	1	0.951**	0.910*	-0.857*	-0.811*
	Sig. (1-tailed)		0.003	0.014	0.030	0.045
85th Per. Speed	Pearson Correlation	0.951**	1	0.973**	-0.944**	-0.910*
	Sig. (1-tailed)	0.003		0.001	0.008	0.014
15th Per. Speed	Pearson Correlation	0.910*	0.973**	1	-0.979**	-0.960**
	Sig. (1-tailed)	0.014	0.001		0.001	0.004
TTI (%)	Pearson Correlation	-0.857*	-0.944**	-0.979**	1	0.986**
	Sig. (1-tailed)	0.030	0.008	0.001		0.000
PTI (%)	Pearson Correlation	-0.811*	-0.910*	-0.960**	.0986**	1
	Sig. (1-tailed)	0.045	0.014	0.004	0.000	

** Significant at 5% significance level
* Significant at 10% significance level

moving vehicles. By associating congestion indices with these percentile speeds, the evaluation becomes more accurate and meaningful, offering a direct link between the congestion severity and key traffic speed parameters.

In this study, the 15th, 85th, and 98th cumulative percentile speed curves were computed for several road stretches. These curves represent the speed distribution across different percentiles of vehicles on the road. After determining these percentile speeds, the identified congestion indices were compared to them, to assess how well the current congestion indices reflect these key speed percentiles. In addition to this comparison, in the study is introduced a novel method of evaluating traffic congestion using percentile speeds, which led to the creation of a congestion severity index, a new metric designed to quantify congestion based on speed variations. Table 2 presents a visual summary of the cumulative percentile speed curves, showcasing the differences observed across various road stretches. This approach helps to better understand how speed distribution relates to congestion, offering a more precise means of evaluating road performance in terms of congestion levels.

The analysis of different percentile speeds, i.e., 98th, 85th, and 15th, reveals a consistent decreasing trend as traffic volume increases. This pattern corresponds to the expected behavior observed in established congestion indices. To further explore the relationship between these percentile speeds and the congestion indices, a Pearson correlation analysis was conducted, specifically examining the correlation between the congestion indices (TTI and PTI) and the 98th, 85th, and 15th percentile speeds. The Pearson correlation analysis assesses the strength and direction of the linear relationship between the congestion indices and the speed percentiles. The results, summarized in Table 3, offer insights into whether there is a statistically significant connection between these variables, helping to understand how well the congestion indices are aligned with the percentile speeds. This correlation helps to validate the effectiveness of percentile speeds in reflecting traffic congestion levels.

The results from the Pearson correlation analysis yielded some unexpected findings. Notably, the PTI and TTI exhibited a significant association with the 15th and 85th percentile speeds, contrasted to the 98th percentile speeds. This observation indicates that TTI and PTI can be effectively estimated directly from either the 15th or 85th percentile speeds, suggesting that these two percentile speeds offer more accurate insights for congestion evaluation than the 98th percentile speed. This highlights the practical utility of focusing on these speeds when assessing the congestion levels.

Table 4 presents the generalized linear regression equations for estimating TTI and PTI directly from the percentile speeds, along with the associated p-values and R-squared values for each independent parameter. As shown, each equation shows statistical significance at a 95% confidence interval (or 5% level of significance), as the p-values for the models are below 0.05 under every instance, except for the equations related to TTI and PTI when using the 98th percentile speed. This

***Table 4** Applying linear regression models for estimating TTI and PTI*

Developed model	p-value	R-Square
TTI = 366.036 - 5.865 X (98th Per. Speed)	0.064 > 0.05	0.75
TTI = 349.011 - 6.831 X (85th Per. Speed)	0.014 < 0.05	0.86
TTI =358.615 - 10.907 X (15th Per. Speed)	0.004 < 0.05	0.96
PTI = 532.833 - 8.767 X (98th Per. Speed)	0.078 > 0.05	0.66
PTI = 511.943 - 10.243 X (85th Per. Speed)	0.040 < 0.05	0.84
PTI = 527.645 - 17.143 X (15th Per. Speed)	0.008 < 0.05	0.91
X represents multiplication		

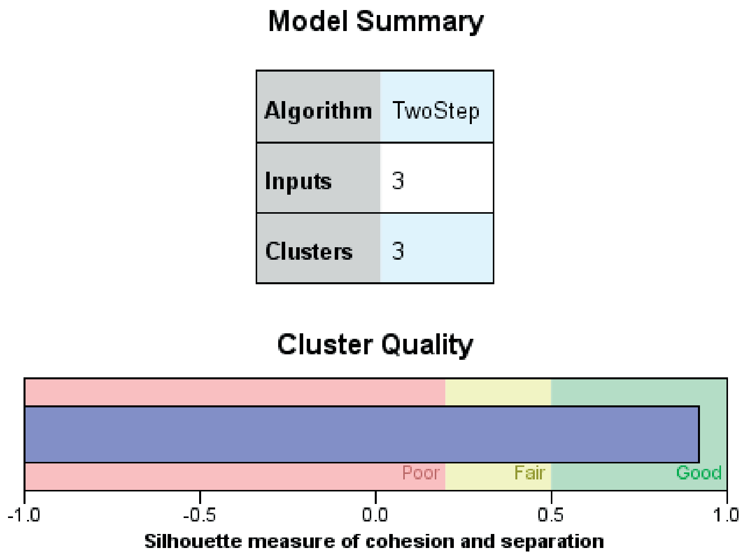

***Figure 2** Silhouette metric for clusters*

indicates that the relationship between TTI, PTI, and percentile speeds is significant, except in the case of the 98th percentile speed. Additionally, the R-squared values for these equations are all above 0.65, implying that the models explain a considerable proportion of the variability in the data, making them reliable for predicting congestion indices from percentile speeds.

While average and 95th percentile travel times are commonly used to evaluate congestion indices, it is significant to note that stronger R-squared values are observed when these indices are derived from the 85th and 15th percentile speeds. This finding highlights the potential to estimate congestion indices based solely on speed data, eliminating the need to calculate travel times. However, it is important to recognize that relying solely on congestion indices may not provide a complete picture, especially in scenarios with severe congestion. A comprehensive congestion assessment should incorporate both percentile speeds and congestion indices to accurately reflect traffic conditions. The values of the 98th, 85th, and 15th percentile speeds provide valuable insights into actual traffic flow patterns. The results indicate a strong correlation between these percentile speeds and congestion indices. In light of this, a congestion severity index could be developed using the values of the 98th, 85th, and 15th percentile speeds, effectively making traditional congestion index calculations redundant. This approach allows for a more direct and efficient assessment of traffic congestion levels.

In this study, clustering techniques were applied to classify the congestion levels according to percentile speeds. Clustering is a widely used method for grouping data points into a specified number of clusters by evaluating the Euclidean distances between them. The K-means algorithm, commonly used for large datasets with normally distributed data, was selected for this research. It divides the dataset into a predetermined number of clusters (K), based on the Euclidean distance, a method of calculating the straight-line distance between the two points between data points. The algorithm assigns each point to the nearest cluster center (called a centroid), and this process is repeated iteratively until the centroids stabilize, ensuring that each point is placed in the most suitable cluster. The challenge with K-means, however, lies in selecting the correct number of clusters (K). To address this, the study adopted a two-step clustering process. A two-step clustering approach was first employed to identify the optimal number of clusters. The first step involves an algorithm that can estimate the optimal number of clusters based on the input data, rather than pre-defining the number.

Once the optimal number of clusters is identified, the K-means algorithm is applied in the second step to finalize the clustering. After the clustering is performed, the quality of these clusters are validated with the help of silhouette values. A silhouette value measures how similar a data point is to its assigned cluster compared to other clusters. Silhouette is used for interpretation and validation of the internal consistency of data within a cluster [28]. Previous studies [24, 29] have concluded that silhouette could be used to define the number of clusters (K) for clustering analysis. A few studies [28-29] identified that silhouette width index performed well in many comparative experiments. The silhouette value ranges from -1 to 1, with higher values indicating well-defined clusters where the data points are closer to their assigned cluster center and farther from other clusters. In this analysis, the high silhouette value (0.89 as shown in Figure 2) demonstrates that the percentile speed data were effectively grouped, confirming the accuracy and reliability of the clustering process. For traffic engineers, this validation holds significant practical value. By ensuring that the clusters represent distinct congestion levels, engineers can confidently interpret the results and apply them to real-world scenarios. Additionally, a robust clustering approach ensures that the proposed congestion severity index can be effectively used to prioritize interventions, allocate resources, and design the traffic management strategies that address specific congestion challenges. The high silhouette value thus reinforces the applicability of the methodology in assisting traffic engineers to make data-driven decisions aimed at improving traffic flow, enhancing road safety, and minimizing the environmental and economic impacts of congestion.

In the present study, high silhouette value of 0.89 suggests that three clusters provide the best representation for the data in this context. In this research, silhouette values were calculated to determine the quality of clustering, with a particular focus on identifying how well data points were grouped. As shown in Figure 2, the obtained silhouette value was 0.89, which is considered very high. A value of 0.89 indicates that the clusters are well-separated, meaning that the data points within each cluster are highly similar, while the points across clusters are quite distinct. This level of clarity and separation suggests a robust clustering outcome. The analysis determined that three clusters provide the most accurate and meaningful classification of congestion levels based on the percentile speed data. The silhouette value of 0.89 signified that three clusters best represented the dataset, ensuring a precise and reliable classification system for congestion severity, which can guide traffic management and decision-making in real-world scenarios.

Table 5 presents the final cluster centers, which is the direct output from the clustering analysis. The values from Table 5 have been utilized to define the ranges for congestion severity index, which is provided in Table 6. Table 6 illustrates the traffic conditions based on the average speeds of the 98th, 85th, and 15th percentiles for a specific road segment. When these average speeds exceed 44.15 km/h, 35.15 km/h, and 22.43 km/h, respectively, the traffic flow is considered smooth, indicating that there is no congestion. This situation is classified as Congestion Level 0. Conversely, in the case where the mean speed of the 98th percentile falls between 44.15 km/h and 30.65 km/h, the 85th percentile speed ranges from 35.15 km/h to 25.30 km/h, and the 15th percentile speed is between 22.43 km/h and 17.25 km/h, the traffic is categorized as mildly congested. This scenario marks the onset of congestion and is designated as Congestion Level 1. Finally, when the average speeds

Table 5 *Final cluster centers derived from K-means clustering.*

	Cluster Centers		
	1	2	3
98th Per. Speed	50.90	37.40	23.9
85th Per. Speed	40.80	29.50	21.1
15th Per. Speed	25.40	19.45	15.05

Table 6 *Congestion Index formulated through clustering*

98th Per. Speed (km/h)	85th Per. Speed (km/h)	15th Per. Speed (km/h)	Level of congestion severity	Remarks
> 44.15	>35.15	>22.43	Level 0	Free-flowing traffic/Uncongested roads
44.15-30.65	35.15-25.30	22.43-17.25	Level 1	Reasonable Traffic Flow/Mild-to-Moderate Congestion (Road users unable to operate at their desired speed)
<23.90	<21.10	<15.05	Level 2	Overwhelming traffic/Extreme traffic congestion (Vehicles traveling at significantly reduced speeds)

for the 98th, 85th, and 15th percentiles drop below 23.90 km/h, 21.10 km/h, and 15.05 km/h, respectively, it signifies a state of extreme traffic congestion. In this case, the traffic flow can be described as overwhelming, indicating a severe level of congestion.

In the real-world conditions, it is unlikely that the exact speed ranges specified in the proposed congestion severity index will always be maintained consistently. The suggested speed thresholds are tailored for heterogeneous traffic environments and offer a more holistic approach to assessing congestion. This method goes beyond relying solely on congestion index values, providing a more nuanced evaluation of traffic flow and congestion levels by accounting for the variability in traffic patterns. Consequently, these levels present a practical framework for understanding and managing congestion in diverse traffic conditions.

The present study introduces an innovative approach to traffic congestion assessment by utilizing percentile speeds - specifically the 98th, 85th, and 15th percentiles - as direct indicators of congestion severity. Unlike the traditional methods that rely on travel times (e.g., TTI and PTI) and neglect critical speed variations, in this method the 15th percentile speed was highlighted as the key metric reflecting the slowest vehicles, offering a more comprehensive view of congestion.

Using the K-means clustering, congestion levels were categorized into distinct groups based on speed data, providing a practical framework for real-time traffic management. The findings demonstrate stronger correlations between the 15th and 85th percentile speeds and congestion severity compared to traditional indices, showcasing the superiority of this speed-based methodology in capturing urban traffic dynamics, particularly in heterogeneous environments.

6 Conclusion

In this study, a novel framework is proposed for the traffic congestion assessment using percentile speed metrics, specifically the 98th, 85th, and 15th percentiles, to develop a congestion severity index. Applied to urban roads in Bhubaneswar, India, the research highlights the limitations of traditional congestion indices like the Travel Time Index (TTI) and Planning Time Index (PTI) in isolation and emphasizes the predictive power of percentile speeds.

The summary of key findings are as follows.

- Percentile Speed Metrics for Congestion Assessment: The 98th, 85th, and 15th percentile speeds were identified as reliable indicators of traffic congestion, surpassing traditional indices like TTI and PTI in precision
- Correlation and Sensitivity: Strong correlations were observed between the 15th and 85th percentile speeds and congestion indices, with the 15th percentile speed showing the highest sensitivity.
- Clustering and Congestion Levels: K-means clustering revealed three congestion levels with clear speed thresholds:
  - ❑ Smooth Traffic: Speeds > 44.15 km/h (98th), 35.15 km/h (85th), 22.43 km/h (15th).
  - ❑ Moderate Congestion: Speeds in intermediate ranges.
  - ❑ Severe Congestion: Speeds < 23.90 km/h (98th), 21.10 km/h (85th), 15.05 km/h (15th).
- Congestion Severity Index: A robust severity index was developed using percentile speed data, providing a simpler and more intuitive approach for congestion evaluation.
- Practical Implications: This framework eliminates reliance on complex travel time data, making it highly suitable for heterogeneous traffic environments and real-world traffic management.

This approach offers a practical, intuitive alternative to traditional travel time-based methods, particularly in heterogeneous traffic environments, facilitating efficient traffic management and policy-making.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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