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Towards Sustainable Transport: An Analysis of Urban Mobility in Hyderabad, Telangana Using Uber Movement Data

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Abstract

Cities worldwide face traffic congestion, challenging sustainable development and requiring insight into its dynamics, dispersion, and stability. Effective traffic management is pivotal for fostering sustainable urban mobility and enhancing quality of life. Leveraging Uber movement data, this study examines travel times and speeds across Hyderabad over a four-year span from 2016 to 2019. Congestion and friction indices from travel time matrices, along with network analysis, gauge urban accessibility, revealing similar magnitudes of Congestion and Travel Time Delay Transition Indices for inbound and outbound traffic within specific intervals. Notably, there is an inverse proportional relationship between these two indices. The Congestion Index values indicate that most zones experience significant traffic jams, while the Travel Time Delay Transition Index was calculated to affirm its inverse relationship with the Congestion Index. Employing fractal geometry, the study delves into the spatial complexity of the network and its correlation with urban growth parameters, contributing to sustainable urban planning efforts. Furthermore, the fractal dimension value obtained from the Mass-Radius method is 1.6955, with a correlation coefficient of 0.99, indicating a high degree of linearity between the road network and friction index. Results underscore the intricate interplay between traffic congestion, macroeconomic factors, and urban form, highlighting the imperative of integrating sustainability principles into transportation policies. By leveraging readily available Uber movement data, this research provides a comprehensive assessment of citywide traffic conditions, offering valuable insights for crafting sustainable transportation management strategies aimed at mitigating congestion and promoting equitable access to mobility.

Keywords

fractal geometry, congestion and friction indices, sustainable urban mobility

1 Introduction

A sustainable transportation network plays a pivotal role in fostering economic growth within a region (Fazio et al., 2014). Such networks, characterized by well-organized and efficiently designed structures, enhance accessibility, thereby reducing travel time and costs (He et al., 2016). However, in urban street networks, challenges arise in understanding the ramifications of policy implementations (Kiunsi, 2013). Over time, alterations to existing road networks shape both land use patterns and travel demand within an area (Rao and Rao, 2016).

The evaluation of road network analysis methods encompasses a diverse set of approaches aimed at comprehensively assessing road network structure, functionality, and efficiency. Various methods such as shape grammar rules, graph theory, shortest path matrix, geo-morphology, and fractals have been employed for this purpose (Aryandoust et al., 2019; Ataiwe et al., 2012; Morency and Chapleau, 2003; Sreelekha et al., 2017; Wang et al., 2017). Each method has its strengths and limitations, and the choice of method depends on the specific objectives and requirements of the analysis. While numerous studies focus on assessing fundamental structural measures such as connectivity, accessibility, morphology, and density of transportation networks (Aryandoust et al., 2019), the interrelationship among these parameters often remains unexplored, highlighting a research gap in urban road network planning.

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Accurate travel time estimates are crucial for urban commuters, enabling effective trip planning and navigation (Mahona et al., 2019). Even in developing countries where transportation infrastructure development may be slow, travel time estimates play a significant role across various transport services (Sreelekha et al., 2017). In India, for instance, public transport fleets are increasingly equipped with GPS tracking devices, providing real-time trip data that is made publicly accessible (Uber Technologies Inc., 2016). Additionally, there exist proprietary travel-time datasets owned by companies like Google and Uber, sourced from a combination of user inputs and crowd-sourced data from map users, cab passengers, and drivers (Dumbliauskas et al., 2017). These diverse datasets enable travel-time estimation through historical and trend analysis, employing various prediction algorithms (Sun et al., 2020). Subsequently, these estimates are utilized by different transport services, such as predicting bus or cab arrival times, or calculating overall trip durations through navigation apps like Google Maps (Liu et al., 2015).

In 2016, Uber introduced "UBER MOVEMENT", a website designed to harness Uber's ride data for the benefit of urban planners seeking to enhance urban and traffic management decisions (Pearson et al., 2017). The Uber Movement website offers access to zone-to-zone travel time data, including arithmetic and geometric means, as well as standard deviations, for census tracts and Traffic Analysis Zones (TAZ's) across numerous cities. Kumar and Singh (2023) have used Uber Movement data from 2016 to 2019 in New Delhi, employing Python-based techniques like big data analytics, machine learning, and time series forecasting to predict travel times and conduct spatial analysis, offering valuable insights for urban planning and human mobility analysis. Roy et al. (2020) utilizes Uber Movement data from 2016 to 2019 for the Miami metropolitan area, employing harmonic analysis to examine peak travel times and spatial clustering of Uber trips, revealing patterns that align with major transit routes.

The study aims to achieve several objectives. Firstly, it intends to evaluate the urban fabric by measuring the accessibility of the road network. Secondly, it seeks to analyze the spatial complexity of the road network using Fractal geometry. Thirdly, the study aims to identify the most and least accessible zones in the study area through network analysis and travel time analysis. Additionally, it aims to develop travel time profiles within the study area. Furthermore, the study plans to conduct temporal analysis of accessibility parameters utilizing the friction index, congestion index, and fractal dimension. Lastly, it aims to characterize urban traffic conditions by leveraging Uber Movement data.

This study aligns with the sustainable development goals (SDG's) and contributes to creating more sustainable and resilient cities by providing data-driven strategies to optimize traffic flow and reduce congestion, thereby supporting the development of safer, more inclusive urban transport systems. The study's recommendations for expanding public transportation and promoting mixed-use development emphasize the importance of building resilient infrastructure and fostering innovation in urban environments. Additionally, by addressing the environmental impact of traffic congestion and advocating for smarter infrastructure investments, this study plays a critical role in mitigating climate-related challenges. The study not only underscores its contribution to urban sustainability but also positions itself as part of a broader effort to achieve sustainable development.

2 Assumptions in the study

Following are the assumptions framed in the study.

2.1 Use of ward centroids for visualizing the friction index

In this study, the centroids of the wards (the geometric centers of the wards) are used as reference points for visualizing the friction index on thematic maps. This assumption simplifies the spatial analysis by treating each ward as a single point, allowing for a more straightforward computation of travel times between zones.

2.2 Assumption of zero travel time within the same ward

For the purposes of this study, the travel time between locations within the same ward is assumed to be zero. This is based on the premise that the distance between the centroids of a ward and itself is zero, leading to an implied travel time of zero. While this assumption simplifies the calculation and is reasonable for large-scale spatial analyses, it should be recognized that, in reality, some travel time is required even within the same ward, especially in larger or more densely populated wards. However, for the purpose of this study, this assumption allows for a clear and consistent comparison of travel times across different wards.

2.3 Idealization of missing travel times

In cases where travel time data between certain zones is missing, the study idealizes these travel times using a ratio based on the shortest physical distance between the zones and an assumed average velocity. Specifically, the mean velocity is assumed to be 60 km/h, which is typical for sub-arterial roads. This assumption allows for the estimation of missing data points in a way that is consistent with the overall traffic conditions assumed for the study area. The choice of 60 km/h reflects the standard speed limit and typical driving conditions on sub-arterial roads, making it a reasonable estimate. However, it should be noted that actual speeds may vary depending on factors such as traffic congestion, road conditions, and time of day, which could introduce some variability into the travel time estimates.

3 Methodology and data analysis

In this study, the selection criteria for Uber Movement data were carefully considered to ensure the relevance and accuracy of the analysis. The geographical scope was determined by selecting specific cities and regions characterized by varying levels of population density and traffic congestion, providing a comprehensive overview of different urban contexts. The temporal range focused on key periods, such as peak traffic hours and weekdays, to capture critical patterns in congestion. Data resolution, including both hourly and daily intervals, was chosen to align with the study's objectives, ensuring a detailed examination of traffic dynamics. However, it is important to mention the potential biases in the data. Uber Movement primarily reflects rideshare trips, which may not fully represent the travel behavior of the entire population, particularly in areas with lower rideshare adoption. Additionally, the aggregated nature of the data could obscure individual trip details or outlier behaviors, potentially affecting the findings. The study also has limitations, including the exclusion of other modes of transportation which may influence the overall assessment of traffic congestion. Moreover, the urban bias inherent in Uber Movement data, which is more prevalent in densely populated areas, may limit the generalizability of the results to non-urban regions.

In this study, the accessibility of wards within Hyderabad city, Telangana state, India is examined using the friction index derived from the mean travel-time matrix spanning four consecutive years, starting from 2016, leveraging data available from Uber. This analysis focused on factors influencing variations in traffic flow patterns, assessed through impedance based travel time parameters such as the travel time-delay transition index (TD_TI) and congestion index (CI) adopted by Mahona et al. (2019). The transition index measures the ease with which vehicles navigate through a given Comprehensive Traffic Plan, reflecting impedance effects. Low index values indicate high impedance and consequently, traffic congestion, while high values suggest free flow. Two methods were employed to estimate the fractal dimension of urban areas: the box counting method implemented in Harfa, and the mass-radius method computed within a GIS environment. These approaches facilitated a comprehensive understanding of urban mobility dynamics and their spatial complexities within the study area.

Hyderabad, the capital of Telangana, India, sprawls over 650 square kilometers along the Musi River, boasting a population of approximately 6.9 million within the city limits and 9.7 million in the Hyderabad Metropolitan Region. The location of Hyderabad in India is shown in Fig. 1. Spanning 7,257 square kilometers, the Hyderabad Metropolitan Development Authority encompasses seven districts, 70 mandals, and 1,032 villages. Additionally, it includes the Greater Hyderabad Municipal Corporation, housing 175 villages and 12 municipalities/nagar panchayats. The GHMC organizes planning and development activities into corporation zones, circles, and wards, with a total of 150 wards within Hyderabad. However, Uber's dataset covers 145 wards, providing invaluable insights for urban planning and transportation management analysis and decision-making processes.

Uber Movement's Travel Times solution offers cities average travel time computations between two defined "zones" within a region, specifying time and date. This data is categorized into quarters over several years. For this study, travel time data was sourced from the Uber Movement database, focusing on "Travel times by day of the week" for the years 2016, 2017, 2018, and 2019. The collected dataset comprises source ID, destination ID, mean travel time,

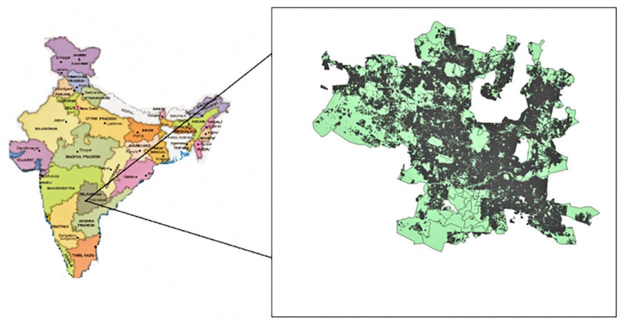

Fig. 1 Study area showing location of Hyderabad in India

mean standard deviation, geometric travel time, and geometric standard deviation. The methodological framework adopted in the study is shown in Fig. 2. The framework for data sources and analytical tools used in the study has been indicated in Fig. 3. The methodology is structured into three modules to facilitate comprehensive analysis:

1. Determination of friction index
2. Determination of congestion index and travel timed delay transition index
3. Determination of fractal dimension.

3.1 Friction index

In Module I of the study, the determination of the friction index involved several phases. Firstly, the study area was delineated based on geographical considerations and data availability. Subsequently, traffic analysis zones (TAZs) were defined within the region, with centroids serving as zone markers. Travel time data was collected from the Uber Movement database, focusing on travel times by day of the week for the years 2016 to 2019. This data encompassed various parameters such as mean travel time and standard deviation. To generate an Origin-Destination (O-D) travel time matrix, mean travel times were aggregated in a matrix format, representing accessibility between different zones. The friction index, indicating the accessibility of each zone relative to others, was calculated based on the total travel times for each zone. The maximum total travel time across all zones determined the denominator for the friction index calculation. This index was then utilized to analyze the accessibility of various zones over the four-year period, with higher values indicating lower accessibility. Finally, the results were visualized using choropleth and heat maps in QGIS to depict variations in accessibility across the study area.

Friction index signifies the accessibility of a particular zone/ward with respect to all the other zones by analysing the times taken to travel across the zones. The Friction Index helps urban planners understand the relative

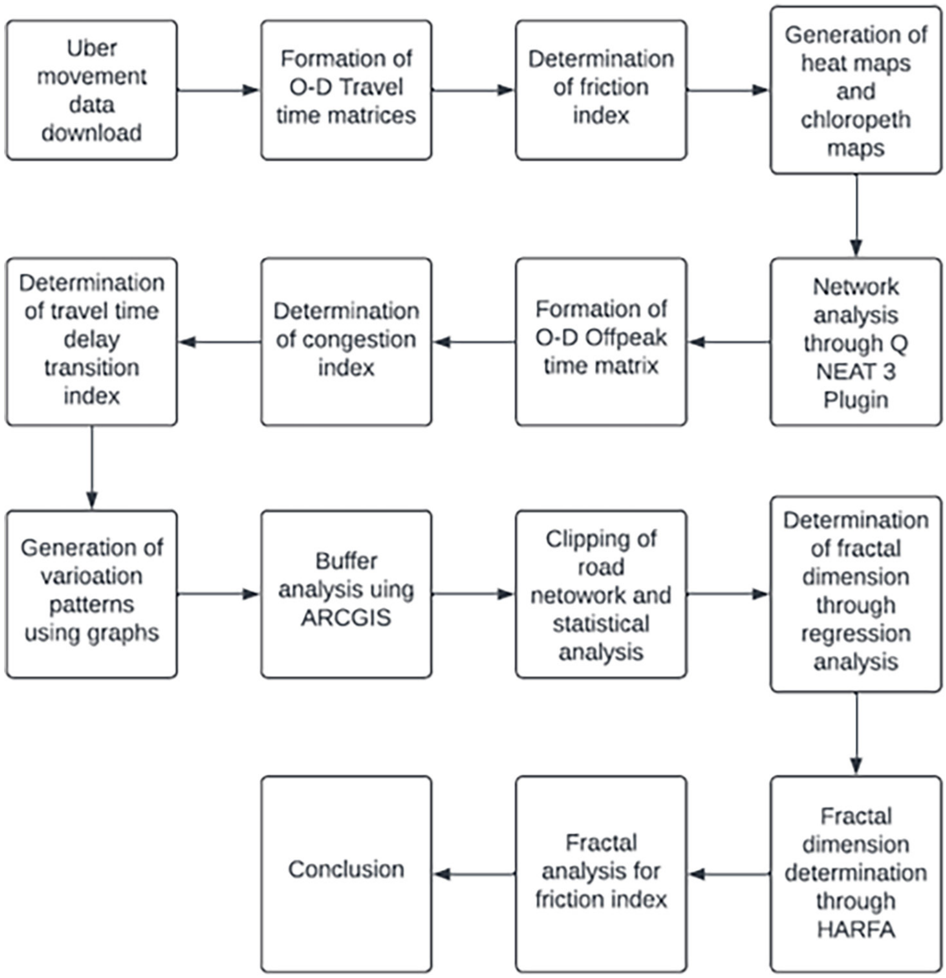

Fig. 2 Diagrammatic representation of the methodological framework

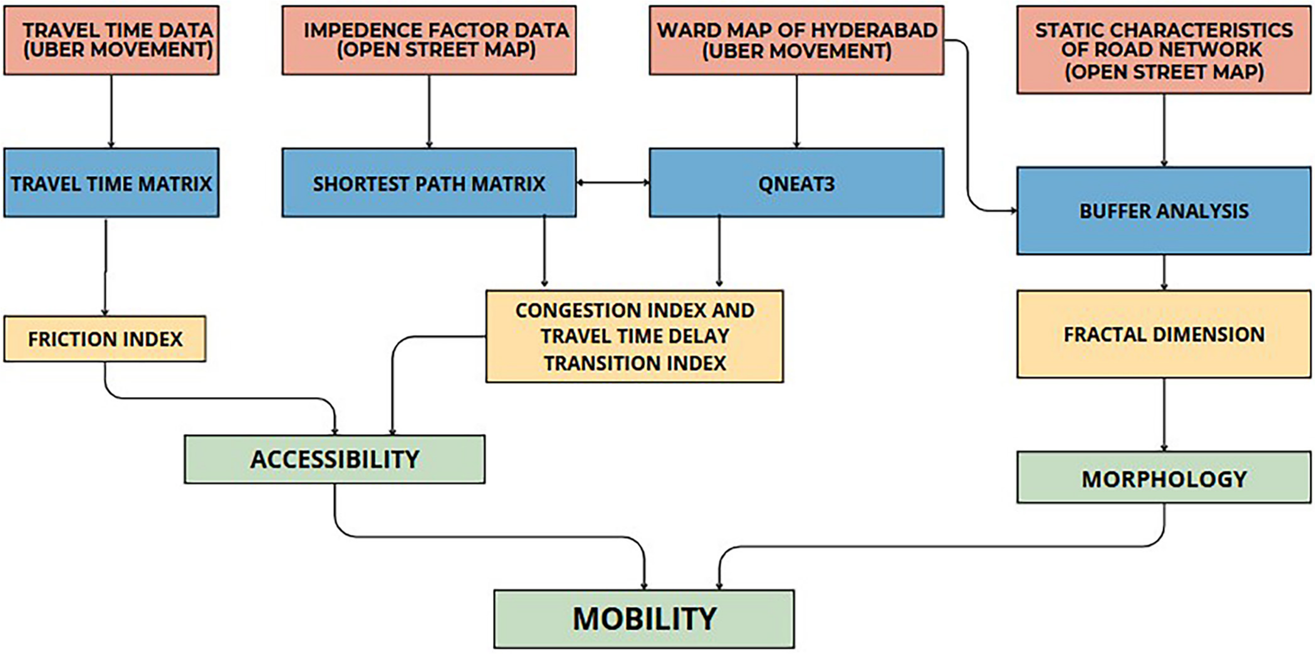

Fig. 3 Framework of data sources and analytical tools utilized

accessibility of different zones within a city. A high friction index indicates that a zone is relatively isolated in terms of travel times, while a low friction index suggests that a zone is well-connected and more easily accessible. This measure is crucial in identifying areas that may need infrastructure improvements or better connectivity to reduce travel times and enhance overall accessibility.

$$\mathrm{FI} = \sum A_i / A_{\max}$$

Where FI is the value of Friction Index for a particular zone i. It represents how accessible zone i is compared to other zones, based on travel times.

$\sum A_i$ = sum of total travel times for zone i. It is calculated by summing up the travel times to and from zone $i = \sum A_i$ row + $\sum A_i$ column.

$\sum A_i$ row = Sum of travel times from zone i to all other zones.

$\sum A_i$ column = Sum of travel times from all other zones to zone i.

$A_{\max}$ = maximum value of total travel times among all the zones. It serves as a normalization factor in the formula.

By dividing $\sum A_i$ by $A_{\max}$ the friction index FI is scaled between 0 and 1. The higher the friction index, the lower the accessibility. The variation has been represented through heat maps using QGIS in Fig. 4. The most and least accessible zones over the years have been found and are given in Table 1.

Zone 133 is Talab Chanchalam and zone 37 is Chandanagar. Heatmaps generated represents the variation in accessibility for all the zones, which help private sectors to decide and invest on properties in highly accessible areas and also for government in increasing the accessibility for the less accessible zones.

3.2 Congestion index and travel time delay transition index

The methodology employed in this study focused on analyzing Travel Time Delay (TD) data to derive Travel Time - Delay Transition Index (TD_TI) and Congestion Index (CI). The study area, comprising the urban road network of Hyderabad in Telangana, was delineated to include both arterial and sub-arterial roads catering to daily intra-urban movements. The concentration of government offices and private organizations in the central business district (CBD) exacerbated traffic congestion, leading to discomfort, delays, and resource wastage for commuters residing in the peripheries. Phase 1 involved network analysis in QGIS to generate an Origin-Destination (O-D) shortest distance matrix using Dijkstra's algorithm. Phase 2 focused on creating an O-D free flow time matrix by dividing the shortest distance matrix by a standard speed of 60 km/h. Phase 3 consisted of data collection from primary sources, emphasizing the identification of the urban road network and the collection of inbound and outbound traffic data for a 4-year period. Phase 4 involved the manual digitization

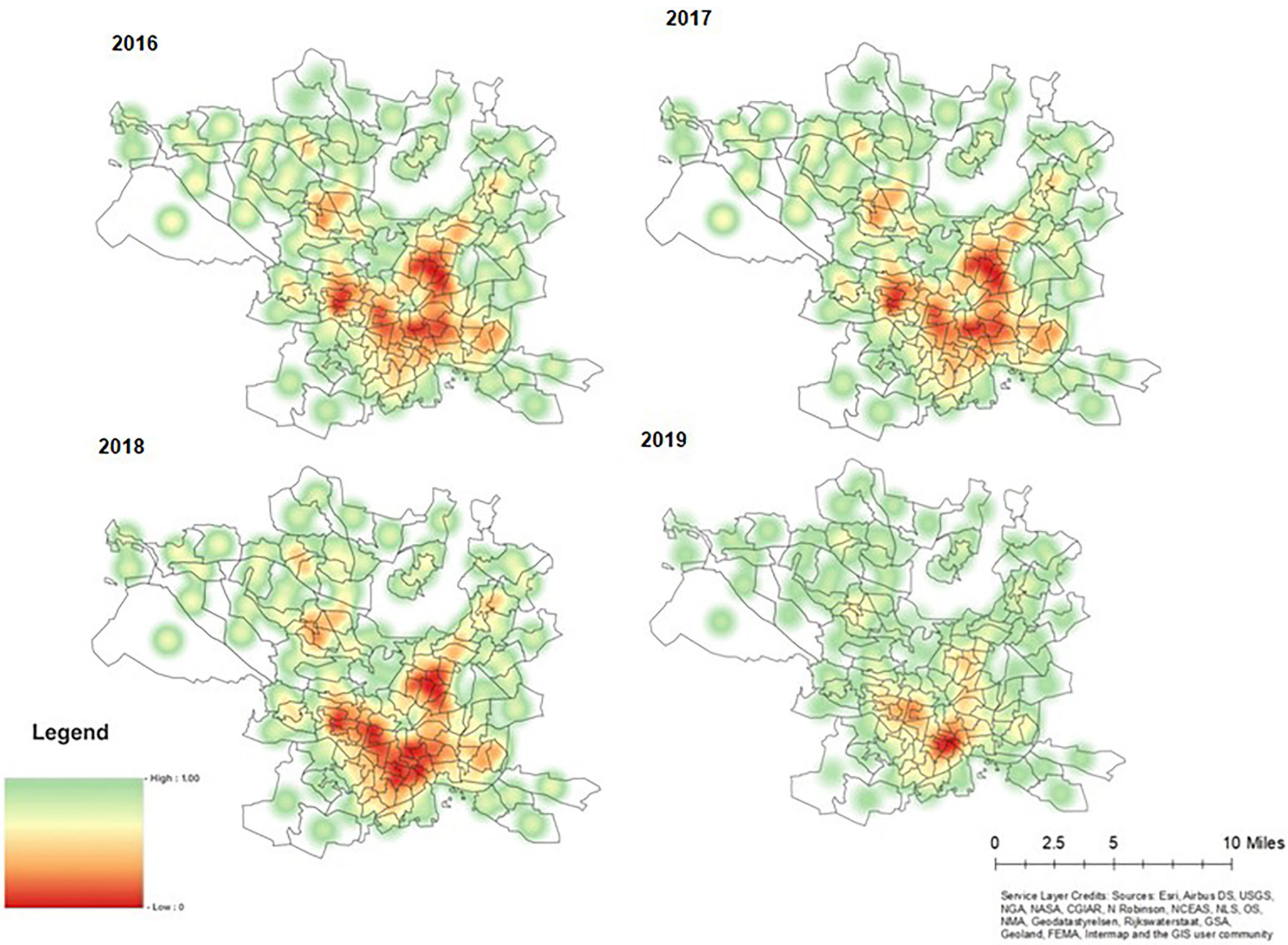

Fig. 4 Heat maps showing the variation of friction index from 2016 to 2019

Table 1 Most and least accessible zone

Year	The most accessible zone	The least accessible zone
2016	53	38
2017	133	37
2018	133	37
2019	72	37

of collected data to calculate Travel Time Delay Index (TD_TI) and Congestion Index (CI) for each travel direction. Phase 5 entailed the calculation of the Congestion Index using the formula (average travel time − free flow time) / free flow time, while Phase 6 involved computing the Travel Time Delay Transition Index using the formula free flow time / average travel time. Average Travel Time is the typical time it takes to travel between two points under current traffic conditions. Free Flow Time is the time it would take to travel the same distance without any traffic, typically under ideal conditions. Phase 7 focused on studying the indices, attributing low TD_TI values and high CI values to factors such as incoming and outgoing roads, bus stops, T-junctions, traffic lights, and road humps along the urban road network.

$$\text{Congestion Index (CI)} = (\text{average travel time} - \text{free flow time})/(\text{free flow time})$$

$$\text{Travel Time Delay Transition Index (TD\_TI)} = \text{free flow time}/\text{average travel time}$$

The range of values of congestion index and travel time delay transition index is shown in Table 2.

The graph showing the variation of Congestion index for the most and least accessible zones for 2017 is shown in Figs. 5 and 6.

The graph showing the variation of Travel time delay Transition index for the most and least accessible zones for 2017 is shown in Figs. 7 and 8.

The observations across the four years highlight distinct traffic patterns between the least and most accessible zones is shown in Table 3.

In 2016, Movement ID 38, representing the least accessible zone, exhibited a Congestion Index of −0.0008 for both inbound and outbound traffic, with corresponding Travel Time Delay Transition Indices of 0.0001 and 0.0002, indicating minimal congestion and stable traffic

Table 2 The range of values of TD_TI and CI with their Interpretations (Source: Mahona et al. (2019))

Traffic flow state	Stabilization of driving	Remarks of TD_TI values	Remarks of CI values
Free flow	Good	0.70 < TD_TI	CI ≤ 0.50
Crowded flow	Bad or alarming situations	0.40 < TD_TI ≤ 0.70	0.50 < CI ≤ 1.00
Jam flow	Depend on the vehicle on the front	TD_TI ≤ 0.40	CI

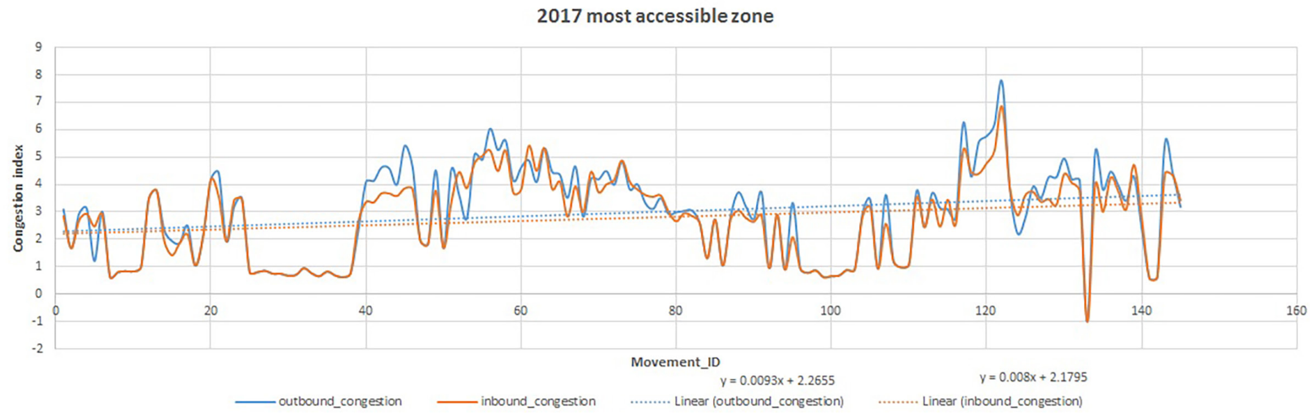

Fig. 5 Variation of congestion index for the most accessible zone

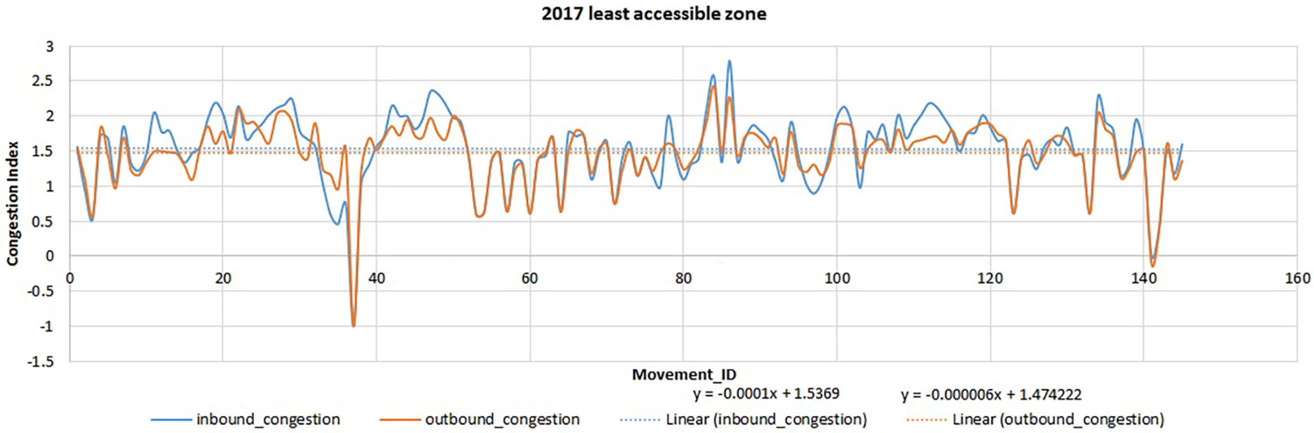

Fig. 6 Variation of congestion index for the least accessible zone

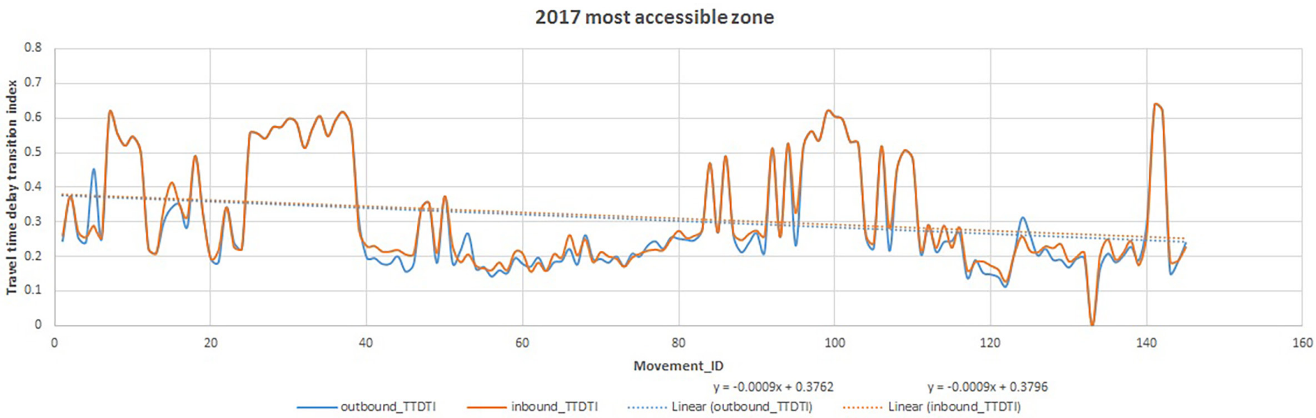

Fig. 7 Variation of travel time delay transition index for the most accessible zone

conditions. Conversely, the most accessible zone, represented by Movement ID 53, showed significantly higher Congestion Index values of 0.0103 (inbound) and 0.0116 (outbound), with negative Travel Time Delay Transition Indices of −0.001 and −0.0011, suggesting severe congestion with diminishing impacts on travel time delays.

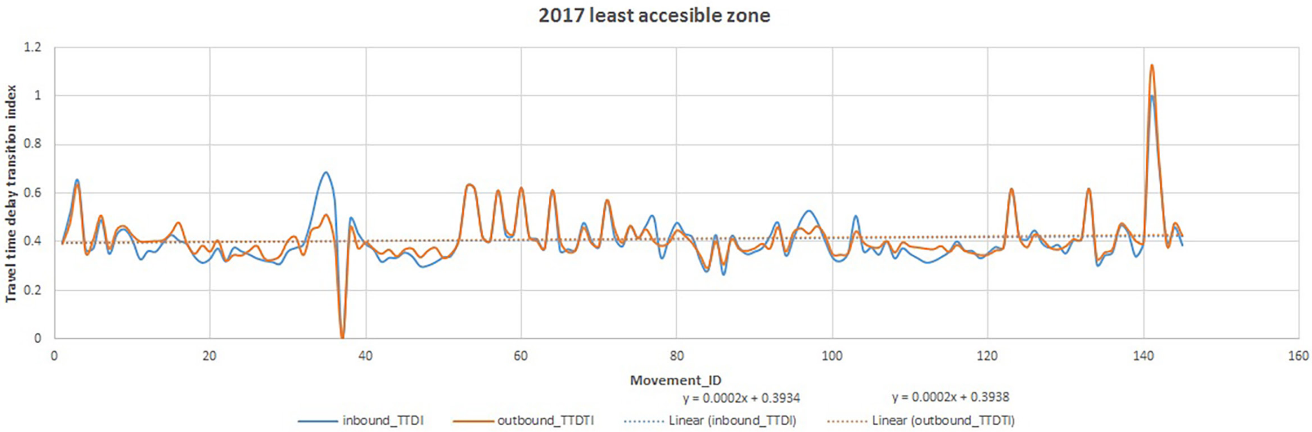

Fig. 8 Variation of travel time delay transition index for the least accessible zone

Table 3 Variation of congestion index and travel time delay transition index for the years 2016, 2017, 2018 and 2019

Year	Movement	Least accessible zone			Most accessible zone		
		Movement ID	Congestion index	Travel time delay transition index	Movement ID	Congestion index	Travel time delay transition index
2016	Inbound	38	−0.0008	0.0001	53	0.0103	−0.001
	Outbound		−0.0008	0.0002		0.0116	−0.0011
2017	Inbound	37	−0.0001	0.0002	133	0.008	−0.0009
	Outbound		0.000006	0.0002		0.0093	−0.0009
2018	Inbound	37	0.00007	0.0001	133	0.0086	−0.001
	Outbound		0.0005	0.0001		0.0118	−0.0011
2019	Inbound	37	−0.0004	0.0003	72	0.0044	−0.0004
	Outbound		0.0003	0.0003		0.004	−0.0003

In 2017, Movement ID 37, representing the least accessible zone, continued to show low Congestion Index values of −0.0001 (inbound) and 0.000006 (outbound), with Travel Time Delay Transition Indices remaining stable at 0.0002. Meanwhile, Movement ID 133, representing the most accessible zone, recorded Congestion Index values of 0.008 (inbound) and 0.0093 (outbound), again paired with negative Travel Time Delay Transition Indices of −0.0009, reflecting persistent congestion.

The pattern persisted in 2018, with Movement ID 37 showing slight changes in the least accessible zone, recording Congestion Indices of 0.00007 (inbound) and 0.0005 (outbound), and consistent Travel Time Delay Transition Indices of 0.0001. The most accessible zone, still represented by Movement ID 133, showed Congestion Index values of 0.0086 (inbound) and 0.0118 (outbound), with negative Travel Time Delay Transition Indices of −0.001 and −0.0011, respectively.

In 2019, Movement ID 37 in the least accessible zone showed a Congestion Index of −0.0004 (inbound) and 0.0003 (outbound), with both directions having Travel Time Delay Transition Indices of 0.0003. Meanwhile, the most accessible zone, now represented by Movement ID 72, showed slightly lower Congestion Index values of 0.0044 (inbound) and 0.004 (outbound), with negative Travel Time Delay Transition Indices of −0.0004 and −0.0003, respectively. Overall, these findings indicate that least accessible zones experience minimal congestion, with stable traffic conditions, while most accessible zones consistently suffer from severe congestion, necessitating targeted interventions to manage traffic effectively.

The study's findings reveal that the Congestion Index and Travel Time Delay Transition Index are consistent across both inbound and outbound traffic, suggesting stable traffic patterns. The key insight is the inversely proportional relationship between these indices: as congestion increases, the relative change in travel time delay decreases. This indicates that zones with high congestion may have reached a saturation point, leading to "jam flow" conditions, where additional traffic causes minimal further delays.

The prevalence of jam flow across most zones highlights significant congestion issues, signaling that many areas are operating near maximum traffic capacity. The Travel Time Delay Transition Index shows that in less congested zones, small increases in traffic lead to significant delays, suggesting that congestion management could be highly effective. In contrast, heavily congested zones may require more intensive interventions, like infrastructure upgrades or advanced traffic management systems. For urban planners and policymakers, these results underscore the importance of tailored congestion mitigation strategies based on zone-specific congestion and delay dynamics.

3.3 Fractal analysis

Fractal measures, when integrated with other analytical tools, offer a fresh perspective on various issues pertaining to the focal points of interest. In this study, fractal analysis has been conducted using the mass-radius method. Log-log graphs have been generated to ascertain the fractal dimension across different entities, including the road network and friction index, revealing their evolution over time. The findings from these graphs are outlined below in Figs. 9 and 10.

The mass dimension quantifies the relationship between the area enclosed within a given radius and the size of that radius (or box), considering multiple radii and points of origin (Dasari and Gupta, 2020). It is estimated from the log-log plot of the area as a function of the radius.

In this study, the fractal dimension obtained through the Mass-Radius method is 1.6955, with a high correlation coefficient of 0.99, indicating a well-defined linear relationship in the traffic congestion patterns. When compared with other cities, distinct variations in fractal dimension values can be observed. For example, studies in China have reported a fractal dimension of around 1.85 (Sun et al., 2012), reflecting the city's complex and highly congested road network. On the other hand, Dallas exhibits a lower fractal dimension, between 1.1 and 1.5 (Lu and Tang, 2004), which is consistent with its historically planned urban core and more regular road network structure. Barcelona's fractal dimension, around 1.7 (Lämmer et al., 2006), closely aligns with the findings, suggesting a comparable level of self-similarity and complexity in the traffic network. This comparison highlights the scalability and applicability of fractal analysis across different urban contexts, demonstrating how variations in urban form and planning can influence the fractal characteristics of traffic congestion. The findings, with a fractal dimension of 1.6955, place Hyderabad a middle range, suggesting a balance between complexity and regularity in its traffic patterns, similar to cities like Barcelona, but with distinctions that reflect local urban dynamics.

The fractal growth observed in the values of fractal dimension of Friction index needs further investigation to understand the accessibility in depth.

4 Conclusion

This study underscores the significance of utilizing travel time data, converted into friction, transition, and congestion indices, to assess the accessibility and congestion levels of various zones within Hyderabad. Variations in congestion and travel time delay transition indices directly impact vehicle speed and traffic flow smoothness, thus warranting detailed examination. The study extensively examines the congestion levels in Hyderabad, India by analyzing travel time data spanning four years sourced from Uber Movement. The fractal dimension emerges as a critical tool for city planners in shaping urban development. By maintaining consistent linearity between two entities, such as road length and increasing radius, the fractal analysis graph enables predictions. Notably, if the fractal

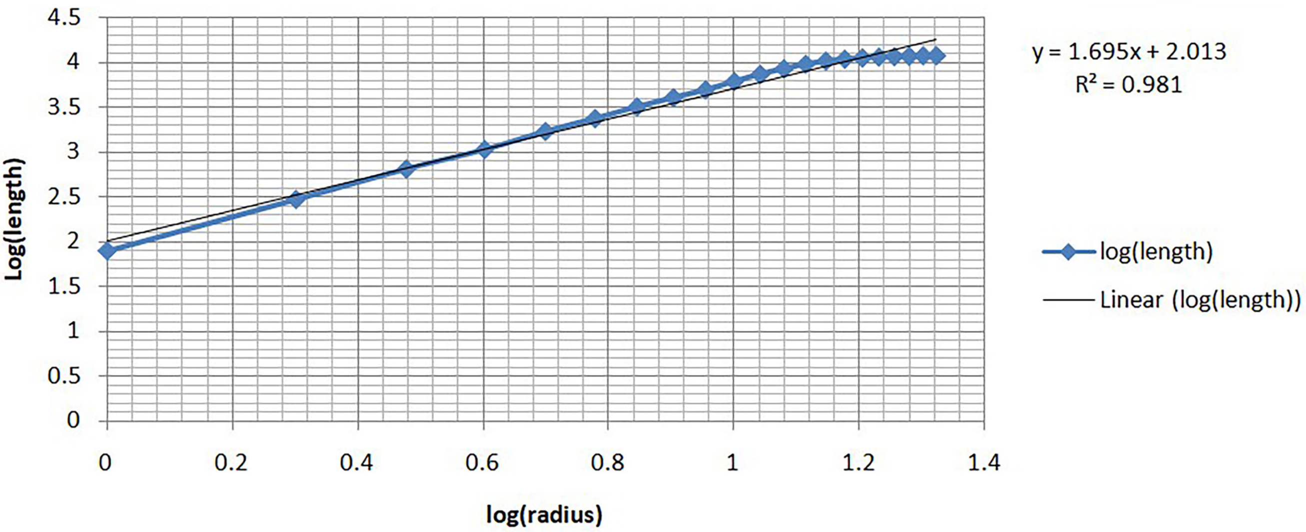

Fig. 9 Fractal analysis of road network using mass radius method

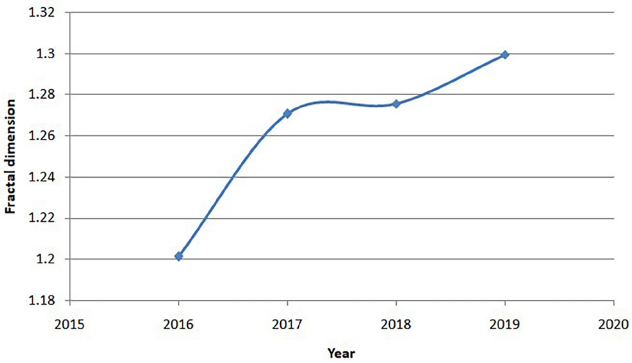

Fig. 10 Graph showing variation of fractal dimension over the years

dimension exceeds 1.5, major additions to the existing road network may not be necessary. The fractal dimension of 1.6955 suggests a balanced yet complex traffic network, highlighting areas where targeted interventions could be most effective. Urban planners could focus on optimizing road connectivity in highly congested areas, through the construction of grade separations, and by implementing smart traffic management systems that adjust traffic signals and reroute vehicles in real-time. Expanding public transportation options, particularly in high-density corridors, helps distribute traffic more evenly, reducing pressure on the road network. Additionally, revising zoning policies to promote mixed-use developments can decrease the need for long commutes, further easing congestion. Finally, policy interventions such as congestion pricing in the most congested zones could be considered to manage traffic flow during peak hours, ultimately contributing to a more efficient and livable urban environment. Furthermore, exploring fractal growth patterns associated with the road network through diffusion-limited aggregation (DLA) algorithms presents a promising avenue for future research in this field. DLA could be used to simulate how traffic spreads through a city, potentially revealing new insights into congestion points and how they evolve over time. Additionally, integrating machine learning techniques, such as predictive modeling and pattern recognition, could enhance the accuracy and applicability of fractal analysis in urban planning. Future studies could explore the use of real-time data from smart city infrastructure—like IoT sensors and connected vehicles—to dynamically analyze traffic patterns and adjust urban designs accordingly. Another promising area is the use of Geographic Information Systems (GIS) combined with fractal geometry to visualize and analyze the spatial distribution of traffic congestion on a more granular level. This approach could be particularly useful for identifying micro-level patterns that are not immediately apparent in broader analyses. Considering the growing emphasis on sustainability, future research could explore the intersection of fractal analysis with environmental impact assessments, aiming to develop more eco-friendly urban planning strategies that minimize carbon footprints and promote greener transportation networks

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