Segment-Based Vehicular Congestion Detection Methods Using Vehicle ID and Loss of Expected Time of Arrival

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***Abstract*—Increasing number of vehicles and rapid urbanization are the significant causes of road traffic congestion. Road traffic congestion is the main issue facing world cities today. Congestion control and mitigation are necessary to mitigate the negative impacts of road traffic congestion, such as delays and increased fuel consumption, among others. There are many congestion detection methods published in the literature; some of these methods, such as the speed threshold, use a single congestion detection metric. Using a single parameter for traffic congestion detection might produce false and inaccurate results. Furthermore, many congestion detection techniques fall short in describing traffic congestion from the user's perspective and vision. To address this, this study develops a segment-based congestion detection method that uses vehicle ID and loss of expected time of arrival. The ID-based method considers both vehicle speed and density, whereas the loss of expected time of arrival focuses on the time loss. These methods are segment-based, where roads are divided into segments using vehicle trajectories. Using a speed threshold of 8.33 m/s, the road is segmented into segments of 8.33 m, 16.66 m, and 24.99 m in length. Vehicle speed and density are monitored using vehicle identification numbers (VINs). Experimental results reveal that the speed threshold and the Microscopic Congestion Detection Protocol recorded false congestion detection. The proposed ID-based congestion detection method is capable of identifying false congestion and accurately detecting real congestion. Moreover, the loss of expected time of arrival shows a promising result in terms of identifying congestion based on motorists' feelings.**

Keywords*—*Vehicle ID; traffic congestion; congestion detection; vehicle trajectories; vehicle speed; vehicle density; loss of expected time of arrival

I. Introduction

One of the main issues facing today's urban cities is road traffic congestion. According to [1], it affects social and economic productivity, contributes to fuel consumption and environmental pollution, it adds delays to personal mobility [2]. Congestion leads to wasted time and increased fuel consumption. Loss time leads to reduced productivity.

ITS-V2X technology is regarded as a key enabler for predicting and managing road traffic congestion, as well as enhancing road safety. V2X is an approach to exchanging information between vehicles and infrastructure that utilizes decentralized wireless technologies. Future vehicles will share information about their current position (GPS), speed, and traffic status, among other vehicle details, and utilize this information to optimize their routes.

This information is shared using a message called CAM (Cooperate Awareness Messages). CAM is a standard proposed by the European Telecommunications Standards Institute [3], which enables vehicles to collect their kinematic information and share it with other vehicles and infrastructure. Researchers are now leveraging these free, continuous, and abundant messages to manage, build, predict, and make more informed decisions about road traffic congestion.

It is known that drivers and passengers in moving vehicles measure congestion with visual and temporal perception. The mind of a person in a travelling vehicle, upon seeing a high density of vehicles through the windscreen, would ultimately tell themselves that congestion occurs. Moreover, a person would, in general, continuously check how soon or later he would arrive at the destination, whether on a congested or non-congested road. Regardless of how fast a vehicle is travelling, the person would be more concerned with temporal perception, which involves the perception of time. When motorists are unable to reach their destination on time, the emotional feeling is that there is congestion. Even when vehicle speed and related parameters are given as the primary criteria for evaluating congestion, they are nevertheless inaccurate and misleading. A practical observation on a major road, conducted as part of this study, found that vehicles may travel at speeds exceeding the 30-kilometer-per-hour speed limit and still experience intense congestion.

This research employs vehicle trajectories (GPS coordinates) and vehicle IDs to develop an ID and Loss of Expected Time of Arrival (LETA) method for detecting vehicular traffic congestion. Roads are segmented using the concept of the Cell Transmission Model (CTM) [4]. Using vehicle trajectories and a speed threshold of 8.33 m/s, the road is segmented into three different segment lengths: 8.33 m, 16.66 m, and 24.99 m. The ID-based traffic congestion detection system considers both speed and density. Vehicle speed and density are tracked and monitored on each segment using vehicle ID. LETA is calculated using a vehicle's expected time of arrival (ETA) and actual time of arrival (ATA).

The remainder of the study is organized as follows: Section II discusses the relevant literature. Section III will cover methodology, including road segmentation techniques and congestion detection methods. Section IV compares the performance of ID-based with a speed threshold and analyzes the results. LETA results are also presented in this section. Section V concludes the study and presents future work.

II. Related Work

Trajectory data can provide valuable insights for decision-making when properly examined, revealing patterns in road traffic congestion, urbanization, and traffic. The beginning, middle, and end of the road are all potential locations for traffic congestion. For easy monitoring, the road needs to be divided into segments. Model-based or criteria-based segmentation is the possible ways of segmenting trajectories. The method of segmenting a trajectory into a limited number of segments that must all satisfy a global criterion is known as criteria-based segmentation [5]. Using predetermined criteria, criteria-based segmentation divides a road into segments that satisfy particular spatiotemporal requirements. Each segment must fit a particular model parameter, which is the foundation of model-based segmentation.

Hausdorff distance was employed in [6], a shape-based distance measurement for trajectory clustering, as one of the related efforts documented in the literature about trajectory segmentation. Origin and destination were employed by [7] to categorize trajectories based on business affairs. In [8], the authors broke the trajectory into segments using a similarity score in an attempt to create a trajectory segmentation map that matches large-scale GPS data. A system that divides trajectories into homogeneous segments based on spatiotemporal parameters, such as heading, speed, and position, was created by [9]. In [10], the authors divide the road lane into a segment of cluster cells, each with a 2-meter length. A protocol for evaluating and detecting traffic congestion on a road segment was presented by [11]. They describe a road segment as a road that connects two intersections without specifying its length or size. Although these works divided roads into segments, they did not utilize the concept of CTM.

There are two ways of detecting road traffic congestion: using fixed equipment and floating vehicles [12]. Fixed equipment-based congestion detection involves using cameras, loop detectors, and other devices to detect road traffic congestion. The accuracy of this method is high; however, its coverage is limited to a specific location [13]. Using floating vehicles involves utilizing vehicles equipped with sensors and GPS technology on the road to detect traffic congestion. This method has the advantage of detecting congestion over large areas. It also provides a cost-effective method of analyzing and detecting road traffic congestion [14].

Congestion can be quantified using various metrics, including speed, trip duration, density, and congestion index, among others. GPS-based congestion detection is the most cost-effective and widely used approach. Vehicles can also be easily tracked [15]. Road traffic congestion is measured using a variety of techniques; however, there is no single, universal method to determine the state of traffic. Congestion can be measured using the following criteria: 1) Average speed, 2) Travel time, 3) Delay, 4) Density, 5) Level of service, and 6) congestion indices [16]. According to [17], speed, density, and degree of saturation are good indicators of traffic conditions.

Both stationary equipment and floating vehicles can be used to identify congestion [12]. Detecting traffic congestion on the road by using vehicles fitted with sensors and GPS technology was known as "floating vehicles". The benefit of this approach is that it can identify congestion over vast areas. Additionally, it offers an economical approach for assessing and identifying traffic jams [14]. Many studies have utilized data from floating vehicles to develop a road traffic congestion detection system, which includes methods developed by [18, 19, 13], all of which employ fuzzy logic for V2V congestion detection. However, the system incurs overhead due to the message exchange between vehicles for congestion validation.

Fuzzy logic was also employed by [20] to estimate traffic flow. Vehicle speed and location were captured using RFID and transmitted to the cluster head. The cluster head will calculate the average speed and density and then use fuzzy logic to determine the flow. RFID is expensive to implement for all vehicles on the road, and vehicle clustering is also a time-consuming process.

Vehicle trajectories were segmented based on the time window in [21] to detect moving clusters. Vehicle speed and density were used to detect slow-moving clusters for congestion detection. The system is based on clusters, and the formation of these clusters is time-consuming.

A congestion detection approach using clustering algorithms was developed in [22]. Vehicle trajectories are clustered, and the distance travelled by the clusters is computed to determine the average speed, which measures congestion. This method is based on historical data.

Pollutant emissions and traffic delays can be successfully decreased using vehicle speed guidance. Driving too fast is a significant contributing factor to traffic accidents, and research indicates that speed is a leading cause of deadly traffic accidents in nearly every nation. The effects of setting a speed restriction of 30-kilometer-per-hour on roads have been extensively studied by transportation researchers.

The study by [23] found that enforcing a 30-kilometer-per-hour speed restriction in 40 European towns significantly reduced traffic accidents, injuries, and fatalities. In [24], the authors analyzed the effectiveness of a 30-kilometer-per-hour speed limit on roads, finding that it reduced energy use and saved lives.

According to [25], speed emerges as the predominant metric used in the congestion detection literature. Utilizing a single parameter, such as speed, for traffic congestion detection might not produce accurate results [26], [27]. The speed threshold was proposed by [28]. The vehicle's speed was calculated from the distance it covered, and the average speed was compared with the threshold to determine road congestion. Speed may overlook how traffic congestion develops across space, leading to incorrect identification of traffic congestion.

This study presents an ID-based congestion detection method to address the issue of relying on a single parameter for traffic congestion detection. Using a speed threshold, time headway for congestion detection may be inaccurate, leading to false detections. Travel time and delay may not predict how early or late a motorist will arrive at their destination. This makes motorists question when they will get to their destination. LETA is intended to determine how late or early a motorist will arrive at their destination.

III. Methodology

A. Road Segmentation

CTM defines cell length as equal to the distance a vehicle travels at free-flow speed [4]. In the speed threshold [28], free flow speed was defined to be 8.33 m/s, which means the vehicle will move 8.33m in one (1) second or above to be considered not in congestion. The use of 1s is driven by the fact that the maximum CAM broadcasting interval is 1 second. In this research, vehicle information is collected every 1 second to determine congestion. A vehicle will drive 8.33m/s in 1s, 16.66m/s in 2s, and 24.99m/s in 3s to be considered congested.

Three different segment lengths are utilized to evaluate the method's effectiveness: 8.33 meters, 16.66 meters, and 24.99 meters. In other words, the road is divided into three segments: 8.33 meters, 16.66 meters, and 24.99 meters. Seongsin-ro 2-gil, 140.06 meters, and part of Gonghang-ro, 101 meters in length, are used for the implementation of the proposed congestion detection methods. Table I shows the lengths of the three segments as well as the number of segments generated.

TABLE I. Segment Lengths and the Number of Segments Generated

Segment Length	Number of Segments Created (Seongsin-ro)	Number of Segments Created (Gonghang-ro)
8.33 m	16	12
16.66 m	8	6
24.99 m	5	4

The road is not physically segmented; rather, the ID-based system virtually segments the road based on the vehicle trajectories collected, as illustrated in Fig. 1. Vehicle speed is monitored using the vehicle ID and its trajectory. Vehicles driving on a segment of 8.33-meter length are expected to exit after one (1) second. With a segment length of 16.66 meters, vehicles are supposed to exit the segment after two (2) seconds. Vehicles will take three (3) seconds to exit a segment of 24.99 meters in length. This process allows for the monitoring of your vehicle speed in each segment using three different segment lengths.

B. ID-Based Congestion Detection

The density metric was used in the majority of research investigating traffic congestion by counting the number of vehicles per unit of road length. Our approach uses the vehicle's ID sent in the vehicular messages to identify slow-moving vehicles within a road segment. In terms of this research is the first study to detect road traffic congestion by using vehicle ID to identify slow-moving vehicles.

In essence, a traffic flow refers to a line of moving vehicles on a specific route. Vehicles are grouped into substantially denser clusters, travelling at extremely slow speeds because there is insufficient space for lane changes or passing when there is heavy traffic [21, 29]. Therefore, the motivation is that tracking and identifying the group of slow-moving vehicles can effectively identify traffic congestion.

ID-based is a centralized system. The system uses the vehicle ID and trajectories to determine congestion, as shown in Fig. 1. At each time t (i.e., 1s), the vehicle broadcasts its status messages to nearby vehicles and RSUs. After receiving status messages from vehicles on a segment, the RSU aggregates vehicle IDs. As previously mentioned, roadways are segmented into 8.33-meter, 16.66-meter, and 24.99-meter segments, and congestion is measured separately in each segment. Congestion is checked after one (1) second, that is, after each message receipt cycle, for an 8.33-meter segment length. For a 16.66-meter segment length, the system will check for congestion after two (2) seconds, i.e., two message-receiving cycles. Congestion is monitored after three (3) seconds, i.e., three message-receiving cycles, with a 24.99-meter segment length.

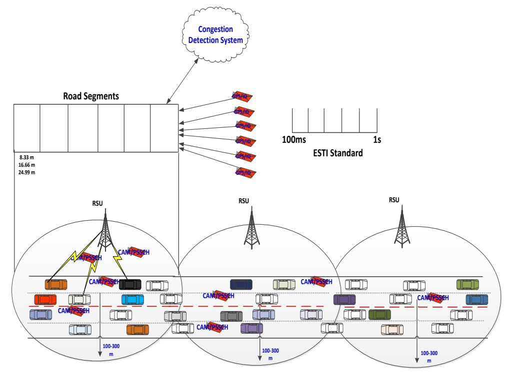

Fig. 1. ID-based congestion detection model.

Let us assume that there are n segments of road Ri. Ri = {Ri1, Ri2, Ri3, …… Rin}. Where i is the road ID, n is the segment ID of road i. Let m be the number of vehicles traversing on Rin such that Rin = {V_1, V_2, V_3, … V_m}, where V represents a vehicle with ID m. Equation 1 shows that all vehicles in Rin can be presumed to be advanced to Ri(n+1) within t seconds (1 second) under light traffic, defined as 30-kilometer-per-hour (8.33 m/s) [see Eq. (1)].

$$R_{i(n+1)(t+1)} = R_{in(t)} \tag{1}$$

Congestion can be detected by detecting slow-moving vehicles [21]. Owing to this notion, an ID-based congestion detection method detects congestion when at least half of the vehicles remain in the segment after the clock tick (1, 2, or 3 seconds, depending on the segment length). It signifies the existence of traffic congestion. This can be evaluated by comparing the vehicle IDs of segment n at time *t* with the IDs of the same segment at time *t* + *i*, where *i* can be 1, 2, or 3, depending on the segment length.

Let Vn (ID) be a vehicle n ID. Let XRin(t) = {V_1(ID), V_2(ID), V_3(ID), … Vn(ID)}, where X_{Rin}(t) is the total vehicle IDs of segment Rin at time t. Congestion occurs if Eq. (2) is valid.

$$X_{Rin(t+1)} \geq \frac{1}{2} X_{Rin(t)} \tag{2}$$

C. LETA

LETA is a segment-based congestion monitoring system. Congestion is tracked on a segment-by-segment basis rather than the road as a whole. It is presumed that RSUs have full coverage of the road. To determine if vehicles may gain or lose time on a specific segment, LETA is computed for each segment. LETA is capable of monitoring traffic congestion on every segment of the road. LETA is proposed with the intention of estimating the level of traffic a vehicle entering the road would have to experience. A congested road is indicated by loss time, and one that is free-flow is indicated by gain time. The estimated time of arrival (ETA) and actual time of arrival (ATA) must be ascertained in order to compute LETA.

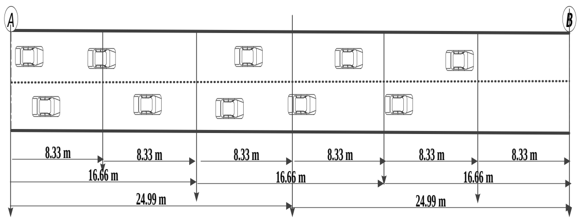

Fig. 2. Shows vehicles moving from A to B across segments.

Let Ri be a road with nth segments, i.e., Ri = {S1, S2, S3, ….., Sn}, where Sn is a road segment with index n of Ri. ETA is the estimated time a vehicle will arrive at destination B from origin A, as shown in Fig. 2. To compute ETA, the distance between two points must be defined. In this work, three different segment lengths are defined: 8.33 m, 16.66 m, and 24.99 m. Using Eq. (3), the ETA can be computed for each segment.

$$ETA_{S_i} = {DSL_{S_i}}/{VS_{S_i}} \tag{3}$$

where, ETASi is the average expected time of arrival for segment Si, DSLSi is the segment length, and VSQi is the segment’s average vehicle speed. ATA represents the vehicle's movement on the freeway at the recommended vehicle speed. Using Eq. (4), ATA can be calculated:

$$ATA_{S_i} = {DSL_{S_i}}/{RVS_{S_i}} \tag{4}$$

where, ATASi represents the actual time of arrival for segment Si, DSLSi represents segment length, and RVSSi is the recommended vehicle speed for segment Si. LETA for a segment determines whether there is congestion and how late the vehicle is expected to arrive. LETA is determined by subtracting ETA from ATA and can be computed using Eq. (5).

$$LETA_{S_i} = ATA_{S_i} - ETA_{S_i} \tag{5}$$

where, LETASi is the time loss from the actual time of arrival for segment Sj, ATASi is the actual time of arrival, and ETASi is the expected time of arrival. The total loss of expected time of arrival for road Ri is the sum of the LETA for each of the road's segments. Eq. (6) can be used to calculate the total time loss for road Ri.

$$TLETA_{R_i} = \sum_{i=0}^{n} LETA_{S_i} \tag{6}$$

Where TLETARi is the total time loss for road Ri, LETASi is the loss of expected time of arrival for segment Si, and n is the total number of segments in Ri.

IV. Evaluation of Approaches

A. Dataset

Jeju vehicular traces [30] were used. Seongsin-ro 2-gil and Gonghang-ro road are selected for implementation of the ID-based and LETA methods for vehicular traffic congestion detection. Jeju dataset was chosen because it has CAM data properties, and its transmission timing is consistent at (1) second intervals. Seongsin-ro 2-gil is a one-way road measuring 140.06 meters. At the same time, a part of Gonghang-ro, which is 101 meters in length, is also used. These routes were chosen since they have a substantial number of trajectories, and their GPS coordinates do not deviate from the actual road map. The Jeju dataset contains kinematic information collected from vehicles, with 5000 seconds of heterogeneous vehicle simulation traces totaling 8,495,739 traces. The dataset is generated using the SUMO simulator.

B. Data Preprocessing

Working with GPS trajectories requires preprocessing, as some of the GPS points may deviate from the actual road map. Inaccurate results could arise from anomalies and mistakes if preprocessing were not done [8]. Seongsin-ro 2-gil and Gonghang-ro GPS points (trajectories) were matched on Google Maps. The actual road and the GPS position coincided.

C. ID-Based Results

1) Seongsin-ro: To evaluate the effectiveness of the ID-based congestion detection method, a comparison was made with the speed threshold [28] and the microscopic congestion detection protocol (MCDP) [31]. MCDP used vehicle information to calculate the number of vehicles and the time headway between them. If the time headway is less than two seconds, congestion occurs. At the same time, the ID-based method calculates the vehicle's speed based on the distance it covers and compares it with the speed threshold, i.e., 8.33 m/s.

Since the ID-based method was developed to determine whether congestion exists, the number of detection points was used as a metric; the number of detection points is the total number of points where congestion has been identified. This enables a comparison of two congestion detection systems to determine which one has the highest detection rate.

Fig. 3 illustrates the comparison results for an 8.33-meter segment length. The results reveal that both the ID-based speed threshold and the headway-based approach recorded similar patterns. It can be observed that both ID-based and speed thresholds recorded almost the same congestion detection values for all 16 segments. At the same time, a little difference was observed with the headway-based detection method.

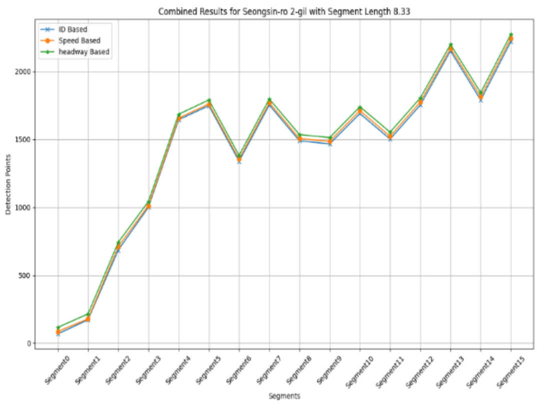

Fig. 3. Shows a comparison between ID-based, speed threshold, and time headway-based results for an 8.33-meter segment length.

Fig. 4 compares the results of ID-based, speed threshold, and headway-based methods using a segment length of 16.66 meters. Both methods recorded a detection point of less than 200 at the first segment, i.e., segment 0, with the ID-based and speed threshold methods being slightly lower than the headway-based method. In both the eight (8) segments, it is clearly shown that ID-based and speed threshold recorded lower detection compared to the headway-based method. It is also notably clear that the ID-based method recorded low detection in comparison to the speed threshold, especially from segment two onward, even though the difference is minimal. This means the base congestion detection method can detect actual (true) congestion.

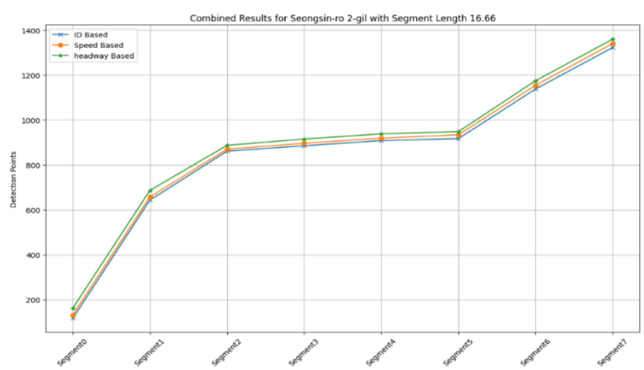

Fig. 4. Shows a comparison of results of headway-based, speed threshold, and ID-based for a 16.66-meter segment length.

Fig. 5 shows a comparison of the ID-based speed threshold and headway-based results for a 24.99-meter segment length. As can be observed, only at the segment0 speed threshold did the detection point go below that of the ID-based method. Even though the difference is minor, in the rest of the segments 1 to 3, it is seen that ID-based recorded lower detection than speed threshold and headway-based.

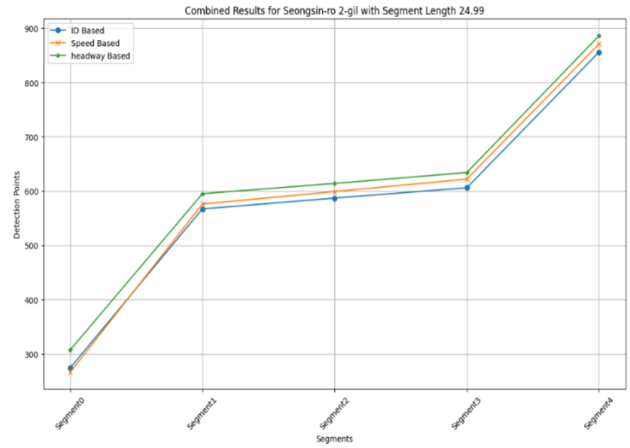

Fig. 5. Shows a comparison of headway-based, speed threshold, and ID-based results for the length of a 24.99-meter segment.

2) Gonghang-ro road: To validate the effectiveness of the base congestion detection method, another road was also considered. Vehicular traces from the Gonghang-ro road are also used to evaluate the ID-based detection method. Fig. 6 compares ID-based results with speed threshold and time headway-based for the 8.33-meter segment length. Congestion detection points are shown for each segment. Segment 0 marks the beginning of the road for all segment lengths.

It can be seen from the results in Fig. 6 that the detection points fluctuate over the segments, with segment 11 recording the lowest values for all the detection methods. The results reveal that with an 8.33-meter segment length, both methods observe the same pattern, with the headway-based method reporting higher detection points than the ID-based and speed threshold. Though the difference between ID-based and speed threshold is not significant, ID-based reported lower detection points.

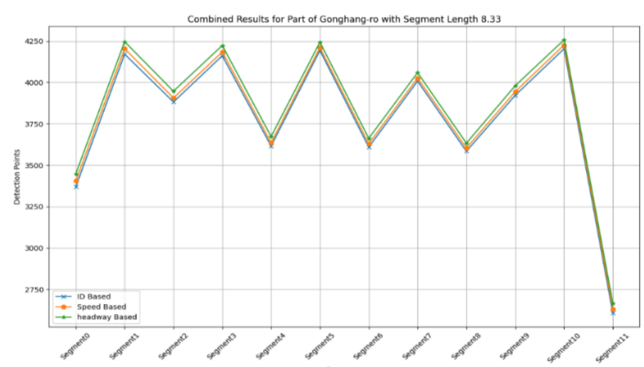

Fig. 6. Congestion detection comparison of the three detection methods using segment lengths of 8.33-meter.

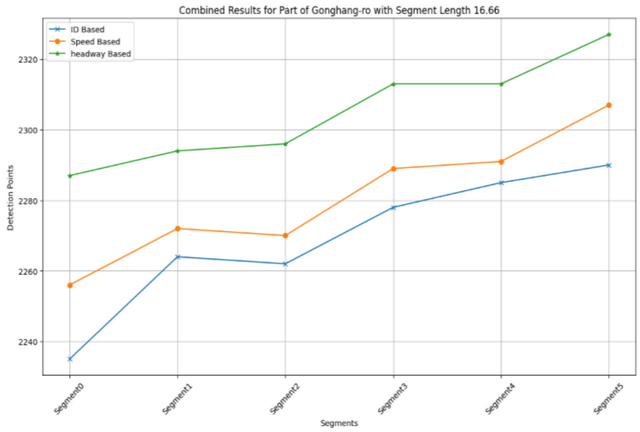

Fig. 7. Congestion detection comparison of the three detection methods using segment lengths of 16.66-meter.

The results in Fig. 7 showed a steady increase in detection points from the first to the last segment for the headway-based method, while ID-based and speed threshold observed a sharp drop in segment 2, then continued to rise till the last segment. With a 16.66-meter length, a clear varying result was observed. Headway has the highest detection points for all six segments, followed by speed threshold, and ID-based has the least.

Similar to results with 16.66-meter segment length, results with 24.99-meter segment length also recorded a drop of detection points on segment 1, as shown in Fig. 8. It was observed that there is a significant difference between the three congestion detection methods in terms of detection points for a 24.99-meter segment length in all four segments.

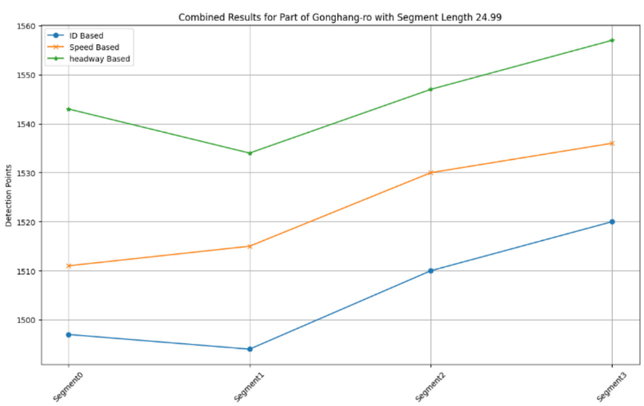

Fig. 8. Congestion detection comparison of the three detection methods using segment lengths of 24.99-meter.

Overall, the results presented show that the ID-based road traffic congestion detection system performed better than the speed threshold (Ahmed, Shariff, and Abubakar, 2024) and headway-based (Ahmad, Chen, and Khan, 2018) in identifying actual congestion in all three different scenarios (8.33m, 16.66m, and 24.99m). ID-based creates a two-layer check by combining density estimation with the speed threshold technique. The ID-based approach employs density estimates to identify congestion that is not bogus congestion after verifying it with a speed threshold.

D. LETA Results

A comparison of the three scenarios—at 8.33meters, 16.66meters, and 24.99 meters—is shown in Fig. 9. The findings indicate that while ETA and ATA are all influenced by speed and the distance between the source and the destination, segments with a length of 24.99 meters have the most significant LETA values in all the segments. The longer the segment distance, the greater the density of the vehicles. Segment 0 has the lowest LETA value in the 24.99 and 16.66 scenarios, as compared to the 8.33-meter scenario, where segment 1 has the lowest LETA value.

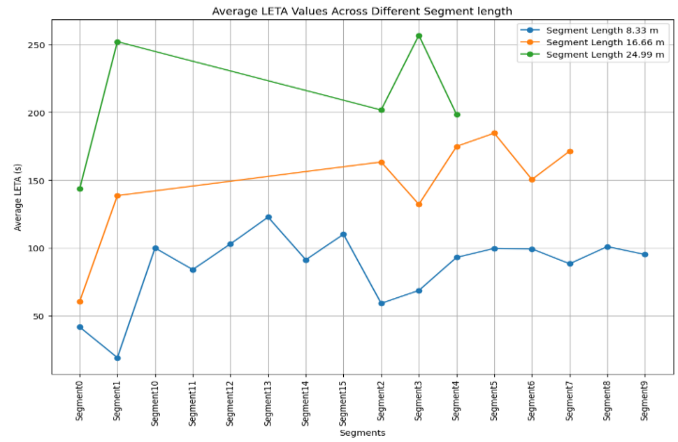

Fig. 9. LETA results over segments for all three scenarios.

A fine-grained LETA study is made feasible by calculating LETA for ten carefully selected vehicles, ensuring that the analysis focuses on specific entities of interest. To produce a combination of the most and least crowded vehicles, ten (10) vehicles were chosen, five with the most traces and five with the fewest. The 10 chosen vehicles are tested in 24.99-meter segments.

Fig. 10 shows the LETA findings for ten (10) chosen automobiles during the simulated period. According to the findings, the LETA of several vehicles, including the JTr450, JBr450, JTx973, JPs973, and JTr832, grows dramatically over time. These are the vehicles with the most traces, and the spikes represent occasions when the vehicles lose a significant amount of time owing to traffic congestion they encountered throughout time. The 5000 to 15000 second LETA spikes observed by several vehicles may represent periods when most vehicles lose time due to traffic or driver behavior. These spikes can indicate specific places or periods of significant traffic congestion.

Throughout the observed time period, vehicles such as JPs967, JTx688, and JPs688 consistently displayed low LETA values, implying that they did not waste much time and most likely moved faster in the absence of significant traffic congestion. All vehicles exhibit low LETA values toward the end of the time period, indicating that they either arrived at their destinations, exited congested regions, or experienced less traffic near the end of their journey.

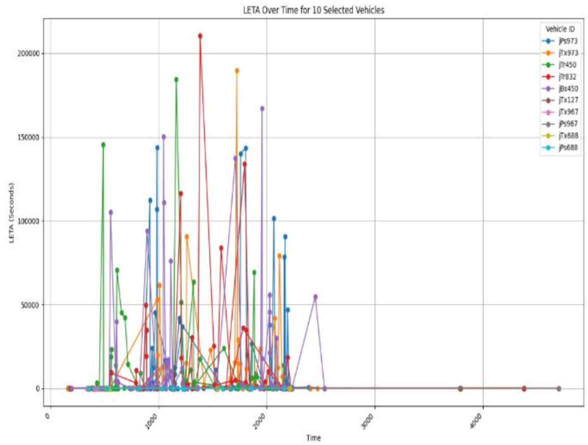

Fig. 10. LETA results of 10 selected vehicles for the entire simulation time.

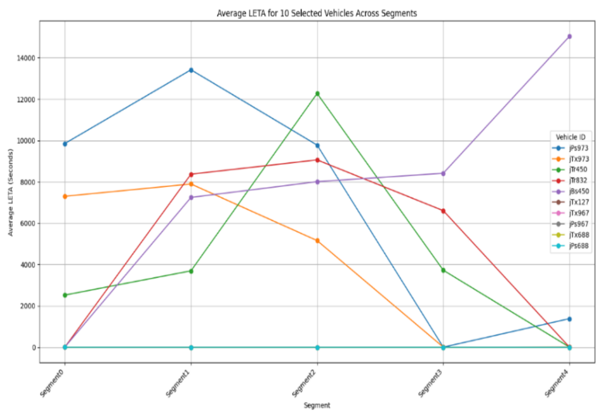

Fig. 11. LETA results of 10 selected vehicles over the segment.

LETA results of the ten (10) selected vehicles are plotted against segments, as illustrated in Fig. 11. The graph depicts the average LETA measurements for 10 distinct vehicles over five (5) road segments of length 24.99. The figure depicts how each vehicle's LETA patterns vary across the segments. Five of the vehicles had a high LETA value, indicating a significant loss of expected arrival time, whilst the remaining five had a continuously low LETA value, indicating smooth movement with little time loss.

Fig. 11 also shows that JPs967, JTx688, JPs688, JTx127, and JTx967 vehicles have a flat trend or almost no decrease in expected time of arrival throughout all segments, with consistently low LETA values, indicating that these vehicles met less traffic on all road segments. Furthermore, Fig. 11 shows that some segments, particularly segments 1 and 2, have higher average LETA values for numerous vehicles, implying that these segments are congested.

Five vehicles with the lowest LETA values and five vehicles with the highest LETA values were analyzed independently to further analyze the results displayed. Fig. 12 depicts the average LETA for five vehicles chosen, as having the lowest LETA along various road segments.

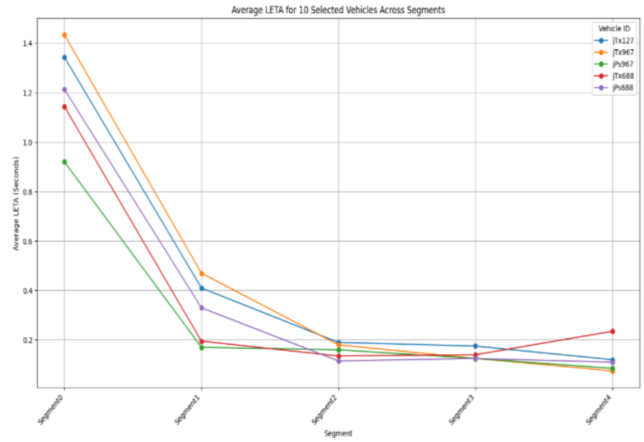

Fig. 12. LETA results of 5 selected vehicles with the least traffic traces.

Fig. 12 shows that each vehicle's LETA decreases significantly from segment 0 to segment 2. This suggests that traffic conditions improved throughout the route since the vehicles' LETA reduced as congestion lessened along the road segments. Only segment 0 of the four vehicles had a LETA value of less than 1 second, while JPs967 had a LETA value greater than 1 second. Between segment 0 and segment 1, the LETA for all vehicles declined by 0.47, and from segment 2 to segment 4, the LETA values for most vehicles remained reasonably steady.

At segment 0, JTx967 has the highest LETA; however, after segment 1, it drops rapidly and stabilizes. Vehicles JTx688 and JPs688 follow similar trajectories, with LETA from Segment1 stabilizing at around 0.2 seconds. JPs967 rises somewhat in Segment 4, but JTx127 and JPs967 continue their downward trajectory.

Overall, the decrease in LETA for each vehicle from segment 0 to segment 1 indicates that the vehicles first encountered traffic, which then subsided after segment 1. In other words, when there was traffic, vehicles moved onto the road, and the bottleneck ultimately disappeared.

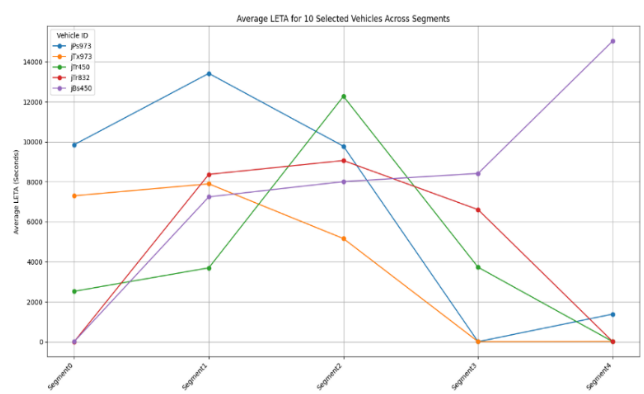

Fig. 13. LETA results of 5 selected vehicles with the most traffic traces.

Fig. 13 displays the average LETA for segment 0 to 4 for the five most congested vehicles (JPs973, JTx973, JTr450, JTr832, and JBs450). The findings shed light on how these vehicles lose LETA when traveling through various parts, whether due to traffic bottlenecks, poor road conditions, or driver conduct.

Fig. 13 indicates that the LETA trend for JBs450 cars is increasing steadily from segment 0 to segment 4, with a particularly noteworthy leap between segment 3 (8413s) and segment 4 (15034s). JTr450 began in segment 0 with a reasonably high LETA value of 2523s, increased to 12271 in segment 2, and then dropped to a low of 7 seconds in segment 4. Vehicle JTr832's LETA grows from 2 seconds in segment 0 to a maximum of 9058 in segment 2, following which it rapidly declines in segment 3 to 4, with segment 4 recording a LETA of 5 seconds.

In segment 0, the JTx973 vehicle had a high LETA value of 7299s. In segment 1, it increased to 7894s, whereas in segment 4, it reduced to 16 seconds. In segment 0, JPs973 has the highest LETA value of 9851s. In segment 1, it climbs to 13416s, whereas segment 3 and segment 4 dip and rise by 3s and 1381s, respectively. Some vehicles experienced increased LETA as they progressed, while others saw LETA drop at the end of their journey. The trend inconsistencies in Fig. 13 suggest that vehicles suffered LETA at different times and segments.

TABLE II. LETA VALUES FOR ALL TEN VEHICLES ACROSS THE SEGMENTS AND THE TOTAL LETA

	Segment0	**Segment1**	**Segment2**	**Segment3**	**Segment4**	**Total LETA**
jPs967	0.92	0.17	0.16	0.125	0.085	1.46
jTx688	1.143333	0.195	0.135	0.14	0.235	1.85
jPs688	1.213333	0.33	0.115	0.125	0.11	1.89
jTx127	1.343333	0.41	0.19	0.175	0.12	2.24
jTx967	1.433333	0.47	0.18	0.125	0.075	2.28
jTx973	7299.101	7894.033	5157.802	6.00875	16.84625	20373.79
jTr450	2523.266	3694.31	12271.22	3724.643	7.425	22220.86
jTr832	2.32	8368.568	9058.859	6604.972	5.02	24039.74
jPs973	9851.517	13416.29	9776.06	3.063333	1381.45	34428.38
jBs450	5.62	7243.885	8006.662	8413.615	15034.56	38704.34

Table II displays the LETA values for each segment of the ten vehicles, as well as the total LETA for the entire trip. As previously stated, the table shows that the LETA values for vehicles JTx973, JTr450, JTr832, JPs973, and JBs450 are significantly higher than those for the other vehicles. While the remaining vehicles maintain LETAs below three seconds across all segments, some vehicles have LETAs in the thousands of seconds.

The table also shows that, with a total LETA of 38,704.34 seconds, vehicle JBs450 has the most significant overall time loss across all segments. Surprisingly, the LETA of 15,034.56 seconds is very high in segment 4. Vehicle JPs967, on the other hand, has the least loss of expected time of arrival throughout all segments, with a total LETA of only 1.46 seconds.

E. Discussion

The ID-based results presented showed great improvement compared to MCDP and speed-based congestion detection methods. This is because of the ID-based congestion detection method check vehicle speed and density in order to ascertain congestion on the road segment. It also clear that segment length has a significant impact on ID-based congestion detection, with a 24.99-meter segment length presenting the best performance result of ID-based. Additionally, the results illustrated that a longer segment length allows the ID-based congestion detection system to accurately check for vehicle density, whereas a shorter segment length limits the system's ability to detect congestion using vehicle density. Consequently, the results clearly reveal that segment length has a significant effect on congestion detection.

LETA provided a positive result. A basic method of monitoring traffic congestion in relation to vehicle destination. This provided motorists with awareness and temporal comprehension of their trip by taking into account their arrival time.

These two ways are simple to implement in the RSU of the ITS infrastructure, since it is built on the current V2X communication protocol. Both ID-based and LETA were developed to employ vehicle information, whereas ITS allows vehicles to communicate kinematic information, resulting in no communication overhead.

V. CONCLUSION AND FUTURE WORK

This study developed an ID-based congestion detection method that monitored vehicles' speed and density and loss of expected time of arrival on road segments. ID-based congestion detection method utilizes a vehicle's ID and trajectories contained in vehicular messages. Roads were divided into lengths of 8.33 meters, 16.66 meters, and 24.99 meters using vehicle trajectories. According to experimental results, the ID-based congestion detection method detects actual (true) traffic congestion with long segment lengths.

The ID-based congestion detection system combined the concept of speed threshold congestion detection with density monitoring and was applied to road segments to monitor traffic congestion. Its performance was evaluated against the speed threshold and MCDP congestion detection method. The results presented show that the ID-based congestion detection method detects congestion more accurately. Speed threshold and MCDP detect false congestion when compared with the ID-based congestion detection method. This work shows that by using two or more congestion detection metrics, traffic congestion can be accurately detected.

This work also defines and calculates LETA by taking into account segment length, vehicle speed, and the road recommended speed. The vehicle's LETA was displayed, as well as their overall LETA for the trip. The results demonstrate that LETA can be an effective measure of traffic congestion because it displays to the motorist how much time they are losing or gaining.

This accomplishment is practical enough to be utilized in road design, moving object monitoring, and might be adapted to analyze traffic congestion in the city. To improve the ID-based congestion detection method accuracy, vehicle density monitoring must take into account the road segment length.

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