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Enhancing Sustainable Mobility: A Comparative Analysis of C-ITS and Fundamental Diagram-Based Traffic Jam Detection

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Abstract

Traffic congestion is a primary obstacle to sustainable mobility, leading to increased fuel consumption, harmful emissions, and significant economic losses. Effective and timely congestion detection is therefore a critical enabler for proactive traffic management strategies that can mitigate these negative impacts. This study contributes to this goal by conducting a rigorous comparative analysis of two key detection paradigms: a modern, vehicle-centric approach using a Cooperative Intelligent Transportation Systems (C-ITS) service, and a traditional, infrastructure-based method relying on the fundamental diagram (FD). Using a comprehensive simulation campaign on a bottleneck scenario, we evaluate the performance of both methods under various conditions. The results demonstrate that while the FD-based method can offer faster detection under optimal sensor placement for severe events, the C-ITS approach provides fundamentally greater spatial flexibility and reliability across a wider range of congestion severities. Our techno-economic analysis further reveals that the paradigms rely on distinct investment models, with C-ITS offering superior scalability and a promising path toward network-wide coverage. This highlights the complementary nature of the two approaches and underscores the potential of C-ITS as a key technology to support dynamic, efficient, and sustainable transportation networks.

Keywords: sustainable mobility; C-ITS; congestion detection; traffic management

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1. Introduction

Traffic congestion represents a critical challenge to sustainable urban and highway development, imposing significant economic, social, and environmental costs. For instance, in 2024, the average American driver lost 43 h to traffic delays, equivalent to over a full work week and costing USD 771 in lost time and productivity [1]. On a national scale, these delays translate into a drain of over USD 74 billion on the United States economy and an estimated USD 200 billion annually when broader impacts on supply chains are considered [2]. The environmental and social burdens are equally severe. The transport sector is the largest source of noise pollution in Europe—a stressor linked to thousands of premature deaths and cardiovascular diseases annually [3]—and remains a primary source of harmful air pollutants and greenhouse gas emissions, responsible for a quarter of the total amount of emissions of Europe [4]. Effectively detecting and mitigating congestion is therefore not merely a matter of convenience, but a critical imperative for economic vitality, environmental sustainability, and public health.

Cooperative Intelligent Transport Systems (C-ITS) are advanced traffic management solutions expected to enhance road safety, traffic efficiency, and driving comfort by enabling real-time communication and data exchange among vehicles, infrastructure, and other road users [5–7]. At the core of traffic monitoring lie two distinct paradigms for Traffic State Estimation (TSE) [8,9]. The first is the established, infrastructure-centric approach, which relies on data from fixed roadside sensors (e.g., induction loops) to reconstruct the Fundamental Diagram (FD)—the macroscopic relationship between traffic flow, speed, and density that has been a cornerstone of traffic flow theory for decades [10,11]. The second is the emerging vehicle-centric approach, which leverages the C-ITS framework to turn connected vehicles into mobile sensors that provide high-resolution, real-time data on traffic conditions [12,13].

However, the practical application of traditional FD-based methods faces significant and well-documented challenges. The reliance on fixed sensors creates a fundamental limitation: these systems provide only localized, point-based measurements, leaving vast spatial gaps in network coverage where traffic events can go completely undetected [14]. While increasing sensor density or optimizing RSU positions could theoretically mitigate this issue [15], the high capital and maintenance costs associated with widespread deployment make such a solution economically impractical for most road authorities [16]. Consequently, infrastructure-based systems often struggle to capture the full spatiotemporal dynamics of congestion, particularly for non-recurring events that do not form at predictable locations [17].

The C-ITS paradigm, while promising unparalleled spatial coverage [18,19], is not without its own set of practical deployment hurdles. Its effectiveness is critically dependent on achieving a high market penetration rate of equipped vehicles. This creates a classic network effect dilemma, where the benefits for individual users are limited until a critical mass is reached, potentially slowing widespread adoption [20]. Furthermore, the reliability of C-ITS services hinges on the performance of wireless communication, which can be susceptible to challenges such as latency, data packet loss, and cybersecurity vulnerabilities that could compromise the integrity of the data exchanged [21].

Such lane-drop scenarios are a common and critical cause of recurring congestion on motorways. They frequently occur at merges where on-ramps join the mainline, at the approaches to bridges or tunnels where the roadway narrows, or where auxiliary or peak-hour travel lanes terminate. Indeed, such infrastructural features are formally recognized by transportation authorities as 'physical bottlenecks,' which are considered a primary root cause of recurring congestion and a major focus for mitigation efforts on national highway systems. The predictable yet severe impact of these infrastructural features makes their analysis essential for traffic management authorities seeking to deploy effective mitigation strategies.

To overcome some of these challenges, such as the need to process large volumes of continuous data from periodic messages (e.g., CAMs), one approach is to leverage event-triggered C-ITS services that use Decentralized Environmental Notification Messages (DENMs) [22]. In this paradigm, each C-ITS station acts as a distributed sensor, broadcasting a notification only when specific conditions, such as a sudden drop in speed, are met.

These two paradigms—the established, infrastructure-based FD approach and the emerging, vehicle-centric C-ITS approach—represent the primary methods for gathering the real-time data necessary for advanced traffic management. In recent years, the field has rapidly evolved beyond simple detection towards proactive traffic state prediction, largely driven by advancements in Artificial Intelligence (AI) and Machine Learning (ML) [23,24]. These data-driven models promise to forecast and mitigate congestion before it fully develops [25,26], but their performance is fundamentally constrained by the quality, resolution, and timeliness of the input data. Therefore, a rigorous comparison of the underlying data-gathering mechanisms is not merely an academic exercise; it is a critical prerequisite for developing and deploying the next generation of intelligent transportation systems.

While the FD and C-ITS paradigms represent two foundational approaches to real-world traffic data collection, the broader field of congestion research encompasses a diverse range of modelling and prediction methodologies [27]. One significant stream of research utilizes microscopic simulation models, such as Cellular Automata (CA), to investigate the underlying mechanisms of traffic dynamics. CA models simulate complex, emergent traffic phenomena like jam formation and shockwave propagation from a set of simple, rule-based interactions between individual vehicles or 'cells' on a grid [28,29]. This bottom-up approach is particularly valuable for analyzing the spatiotemporal evolution of congestion and understanding how local vehicle behaviors aggregate into macroscopic traffic states [30,31]. More recently, with the advent of V2X communication, a prominent trend has emerged towards proactive traffic state prediction using Artificial Intelligence (AI) and Machine Learning (ML). Rather than simply detecting existing congestion, these data-driven models aim to forecast it. Researchers are increasingly applying deep learning architectures, such as Long Short-Term Memory (LSTM) networks, to V2X data streams to predict future traffic conditions with notable accuracy [32,33].

Despite the well-understood theoretical strengths and practical limitations of each approach, to the best of our knowledge, no prior studies have directly compared their performance for the specific task of early traffic jam detection in a controlled, simulated environment. This paper addresses this gap by evaluating the efficiency and effectiveness of a standardized C-ITS service (the Traffic Jam Ahead warning) against a traditional fundamental diagram-based method. By analyzing their performance under various traffic conditions, we identify the strengths and limitations of each method and discuss their potential integration for improved traffic management. Through this comparative analysis, we pose two key questions: How does the real-time C-ITS approach compare with the model-based fundamental diagram approach in detecting traffic jams? Under what specific conditions does each method excel or falter? By addressing these questions, this research contributes to the ongoing development and optimization of intelligent transportation systems. A thorough understanding of the quality, timeliness, and reliability of these primary data sources is essential, as they form the fundamental input upon which these more advanced simulation and prediction models ultimately depend.

2. Modelling

2.1. Fundamental Diagram

The fundamental equation of traffic flow $q = k \times v$ is a simple yet powerful relationship that links the three macroscopic variables characterizing a traffic flow stream (see Figure 1): the traffic flow q [veh/h], the traffic density k [veh/km], and the traffic speed v [km/h]. The relation among the variables is a function of the different properties of the road (width of the lanes, grade), fleet composition (percentage of trucks, motorcycles, cars), external conditions (weather and ambient conditions), traffic regulations, etc.

Among these, the most important is the flow–density relationship (the *fundamental diagram*) under steady-state traffic conditions for identical driver–vehicle units [10]. The FD allows making a number of statements on the macroscopic (i.e., average) features of the traffic flow, such as the value of free-flow speed and flow capacity, distinction between uncongested and congested regimes, and breakdown phenomena [11].

Indeed, from an FD one can derive several key traffic quantities:

- Free-flow speed (v_0): the average speed as $q, k \to 0$, equal to the slope of $q(k)$ at the origin.
- Capacity (q_c): the maximum flow (per lane) on the $q(k)$ curve.
- Critical density (k_c): the density corresponding to q_c.

- Jam density (k_j): the maximum density (when $q = 0$), approximately the inverse of the average vehicle spacing (vehicle length plus gap).
- The slope of the flow–density curve at any point gives the propagation velocity of traffic disturbances (e.g., jam front speeds).

Note that the portion of the $q(k)$ curve for $k < k_c$ is called the *stable branch*, while the region with $k > k_c$ is called the *unstable branch*.

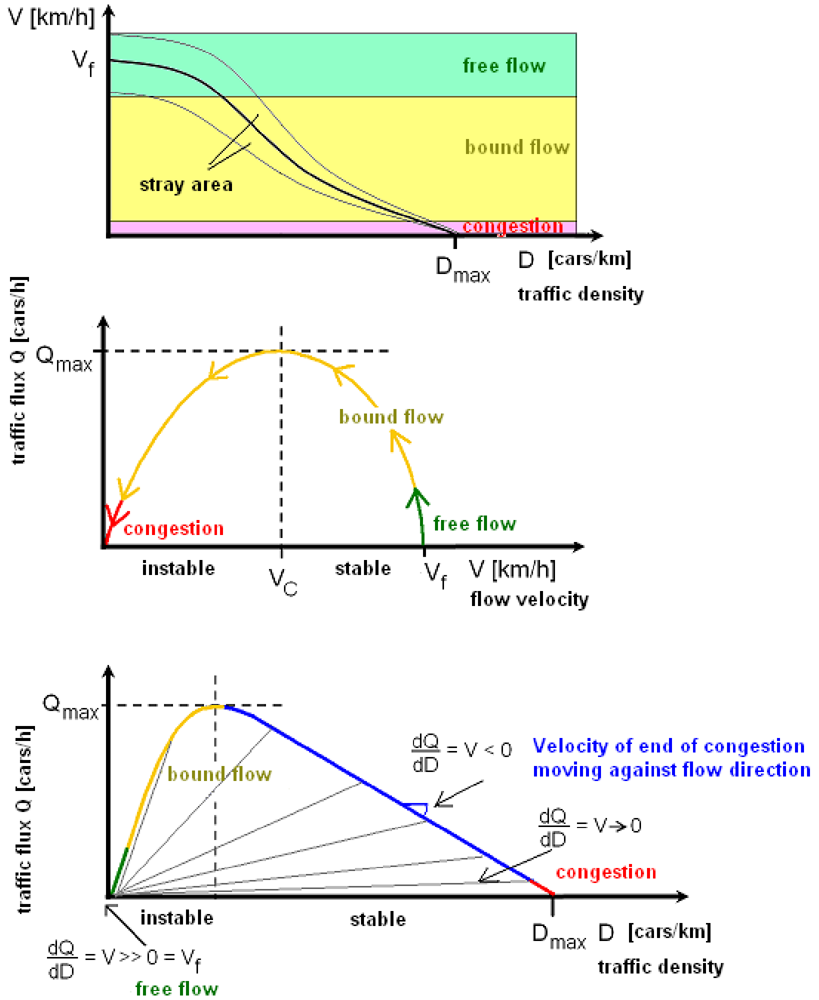


Figure 1. Fundamental diagram of traffic flow.

To estimate a parametric FD, it is necessary to collect data from real traffic, assume the functional form of the FD, and estimate its parameters by fitting a curve to the data. Here we consider cross-sectional data captured by sensors such as stationary induction loops, radar, or infrared sensors. Single-vehicle data are aggregated into macroscopic quantities by averaging over fixed time intervals Δt. The aggregation time can range from 20 s to 15 min, but the most common are $\Delta t = 1$ min and $\Delta t = 5$ min [34]. Longer aggregation periods smooth out short-term fluctuations and random noise (i.e., more stable and reliable FD estimations) and reduce the volume of data, making it easier to handle and analyze. However, short-term variations and transient traffic phenomena may be averaged out and missed, which could produce bias in the results by smoothing out peak and off-peak conditions. Short aggregation periods can capture rapid fluctuations in traffic conditions, as well as transient phenomena such as shockwaves and stop-and-go waves. However, shorter periods tend to include more random variations and noise in the data, potentially leading to less stable FD estimations and requiring the handling of large volumes of data.

It is worth noting that density, being a spatially defined quantity, cannot be directly measured using cross-sectional sensors, but can be derived from the observation of speed and flow. This limitation could affect the quality of the estimation. Finally, it is crucial to distinguish between measured flow–density data and the fundamental diagram. The two do not coincide due to (*i*) the measurement process inducing systematic errors; (*ii*) traffic flow not being at equilibrium; and (*iii*) spatial inhomogeneities in the traffic flow and/or the presence of non-identical vehicles.

2.2. Newell Model

One can apply curve-fitting techniques to match a model to the empirical observations. Here, we employ Newell's three-parameter macroscopic model, given by the following equation [35]:

$$v(t) = V_f \left(1 - e^{-\frac{\lambda}{V_f}\left(\frac{1}{k} - \frac{1}{k_j}\right)} \right)$$

where λ (in s^{-1}) is the slope of the speed-spacing curve.

The choice of a traffic flow model is critical, as it must appropriately represent the phenomena under investigation. While a spectrum of macroscopic models exists, including classic single-regime models like the linear Greenshields model and the exponential Underwood model, these possess well-documented limitations for specific traffic regimes [36]. For instance, the Underwood model can inaccurately represent traffic behavior at high, near-jam densities—a critical condition for this study's focus on bottleneck congestion [36,37]. The Newell model was chosen for this study because, despite its parametric simplicity, it has been shown to accurately describe vehicle behavior specifically in congested conditions and during queue discharge processes, which are central to the formation and dissipation of traffic jams [36,38].

Furthermore, Newell's model is not merely an empirical convenience; it can be interpreted as a microscopic formulation of the foundational Lighthill–Whitham–Richards (LWR) kinetic wave model [39]. This provides a strong theoretical basis for its use in this study, which focuses explicitly on the formation and propagation of congestion waves (i.e., shockwaves) at a bottleneck.

2.3. Traffic Jam Ahead Service

The C-ITS service *Traffic Jam Ahead* is categorized as a Day-1 service according to the Car2Car consortium [40], and is considered a production-ready, standardized service with the goal of increasing driver awareness through traffic warnings. The *Traffic Jam Ahead* service transmits V2V information via a DENM when a Cooperative and Connected Vehicle (CCV) detects a congestion (i.e., it is surrounded by stationary or heavy-volume traffic). The standardized DENM profile can be found in Directive 2010/40/EU of the European Parliament [41]. Note that DENMs are triggered only when a specific event is detected, whereas CAMs are broadcast periodically (1–10 Hz) and contain status data about the sender (e.g., position, speed, and driving direction). Annex I of the aforementioned Directive provides the formal specification of the *Traffic Jam Ahead* service; for completeness, we outline the service's activation conditions below.

In order to trigger the activation of the service and generate the related DENM, both pre-conditions and service-specific conditions must be satisfied. The pre-conditions are the following:

- No *stationary vehicle warning* or *special vehicle warning* services are active. These two are special cases of the *Traffic Jam Ahead* service, so if either is active, the *Traffic Jam Ahead* service is already in effect.

- The vehicle is located in a non-urban environment. The location is determined in one of the following ways:
  - The vehicle's speed exceeded 80 km/h for at least 30 s in the 180 s prior to detection, and the absolute steering wheel angle was less than 90° for at least 30 s in the 60 s prior to detection;
  - Via on-board camera sensors;
  - Via an on-board digital map.
- The speed and steering angle values are measured continuously.

If the pre-conditions are satisfied, at least one of the following service-specific conditions needs to be fulfilled:

- TRCO_0;
- TRCO_1 AND (TRCO_2 OR TRCO_3 OR TRCO_4 OR TRCO_5).

The service conditions are described below:

- TRCO_0: The average speed of the CCV is lower than 30 km/h but strictly higher than 0 km/h over a period of 120 s. In this case, the vehicle is either moving slowly in a non-urban environment or is in stop-and-go traffic. The strict requirement of an average speed above 0 km/h prevents overlap with TRCO_1.
- TRCO_1: The average speed of the CCV is 0 km/h over a period of 30 s, indicating full stoppage of the vehicle. However, this condition alone is not sufficient to declare a traffic jam, so it must occur together with another condition.
- TRCO_2: At least one DENM corresponding to the traffic jam service has been received by the CCV with the same driving direction.
- TRCO_3: At least one traffic jam notification with the same driving direction has been received via mobile radio communication.
- TRCO_4: CAM data indicate that at least five other vehicles are driving below 30 km/h in the same direction.
- TRCO_5: On-board sensors detect that at least five other vehicles within 100 m are driving below 30 km/h in the same direction.

Note that TRCO_3 was not implemented in our simulation (which lacks mobile radio communication), and TRCO_5 was also not implemented since vehicles were assumed not to have on-board ranging sensors. It is important to acknowledge that the non-implementation of these trigger conditions affects the generalizability of the results. These conditions provide alternative data channels (V2I via cellular networks and on-board sensor data, respectively) that could allow a connected vehicle to detect a traffic jam even in the absence of direct V2V communication. By omitting them, our simulation represents a conservative test case for C-ITS performance, as its effectiveness relies solely on direct V2V communication via CAMs and DENMs. The results should therefore be interpreted as a likely lower bound on the real-world performance of the Traffic Jam Ahead service, which would be further enhanced by these additional data sources.

3. Simulation Environment

To test the *Traffic Jam Ahead* service, we employed a co-simulation platform to exchange CAM messages and implement the service's activation and verification logic. We chose the Eclipse MOSAIC platform [42], which is illustrated in Figure 2. This open-source platform connects heterogeneous simulators within a single simulation environment via a Run-Time Infrastructure (RTI) that handles synchronization and data transfer. Using Eclipse MOSAIC enabled an integrated testing setup: the traffic simulator (SUMO) provides vehicle positions to the network simulator (SNS), which in turn sends and receives V2X messages for each vehicle application. Meanwhile, an application simulator runs the service logic (written in Java), including the activation and monitoring condition checks.

Figure 2. Eclipse MOSAIC co-simulation platform overview.

4. Case Study

4.1. Simulation Scenario

The road network consists of a three-lane straight, flat road with a lane-drop bottleneck where the number of lanes is decreased to two. This allows us to emulate a bottleneck activation, which may be caused by roadwork or an incident, among other reasons. In the literature, this kind of simulation scenario has been shown to exhibit representative characteristics of an incident in SUMO [43]. The three-lane segment is 7.5 km long, while the two-lane one is 1.5 km; this results in a total length of 9.0 km. In Eclipse SUMO, the bottleneck is modelled as a zipper where both the middle and left lanes must be used until the merging point and vehicles interleave. The maximum allowed speed on the road is assumed to be 120 km/h. These characteristics ensure that the segment qualifies as a non-urban road, satisfying the context requirements for the *Traffic Jam Ahead* service.

Three cross-section detectors are located along the road at approximately 6800, 7050, and 7300 m downstream of the starting point. In each counting section, one detector per lane is considered. Each cross-section detector collects data about passing vehicles and their individual speeds; the data are aggregated using three different time intervals (1 min, 3 min, and 5 min). Figure 3 shows an illustration of the simulated road stretch.

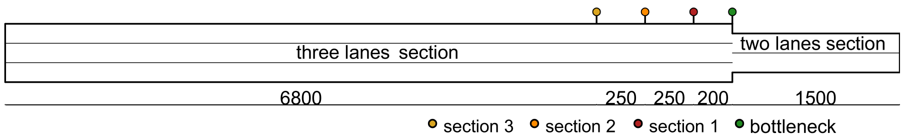


Figure 3. Road stretch layout, also indicating the location of induction loops.

The traffic demand is synthetically generated as shown in Figure 4, and the simulation lasts for 175 min. The input flow is held constant at 1500 [veh/h] for 10 min, then it is increased to 4500 [veh/h] for 25 min to activate the bottleneck. The flow is then decreased to 1500 [veh/h] for 25 min and further down to 1260 [veh/h] for 10 min. The flow increases again to 3420 [veh/h] for 25 min to activate another bottleneck, and is subsequently decreased to 1260 [veh/h] for the congestion to clear. Finally, the flow increases once more to 2340 [veh/h] for 15 min, and then it drops to 720 [veh/h]. This pattern creates three distinct peaks in demand, stressing the road network under both congested and uncongested conditions and including multiple phases of congestion formation and dissolution.

The fidelity of the simulation heavily relies on a realistic parametrization of individual driver behaviors. For this study, all microscopic parameters were drawn from the comprehensive calibration and validation work presented in Berrazouane et al. [44], which established these values against real-world traffic data. Fundamental vehicle characteristics were standardized, with all vehicles having a length of 4.5 [m] and being capable of a maximum acceleration of 2.78 [m/s^2] and a maximum deceleration of −7.43 [m/s^2]. Longitudinal movement (car-following) is governed by the widely-used Krauss model [45], coupled with a Constant-Time-Gap (CTG) spacing policy set at a time gap of 1.2 [s] and a standstill distance of 2.33 [m]. To avoid an overly uniform traffic stream and better replicate real-world conditions, driver heterogeneity was introduced. Desired speed factors were sampled from a normal distribution with a mean of 1.193 and a standard deviation of 0.091, allowing for natural variations in preferred speeds. Driver imperfection, which accounts for minor deviations in following behavior, was set with the parameter $\sigma = 0.292$. Finally, and crucial for modelling the bottleneck dynamics, lateral movements are characterized by the following lane-changing model parameters: *lcAssertive* (1.616), *lcSpeedGain* (0.887), and *lcKeepRight* (0.835). The adoption of these specific values is explicitly justified by their validation in the work of Berrazouane et al. [44]. In particular, the *lcAssertive* value captures the more aggressive merging behavior and acceptance of smaller longitudinal gaps typically observed as drivers approach a congested lane-drop bottleneck, a behavior that is essential for realistically simulating queue formation.

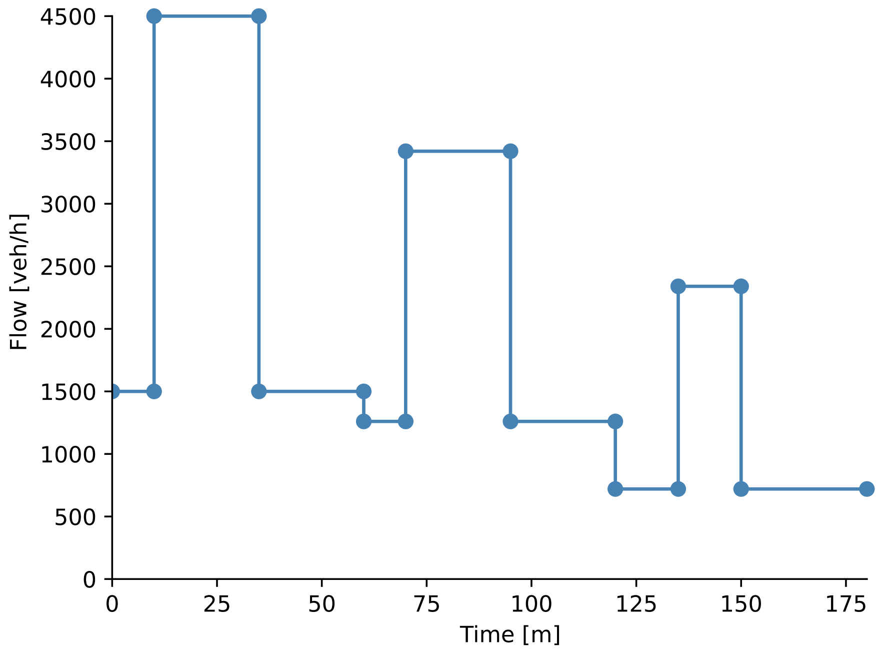


Figure 4. Traffic flow profile for the considered scenario.

4.2. FD Calibration

The calibration of the Fundamental Diagram (FD) ensures that the model reflects real-world traffic behavior, improving the accuracy of traffic management and prediction systems. For calibration purposes, we perform 100 simulations with different random seeds, randomly sampled from the set [1, 1,000,000]. Flow and speed data are collected using cross-section detectors, considering the three aggregation periods 1 min, 3 min, and 5 min. The density in then estimated using the fundamental equation of the traffic flow described in Sections 2–2.2.

To calibrate the Newell Model, we employ the Least Squares Regression: fit the observed data to the model's mathematical form using the least squares to minimize the difference between observed and predicted values. Then, a Goodness-of-Fit (GoF) metric is used to assess the accuracy of the model. Here we use Root Mean Squared Error (RMSE) as GoF metric, but for the sake of completeness we report also the R-Square and the Adjusted R-Square. The results of the calibration are summarized and listed in Table 1. In the same table, the last three columns also report the critical values q_m, k_c, and v_c that can be deduced after the calibration. As expected, the results of the calibration (and of the critical values of the quantities) depend not only on the distance to the bottleneck, but also on the aggregation period. Since the variation in the results are not negligible, but are significant, this shows that the first condition of uncertainty regarding the FD estimation is actually represented by the choice of the location of the sensors and the aggregation period.

Table 1. Calibrated parameters of the Newell Model for each set of cross-section detectors and aggregation period.

Sec.	Agg. [min]	v_0 [km/h]	k_j [veh/km]	λ [1/s]	R^2	Adj. R^2	RMSE	q_m [veh/h]	k_c [veh/km]	v_c [km/h]
1	1	136.82	150.00	0.85	0.99	0.99	3.79	1851	34.24	54.97
2	1	136.81	144.17	1.02	0.98	0.98	3.63	2115	36.16	58.49
3	1	136.75	90.96	1.59	0.98	0.98	2.75	2500	32.56	76.79
1	3	136.69	150.00	0.78	0.99	0.99	3.52	1762	33.48	52.63
2	3	136.88	143.30	1.01	0.96	0.96	3.80	1916	34.98	54.78
3	3	136.60	76.62	1.72	0.96	0.96	2.58	2237	30.58	73.15
1	5	136.74	150.00	0.77	0.99	0.99	3.45	1723	32.74	52.64
2	5	136.95	141.03	1.03	0.95	0.95	3.60	1834	33.86	54.17
3	5	136.54	58.02	1.87	0.94	0.94	2.53	2033	27.26	74.59

4.3. Simulation Analysis Setup

A real traffic environment is stochastic. Thus, in order to obtain reliable results, it is crucial to obtain as much realism as possible in a simulation scenario. To this end, we perform 1000 simulations for each penetration rate by using random seeds, resulting in a truly random behavior. Different seeds will result, for instance, in randomness when loading vehicles (e.g., speed deviation) and probabilistic insertion of vehicles as well as different vehicles being equipped with the vehicular application and messaging capabilities. To ensure statistical independence between runs, the 1000 seeds for the analysis were sampled uniformly at random and without replacement from the integer set [1, 1,000,000]. It is worth noting that the seeds used for the analysis are different from the seeds used for the calibration of the FD.

To verify the behavior of the implemented C-ITS service under different mixed traffic conditions, a penetration rate of 0–5–10–20–30–40% of connected vehicles (equipped with the C-ITS service) within the total traffic demand is considered. The test case with no connected vehicles overlaps with the analysis conducted exclusively using the traffic detectors.

For each penetration rate, each simulation and each CCV, data is gathered about the (first) time instant of activation of the C-ITS service (if any), as well as the latitude and longitude positions at the time of activation and the condition of the C-ITS service activated.

Through data analysis, a log filtering step was deemed necessary for various reasons: first, the latitudinal position is neglected since the road is a straight segment and only the longitude varies, and no assumptions on the various lanes are inferred. Secondly, as different simulation yielded similar results in both position and time of activation, an aggregation step helped us to frame the occurrence of the C-ITS service through the various penetration rates. Finally, for each non-zero penetration rate only the TRCO_0 condition was activated; this was validated by a thorough SUMO scenario inspection as the bottleneck only produced slow vehicles, but crucially no completely stationary ones, hence never validating the TRCO_1 condition. As for the simulation with no CCVs, through the offline evaluation of the traffic flow, we gathered data about all the three aggregation times in which the traffic flow had surpassed the critical density threshold.

5. Results

This section presents and discusses the results of the analysis. By inspecting the gathered results, we found that there are two distinct time windows during which a traffic queue is formed, consistent with the traffic flow profile plotted in Figure 4: the first wave causing the bottleneck can be observed from minute 10 to 40, and the second one from minute 70 to 100. For this reason, we separate our analysis accordingly into an *Hour 1* and an *Hour 2* period. Table 2 reports the percentage of simulation runs (out of 1000) in which a congested traffic state is detected for each combination of aggregation period and penetration rate. The first three blocks of rows correspond to the detector-based method (with threshold $q \geq q_c$), while the last block corresponds to the C-ITS *Traffic Jam Ahead* service.

Table 2. Percentage of occurrences, out of the total of 1000 simulations, in which a congested traffic state is detected. The first three row blocks are related to the detectors, while the last one is related to the C-ITS service *Traffic Jam Ahead*.

Test Case	Hour 1	Hour 2	Test Case	Hour 1	Hour 2
Sec-1-1 min	100%	61.7%	Sec-2-1 min	100%	0%
Sec-1-3 min	100%	28.7%	Sec-2-3 min	100%	0%
Sec-1-5 min	100%	23.3%	Sec-2-5 min	100%	0%
Sec-3-1 min	100%	0%	Pen-5%	100%	97.6%
Sec-3-3 min	99.4%	0%	Pen-10%	100%	100%
Sec-3-5 min	99.8%	0%	Pen-30%	100%	100%
			Pen-40%	100%	100%

5.1. Hour 1

As expected, higher penetration rates of connected vehicles lead to more frequent activations of the *Traffic Jam Ahead* service. Notably, even a low penetration rate of 5% is sufficient to trigger the service at least once in this scenario. Some activations occur just downstream of the bottleneck; this is because the TRCO_0 condition uses a 120 s average speed window, so a vehicle can pass the bottleneck and still have a low enough average speed (over the previous 120 s) to trigger a warning.

Here we are discussing the results of the bottleneck happening during the first simulated hour, specifically between minutes 10 to 40. The distribution of the traffic service activations for each penetration rate can be appreciated in Figure 5, noting with a deeper blue color the number of occurrences for each pair Longitude/Time, each one rounded at the third and second digit, respectively. As we can expect, the higher the penetration rate, the more vehicles trigger the activating condition for the Traffic Jam Ahead service. Crucially, even a very low penetration rate of 5% is more than enough to trigger the activating condition and send the related DENM. It might seem out of place that some vehicles trigger the traffic service after surpassing the bottleneck. However, it is worth noting that the TRCO_0 activating condition specifically expresses an average speed during the last 120 s lower than 30 km/h. Hence, the bins with a longitude greater than the bottleneck are vehicles which have surpassed the bottleneck, but their increase in speed in the subsequent seconds is not reflected in an average speed higher than 30 km/h.

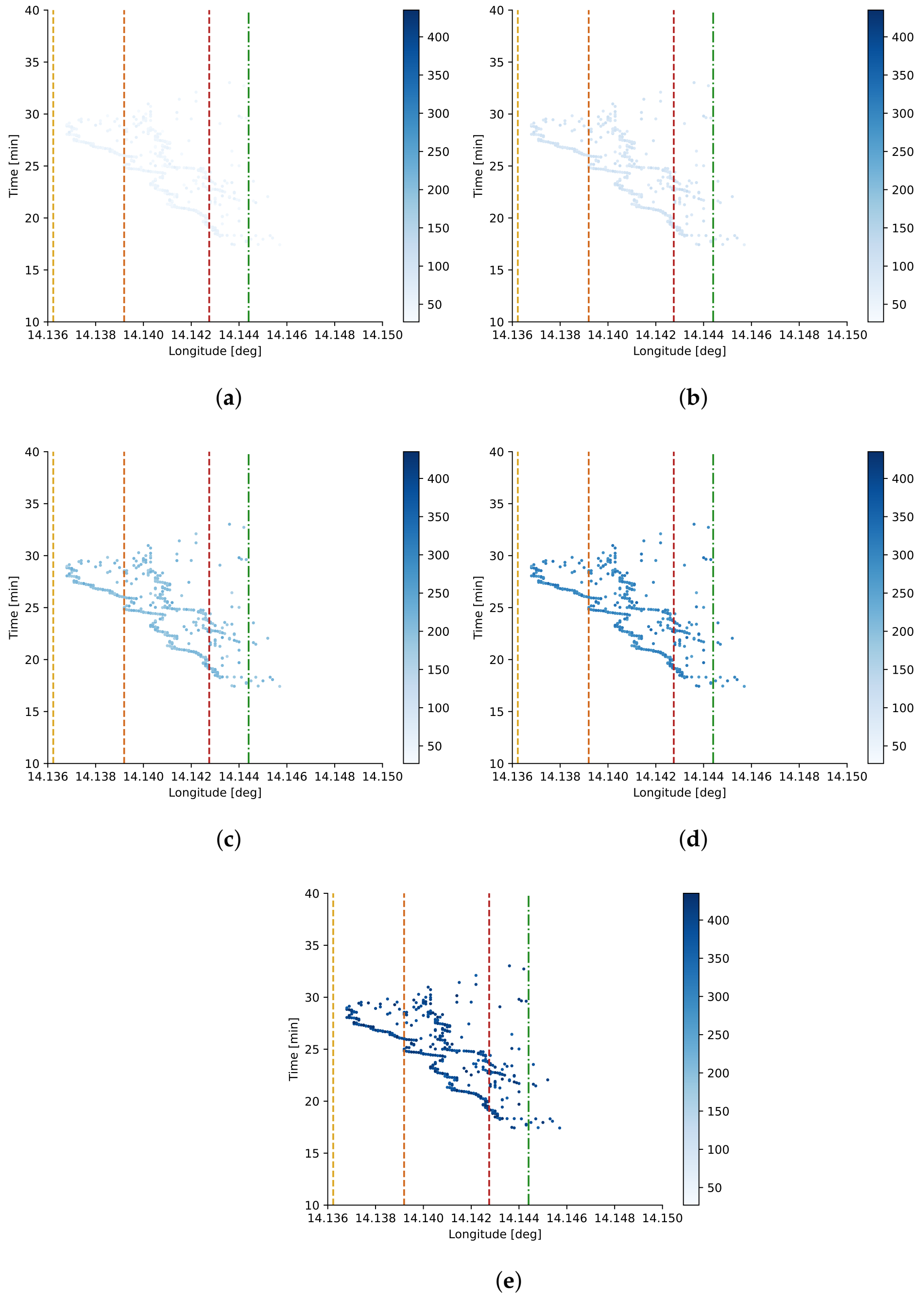


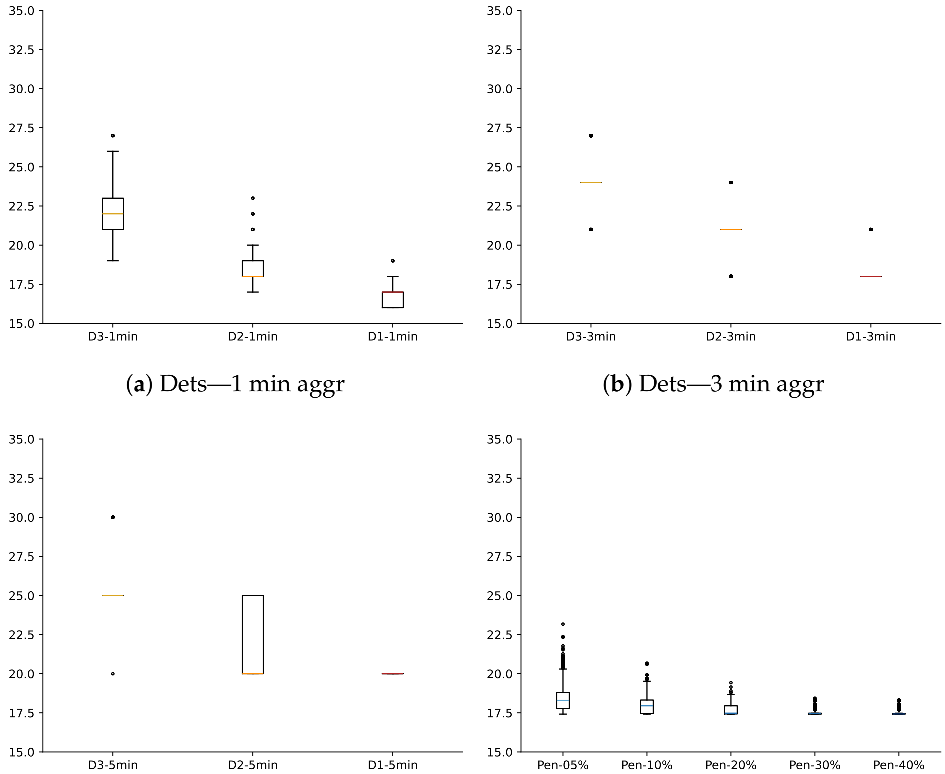
Figure 5. Distribution of the first activations for each CCV in the first hour of simulation, divided by penetration rate. In red, orange, and yellow, the longitudinal positions of detectors 1, 2, and 3, respectively. In green, the bottleneck position. (**a**) 5% penetration. (**b**) 10% penetration. (**c**) 20% penetration. (**d**) 30% penetration. (**e**) 40% penetration.

Looking at the distribution of the first instant of traffic jam detection for the first hour in Figure 6, we can see that the traffic detectors only manage to outperform the detection via C-ITS service with detectors 1 and 2 and consistently only with an aggregation period of 1 min. Penetration rates as low as 20% already manage to detect the traffic jam at the 17:30 mark, while an aggregation period of 3 min forces the detection to take place at the 18 min mark, extended to the 20 min mark for the 5 min one. However, while the comparison is close in some test cases, there are two major considerations to take into account:

1. Despite the good results, the detector analysis is completely offline due to the required traffic flow analysis. While a previous analysis of similar conditions or inference

through historical data could grant the possibility to do the traffic jam detection online, the C-ITS one is completely online and easily repeatable, also enabling the detection of stationary traffic through TRCO_1.

2. Even though the vehicular detection is obtained at an average longitude higher than the one of the detectors, the communication range of the vehicular wireless technology would more than suffice for this deficit. For instance, even a wireless range of 300 m would forward the Traffic Jam Ahead DENM message of a vehicle found right under detector 1 50 m beyond detector 2.



(**a**) Dets—1 min aggr (**b**) Dets—3 min aggr

(**c**) Dets—5 min aggr (**d**) Penetration rates

Figure 6. Boxplots of the first detection time in the first hour of simulation. (**a**) Detectors with 1 min aggregation. (**b**) Detectors with 3 min aggregation. (**c**) Detectors with 5 min aggregation. (**d**) *Traffic Jam Ahead* service (varying penetration rates).

5.2. Hour 2

During the second hour of simulation (minutes 70 to 100), a traffic jam does form, but it is more sparse and less severe than the one in the first hour (as shown in Figure 7). As before, higher penetration rates lead to more vehicles detecting the jam, with several activations only occurring after vehicles have passed the bottleneck. The reduced severity of this congestion is evident from the fact that no vehicle triggers the C-ITS service before reaching detector 1.

Figure 8 provides further insight. First, detectors 2 and 3 failed to detect the congestion, as they were too far from the bottleneck. However, a traffic queue still formed, as evidenced by vehicles registering low average speeds during the second hour. This finding highlights that detector placement is crucial: in a general road network, whether a traffic jam is detected can depend heavily on how close detectors are to the bottleneck (in our controlled scenario, detector locations were chosen to facilitate analysis). In this case, the C-ITS-based traffic jam detection is far superior. Only at the lowest penetration rate (5%) did it ever fail to detect the congestion, and even then in just 24 out of 1000 simulations. Secondly, in this less severe traffic jam, the detector-based approach with a 1 min aggregation window detected the jam roughly 3 min earlier on average than the C-ITS service. The 3 min aggregation detector performed worse on average (detecting the jam later) but its detection timing was still generally within the timeframe of the vehicles' experience of congestion. By contrast, the 5 min aggregation detector failed to detect the jam in a timely manner (similar to what was observed in the first hour). Ironically, the detector with a 5 min aggregation was the only one that detected the traffic jam in all simulation runs, whereas the 1 min and 3 min detectors missed the jam in some cases (see Table 2).

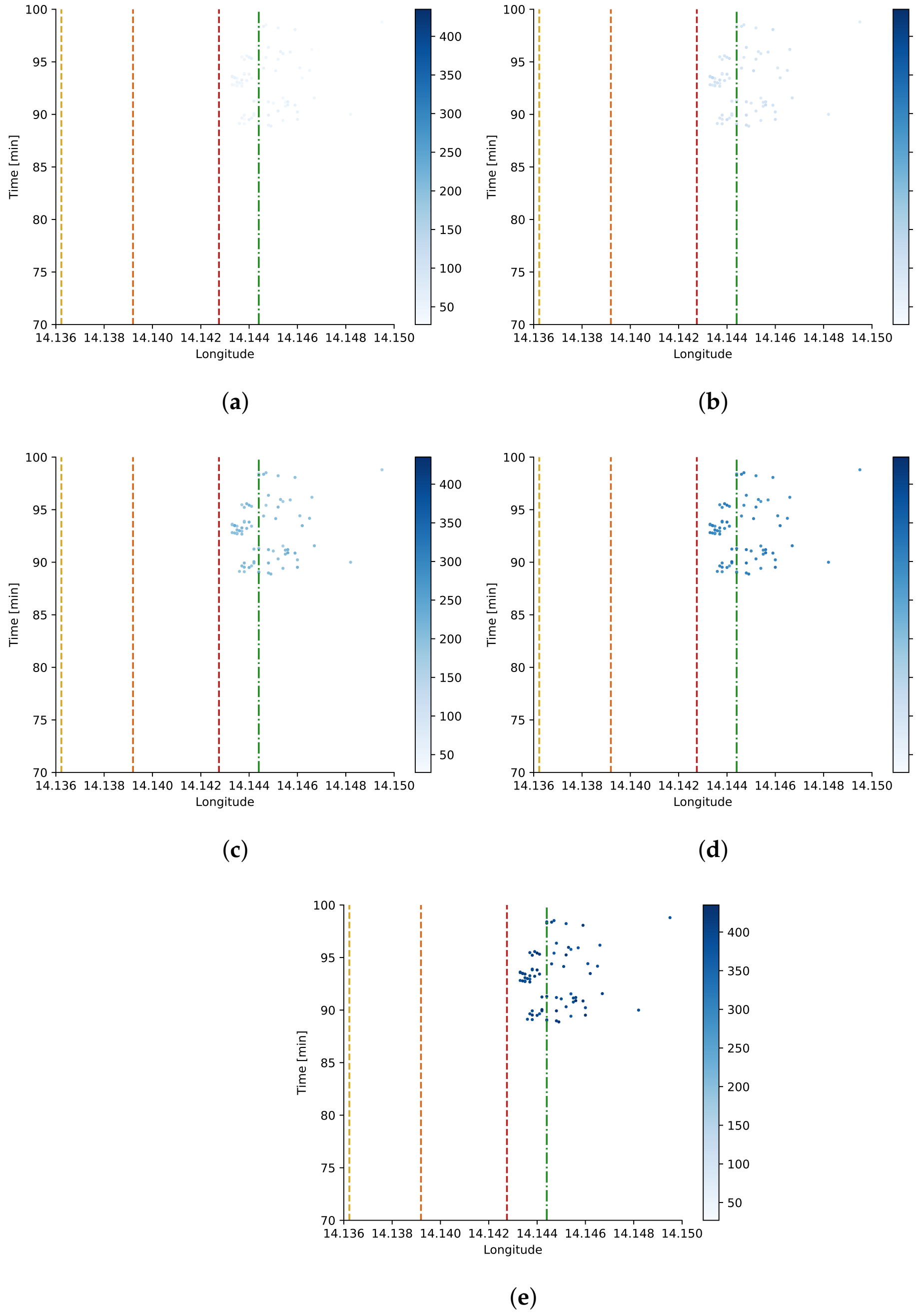
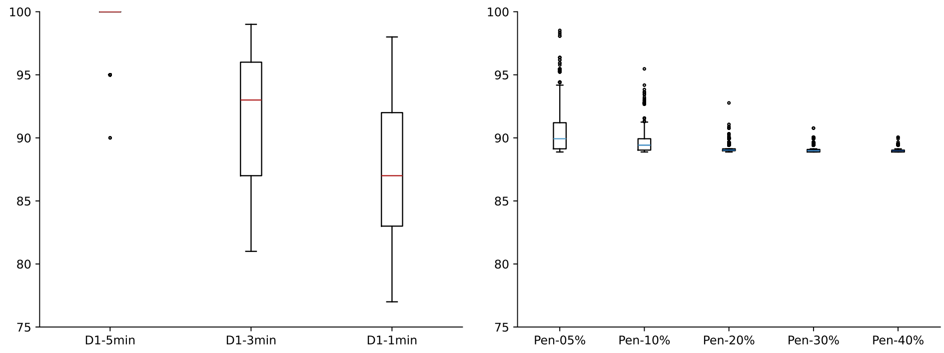


Figure 7. Distribution of the first activations for each CCV in the second hour of simulation, divided by penetration rate. In red, orange, and yellow, the positions of detectors 1, 2, and 3, respectively. In green, the bottleneck position. (**a**) 5%. (**b**) 10%. (**c**) 20%. (**d**) 30%. (**e**) 40%.



(**a**) Dets—1 min aggr (**b**) Penetration rates

Figure 8. Boxplots of the first detection time in the second hour of simulation. Only detector 1 is shown, since detectors 2 and 3 recorded no detections (see Table 2): (**a**) Detector 1 with 1 min and 3 min aggregation; (**b**) *Traffic Jam Ahead* service (varying penetration rates).

These findings from the second-hour simulation starkly illustrate a fundamental trade-off between the two detection paradigms, a dichotomy widely discussed in traffic management literature. The performance of the FD-based method is inherently constrained by its static, infrastructure-bound nature. Its success is critically dependent on the optimal physical placement of sensors relative to a bottleneck's location, a significant challenge given that deploying sensors densely across an entire network is often impractical due to budgetary constraints [16]. As our results show, if congestion does not reach a sensor's precise location, the event goes undetected. This is because fixed detectors provide only localized, point-based measurements, capturing a "singular snapshot" of a vehicle as it passes, thereby lacking the continuous spatial information needed to map the full extent and dynamics of a queue [46,47].

In stark contrast, the C-ITS approach leverages vehicles as a distributed network of mobile sensors, offering an intrinsic spatial flexibility that fixed infrastructure cannot match [48]. This paradigm shift from Eulerian (fixed-point) to Lagrangian (moving-point) data collection allows for detection to occur wherever a connected vehicle encounters congestion, providing a much richer, high-resolution, and network-wide picture of traffic conditions [49]. However, this flexibility introduces its own critical dependency: the effectiveness and reliability of C-ITS services are directly tied to the market penetration rate and the spatial distribution of connected vehicles [50]. While our study demonstrates remarkable reliability even at low penetration rates, the system's performance is fundamentally a dynamic challenge of achieving a critical mass of equipped vehicles, as opposed to the static, capital-intensive challenge of optimizing a fixed sensor layout [16,20].

6. Discussion

The study was guided by two key questions, and the results provide clear answers. The first question asked how the real-time C-ITS approach compares with the model-based FD approach in detecting traffic jams. Our findings show that the C-ITS service is a fundamentally more reliable and spatially flexible detection method. Its key advantage is its ability to detect congestion regardless of where it forms relative to fixed infrastructure. This was most evident in the second-hour scenario, where the C-ITS service successfully detected the less severe congestion in over 97% of simulations, an event largely missed by detectors located further from the bottleneck. The primary disadvantage of the FD method is its rigid dependency on sensor placement; its success is highly contingent on the queue forming at or near a sensor's physical location, making it inherently unreliable for a dynamic road network.

The second question asked under what specific conditions each method excels or falters. Here, the trade-off becomes explicit. The FD-based method's advantage is its potential for slightly faster detection under ideal conditions: when a sensor is placed optimally near a known bottleneck and a short data aggregation period (e.g., 1 min) is used for severe jams. However, its disadvantages are significant: it falters dramatically with non-optimal placement or longer aggregation periods, and it can completely fail to detect less severe congestion. Conversely, the C-ITS approach's primary advantage is its consistent performance across different locations and congestion severities. Its main limitation is its dependency on market penetration, as it falters at very low penetration rates if a connected vehicle is not present at the onset of congestion. These key characteristics are systematically summarized in Table 3.

The detailed comparison in Table 3 reveals that the two methods are not merely competitors but are, in fact, highly complementary. This complementary nature points directly towards the most promising direction for future traffic management: intelligent integration. During the (long) transitional period toward full C-ITS deployment, a hybrid system can leverage the strengths of each to mitigate the weaknesses of the other.

Table 3. Systematic comparison of congestion detection paradigms.

Feature	FD-Based Method (Infrastructure-Centric)	C-ITS-Based Method (Vehicle-Centric)
Detection Principle	Macroscopic flow theory; identifies state transition when density or flow crosses a critical threshold at a fixed point [10].	Microscopic vehicle kinematics; event-triggered based on individual vehicle speed and behaviour over a time window [5,22].
Detection Speed and Temporal Resolution	Potentially faster for severe jams with optimal sensor placement. Highly sensitive to aggregation period (1–5 min), which introduces detection lag [34].	Consistently fast and near real-time. Event-triggered messages (DENMs) are generated and disseminated instantly upon condition fulfilment [5].
Reliability and Robustness	Low. Highly dependent on sensor proximity to the bottleneck. Can miss less severe events. Prone to measurement errors [16].	High. Reliable even at low penetration rates ($\geq$5%). Performance degrades only if no connected vehicle is present at the onset of congestion [50].
Spatial Flexibility and Resolution	Very low (point-based). Provides data only at discrete sensor locations. Cannot detect events occurring between sensors [16].	Very high (network-wide, contingent on penetration). Detection occurs wherever a CCV encounters congestion, offering continuous coverage [48].
Data Granularity	Macroscopic and aggregated (flow, density, average speed). Loses individual vehicle detail [10].	Microscopic and granular (individual vehicle position, speed, heading). Enables high-resolution event data and analysis [12].
Deployment and Scalability	High capital cost for new sensor installation and ongoing maintenance. Poor scalability, as expanding coverage requires new physical installations [16].	Lower physical infrastructure cost over time (primarily RSUs). Excellent scalability, as coverage expands organically with vehicle market penetration [50,51].
Integration Potential	Provides ground-truth data for calibrating and validating the physics-based components of hybrid systems [52,53].	Provides rich, real-time data streams ideal for training and validating the data-driven/ML components of hybrid systems [52,54].

The clear complementary nature of the two methods strongly suggests that an integrated, hybrid approach is the most effective path forward for traffic management in the near future. Indeed, during the long transitional period toward full C-ITS deployment, where penetration rates will remain low for the foreseeable future, a hybrid system can leverage the strengths of each to mitigate the weaknesses of the other. Data from existing loop detectors can continue to provide a baseline macroscopic overview of the network state. Simultaneously, the growing volume of data from CCVs can be fused with this model to fill spatial gaps, provide high-resolution, real-time alerts, and dynamically validate or recalibrate the parameters of the fundamental diagram. This aligns with the state-of-the-art trend in traffic state estimation, which increasingly favors the fusion of physics-based models with data-driven machine learning techniques [52]. Our findings provide crucial empirical support for this trend. The second-hour scenario, where the FD method failed to detect the less severe congestion at detectors 2 and 3 while the C-ITS method achieved a detection rate exceeding 97% even at low penetration rates (Table 2), starkly demonstrates this. It provides direct evidence that C-ITS data can fill the critical spatial gaps inherent in fixed-sensor networks, thereby providing the continuous spatial coverage necessary to effectively train, validate, and constrain these advanced, network-wide hybrid models [53,55]. For instance, a Physics-Informed Neural Network (PINN) could use granular C-ITS vehicle data as its primary input but incorporate a term in its loss function that penalizes solutions violating the conservation law of a first-order traffic model like the Lighthill–Whitham–Richards (LWR) model [52,55]. This approach leverages the theoretical consistency of the FD-based model while capitalizing on the predictive power of ML. The result is a hybrid model that is more robust, accurate, and generalizable, particularly in data-sparse conditions where pure ML models might fail [52]. Our findings strongly support this trajectory; we demonstrate that the data from C-ITS can effectively overcome the critical spatial limitations of fixed sensors, thereby providing the necessary network-wide input for these advanced, integrated models to function effectively.

Techno-Economic and Deployment Comparison

A purely technical comparison of detection performance is incomplete without considering the practical aspects of deployment, cost, and long-term economic feasibility. The two paradigms are underpinned by fundamentally different investment and maintenance models, which has significant implications for traffic management authorities. Table 4 provides a systematic comparison of these techno-economic factors.

The traditional FD-based method relies on a centralized public expenditure model. The primary costs are the high initial capital investment for installing fixed sensors like inductive loops—which can be disruptive and costly—and the significant ongoing operational budget required for their maintenance, recalibration, and eventual replacement [56,57]. Furthermore, this approach scales poorly; expanding network coverage requires a linear increase in capital investment for new physical installations. In contrast, C-ITS operates on a distributed, mixed public–private investment model. The vast majority of the hardware cost (estimated at over 85%) is borne by consumers and vehicle manufacturers through the integration of OBUs into new vehicles [20]. Public investment is then strategically focused on deploying essential infrastructure, such as RSUs, and maintaining the back-end data management systems. This model is inherently more scalable, as network coverage and data richness grow organically with the market penetration of equipped vehicles, rather than depending solely on public works projects [20,52].

Large-scale economic analyses support the viability of this transition. The benefits are driven primarily by improvements in traffic efficiency (reduced travel time and fuel consumption) and enhanced safety (fewer accidents) [20]. During the long transition to full C-ITS adoption, the most economically prudent path forward is a hybrid strategy: leveraging the existing investment in FD infrastructure for baseline monitoring while strategically investing in C-ITS to fill spatial gaps, enhance data granularity, and unlock the significant network-wide efficiency gains that vehicle-centric data provides.

Table 4. Techno-economic and deployment comparison of detection paradigms.

Feature	FD-Based (Infrastructure-Centric) Method	C-ITS-Based (Vehicle-Centric) Method
Primary Cost Driver	High capital cost for physical sensor installation and ongoing physical maintenance [57,58].	Distributed cost of in-vehicle On-Board Units (OBUs), supplemented by public cost for RSUs and data systems [20].
Investment Model	Public Expenditure. Requires significant upfront public funding for infrastructure projects.	Distributed Public–Private Model. Leverages consumer and automotive industry investment in vehicles.
Scalability	Low. Expanding coverage requires new, costly physical installations at each desired location.	High. Coverage and data density scale organically with the market penetration rate of equipped vehicles [52].
Maintenance	High. Physical sensors are prone to failure from road wear and require periodic, on-site maintenance and recalibration [56].	Moderate. Primarily involves software updates and maintenance of a smaller number of fixed RSUs.
Spatial Coverage	Point-based and static. Provides data only at discrete, pre-defined locations.	Network-wide and dynamic. Provides data wherever equipped vehicles are present.
Benefit-Cost Ratio	Established but provides localized benefits. Overall network impact is limited by sensor density.	High projected network-wide benefit. EU-level studies project BCRs from 2–8, driven by efficiency and safety gains [20].

7. Conclusions

This work performed a comparative analysis of a traditional, infrastructure-based congestion detection method (based on Fundamental Diagram) and an emerging, vehicle-based method (C-ITS service). The comparative analysis was performed considering a simple but effective use case: a three-lane straight road with a lane-drop was used to reproduce the formation of bottlenecks. A comprehensive simulation campaign (1000 simulation runs) was carried out, taking into account the stochasticity of simulations, different penetration rates of connected vehicles, and different detector locations and data aggregation intervals. The results provide clear insights into the strengths and limitations of each method, informing their potential integration for enhanced traffic management solutions. More specifically, the results show that the C-ITS-driven *Traffic Jam Ahead* service offers superior reliability and spatial flexibility (only constrained by market penetration rates) than the detector-based approach, which is strictly dependent on the detectors' position within the traffic scenario and yields inconsistent results when dealing with less severe traffic jam conditions.

However, since a full transition to C-ITS services is impractical in the near future, the most pragmatic and effective path forward is a hybrid strategy. The joint use of data from existing fixed sensors and emerging C-ITS services can provide a more complete and robust picture of the traffic state, leveraging the strengths of each paradigm to mitigate the shortcomings of the other. This confirms that the future of traffic management lies not in replacement, but in intelligent integration. Ultimately, this integrated approach is paramount for enabling the proactive traffic management strategies necessary to reduce the significant and costly time lost by users in traffic jams, particularly those caused by recurring bottlenecks such as a reduction in the number of traffic lanes.

7.1. Limitations and Future Directions

The analysis was conducted on a simplified road network consisting of a straight segment with a single bottleneck. This scenario was deliberately chosen to create a controlled environment for a direct comparison, and it is a well-established approach in the literature for representing recurring congestion on motorways, as demonstrated in studies like Grumert et al. (2018) [43]. We contend that the fundamental principles revealed by our comparison—specifically, the trade-off between the FD method's spatial dependency and the C-ITS method's penetration dependency—remain valid for other extra-urban and motorway contexts.

Furthermore, as discussed, not all activation conditions of the C-ITS service were implemented, making our C-ITS performance estimate a conservative one.

Future developments should address these limitations and explore new avenues. A crucial next step is to extend the comparative analysis to more complex and realistic road networks, including urban corridors and multiple-bottleneck scenarios, likely requiring different modelling paradigms. Specifically, future simulations should implement the remaining activation conditions, TRCO_3 (congestion notification via mobile radio communication) and TRCO_5 (detection via on-board sensors), to provide a more comprehensive assessment of the service's full capabilities, especially at low penetration rates where alternative data sources are most critical. Future developments should also address other limitations and explore new avenues.

It is also important to recognize that non-recurring events, such as traffic accidents or adverse weather conditions, can drastically alter traffic dynamics and the performance of both detection methods. While a detailed simulation of such scenarios is beyond the scope of this paper, it is worth noting that the standardized C-ITS framework is designed as a suite of services. Specific events like an accident are intended to trigger dedicated services, such as the 'Hazardous Location Warning', as specified in standards like ETSI EN 302 637-2 [59]. The Traffic Jam Ahead service, which we analyze, is primarily focused on detecting congestion resulting from traffic demand. Analyzing the complex interplay and performance of this full suite of C-ITS services under stochastic, non-stationary conditions remains a critical and compelling area for future research.

Finally, it would be valuable to compare these traditional and C-ITS methods against more advanced, AI-driven traffic prediction models and to develop a fully integrated hybrid detection algorithm that actively fuses FD and C-ITS data in real-time.

7.2. Practical Implications for Traffic Management and Policy

The findings of this study have direct implications for traffic management authorities and policymakers. Firstly, they suggest that future infrastructure investments should be strategically allocated. Rather than focusing on increasing the number of costly and maintenance-intensive loop detectors along a road network, investments could be more effectively directed towards deploying C-ITS infrastructure, such as RSUs, at known, recurring bottleneck locations. This targeted deployment would enhance the reliability of C-ITS services where they are most needed, ensuring robust communication even with moderate vehicle penetration rates and providing a more flexible and scalable solution than a fixed sensor layout. Secondly, traffic management centers can begin preparing for the integration of C-ITS data as a supplementary source to enhance their existing monitoring systems. Even at low penetration rates, this data can provide valuable, early warnings of developing congestion in areas not covered by fixed sensors, improving situational awareness and enabling more proactive traffic control strategies. By enabling such proactive strategies, the integration of C-ITS data represents a direct and scalable pathway to mitigating the multi-billion-dollar economic losses imposed by traffic congestion annually, offering a substantial return on investment through increased efficiency and productivity.

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Abbreviations

The following abbreviations are used in this manuscript:

ADSs	Automated Driving Systems
AI	Artificial Intelligence
CA	Cellular Automata
CAM	Cooperative Awareness Message
CCV	Cooperative and Connected Vehicle
C-ITS	Cooperative Intelligent Transportation Systems
DENM	Decentralized Environmental Notification Message
FD	Fundamental Diagram
LSTM	Long Short-Term Memory
LWR	Lighthill–Whitham–Richards
ML	Machine Learning
OBU	On-Board Unit
PINN	Physics-Informed Neural Network
RSU	Road Side Unit
RTI	Run-Time Infrastructure (co-simulation)
SNS	Simple Network Simulator
TSE	Traffic State Estimation
V2I	Vehicle-to-Infrasctructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

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