Real-time Road Traffic Data Monitoring using Novel Leaky-Wave Antennas in a Connected and Autonomous Vehicles Environment

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Abstract

Inductive loop detectors (ILD) systems have been employed on motorways to effectively monitor road traffic, providing insights for data-driven strategies for smart cities. However, traditional ILDs encounter several challenges, such as complex integration with other technologies, high installation costs, and demanding maintenance processes. To address these issues and create future-proof flexible traffic monitoring systems with high accuracy of current solutions, significant advancements in standard ILDs are crucial. This paper presents a new leaky-wave antenna on-road sensor, showcasing its efficient, and reliable monitoring and data collection which includes vehicle count, average speed, and lane changes. It utilises frequency-dependent beam scanning capabilities to explore multiple directions on the road without any physical movement. By intercepting electromagnetic waves emitted by vehicles from different angles, the proposed system efficiently processes this information to gain valuable insights into traffic behaviour and patterns. Initial experimentation in a simulated environment has validated the proposed solution, highlighting its robustness and accuracy, outperforming existing alternatives. The antenna-based sensor exhibits an efficiency surpassing 99% in simulations even in challenging simulations with random noise figures and effectively captures 98% of lane changes. Additionally, the system provides real-time insights into road conditions with minimal operational and capital expenses compared to previous approaches. This innovation will make a valuable contribution to the progress of smart cities and the successful deployment of CAVs. By leveraging the potential of electromagnetics, this research aims to enhance efficient traffic data collection, ultimately fostering safer and more efficient transportation systems.

Keywords: leaky-wave antenna, inductive loop detectors, connected and autonomous vehicles, on-road sensor, smart motorways.

INTRODUCTION

In the era of smart cities and the rise of connected autonomous vehicles (CAVs), data has become a crucial element in shaping the future of urban mobility. The effective collection, analysis, and utilisation of data hold the potential to revolutionise transport systems, improve traffic management, enhance safety measures, and optimise overall urban infrastructure. It is evident that the importance of data cannot be overstated in enabling the efficient functioning of smart cities and the successful deployment of CAVs.

Recent studies have emphasised that cities worldwide generate an enormous amount of data related to transportation (*1*, *2*). Among the various types of data crucial for smart cities and CAVs, this paper specifically focuses on the significance of traffic data and incident data. Transport authorities heavily rely on inductive loop detectors (ILDs) strategically placed across the road network every 400 metres to gather accurate and real-time traffic data. These ILDs detect and monitor vehicles passing over the loops, providing valuable insights into congestion patterns, traffic flow dynamics, and travel demand. For instance, the well-established MIDAS (Motorway Incident Detection and Automatic Signalling) data collection system in the United Kingdom utilises ILDs to capture traffic data, enabling informed decision-making for efficient traffic management and infrastructure planning.

In addition to traffic data, incident data, plays a critical role in ensuring swift response and effective management of emergencies. Accidents and road closures can significantly impact traffic flow and overall urban mobility, costing billions of dollars in wasted fuel and productivity loss (*3*). Therefore, access to timely and accurate incident data allows authorities to respond quickly and implement appropriate measures to mitigate their impact, thereby improving safety and minimising disruption to the transport system. ILDs and data collection systems like MIDAS provide valuable insights into traffic behaviour and incident occurrences, facilitating the development of data-driven strategies for smart cities and CAVs.

However, there are several limitations associated with ILD data collection (*4*). One key limitation is the limited coverage of ILDs, as they are typically installed at specific locations within the road network (*4*). This restricted coverage hampers the ability to obtain a comprehensive understanding of traffic conditions across the entire network, impacting the accuracy of traffic flow analysis and decision-making processes (*5*). Additionally, the installation and maintenance of ILDs can be complex and costly, requiring road closures and disruptions during installation as well as ongoing maintenance to ensure accurate functionality (*5*). Malfunctioning or faulty detectors can also lead to inaccurate or incomplete data, undermining the reliability of the collected information (*6*) while the periodic replacements of detectors due to road repairs and maintenance further escalates the overall cost. Such additional expenses for upkeep and replacement pose challenges to the long-term viability and economic feasibility of implementing and maintaining lane detection systems in CAV infrastructure. Furthermore, ILDs provide limited data granularity, typically offering information on traffic volume, occupancy, and speed, but may not capture more detailed parameters for comprehensive analysis. Their design primarily caters to detect and monitor motorised vehicles, which means they may not effectively capture data related to non-motorised modes of transport, limiting insights into alternative forms of transport modes (*7*).

Hence, to fully leverage the potential of smart cities and CAVs, it becomes evident that accurate and real-time data, including traffic data and incident data, is indispensable (*6*). The effective collection, analysis, and utilisation of this data can result in enhanced traffic management strategies, optimised resource allocation, improved safety measures, and the development of more sustainable urban transportation systems. Therefore, there is a need to establish robust data collection methods and secure data sharing frameworks, facilitating the seamless integration of data-driven technologies in urban mobility.

One promising alternative to ILDs is the utilisation of camera-based sensors in conjunction with computer vision techniques (*8*). However, there are also limitations associated with this approach in real-world scenarios: (a) the cost of high-resolution cameras can pose a challenge to their widespread adoption, (b) cameras are restricted by their field of view, which means that certain areas may not be adequately monitored, especially if there are obstructing objects such as heavy goods vehicles (HGVs) can result in the generation of false data, undermining the reliability of the collected information, (c) adverse weather conditions can significantly degrade picture quality, thereby negatively impacting the accuracy and quality of the collected data and (d) the implementation of computer vision algorithms necessitates substantial processing power, particularly when covering a large expanse of road network.

Another way to augment data collection and communication capabilities within smart cities and urban mobility systems is by using the lower sections of the electromagnetic (EM) spectrum. Utilising microwave and millimeter-wave frequency ranges have already demonstrated significant success in the field of telecommunication and sensing over large distances (*9*, *10*). The deployment of antennas on the road network, particularly in conjunction with 5G technology, presents a tremendous opportunity for collecting traffic data. Antennas play a critical role as essential components for establishing robust wireless connectivity, enabling seamless transmission of data between vehicles, infrastructure, and central control systems (*11–14*). While some systems have relied on radar-based technology for decades to monitor vehicle speed on road (*5*) the emergence of 5G technology further amplifies the importance of using new innovative solutions such as beam-scanning antennas. These antennas offer higher bandwidth, lower latency, and increased data transmission capacity (*15*). By strategically placing antenna-based sensors along the road network, authorities can ensure widespread coverage and reliable connectivity, facilitating real-time data collection from diverse sources, including connected vehicles, sensors, and surveillance systems (*16*, *17*). This extensive network coverage empowers transport authorities to gather comprehensive and accurate data, facilitating advanced analytics, intelligent incident detection, and efficient traffic management strategies.

As a result, this research paper aims to explore the adoption of a new leaky-wave antenna on road sensor for traffic data collection system as a superior alternative to existing on-road systems. By harnessing the data acquired through this new sensor, this study aims to provide reliable and comprehensive data collection system to support decision-making processes in smart cities and optimise the performance of CAVs. This sensor will make a valuable contribution to the progress of smart cities and the successful deployment of CAVs in urban environments. By leveraging the potential of novel leaky-wave antennas, this research aims to elevate incident detection capabilities and more efficient traffic data collection, ultimately fostering safer and more efficient transportation systems.

OVERVIEW OF THE EXISTING SYSTEM

The current ILD systems comprise three main components: induction coils, an analogue detection board, and a GSM modem. ILDs collect data by utilising induction coils beneath the road surface. When a vehicle passes over the coil, it induces a change in the magnetic field, creating an electrical signal (*18*). This signal is then transmitted to the detection board, where it is processed and counted. The detection board is linked to the modem, utilising 2G technology to establish communication. The road loops are directly connected to a central hub, from which they are then linked to the detection unit. The power the unit and supply energy to the loops, a reliable battery is employed. Although some systems have small solar cell panels placed on top of the hub, but, these are mostly ineffective, exacerbating the existing power consumption challenges (*4*). A representation of the current system deployed on the road network is presented in **Figure 1**.

Figure 1: Overview of existing systems (red arrow highlight ILDs installed on the road)

The collected traffic data collected by these systems is then transmitted back to a central location through the current data backhaul. At this location, one can access and analyse the data. However, the process currently endures a delay of up to 7 minutes (*4*). This is attributed to the lack of direct database access and instead rely on an Urban Traffic Management and Control (UTMC) API interface. This limitation significantly restricts the availability of external real-time applications and data analysis.

Additionally, the data collected is gathered at a minute-level granularity. However, for future applications the disaggregated data goal is to minimise the prediction horizon, aiming for intervals of less than 1 second for CAVs, intelligent transportation systems, and vehicular communication (*19*, *20*).

NEW LEAKY-WAVE ANTENNA ON-ROAD SENSOR

This study introduces a new leaky-wave antenna on-road sensor, and its methodology is outlined in this section. It consists of two key components: (a) a comprehensive description of leaky wave antennas to enable seamless and rapid data transfer within the traffic network system and (b) the sensor-operation approach demonstrating how real-time data, such as traffic flow, vehicle speed, and road conditions can be efficiently collected from CAVs, to provide valuable insights for traffic management and optimisation.

Leaky Wave Antennas (LWAs)

LWAs are generally characterised by their operation on a one-dimensional guiding structure, where the EM wave and surface currents are manipulated along its length (*21*). Several LWAs have been proposed and extensively studied in the literature such as periodically corrugated microstrip lines, longitudinal slot arrays on a 1D rectangular waveguide (*22–26*). Similar to travelling wave antennas, LWA generate a fan-shaped EM beam, exhibiting a distinctive radiation pattern. This pattern is characterised by a narrow half-power beamwidth (HPBW) in one direction and a wider HPBW in the orthogonal direction (*27*) (as shown in **Figure 2**). Moreover, the beam angle sweeps in one direction with the change in frequency. This is because of the phase shift among the radiating elements resulting from the variation in operating frequency. The beam angle in relation to the operating wavelength (or frequency) is defined in **Equation 1**:

$$\theta = \sin^{-1}\left(\frac{\lambda}{\lambda_g} - \frac{\lambda}{2g}\right) \tag{1}$$

Where, λ is the operating wavelength in free space; λ_g is the guide wavelength or wavelength of the EM wave within the guiding structure, g is the space between radiating elements, and Θ is the angle of the radiated beam as shown in **Figure 2**. Hence, by carefully controlling these parameters, the beam-scanning capabilities of the LWA's can be used to produce the radiated beam in different directions within the azimuth plane. This implies that by adjusting the operating frequency or wavelength, the angle of the beam can be modified, enabling beam steering, or scanning functionality. The capability to dynamically change the direction of the radiated beam is highly advantageous in many transport applications.

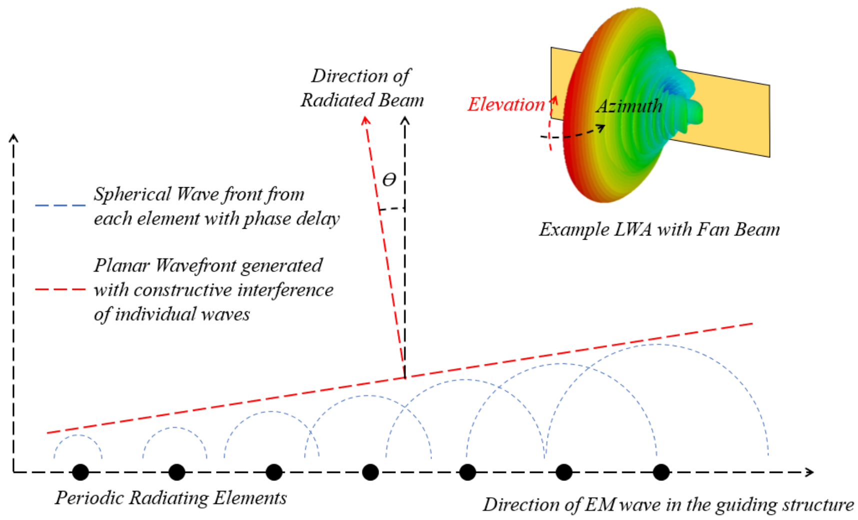


Figure 2: Working principle of leaky-wave antennas (LWA) and a 3D representation of fan beam generated by LWA with narrow HPBW in the Azimuth plane and wide HPBW in the Elevation plane.

In addition to the frequency based beam-scanning capabilities of the LWA, the literature also presents the potential for generating a fixed-frequency beam-steering in the elevation plane (*24*, *28*–*30*). These techniques offer an alternative approach to beam control, where the angle of the radiated beam can be adjusted without changing the operating frequency.

By combining the advantages of frequency-controlled beam-scanning and fixed-frequency beam-steering, a smart sensor can be created for on-road traffic data collection, particularly in the context of connected and autonomous vehicles. This integrated system has the potential to enhance the sensing capabilities and enable efficient data gathering.

To facilitate the understanding and design of the proposed sensor system, a reference beam-steering antenna described in (*24*) is utilised as a point of reference. The antenna configuration is depicted in **Figure 3**, illustrating the practical implementation of the beam-steering concept. This reference design serves as a basis for further discussion and exploration of the proposed technique in the subsequent section.

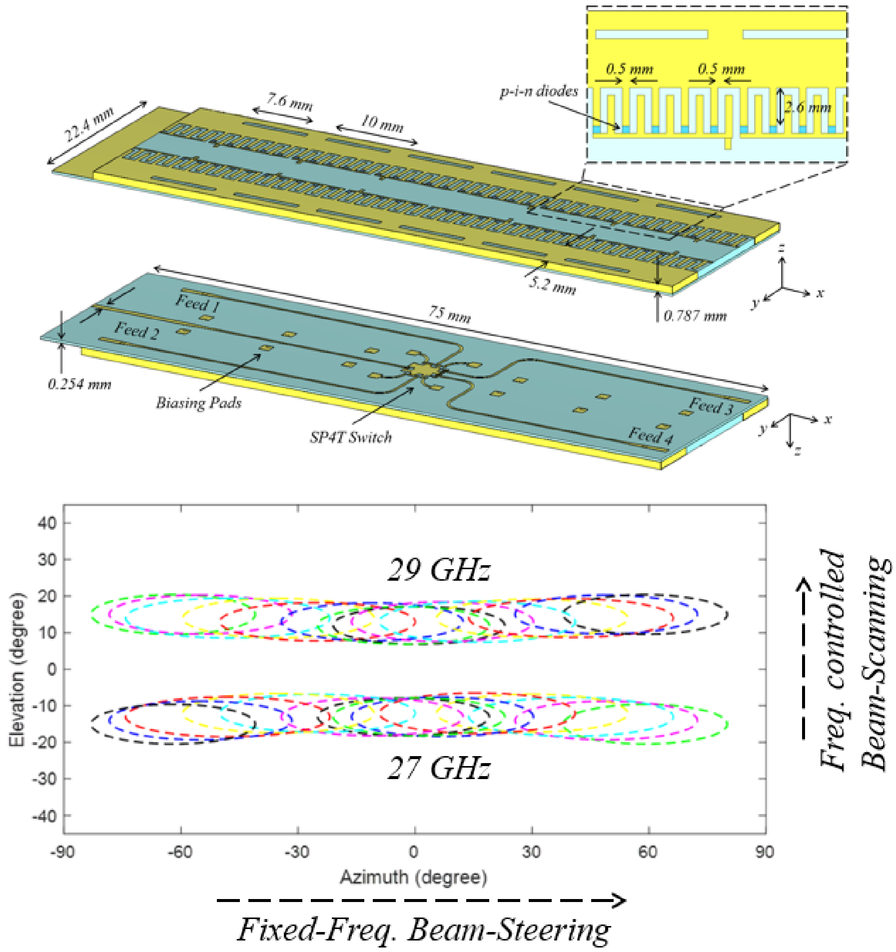


Figure 3: Antenna design and 2D-representation of the measured pattern for the proposed antenna demonstrating fixed-frequency beam-steering in the azimuth plane and frequency-controlled beam-scanning in the elevation plane.

The beam-steering antenna employed in the new leaky-wave antenna on-road sensor is a longitudinal slot array implemented on a corrugated substrate integrated waveguide structure, operating at a frequency band of 26 to 30 GHz. This antenna design exhibits remarkable performance characteristics, including an efficiency exceeding 80% and a gain greater than 13 dBi. The compact size of the antenna measures 75 × 22.5 mm.

The antenna sensor offers a dual functionality of a fixed-frequency beam-steering in the azimuth plane and frequency-controlled beam-scanning in the elevation plane. In the azimuth plane, the antenna achieves a fixed-frequency beam-steering capability with a range of ±60°. This means that the radiated beam can be dynamically adjusted within a wide angular span, facilitating effective coverage of the desired area of interest.

Additionally, in the elevation plane, the antenna provides frequency-controlled beam-scanning with a range of ±30° in the elevation plane. By manipulating the operating frequency, the elevation angle of the radiated beam can be precisely controlled, enabling versatile beam positioning for targeted data collection.

The antenna's working principle, detailed explanations of its design, fabrication, and measurement are presented in (*24*). This reference provides in-depth insights into the antenna's construction, outlining the step-by-step process employed to achieve its performance characteristics.

Sensor-Operation Methodology

Given the rapid advancement of CAVs, the implementation of 5G technology for vehicle-to-everything (V2X) communication networks emerge as a crucial solution to address road congestion and enhance safety. The new leaky-wave antenna on-road sensor capitalises on the concept of a network comprising interconnected vehicles and infrastructure, facilitating the exchange of information among them is presented. Specifically, the proposed sensor leverages passive transceiver (TRx) antennas installed in vehicles, enabling simultaneous broadcasting and reception of information.

To achieve effective communication, the new sensor methodology is designed based on the 5G new-radio millimetre-wave band, operating within the frequency range of 26 to 30 GHz. By utilising the wireless channel to regularly transmit data, each vehicle establishes a communication link that can be exploited to track its precise location and speed on the road. This data can subsequently be utilised to derive essential parameters, such as road congestion levels. As detailed in section 3.1, the antenna design incorporates a fan-shaped beam (see **Figure 3**) which can be dynamically steered using p-i-n diodes integrated within the antenna system (*24*, *25*). By deploying this antenna at an elevated height, h, on a motorway and tilting it at an angle θ, the radiated beam can effectively scan a substantial stretch of the road. **Figure 4** provides a perspective view of the proposed setup, showcasing how each beam of the antenna corresponds to a specific section of the lane. A perspective view of the new sensor setup shown in **Figure 4** also shows how each beam of the antenna corresponds to a specific section of the lane.

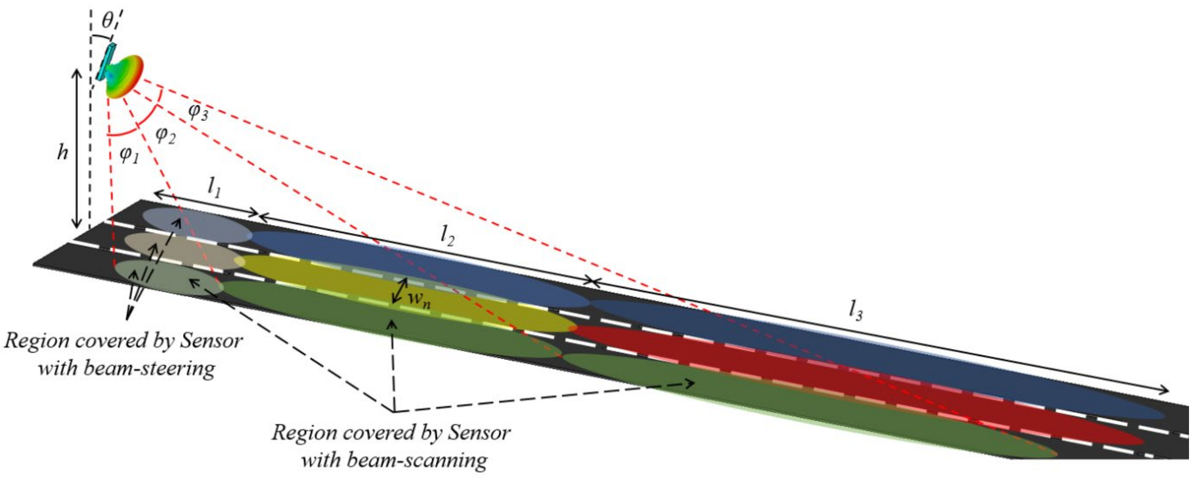


Figure 4: Placement of the sensor on road and a pictorial representation of different regions covered by the antenna sensor.

The width of the region covered by each beam, w_r, can be determined by using the half-power beamwidth of the antenna in elevation plane, θ_{el}, and can be expressed as shown in **Equation 2**:

$$w_n = 2h\frac{\sin\theta_{el}}{\cos\sum\varphi_n} \tag{2}$$

Where, φ_n is the half-power beamwidth of the n-th beam in azimuthal plane, and w_n is the width of the region covered by the n-th beam. **Equation 2** refers to an ideal situation and does not take noise referring to poor signal quality at the far end of each section into consideration. The length of each region covered can also be calculated as shown in **Equation 3**:

$$l_n = h \tan\left(\sum \varphi_n\right) - \sum l_{n-1} \quad (3)$$

Where, φ_n is the azimuthal half-power beamwidth of the n-the beam with no overlap with $(n\text{-}1)^{th}$ beam and $l_0 = 0$. This equation can be used to calculate the length of region covered by each beam. By utilising **Equation 3**, the specific regions covered by each beam can be determined. However, due to factors such as low signal-to-noise ratio and overlap with other frequency bands, the boundaries of these regions may experience strong noise interference. Hence, a smaller section can be selected within each region which has minimal overlap leading to low noise interference, as shown in **Figure 5**.

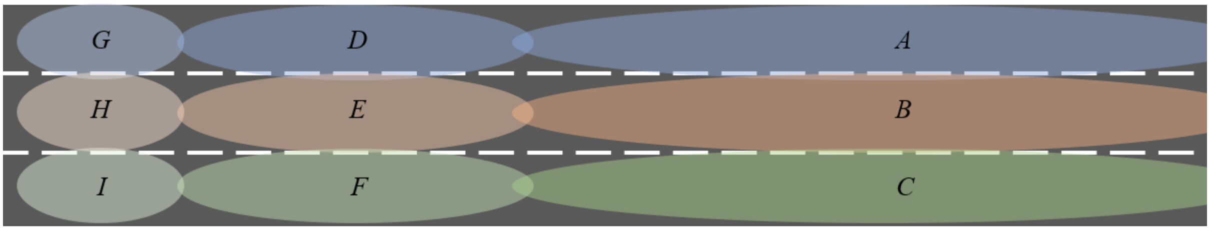


Figure 5: Road layout with regions covered by the antenna with minimal overlap and low signal-to-noise ratio.

To ensure comprehensive coverage of each lane, the antenna employs beam-scanning techniques. Specifically, Region A of the road is proposed to be covered by two 400 MHz channels operating in the frequency ranges of 26 to 26.4 GHz and 26.5 to 26.9 GHz, with a 100 MHz guard band in between. Similarly, Region B is covered by the frequency range of 27 to 27.9 GHz, and Region C is covered by the frequency range of 28 to 28.9 GHz. The sections within the same lane are governed by the beam-steering capability of the antenna. Consequently, Region B, Region E, and Region F are covered by three distinct beams, each created by applying different switch conditions on the antenna. This allows for tailored coverage of specific sections within the lane. It is important to note that the broadcasted signal from a vehicle is hypothesised to be a broadband signal spanning the 26 to 29 GHz frequency band. As a result, the antenna sensor remains capable of capturing the transmitted signal throughout the monitored region of the motorway, ensuring continuous visibility of the signal within its operating frequency range.

Furthermore, when a vehicle enters the monitored region of Lane 2 on the motorway at a specific time stamp, denoted as t_0, it will be located within Region B. Consequently, the broadband broadcast signal transmitted by the vehicle will be received by the antenna sensor within the frequency band 27 to 27.9 GHz. The received signal within this frequency range serves as confirmation of the vehicle's lane on the road. To assess, the strength of the received signal, the receiver antenna sensor calculates the receiver signal strength indicator (RSSI). The RSSI provides a quantitative measure of the signal's intensity and can be utilised to estimate the distance between the transmitter (i.e., the vehicle) and the receiver (i.e., the antenna sensor) in a line-of-sight scenario. By leveraging the RSSI data, the antenna sensor can accurately determine the precise location of a vehicle on the road and its distance from the sensor at the given timestamp, t_0. By continuously collecting this data over time, the sensor system can effectively track the movement and positions of all vehicles on the road. This information enables the system to calculate the speed of each vehicle based on their position changes over time. By monitoring vehicle speeds, the system can make informed decisions to mitigate congestion on the road, allowing for more efficient traffic control measures to be implemented.

The length of the motorway covered by seven beams, spanning from 0 and 60º, for the leaky-wave antenna operating at a fixed frequency of 27-27.4 GHz was theoretically calculated using eq. (3) and is shown in **Figure 6**.

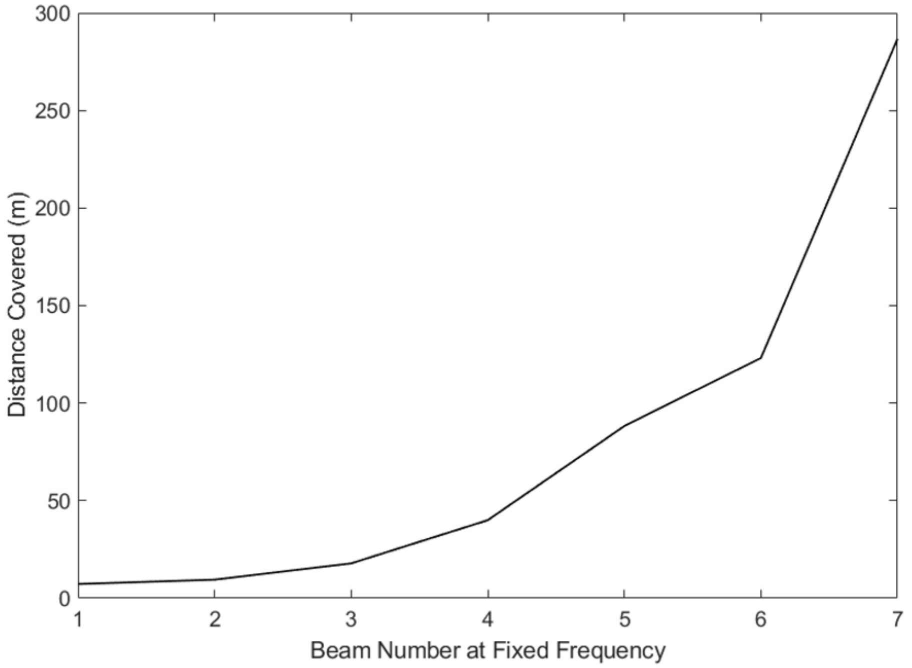


Figure 6: Theoretically calculated distance covered by each beam at a fixed frequency within the same lane; total distance adding up to approximately 570 m.

A total length of approximately 570 metres was covered by a single sensor facing in one direction. To expand the coverage area, another sensor can be positioned in the opposite direction of the road, providing an additional cover length of 570 m. This results in an overall coverage area of over 1 km along a straight section of the motorway. While the proposed methodology has been presented for a straight stretch of the road; it can be easily adapted to accommodate bends and curves by adjusting the placement of the sensor. By defining similar regions in different orientations on various sections of the motorway, the methodology can be applied to compute several parameters related to road congestion. This approach offers a cost-effective and practical solution compared to traditional methods such as ILDs, offering easier implementation.

EXPERIMENT SETUP

To assess the viability of the new sensor, a simulation-based testing experiment was devised and conducted on a traffic network. This approach allowed for the evaluation of the methodology's efficacy and resilience without the need for direct implementation in a real-world scenario.

Simulation Framework for New System

PTV VISSIM serves as a valuable tool to represent the network section, enabling the generation of surrounding traffic flow based on real data. The development of the network entails defining crucial model parameters, vehicle composition, the number of lanes, required input traffic data, and driving behaviour characteristics. By meticulously repeating the simulation, the accuracy and reliability of the results are enhanced, reinforcing the validity of the study's findings.

The typical parameters, such as the simulation period (3600s), resolution (1/10 s) and random seed number (42) are set by VISSIM. Real-world traffic counts of mode wise flow, speed, and default VISSIM headway are used as inputs for the simulations. A total number of ten simulation runs were executed to generate simulation outputs. It is well-established that ten simulation runs are sufficient to achieve accurate results *(31, 32)*. The average of these outputs is then compared to the corresponding real-world values.

Demonstration simulation experiment

The experiments developed aim to provide a comprehensive evaluation of the framework's efficacy in the motorway setting, while considering the specific traffic regulations and driving conventions relevant to the UK. Scenario testing was conducted on a specific stretch of the M1 motorway spanning approximately 6km between Junction 18 and 19. This study considers only the northbound section, and it comprises of three lanes as shown in **Figure 7**. To ensure a realistic representation, this section was meticulously designed to resemble the actual real-world motorway, serving as the backdrop for the simulation experiments. A key advantage of using this approach lies in the incorporation of environmental parameters derived from an on-site inspection, such as the precise position of roadside elements, lane widths, and shoulder widths. By utilising real-world data for the environmental parameters, the simulated scenery closely aligns with the physical characteristics of the motorway, enhancing the authenticity and reliability of the simulation results.

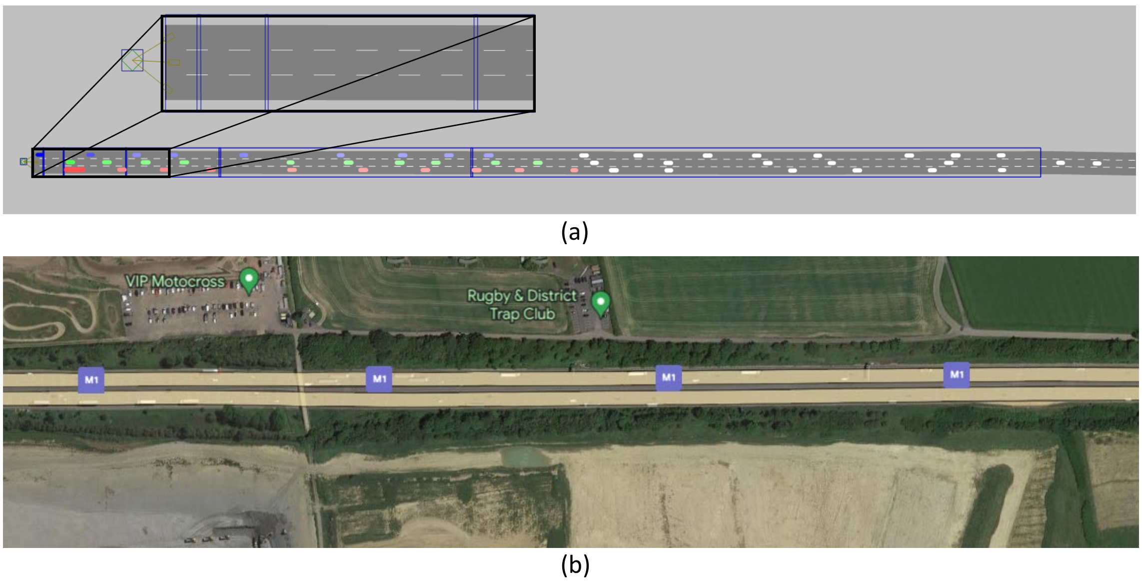


Figure 7: Snapshot of Data Location in (a) VISSIM simulation and (b) Real-World Scenario

The new sensor methodology was thoroughly examined through simulation using the VISSIM vehicle simulator. The primary objective of the study was to assess the accuracy of vehicle counts using antennas. To achieve this, the default parameters of the VISSIM vehicle simulation software were employed such as standstill distance (1m), headway (0.6s), acceleration (4 m/s^2) *(33)* and vehicle dimensions (length: varies between 3.8 to 4.2; width: varies between 1.8 to 2 m). Antennas were strategically placed along the road network, that created 12 monitoring zones on the road at the distances as shown in **Figure 6**. The new antenna sensor was precisely modelled and integrated with VISSIM using the Python API. An example of the pseudocode adopted for vehicle count assessment using the new antenna sensor in VISSIM simulator is presented in **Table 1**.

TABLE 1*:* Pseudo code for vehicle count using new antenna sensor integrated in VISSIM.

```
1. Import necessary libraries
2. Set the path to the VISSIM network file
3. Connect to VISSIM
4. Load the network file
5. Set the distance threshold for transmitting data for each region based on frequency
6. Initialise lists to store received counts, vehicle ID, lane change, position, and simulation
time for each simulation step
   received_counts = []
   vehicle_ids = []
   vehicle_type = []
   lane_changes = []
   positions = []
   simulation_times = []
7. Run the simulation for the full simulation time
8. For each simulation step:
   a. Run a single simulation step
   b. Get all vehicles in the network
   c. Initialize a counter for the number of vehicles that received the data
      received_data_count = 0
   d. Loop through all vehicles:
      for vehicle in all_vehicles:
         i. Get the distance of the vehicle from a reference point and its current lane
         ii. Check if the distance is within the threshold, if the vehicle is in a specific lane:
            1. Transmit data of the vehicle to the antenna and set its colour attribute accordingly
            2. Record desired data (lane change, vehicle ID, position, and simulation time) for
respective lists
```

To emulate real-world conditions, and enhance the study's robustness, noise was intentionally introduced into the experimental setup. Randomness was introduced to the noise factor. Randomising the errors in the distance initial range will better mimic the unpredictability of real-world conditions, where disturbances and environmental factors can vary unpredictably. This noise factor reflected real-world elements such as HGVs disturbances, buildings, and other environmental factors that can affect signal reception and transmission. By incorporating these real-world complexities, the study's findings become more relevant and applicable to practical traffic monitoring scenarios. The results obtained under noisy conditions further validate its potential in real-world implementation. The noise term in the antenna was modelled as 10% error in each section of the road covered by antenna sensor.

Results

The simulation involved a total of 2000 vehicles within a 60-minute timeframe. Among this traffic, 10% were identified as HGVs, while the majority consisted of cars. To facilitate comparative analysis, the results have been compiled and summarised in **Table 2** alongside the actual data, for every 5-minutes interval.

TABLE 2: Measurement Results for Volume (V) with 10 to 100 Increments and Time Gap

	Volume (V) with 10 to 100 increments											
Time Gap	Actual						Antenna					
	V	**1.1V**	**1.2V**	**1.3V**	**1.7V**	**2V**	**V**	**1.1V**	**1.2V**	**1.3V**	**1.7V**	**2V**
0-5 Min	1092	1195	1349	1452	1786	2125	1089	1194	1347	1449	1784	2122
5-10 Min	1054	1157	1167	1285	1782	2074	1055	1157	1168	1285	1781	2075
10-15 Min	1026	1144	1304	1359	1657	1943	1023	1142	1304	1360	1653	1940
15-20 Min	1056	1072	1130	1243	1637	1938	1054	1072	1127	1240	1639	1938
20-25 Min	919	1052	1204	1314	1667	2163	917	1052	1203	1315	1665	2161
2530 Min	1019	1129	1103	1208	1866	2032	1016	1129	1103	1205	1862	2028
30-35 Min	898	1002	1184	1392	1781	2075	899	1001	1182	1394	1779	2069
35-40 Min	1036	1157	1355	1376	1686	1863	1032	1156	1352	1377	1685	1861
4045 Min	1028	1280	1187	1363	1743	1981	1032	1277	1186	1359	1743	1973
45-50 Min	1130	1018	1306	1259	1508	2047	1129	1016	1306	1262	1511	2049
50-55 Min	951	1186	1169	1465	1703	2010	952	1182	1167	1465	1701	2007
55-60 Min	1081	1072	1346	1138	1790	2020	1078	1068	1346	1135	1788	2016

The proposed system is also able to distinguish between vehicles and HGVs. The ability to identify HGVs separately is particularly valuable in traffic management. Results from the experiment showcase the sensor's accuracy as it identified all vehicles in the simulation runs.

Furthermore, to showcase the real-time data analysis capability of the new sensor, **Figure 8** illustrates a graph demonstrating its data reception and processing. This aspect is of paramount importance for live traffic monitoring. It is also worth noting the granularity of the data collected, with updates occurring every second, in stark contrast to the one-minute intervals aggregated data of traditional ILDs.

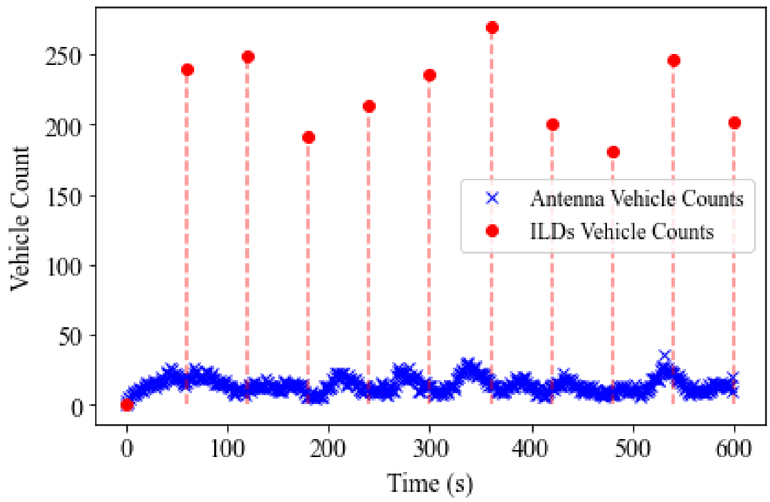


Figure 8: Real-time data collection with antenna-based sensor compared to aggregated information at regular intervals from ILD.

To assess the accuracy of the proposed sensor in estimating vehicle counts, the simulated data and data collected from the new sensor were meticulously grouped at 1-minute intervals. Subsequently, the vehicle counts obtained from both sources were carefully compared to the actual vehicle counts observed in the road network. The findings of this comparison are illustrated in **Figure 9**.

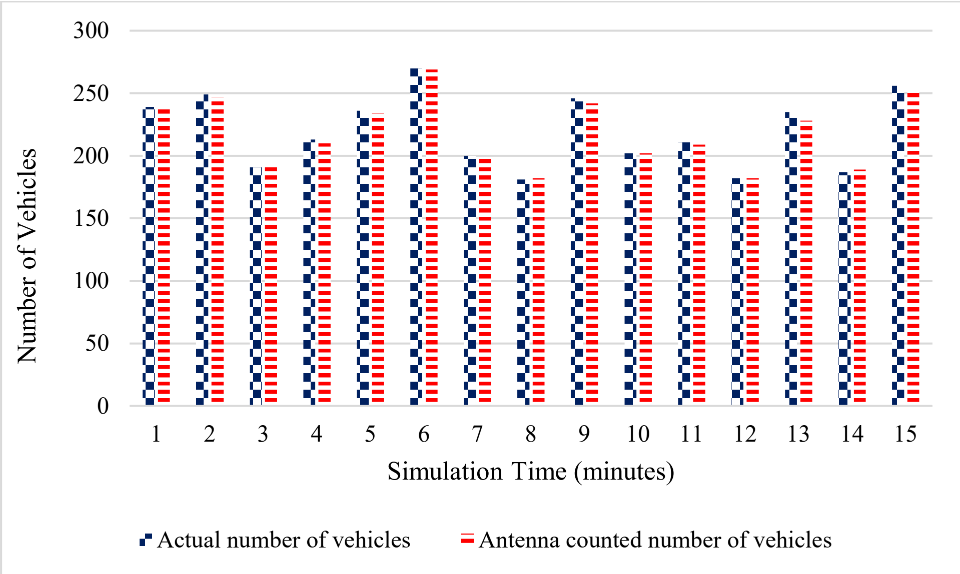
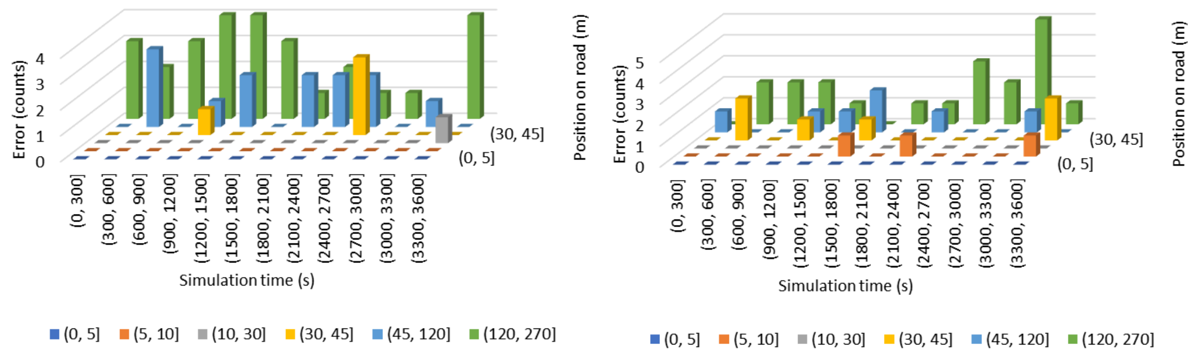


Figure 9: Estimating accuracy of vehicle counts from the proposed system and actual vehicle counts.

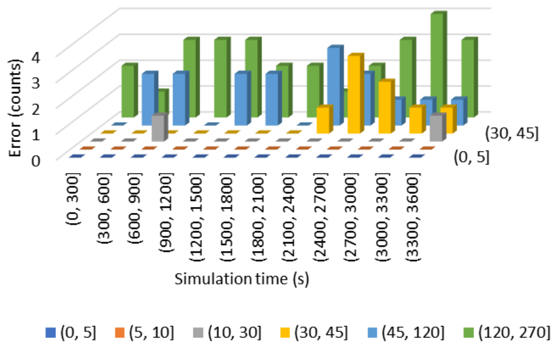
Figure 9 provides a visual representation of the alignment between the estimated counts and the ground truth values. This graphical presentation serves as a clear and concise means to evaluate the sensor's performance and its ability to accurately capture real-world traffic flow. Results show an approximate error rate of < 1%, further emphasising the reliability and efficacy of the proposed sensor.

In addition to the previous evaluations, the study further investigated the proposed sensor's counting accuracy under varying traffic conditions by systematically increasing the traffic volume in a gradual manner. **Figure 10** shows the error in vehicle counts at different locations and during various simulation periods, captured at 5-minutes intervals (300 s).

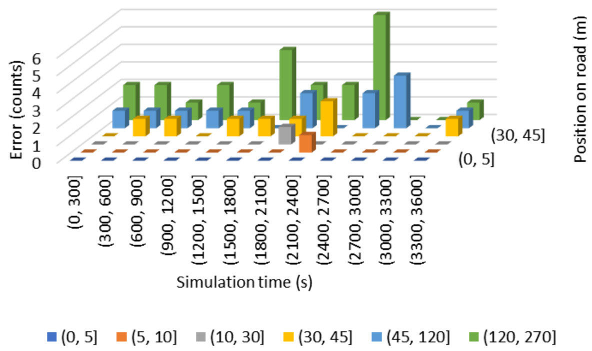


(a) Normal traffic condition

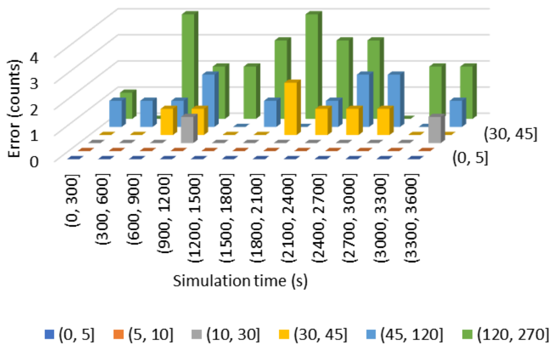
(b) 10% traffic volume increment



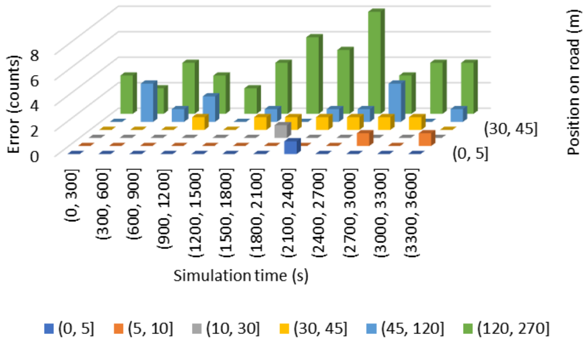
(c) 20% traffic volume increment



(d) 30% traffic volume increment



(e) 70% traffic volume increment



(f) 100% traffic volume increment

Figure 10: Error in vehicles count at different traffic volumes

To evaluate the alignment between the vehicle counts recorded in different time and location segments and the actual counts, a chi-square test was conducted. The obtained chi-square value was calculated to be 0.001, and the accompanying p-value was found to be 1, indicating the inability to reject the null hypothesis. Thus, it can be confidently asserted that the vehicle counts obtained from the new antenna sensor reliably and accurately mirrors the actual traffic volume. The results of the chi-square test validate the new sensor's precision in capturing and reflecting real-world traffic data, reinforcing its credibility and effectiveness.

Results also show that when vehicles are in close proximity to the sensor (within 0-5 meters), the counting error is considerably lower compared to instances when they are farther away (between 120-270 meters and more). As the traffic volume intensifies, the number of vehicles contributing to the error also increases. This is primarily attributed to the weakened signal strength emitted by the vehicle antenna, which impacts the data transmission to the sensor. Additionally, the presence of HGVs and the surrounding environment can act as potential obstructions, casting shadows over the onboard transmitter and further affecting accuracy. Despite these challenges, it is essential to note that the overall percentage of error remains relatively low, registering at less than 1%. This suggests that the proposed sensor demonstrates robustness and efficiency in capturing vehicle counts, with most data being accurately recorded despite potential signal weaknesses and environmental interferences.

The new proposed sensor demonstrated a high accuracy in detecting lane changes, with a detection rate of 98% compared to the actual number of lane changes observed in the simulation. This reflects its effectiveness in capturing dynamic traffic behaviour. Accurate lane change detection provides aids in understanding traffic dynamics and potential areas of congestion. Additionally, it plays a crucial role in enhancing road safety by identifying risky driving behaviours.

Although the findings of this study are primarily based on a motorway scenario due to the prevalence of ILDs in such settings, this study holds significant transferability to urban areas. The new sensor exhibits remarkable versatility, allowing extension to urban settings where higher vehicle densities are common. As a result, the sensor's accurate and efficient monitoring of traffic data becomes an invaluable asset for addressing the challenges of urban congestion. By providing real-time data with precision, the proposed sensor emerges as a tool for optimising traffic flow and enhancing mobility, further enhancing its practicality and impact on smart city initiatives.

Moreover, while latency measurements may not be directly obtained in a simulation setting, it is important to highlight that the proposed sensor's latency exhibits significantly lower latency compared to the typical 7-minute delay observed in the existing solution. This reduced latency is attributed to the antenna's high-speed data reception and processing capabilities, measured in milliseconds. To validate and evaluate the system's latency performance in practical scenarios, real-world testing will be conducted, enabling accurate assessments for practical applications.

CONCLUSION

This paper has shown the potential for an emerging technology, specifically a real-time road traffic data monitoring using electromagnetics and wireless communications. A new leaky-wave antenna on-road sensor was proposed. This sensor not only gathers accurate traffic data but also obtains information in real-time. The presented methodology offers a comprehensive explanation of the working principles behind the new on-road sensor, capable of detecting crucial information such as vehicle speed, lane changes, and traffic volume. Through the utilisation of VISSIM with Python API, the methodology for the proposed sensor model was constructed. Results showed a strong correlation between the new proposed system vehicle count and the actual vehicle counts, affirming the validity of this approach. The vehicle counting from the new system exhibited higher accuracy during low traffic volume situations, with a slight increase in error rates as traffic volume rose. However, even with substantial traffic volumes, the system consistently maintained a percentage error below 1% within simulation, indicating its remarkable accuracy.

These findings show the effectiveness and efficiency of the proposed sensor, showcasing its potential applicability in motorway scenarios and its capability to provide real-time data for prompt traffic analysis in smart cities. Moreover, the technology's resilience in congested scenarios highlights its robustness in handling varying traffic volumes. Such insights are invaluable to key stakeholders, including road traffic operators, town planners, and environmental officers.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: A. Bansal, M. Singh, N. Formosa, data collection: A. Bansal, M. Singh, N. Formosa; analysis and interpretation of results: A. Bansal, M. Singh, N. Formosa; draft manuscript preparation: A. Bansal, M. Singh, N. Formosa. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Gohar, M., M. Muzammal, and A. Ur Rahman. SMART TSS: Defining Transportation System Behavior Using Big Data Analytics in Smart Cities. Sustainable Cities and Society, Vol. 41, 2018, pp. 114–119. https://doi.org/10.1016/J.SCS.2018.05.008.

2. Gonzalez, R. A., R. E. Ferro, and D. Liberona. Government and Governance in Intelligent Cities, Smart Transportation Study Case in Bogotá Colombia. Ain Shams Engineering Journal, Vol. 11, No. 1, 2020, pp. 25–34. https://doi.org/10.1016/J.ASEJ.2019.05.002.

3. National Highways. Managing Delay on the Strategic Road Network. 2021.

4. Aneiba, A., J. Hayes, B. Nangle, and M. Albaarini. Real-Time IoT Urban Road Traffic Data Monitoring Using LoRaWAN. 9th International Conference on the Internet ofThings, October 22–25, 2019, Bilbao, Spain., 2019, p. 8 pages. https://doi.org/10.1145/3365871.3365891.

5. Gulati, I., and R. Srinivasan. Image Processing In Intelligent Traffic Management. International Journal of Recent Technology and Engineering, Vol. 8, No. 2, 2019, pp. 213–218. https://doi.org/10.35940/ijrte.B1040.0782S419.

6. Formosa, N., M. Quddus, S. Ison, M. Abdel-Aty, and J. Yuan. Predicting Real-Time Traffic Conflicts Using Deep Learning. Accident Analysis and Prevention, Vol. 136, 2020. https://doi.org/10.1016/j.aap.2019.105429.

7. Sheik Mohammed Ali, S., B. George, L. Vanajakshi, and J. Venkatraman. A Multiple Inductive Loop Vehicle Detection System for Heterogeneous and Lane-Less Traffic. IEEE Transactions on Instrumentation and Measurement, Vol. 61, No. 5, 2012, pp. 1353–1360. https://doi.org/10.1109/TIM.2011.2175037.

8. Marszalek, Z., T. Zeglen, R. Sroka, and J. Gajda. Inductive Loop Axle Detector Based on Resistance and Reactance Vehicle Magnetic Profiles. Sensors, 2018, pp. 241–246. https://doi.org/10.3390/s18072376.

9. Rappaport, T. S., S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. N. Wong, J. K. Schulz, M. Samimi, and F. Gutierrez. Millimeter Wave Mobile Communications for 5G Cellular: It Will Work! IEEE Access, Vol. 1, 2013, pp. 335–349. https://doi.org/10.1109/ACCESS.2013.2260813.

10. Madhow, U. MultiGigabit Millimeter Wave Communication: System Concepts and Challenges. 2008.

11. Abdel Hakeem, S. A., A. A. Hady, and H. W. Kim. 5G-V2X: Standardization, Architecture, Use Cases, Network-Slicing, and Edge-Computing. Wireless Networks, Vol. 26, No. 8, 2020, pp. 6015–6041. https://doi.org/10.1007/s11276-020-02419-8.

12. Sakaguchi, K., T. Haustein, S. Barbarossa, E. C. Strinati, A. Clemente, G. Destino, A. Pärssinen, I. Kim, H. Chung, J. Kim, W. Keusgen, R. J. Weiler, K. Takinami, E. Ceci, A. Sadri, L. Xian, A. Maltsev, G. K. Tran, H. Ogawa, K. Mahler, and R. W. Heath.

Where, When, and How Mmwave Is Used in 5G and Beyond. IEICE Transactions on Electronics, Vol. E100.C, No. 10, 2017, pp. 790–808. https://doi.org/10.1587/transele.E100.C.790.

13. Alalewi, A., I. Dayoub, and S. Cherkaoui. On 5G-V2X Use Cases and Enabling Technologies: A Comprehensive Survey. IEEE Access. Volume 9, 107710–107737.

14. Abdel Hakeem, S. A., A. A. Hady, and H. W. Kim. Current and Future Developments to Improve 5G-NewRadio Performance in Vehicle-to-Everything Communications. Telecommunication Systems. 3. Volume 75, 331–353.

15. Bansal, A. Active Beam-Steering Millimetre-Wave Antenna Array System for 5G and Beyond. Loughborough University, 2022.

16. Liu, K., Y. Cheng, X. Li, and Y. Gao. Microwave-Sensing Technology Using Orbital Angular Momentum: Overview of Its Advantages. IEEE Vehicular Technology Magazine. 2. Volume 14, 112–118.

17. Bu, X. X., Z. Zhang, L. Y. Chen, K. H. Zhu, S. Zhou, J. P. Luo, R. Cheng, and X. D. Liang. Synthetic Aperture Radar Interferometry Based on Vortex Electromagnetic Waves. IEEE Access, Vol. 7, 2019, pp. 82693–82700. https://doi.org/10.1109/ACCESS.2019.2908209.

18. Anderson, R. L. Electromagnetic Loop Vehicle Detectors. IEEE Transactions on Vehicular Technology, Vol. 19, No. February 1970, pp. 22–30. https://doi.org/10.1109/T-VT.1970.23428.

19. Katrakazas, C., M. Quddus, and W. H. Chen. A New Integrated Collision Risk Assessment Methodology for Autonomous Vehicles. Accident Analysis and Prevention, Vol. 127, 2019, pp. 61–79. https://doi.org/10.1016/j.aap.2019.01.029.

20. Formosa, N., M. Quddus, S. Ison, and A. Timmis. A New Modeling Approach for Predicting Vehicle-Based Safety Threats. IEEE Transactions on Intelligent Transportation Systems, 2022, pp. 1–11.

21. Balanis, C. A. Antenna Theory: Analysis and Design. Wiley, New York, NY, USA, 2005.

22. Wang, M., M. Tang, L. P. Zhang, H. C. Zhang, J. Xu, T. J. Cui, and J. Mao. Miniaturization of Frequency-Reconfigurable Antenna Using Periodic Slow-Wave Structure. IEEE Transactions on Antennas and Propagation, Vol. 69, No. 11, 2021, pp. 7889–7894. https://doi.org/10.1109/TAP.2021.3076570.

23. Javanbakht, N., B. Syrett, R. E. Amaya, and J. Shaker. A Review of Reconfigurable Leaky-Wave Antennas. IEEE Access. Volume 9, 94224–94238.

24. Bansal, A., C. Panagamuwa, and W. Whittow. Millimeter-Wave Beam Steerable Slot Array Antenna Using an Inter-Digitated Capacitor Based Corrugated SIW. IEEE Transactions on Antennas and Propagation, Vol. 70, No. 12, 2022, pp. 11761–11770. https://doi.org/10.1109/TAP.2022.3211013.

25. Bansal, A., C. J. Panagamuwa, and W. G. Whittow. Full 360 ° Beam Steering Millimetre-Wave Leaky-Wave Antennas Coupled with Bespoke 3D-Printed Dielectric Lenses for 5G Base Stations. Electronics Letters, Vol. 59, No. 8, 2023, pp. 5–7.

26. Bansal, A., C. J. Panagamuwa, and W. G. Whittow. Fixed Frequency Beam-steering Using Bow-tie Slot Based Dielectric Filled Waveguide Antenna Array. Electronics Letters, Vol. 59, No. 13, 2023, pp. 1–3. https://doi.org/10.1049/ell2.12864.

27. Bansal, A., C. Panagamuwa, and W. G. Whittow. Novel Design Methodology for 3D-Printed Lenses for Travelling Wave Antennas. IEEE Open Journal of Antennas and Propagation, Vol. 4, No. January, 2023, pp. 196–206. https://doi.org/10.1109/OJAP.2023.3243408.

28. Lv, H. H., Q. L. Huang, J. Q. Hou, and X. W. Shi. Fixed-Frequency Beam-Steering Leaky-Wave Antenna with Switchable Beam Number. IEEE Antennas and Wireless Propagation Letters, Vol. 19, No. 12, 2020, pp. 2077–2081. https://doi.org/10.1109/LAWP.2020.3022810.

29. Kasim, J. S., M. S. M. Isa, Z. Zakaria, M. I. Hussein, and M. K. Mohsen. Review on Fixed-Frequency Beam Steering for Leaky Wave Antenna. Telkomnika (Telecommunication Computing Electronics and Control), Vol. 17, No. 6, 2019, pp. 2895–2902. https://doi.org/10.12928/TELKOMNIKA.v17i6.13291.

30. Serhsouh, I., M. Himdi, H. Lebbar, and H. Vettikalladi. Reconfigurable SIW Antenna for Fixed Frequency Beam Scanning and 5G Applications. IEEE Access, Vol. 8, 2020, pp. 60084–60089. https://doi.org/10.1109/ACCESS.2020.298

31. J. D. Wiegand and C. Y. Yang, “Traffic Simulation Runs: How Many Needed?”, Public roads, vol. 74, no. 4, 2011.

32. D. Henclewood, W. Suh, M. O. Rodgers, R. Fujimoto, and M. P. Hunter, “A calibration procedure for increasing the accuracy of microscopic traffic simulation models,” Simul. Trans. Soc. Model. Simul., vol. 93, no. 1, pp. 35–47, 2017.

33. Sukennik, P., “CoExist - Deliverable 2.3 Default behavourial parameter sets for Autonomous Vehicles (AVs)”, 2018. Link: https://www.h2020-coexist.eu/wp-content/uploads/2018/10/D2.3-default-behavioural-parameter-sets_final.pdf.