An Experiment and Simulation Study on Developing Algorithms for CAVs to Navigate Through Roadworks

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Abstract - **Navigating through roadworks represents one of the main sources of safety risk for Connected and Autonomous Vehicles (CAVs) due to the altered road layouts. The built-in base maps do not normally reflect these changes, causing CAVs to experience difficulties in sensing and trajectory generation. Therefore, the objective of this paper is to evaluate different collision-free trajectory generation for CAVs at roadworks to improve safety and traffic performance. Trajectory generation algorithms using lane-level dynamic maps were examined for: (1) CAVs rely on data from in-vehicle sensor only and (2) CAVs receive additional information via a Smart Traffic Cone (STC) in advance regarding roadwork configurations. Experiments were conducted at a controlled motorway facility operated by National Highways (England) using a vehicle instrumented with a suite of sensors. Schematics of the roadworks scenario were translated into an integrated simulation platform consisting of a traffic microsimulation (VISSIM) to simulate traffic dynamics and a sub-microscopic simulator (PreScan) capable of simulating vehicle autonomy and connectivity. Results indicate that traffic conflicts and delays decrease by 40% and 3% respectively when CAVs receive additional information in advance (i.e., Scenario 2) compared to the other scenario. These findings would assist road network operators in developing 'CAV-enabled roadworks' and vehicle manufacturers in designing a vehicle-based 'roadworks assist' system.**

Index Terms—**roadworks zone, CAVs, smart traffic cone, in-vehicle sensors, simulation**

I. Introduction

Globally, 1.35 million lives are lost annually due to traffic incidents, which is the main cause of death for people aged between 5-29 [1]. Over 90% of traffic accidents are attributed to human errors [2]. Reducing human errors by curtailing human involvement in driving represents a major motivation in accelerating the advancement of vehicular technologies [3]. Connected and Autonomous Vehicles (CAVs) offer a means to reduce human error in the driving as well as unlocking the potential to offer ancillary benefits such as reducing traffic congestion and vehicle emissions [4], [5].

CAVs are defined as vehicles which can communicate with other vehicles (V2V), infrastructure (V2I) and everything (V2X) with the capability to drive in all weather and road conditions without human intervention [6]. In the UK, the development of CAVs is still in an embryonic stage, with some industry analysts predicting that CAVs will account for about 30% of sales in 2035 [7]. The development of CAVs is propagated on continuous improvements in complimentary technologies such as advanced camera and sensor systems to allow vehicles to detect road conditions. Software programmes are also developed which can take the input data of the road conditions and use it to safety control vehicles driving behaviour. As such, much of the focus in CAV research and development has been on the performance of sensor systems to generate accurate measurements of the environment. However, an issue that often overlooked is how the format of the environment can facilitate CAV operations. To consider this issue, operators of road infrastructures have started to appraise their networks for the readiness of CAVs. For instance, the UK government is currently implementing policies to prepare the Strategic Road Network (SRN) for CAV operations with over £27.4 billion to be invested over the next five years in modernising and upgrading the entire SRN [8].

While CAVs can remarkably improve highway mobility and safety [9], they will bring many technological and infrastructural implications and challenges. This is because CAV performance can be influenced by a number of factors such as roadworks, road surface conditions, merging and diverging sections, which can result in CAV disengagements [10], [11]. Roadworks are common along highways, present due to improvement and maintenance activities [9]. Therefore, this paper focuses on the CAV operations in a highway environment during roadworks. In roadworks, the road layout is altered and vehicles have to adapt their usual trajectories to travel reliably within the new road configuration [11]. However, CAVs may fail to navigate safely and experience difficulties because the base map available in their path planning module does not reflect the altered road layout [12]. Therefore, the localisation and navigation systems implemented in the CAV trajectory generation planning modules are required to reliability sense their dynamic surroundings and understand the new environment with a high degree of precision [13]. These modules need to make use of a combination of detailed mapping of the road network as well as the information gathered from the in-vehicle sensors [14].

CAVs rely heavily on vehicles' sensors data but they are prone to misinterpret roadworks conditions due to the ever-changing road conditions [12]. This could be due to obstruction from objects ahead of the sensors blocking the sensors' field-of-view. One plausible solution to improve mobility performance in such situations is to transmit details of roadworks to oncoming CAVs via V2I in advance [15], [16]. This would improve the quality of traffic services and facilitate the development of collision-free trajectories when approaching roadworks zone [14]. One approach to distributing information of roadwork configuration to oncoming CAVs is to employ Road Side Units (RSUs) such as a Smart Traffic Cone (STC). The STC shares an information package which provides accurate information about the modifications in the road environment. Once received, CAVs take this information package and incorporate it into their high-definition (HD) road maps. Conventionally, the road maps implemented for navigation use road-center lines based on static map to provide a route from an origin to a destination based on the vehicle's position and orientation which must be collision-free and according to the traffic rules [14], [17]. CAVs require a higher level of detail about the surroundings and road surfaces for self-position estimation [18]. To aid this, novel navigational dynamic maps are required as they provide centimeters level accurate references [19] allowing overlay of sensor data onto an HD map making use of lane-level [20] rather than road-level lines [18]. This allows for the computation of new trajectories with maximum safety, enough planning time and a smooth transition [21], [22].

Simulation can be a highly effective solution to appraise how the roadworks configurations may affect CAV operations and the effectiveness of RSUs to improve mobility through roadworks [23], [24]. This approach improves the cost-effectiveness of the roadworks development stage and allows the maximum number of scenarios to be tested against different factors [9], [25]. However, a highly detailed integrated simulation platform with a combination of different simulation layers, namely a traffic microsimulation tool (network-level simulation) and a sub-microscopic simulation (vehicle-level) tool is required for conducting infrastructure appraisal in a virtual environment [26], [27].

To effectively model the operations of CAVs in highway environments, this paper examines whether the use of an HD digital maps at roadworks would result in an increase in traffic safety and efficiency of CAV though testing two scenarios: (i) employing the data collected via in-vehicle sensor only and (ii) fusing the data from in-vehicle sensors with an information package received from a STC. This study makes use of an instrumented vehicle equipped with a suite of sensors to collect high quality data, which mimics the data input a CAV would receive in a roadworks scenario. Experiments were conducted using the instrumented vehicle at a controlled motorway facility operated by National Highways. From the data collected, an integrated simulation platform is developed to evaluate each scenario.

To the authors' knowledge, the novelty of this study contributes to the following aspects: (1) This study quantifies the impacts on traffic safety and efficiency in the context of connected and autonomous vehicle (CAV) operations at roadworks, utilising lane-level data from real-world trials which existing literature failed to provide. (2) This study utilises a controlled real-world environment to accurately replicate real-world roadworks specifications on a motorway rather than simulated data. The use of real-world lane-level data to effectively calibrate and validate simulation models to estimate traffic safety and traffic efficiency of CAV operations at roadworks has been a breakthrough from current research. (3) Novel approaches to address the data requirements for roadworks and develop collision-free trajectories for CAVs operating in roadworks situations are introduced in this study. These algorithms were implemented within a simulation environment that accurately represents real-world roadworks conditions along the motorway. (4) The effectiveness on vehicle safety and traffic performance of a smart traffic cone (STC) serving as a Road Side Unit (RSU) has been evaluated. The proposed STC can transmit roadworks messages to CAVs using a High Definition (HD) lane-based digital map. The evaluation of the effectiveness on STC makes our research comprehensive and unique in its approach.

The rest of the paper is organised into six sections. First, a literature review is presented on contribution of CAVs to improve traffic performance at roadworks, technological and infrastructure consideration related to CAV deployment at roadworks and research surrounding testing in a virtual simulation are discussed. The data collection and preparation procedure adopted in this research are then introduced. The subsequent section provides an in-depth explanation of research methodology adopted to test the two scenarios, followed by an explanation of the results. The paper is wrapped up with discussion and conclusion derived by integrating CAV technologies and concepts in a roadworks setting.

II. Literature Review

The interaction between roadworks and CAVs introduces many technological and infrastructural challenges such as detection of roadworks traffic control devices and roadworks setting. A major impact of these challenges is on the collision-free trajectory generation algorithms of CAVs given the CAV needs to reliably and efficiently traverse the roadworks despite the sudden dynamic changes in lane configurations [9]. To enhance the decisions emerging from the collision-free trajectory generation algorithms during roadworks, comprehensive testing is required. Typically, this testing is carried out virtually using computer simulation models. This can comprise of high numbers of scenarios with combinations of varying factors leading to more flexibility and repeatability. Current applications of traffic simulation pertaining to roadworks are scarce, though the topic is growing in interest. The relevant studies related to the CAV impact to improve traffic performance during roadworks, detection systems of a roadworks setting using smart traffic devices and navigation of CAVs in roadworks are discussed.

A. CAV impact on traffic performance during roadworks

Roadwork areas tend to bring about negative impacts on the traffic performance such as increased travel time, queue length, accidents and dissatisfaction among road users [9], [28]. With the introduction of advanced technologies, CAVs have the potential to improve traffic performance at roadworks by exchanging information of the traffic conditions ahead as well as the recommended driving speed in a timely manner to smooth the traffic flow resulting in a more efficient and safer network [9], [29].

Agriesti et al. [24] explored the impact of lane closure on CAVs with different market penetration rates (MPR) of CAVs. Average delay is reduced between 10-25% when the MPR increased from 10-100%. Similarly, Zou et al. [30] also observed a reduction in average travel time when deploying CAVs. For example, travel time reductions of 25%, 50%, and 90% were achieved with a CAV market penetration rate (MPR) of 34.1%, 62.25%, and 100% respectively in a congested 2-to-1 roadworks area [30]. Another study [16] examined the impact of CAVs at different traffic demand levels. For instance, the mean travel time was reduced by 40% and capacity increased by 65% at 2-to-1 area for a flow rate of 3000 vehicles/hour. However, the results were only significant at a high traffic flow rate. Ramezani et al. [31] tested the effectiveness of speed limits for CAVs in the proximity of roadworks areas. Their results show that by deploying speed management techniques with a CAV MPR of 80% or higher, delays were reduced by 13% while the congestion period was reduced by 26.4% with a 100% MPR. Genders et al. [32] appraised the safety advantages (using TTC as the safety surrogate measure) when diverting CAVs to alternative routes. For moderate MPRs (<40%) early dynamic rerouting improved the network safety because the improved driving behaviour balance the additional trip distances. However, for large MPRs (>40%), the network safety decreased since longer trip distances were added to the network and this increased the risk of safety hazards. Safety related to roadworks was also explored by Abdulsattar et al. [33] but major focus in their research was to reduce rear-end collisions. Their results showed that at a 10% MPR there is a substantial safety improvement. For example, at a 10% MPR with medium and high traffic demand levels, the probability of rear-end collisions was reduced by 50%.

B. *CAVs detection of roadworks*

Roadworks induces unexpected and complex geometric change in the roadway setting with the use of warning signs or devices that mark the beginning and end of the affected lanes. This presents a navigational challenge for CAVs since these new changes may not be updated instantaneously on the HD digital maps implemented within the vehicle. As a result, CAVs cannot depend only on these maps. It is crucial that CAVs must be able to detect that roadworks are taking place in the roadway ahead from warning signs and devices (such as cones, barrels, and lane markings) to react and navigate efficiently and safely in a timely and precise manner. There are several ways to detect roadworks using devices such as cameras, lidars, and communication-based detection.

Camera-based detection systems adopt machine learning techniques such as neural network [34], [35] and deep learning [36] to classify and recognize the predefined and standardised device used as the ground truth from real-time videos of the roadway ahead. For example, in the system developed by Wang et al. [37], the system accurately recognised and detected cones with a 100% success rate and maintained a 90% accuracy when sensing the range. False detection rates were reduced in the system by Lee et al. [38] enhancing the ability of CAVs of identifying objects using a camera. Other studies [35] showed that lane markings can also be recognised by camera systems.

Recent literature adopting LiDAR to detect objects shows promising results [39], [40]. These studies also highlighted that by employing a LiDAR sensor, detection robustness can be improved when compared with camera-based detection methods which can be affected by light conditions, image quality, and occlusions [9]. As a result, more types of objects can be detected. Moreover, some research shows that LiDAR is capable of detecting and tracking lane markings [41], [42].

An I2V communication can be established between a vehicle and a device equipped with a tag that transmits a message. An I2V communication system was proposed by Garcia-Garrido et al. [43] where a wireless sensor was installed on a traffic signpost. This sensor transmits information to all equipped vehicles on the road layout ahead. Similarly, Qiao et al. [44] developed and successfully tested a V2I sign detection system at roadworks. Lane marking detection is also possible using communication-based detection [45].

From all the detection systems, the communication-based detection of devices provides the most advantages for CAV at roadworks. This is because it discards irrelevant detected objects, eliminates the chance for false detection, and it creates and transmits relevant information [9]. However, with regards to cost-effectiveness, the camera-based system is the optimal choice as LiDAR is still expensive and the cost of connected devices is yet to be assessed [9].

C. *Smart traffic devices for CAVs to identify roadworks*

A prerequisite for CAVs navigating through a dynamic environment is to autonomously recognise and react to the surrounding objects. In roadworks, CAV detection of traffic control devices (e.g., cones and barrels) is essential. Traffic control devices can be equipped with IT systems which use communication technologies to transmit a package of information to warn approaching CAVs towards roadworks and assist into generating new safe trajectories. An overview of several ‘smart’ traffic control devices that enable CAVs to navigate roadworks is presented in this section including connected and robotic traffic control devices.

Connected devices can be equipped with sensors and modules to monitor the traffic environment and report the current dynamic situations to an operator through wireless communication [46], [47]. Examples of these devices include cones, barrels, panels, and arrow boards [9] and they are becoming more common in modern highways [48], [49]. They have been applied to provide real-time data to validate roadworks location, identify errant vehicles, debris detection, sends alarms to workers on site if a potential risk is detected and can also sense the public trespassing the roadworks areas [48], [50]. This study considers a smart traffic cone (STC) as the traffic control device to identify roadworks and its application in the literature is reviewed. Intellinium developed a prototype of a STC which is able to connect to smartphones and sends notifications if a cone falls in the roadwork area [51]. Schönrock et al. [52] produced a STC prototype to detect and localize traffic disruptions to assist in police operations for information dissemination to surrounding drivers, RSUs and servers. Kantawong and Phanprasit [46] proposed a STC which can detect vehicle accidents. In [53] an STC application was placed in front of roadworks area to send information to RSUs so as to warn incoming traffic and ensure safety.

Robotic Traffic Control Devices are intelligent devices that can move autonomously and are connected to a central management station. Robotic traffic control devices include barrels, cones, barricades, and sign bases [9]. Since the positions of these devices can be moved remotely the size and duration of roadworks can be reduced as well as the workers exposure to traffic. Shen et al. [54] developed and tested in a roadworks area using robotic safety barrels which move autonomously for human driven vehicles. The central management station was able to pinpoint the location of each barrel and transmit the planned trajectory for each. The system was tested in real-world trial and the maximum positioning error for all robots was 11 cm.

D. Guidance for CAVs through Roadworks

Human drivers are normally capable to pass through roadworks by navigating around traffic cones and barricades while obeying traffic signs and may alter travel paths based on public service notifications of road closures. This capability is also expected from CAVs, by using detailed mapping of the road network, and comparing the information received from sensors with the historical information within the maps for localisation and determining which lane to use [55]. However, some challenging conditions, for example, adjustments in lane geometry and speed related to roadworks have a great impact on the collision-free trajectory generation and decision-making of the CAV [55].

The guidance frameworks for navigation follow a data-processing scheme consisting of five parts [55]. Initially, the in-vehicle sensors receive data from the dynamic environment surrounding the CAV through (e.g., image recognition, positional data) [56], [57]. Secondly, the state estimation section recognises the location of the vehicle relative to the data obtained from sensors [58]. Thirdly, based on all possible vehicle actions the local planning section identifies the geometrical and dynamic constraints [59]. The trajectory generation section predicts vehicle trajectory based on vehicle controls and physics constraints. The controllers section carries out the manoeuvre by using data from the trajectory generation section [60]. However, to enhance this guidance framework, CAVs require a new framework for data collection in which information from external sources establish communication channels, including V2I communication, V2V communication, RSUs, and HD maps are fused together [49], [61]. These sources aim to augment the data collection capabilities of CAVs, simultaneously increasing their hierarchal data processing. The additional information from the communication line allows updates on several attributes for example: change in lane geometry, closure of lanes, emergencies, diversions, variable speed limit adjustments and new construction [55].

The novelty of this study lies on its exploration of vehicle operations in roadwork environments, addressing the need to maintain and enhance existing road infrastructures. Whilst research on CAV operations during roadworks is limited, this study fills the gap of knowledge by evaluating the behaviour of CAVs in such scenarios to ameliorate traffic disruptions. By collecting empirical data using an instrumented vehicle alongside with developing an integrated simulation framework, this research effectively mimics CAV behaviours in a highway environment, specifically focusing on roadworks settings. The impact on safety and efficiency of CAVs when approaching roadworks are investigated, considering camera-based and I2V systems as guidance for obtaining collision-free trajectories. Additionally, the study introduces the use of Smart Traffic Cone (STC) as a road side unit, to transmit timely information packages to CAVs. Key performance indicators such as traffic conflicts and delays are estimated, which helps to strengthen the understanding of CAV behaviours and quantifies the effects of I2V systems in roadwork scenarios. Furthermore, the study contributes to determine the optimal roadworks detection system. Overall, this research offers novel insights into CAV operations in roadworks and their impact on traffic performance and safety.

III. DATA

To adequately represent CAV operations in highway environments, it is necessary to gather similar data that such vehicles would receive in real-world operations. This data covers the measurement of different features of the traffic environment including the detection of organically changing ‘objects’ (e.g., cones and construction vehicles) and surrounding vehicles. The data used in this paper is collected using a vehicle instrumented with a suite of sensors from real-world trials to calibrate the simulation model. Due to inherent risk and safety associated with live highway operations, the experiments were not conducted on the SRN but at a controlled motorway facility operated by National Highways. A series of experiments were carried out to examine how a CAV can safely navigate within an artificial roadworks area using different configurations derived from the Traffic Signs Manual.

A. Vehicle Instrumentation and Controlled Experiments

A 2017 Ford Focus Zetec was procured as the base vehicle to be instrumented. Multiple sensors were installed in this vehicle to allow it to collect the same variety of data as a fully CAV. A sensing subsystem was installed in an instrumented vehicle to gather microscopic data comprising a LiDAR sensor, two radar sensors (front and rear), two camera sensors (front and rear), localisation sensor, weather sensor, gyroscope, accelerometer and a MobilEye camera sensor. It is important to clarify that whilst multiple sensors were equipped in the instrumented vehicle, not all of them were utilised in the present study. Specifically, our study utilised GPS, cameras, and radar sensors to navigate through the created scenarios. A schematic diagram of the instrumented vehicle is shown in Fig. 1.

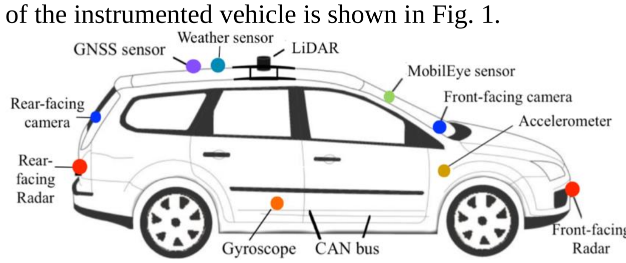

Fig. 1. Sensor configuration on the instrumented vehicle used

However, a large amount of data cannot be processed using conventional systems because of many forms of data, their complexity, and their varying sampling frequencies. Hence, to examine the information and patterns within the data, a system architecture is needed for data collection, transmission, and storage. All the information was unified on a central computational unit and a data integration architecture was developed to satisfy the requirements of various sensor environments and provide a run-time environment.

To mimic the setup of roadworks, specifications of a roadworks zone were obtained from the 'Traffic Signs Manual' developed by the Department for Transport and National Highways [62]. Roadworks typically include an advance warning zone (zones to warn driver to reduce their speed ahead of road work zones), transition zone (zones where the lane width gradually reduces) and the work zone (zones where actual road activity is taking place) [63]. However, the actual layout of the roadworks adopted in this study is slightly modified due to length restrictions. The controlled facility is a motorway testbed with a total length of 650m with lane width of 3.2m for Lane 1 and 3.45m for both Lanes 2 and 3 (represented in Fig. 2.). The lane closure scenario was set up where the entry taper length was 180m with cones placed 1.5m apart. Traffic cones were then placed 9m apart at the edge of Lane 1 for 63m. The exit taper length was restricted to 3.2m. The first 100m of the testbed was reserved for vehicles to accelerate from 0 to 60mph. Schematics of site setup is displayed in Fig. 2.

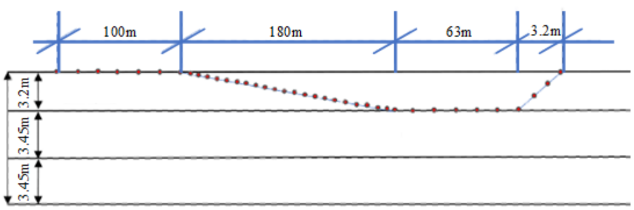

Fig. 2. Schematic of the Roadworks experiment with cone placements at the controlled facility.

Four different traffic vehicle formations were evaluated progressing through the roadworks at the testbed:

1. The instrumented vehicle drives in Lane 2.
2. The instrumented vehicle with a conventional following vehicle in Lane 2.
3. The instrumented vehicle drives with a leading and a following conventional vehicle in Lane 2.
4. The instrumented vehicle drives in Lane 1, merges to Lane 2 with a leading and following conventional vehicle alongside a conventional vehicle in Lane 3.

The vehicle formations are displayed in Fig. 3. The four formations of vehicles are selected by varying the degree of manoeuvrability of the vehicles. Formation 1 is the most flexible while in formation 4 the CAV is surrounded by other vehicles. During the data collection process, each traffic vehicle formation described in Fig. 3. was repeated 10 times to provide accurate data. It is worth noting that previous studies have extensively examined the effect of the number of replications of simulations on the consistencies between results. Results have shown that by taking the average of at least 10 replications can improve the reliability of the findings [64], [65]. Selecting 10 replications can effectively strike a balance between computational resources and obtaining consistent results. While a larger number of repetitions would provide different dynamics, it would also significantly increase the computational time and resources required for the simulations.

These scenarios ensured that realistic data such as acceleration and deceleration profiles are utilised in the simulation model to generate realistic results for a virtual real-world workzone scenario. Since the experiment was conducted under a controlled environment, the data was collected by several authorised personnel including professionals that work in transport engineering industry with full driving license. This ensured that the different driving styles and acceleration and deceleration profiles are employed in the simulation scenario. Additionally, the work zones scenarios developed in the simulation environment are all calibrated and validated using real-world traffic data (such as flow, speed, and headway) so the major issues relating to CAV operations are captured. It was determined that these factors play a crucial role in influencing safety and conflicts within the simulation model. Our findings align with previous studies that have highlighted the significant influence of speeds and headways on conflicts and delays [66], [67]. Other parameters are initiated with the default parameters set by VISSIM.

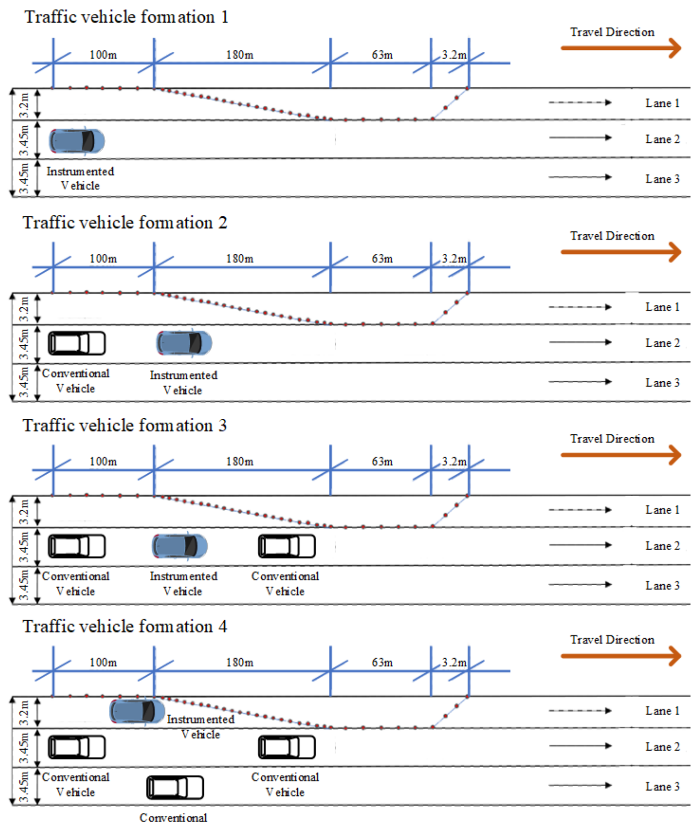

Fig. 3. Schematic of the vehicle formations for the roadworks experiment conducted at the controlled facility

IV. METHODOLOGY

This section explains the experimental framework for the integrated simulation platform to investigate how a CAV can navigate through roadworks. Using the data collected from the real-world trials in the controlled motorway facility; the baseline scenarios were developed in the simulation model. In this stage, PreScan provides the schematics of the testbed and the functional parameters of the instrumented vehicle were replicated in the simulation. Subsequently, VISSIM was used to model realistic surrounding traffic flow. These two simulation platforms are linked together such that the surrounding traffic was simulated at the same time as the CAV operation. When using both simulators simultaneously, a comprehensive integrated platform is built that is more powerful allowing the investigation of scenarios with varying vehicle functionalities with different traffic conditions. This section continues by describing the control details of the scenarios created in PreScan: (1) CAVs rely on data from in-vehicle sensor only and (2) CAVs receive additional data and information in advance regarding roadworks (e.g., location, lane-level road map, road geometry). The collision-free trajectory generation algorithm for the CAV was adjusted to reflect the scenarios.

A. *Experimental Framework*

Using the data collected from the application of the traffic formations in the controlled motorway facility; the baseline simulation scenario was developed in PreScan. In this stage, the schematics of the testbed and the functional parameters of the instrumented vehicle were replicated in the simulation. Subsequently, VISSIM was used to model surrounding traffic flow. These two simulation platforms are linked together such that the surrounding traffic was simulated at the same time as the CAV operation. Different controls of the simulation scenarios were conducted in Simulink. Detailed explanations of each phase of the methodological framework are described in subsequent section. Fig. 4. shows the framework of integrating PreScan with VISSIM.

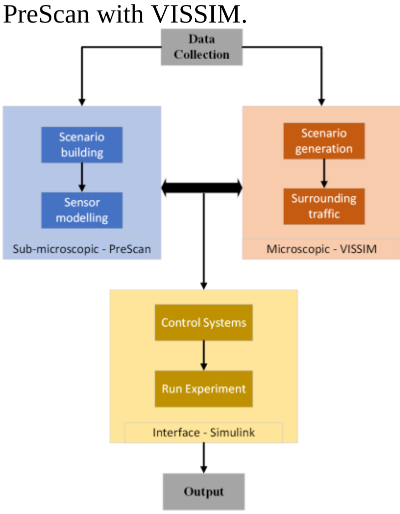

Fig. 4. Framework of integrating PreScan with VISSIM

B. *Baseline Simulation Scenario*

In PreScan, it is essential to develop a baseline scenario without any roadworks, using data collected from the instrumented vehicle. This allows the alternative roadwork scenarios to be compared to a common standard. The baseline scenario development follows a four-stage process consisting of: (i) scenario building, (ii) sensors modelling, (iii) control system implication and (iv) execution of experiment.

Firstly, the network of the testbed was created in PreScan GUI. Dimensions of the simulation network followed the real-world measurements and geographic road configurations of the actual facility. It should however be noted that apart from the static road information, other parameters relating to the CAV model do not vary between the scenarios. Each scenario was defined by the parameters of the CAV and control systems. Vehicles within the PreScan library provide detailed information of the CAV, ranging from vehicle body characteristics to vehicle components such as engine, suspension, steering, tyres, and brakes. A Ford Focus was implemented to replicate the instrumented vehicle which was used to collect real world data as best as possible. The environmental sensors of the CAV system (e.g., radar, laser, camera, GPS) were then modelled within PreScan GUI. Using the GUI, the sensor design and benchmarking were made easier by modifying the sensor type and sensor characteristics (e.g., range and field-of-view). These were placed on the CAV to replicate the information from the dynamic environment.

Subsequently, VISSIM was used to represent the network section to generate surrounding traffic flow based on the real-world data collected from the testbed. In this way, a comprehensive platform was built allowing the investigation of driving behaviours and vehicle functionalities under different traffic conditions. The network development involved defining model parameters, vehicle composition, number of lanes, the required input traffic data and driving behaviour characteristics. Calibration of the road network and simulation parameters were required to accurately replicate real-world road traffic conditions. While some parameters were initiated by default from VISSIM, the speed profile and headway were extracted from the real-world experimental data collected at the testbed. Multiple simulation runs were then performed to obtain simulation outputs comparable to the real-world values. The car-following model used in VISSIM is the Weidmann99 model given in (1):

$$v_n(t+\Delta t) = \min\left\{ \begin{matrix} u_n(t) + 3.6\left(CC8 + \dfrac{CC8 - CC9}{80} u_n(t)\right)\Delta t \\ 3.6\dfrac{(s_n(t) - CC0 - L_{n-1})}{u_n(t)} \end{matrix}, u_f \right\} \quad (1)$$

where t is current time, Δt is the time step, $v_n(t+\Delta t)$ is the speed of the following vehicle in the next time step, $s_n(t)$ is the space headway from the ego-vehicle and following vehicle, u_f is the free flow speed, u_n is the speed of following vehicle and L_{n-1} is the length of preceding vehicle. The parameters used in VISSIM are given as CC0 representing the standstill distance as 1.5 m, CC8 representing the standstill acceleration given as 3.5 m/s^2 and CC9 represents the acceleration as 1.5 m/s^2 when the speed is 80km/hr. The density and velocity of the vehicles on the road in PreScan were determined by VISSIM.

With regards to lane change, vehicles in the VISSIM only change lane if there is a sufficient safety distance available given as [68]:

$$s_{desired} = CC0 + CC1 \text{ x } v \quad (2)$$

where v is the speed of the vehicle, CC1 is headway time and CC0 is the standstill distance. Values of CC1 are given as 0.9 s and 0.6 s for conventional and autonomous vehicles respectively. Values for CC0 are taken as 2 m and 1 m for conventional and autonomous vehicles. The decision to change the lane is triggered by a slow-moving vehicle ahead or the information received from the STC. If the road has a diversion, then the lane change can be forced by the routing decision in the model. PreScan and VISSIM interact in such a way that the motion of vehicles in PreScan respects the trajectories generated by VISSIM, and the trajectories in VISSIM adapted to the motion of the subject vehicle simulated in PreScan.

Next, the microsimulation model was linked to PreScan. Every change in PreScan was associated with a change in the Matlab/Simulink software. This interface allowed the user to design, add, implement, or validate the scenarios tested through a compilation sheet. This interface consists of subsystems made up of blocks which manage driving manoeuvres and vehicle control. As a result, the ego-vehicle travels within the Vissim environment alongside normal traffic. With every run, the output files were stored in a database for post-processing. Key Performance Indicators (KPIs) such as conflicts and delays were monitored for further analysis. Moreover, a 3D visualisation viewer allowed the user to analyse the results of the experiment by providing multiple viewpoints, pictures, and video generation capabilities.

A comprehensive analysis to evaluate the model's performance and its ability to capture real-world complexities was conducted under various conditions and scenarios. The model was tested with different traffic flow patterns, including varying traffic densities, peak hours, and congested traffic conditions. By subjecting the model to these scenarios, it was ensured that it could handle different levels of traffic demand and accurately simulate the resulting interactions and conflicts between vehicles. Furthermore, the model was evaluated under different weather conditions. By examining the model's behaviour in diverse conditions, its adaptability and robustness in capturing the dynamics of lane-changing manoeuvres and potential conflicts were assessed. To validate the model's performance, the simulation results were compared with empirical data collected from real-world observations.

C. Baseline Simulation Scenario

Two simulation scenarios for roadworks were created in PreScan. The objective of these scenarios is to evaluate CAV performance when (i) relying on in-vehicle sensors only to navigate through roadworks zone and (ii) the CAVs benefit from receiving essential information regarding the details of the roadworks and employ this information in developing a collision-free trajectory.

1) CAVs Rely on In-Vehicle Sensors

CAVs may experience difficulties navigating through the road work zones as this alters the traffic network. Therefore, the in-vehicle sensors need to have the ability to detect and understand the new environment with an extremely high degree of accuracy. As a result, for the deployment of CAVs within the SRN network, the scenario of using only in-vehicle data is explored to determine whether such data is sufficient for safe CAV navigation through roadworks.

In this scenario, roadworks were created in PreScan by placing traffic cones as specified in Section 3.1. The CAV gathers the surrounding dynamic information by using the data collected by its sensors (e.g., LiDAR, radars, cameras).

The first test included the CAV driving in Lane 1 where roadworks was taking place. Control algorithms were developed in the Simulink interface to adjust the collision-free trajectory generation algorithm within the CAV. This algorithm was adjusted to receive inputs from sensor data to enhance the road maps information. In this way, as the CAV travels on the road, readings from the sensors and data obtained from the map, transform the representation of the road network. This was essential to inform the CAV about the altered dynamic surroundings due to roadworks.

The vehicle was also able to identify that it was driving in the same lane where road works were taking place. As a result, this required the CAV to reduce its speed to 60 mph and carry out a collision-free mandatory lane change to Lane 2. The distance at which roadworks identification occurred was set to 60m. This value is obtained from the real-world experiments at the position where drivers change lane due to roadworks. This distance value was used as a trigger to notify the trajectory generation algorithm that roadworks was occurring if the cone is also observed and Table 1 presents the pseudocode of this algorithm.

TABLE 1: ALGORITHM TO TRIGGER IDENTIFICATION OF ROADWORKS

Pseudocode of the algorithm
Initialize the Range to 60; % detection takes place within this limit Initialize the ID of smart cone to 15; % ID of the STC Initialize the Message; % Message status from STC on (1) or off (0) if vehicle is driving in the direction of roadworks | for t = simulation_start to simulation_end | if vehicle distance from cone is less than Range & Message of roadwork has been sent | generate new trajectory; | else | keep current trajectory; | end end

The second test included the CAV driving in Lane 2 while the roadworks zone was in Lane 1. Like the previous test, the CAV identified that it was approaching roadworks area through in-vehicle sensors data. As a result, it reduced its speed to 60mph. In this scenario since no mandatory lane change was required, the CAV continues with its own trajectory on Lane 2.

2) CAVs Rely on In-Vehicle Sensors Aided by I2V Communication

This scenario was developed to see how CAVs can fuse essential information from roadworks in developing collision-free trajectories. More specifically, this experiment extends the previous scenario in two-ways (a) CAVs receive a 'roadworks essential information pack' from a STC situated at the start of the roadworks zone in advance, and (b) the input to the collision-free trajectory generation algorithm is further modified to receive the information in advance from the STC fused with the in-vehicle sensors data.

The same traffic cone placement that was utilised in the baseline scenarios (i.e., in-vehicle sensors only) were also employed in this simulation. The main difference is that in this scenario a STC was placed at the start of roadworks. It was able to send 'the information pack' to notify approaching vehicles about the roadworks ahead. This information includes:

i. location of the roadworks in x and y coordinates.,
ii. start and end date/time of the roadworks,
iii. length of the roadworks,
iv. speed limit,
v. geometry (e.g., tapper length, angle),
vi. types of barriers (e.g., cones, temporary fences)
vii. information on lane closures (e.g., Lane 1 is closed)

viii. lane configuration (i.e., a digital map consisting of lane center lines given the road layout within the work zone)

As a result, the CAV receives 'the information pack' and, together with the readings from the sensors, transforms the representation of the road network to plan its trajectory. It is important to highlight that the information pack provides a major advantage to any approaching vehicle (e.g., the CAV in our simulation) as such information is fused with the sensing data and allows the vehicle to navigate safely even with a blocked field-of-view. Table 2 presents the pseudocode of the data transmitted by the STC and received by the CAV.

Once the CAV receives this data and recognises that there is roadworks ahead, the vehicle's collision-free trajectory generation starts to use the dynamic map obtained as part of the information pack. The dynamic map contains a digital map of the road layout consisting of lane-level centerlines of the revised roadworks as opposed to a road-center lines based static map. In this way, the trajectory generation algorithm can create new collision-free trajectories based on the fused data from the in-vehicle sensors and the information pack.

The first test included the CAV driving in Lane 1 which was closed due to roadworks. An information pack was transmitted from the STC to the CAV about the roadworks situation via an I2V message. Control algorithms were developed in Simulink interface to read this message. Vehicles receiving messages from STC can alter their decision-making based on the information received within the STC's range. The vehicle identified that it was approaching a construction zone which triggered a speed reduction to 60mph and the use of a dynamic map to navigate the area. The dynamic map included a trajectory generation algorithm to create a path for the CAV to conduct a lane change manoeuvre to Lane 2 or Lane 3. The distance at which roadworks the message was sent from the STC to the CAV was set at 60m. In most of the simulations, the lane change was performed as soon as the message was received depending on the surrounding traffic.

The second test included the CAV driving on Lane 2 while Lane 1 was closed for the construction works. The CAV received the information that it was approaching a construction zone and reduced its speed to 60mph. However, there was no need to change lanes. Similar to the other scenario, the vehicle was able to identify vehicles from Lane 1 that were changing to Lane 2, resulting in a lower driving speed.

D. Overall Framework

In summary, the collision-free trajectory generation algorithm developed for the ego-vehicle initially generates a trajectory based on the location of the ego-vehicle received from PreScan. The trajectory generation function makes use of a fourth-degree polynomial as shown in equation (3):

$$x(t) = p_0 + p_1 t + p_2 t^2 + p_3 t^3 + p_4 t^4 \quad (3)$$

where $p_0 - p_4$ are the coefficients which can be found based on the current location (t_0) and the end point of the trajectory (t_f). Multiple trajectories are generated from (3) and the optimal one is found by minimising a cost function for the longitudinal and lateral movement as shown in (4) and (5) respectively:

$$C_{longitudinal} = k_j J_t(s) + k_t T + k_s(\dot{s_f} - \dot{s_t})^2 \quad (4)$$

$$C_{lateral} = k_j J_t(d) + k_t T + k_d d_f^2 \quad (5)$$

TABLE 2: ALGORITHM OF STC TO SEND INFORMATION PACKAGE ABOUT ROADWORKS TO CAV

Pseudocode of the algorithm
Initialize the StationID to 1; % ID of the transmission station Initialize the DetectionTime to now(); % current time Initialize the Latitude X to Latitude % Latitude of the smart traffic cone Initialize the Longitude Y to % Longitude of the smart cone Initialize the Direction to 0; % Direction angle of smart cone Initialize the SpeedLimit to 60; % Speed limit at the break down area Initialize the ClosedLaneNumber to 1; % the ID of closed lane % Data of all vehicles in the simulation model if vehicle is driving in the direction of roadworks | for t = simulation_start to simulation_end | X_V(t) = Latitude % Latitude of the Vehicle | Y_V(t) = Longitude % Longitude of the Vehicle | Distance(t) = sqrt((Y_V(t)-Y)²+(X_V(t)-X)²) % | Calculate the distances with the help of coordinates | ReceiveInformationOfLaneClosure | ReceiveWarningMessage | end end

where k_j, k_t, k_s and k_d are adjustable weights, J is jerk, T is the time to execute the trajectory, s is longitudinal trajectory, $(\dot{s_f} - \dot{s_t})$ is the difference in the final velocity from current velocity, d is lateral movement, d_f is distance from desired lateral position. Trajectories that are not on a collision course are considered and the optimal trajectory is selected with the lowest cost calculated from the cost function. The generated trajectory would be rejected if obstacles present within the bounding box of the vehicle. The pseudo-code for trajectory generation function is presented in Table 3.

TABLE 3: ALGORITHM TO IDENTIFY OPTIMAL TRAJECTORY FOR EGO-VEHICLE

Pseudocode of the algorithm
function for all paths generated | if path is impossible | regenerate path; | else if it is on a collision course | regenerate path; | else | calculate the cost function; | end end send the lowest cost to trajectory generation algorithm update the estimated position of the ego-vehicle

The path tracker uses the generated trajectory as input and outputs throttle, steering and breaking for the ego-vehicle to actuate. 'Pure pursuit' [69] is a lateral path tracker (which outputs the steering angle) and with the help of a longitudinal PI controller (which ensures the velocity is maintained, therefore handling the throttle and breaks) for tracking the trajectory generated by the algorithm. To minimise the cost function for the generated trajectory, convex optimisation is adopted under constraints of the path and vehicle dynamics [70]. This optimisation method would ensure an efficient computation of the optimal path.

The control system (See Fig. 5) enables data fusion which allows additional data from multiple sources to be integrated to generate an optimal trajectory. To account for spatial alterations due to roadworks, the control system makes use of additional received information from in-vehicle sensors, ***lane-based map*** and STC to regenerate the trajectory based on the available paths if the ego-vehicle identifies a hazard. Trajectory of the ego-vehicle is hence determined by Multiple Criteria Decision Making and Deterministic Finite Automata employed by Furda and Vlacic [71]. This approach is perceived as the state-of-the-art approach in collision-free trajectory generation when encountering roadworks [14].

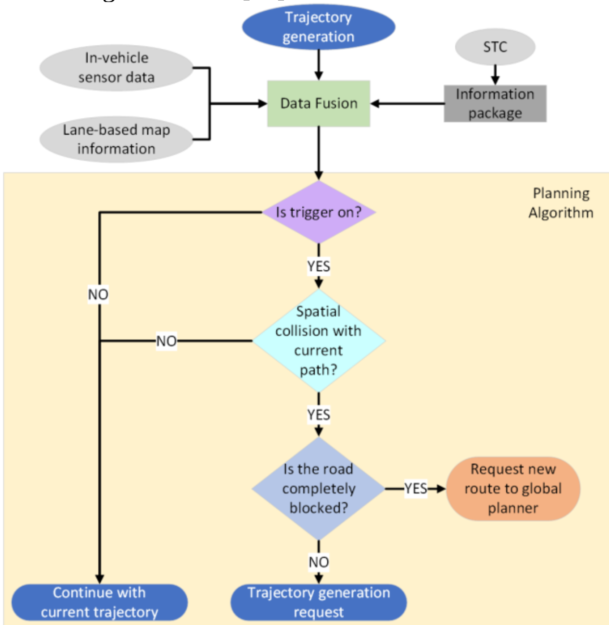

Fig. 5. Overall framework of collision-free trajectory generation algorithm in roadworks

V. RESULTS

From both scenarios developed in the simulation framework, the sensitivity analyses were conducted, and the results were evaluated through key performance indicators (KPIs) covering traffic conflicts and delays. Each scenario was simulated 10 times by utilising 10 different random seeds to generate different traffic dynamics surrounding CAVs. To improve the reliability and accuracy of the estimated results, it is common practice to perform multiple simulations and take the average of the outcomes. By conducting ten simulations and averaging the results, the variability introduced by individual runs can be reduced, leading to more robust findings. This approach is particularly valuable when numerous factors can influence the outcomes. Parameters such as road design, driving manoeuvres and behaviour of the CAV were kept constant. By utilising the evaluation script, the outputs from the simulation were examined.

A. *Traffic Conflict*

A traffic conflict is a traffic event involving the interaction of two or more road users, where one or both road users need to take evasive action, such as braking or swerving to avoid a collision [72]. The most widely used metric to identify traffic conflicts is Time-To-Collision (TTC) [73]–[77]. This measure is defined as the remaining time before an impact takes place between two road users unless an event to change their trajectories and speed occurs, such as braking or a change in steering angle. Its equation is given as:

$$\mathrm{TTC} = \frac{s}{v_{\mathrm{ego-vehicle}}} \tag{3}$$

where $v_{\mathrm{ego-vehicle}}$ is the speed of the CAV and s is the distance between preceding vehicle and CAV. A critical value for TTC must be defined to make a distinction between a relatively safe encounter and a critical one. The majority of studies determined the critical value for TTC to be 1.5s (e.g., [78], [79]).

The values of TTC surrounding the CAV were captured and the 1.5 second threshold was adopted to determine the percentage increase in the number of traffic conflicts in relation to the baseline scenario (i.e., no roadworks) in two situations: (i) lane change, (ii) no lane change for both scenarios. This is represented in Fig. 6.

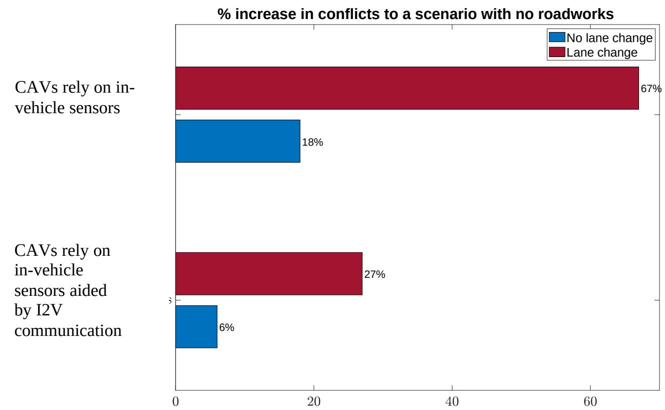

Fig. 6. Percentage increase in conflicts estimated with no roadworks scenario

Referring from Fig. 6., in the scenarios which CAV only used in-vehicle sensors, the number of traffic conflicts increases by 18% (relative to the baseline scenario with no roadworks) when the CAV did not change lane. When the CAV performed a mandatory lane change, the number of traffic conflicts was significantly higher (i.e., 67% relative to baseline scenario).

Under the scenario which the CAV fuses data from 'roadworks essential information package' alongside with in-vehicle sensor data, the number of traffic conflicts only increase by 6% when no lane change occurs and a 27% increase in number of traffic conflicts (relative to baseline scenario) was observed in the situation which the CAV performed a mandatory lane-change event .

During the simulation, it was noticed that in some simulation runs, the CAV performed its lane change at some distance from the start of the roadworks. However, in other simulation runs, the CAV came to a complete stop because its field-of-view of the construction zone was blocked. Shorter ranges were found to result in a higher number of conflicts as all vehicles change lanes over a shorter distance. Conversely, a higher range allows for earlier detection of lane closures and lane change manoeuvres, thus reducing conflicts. Moreover, when the CAV did not change its lane leading to the roadworks, the conflicts were 49% lower compared to when the CAV had to perform a mandatory lane change. The conflicts derived from this test were attributed to the vehicles in roadworks lane cutting in the lane in which the CAV was driving in.

B. *Delay*

Roadworks often involve changes to the capacity of the road which can lead to increases in journey times. The increase in journey time is mainly due to the enforced reduction in speed when navigating through roadworks and can result in delays. Delay in this simulation was estimated as the additional time taken by the vehicles to travel the network as compared to the baseline scenario where roadworks is absent. This KPI was also captured from the output files generated after every simulation run. This KPI is explored and presented in Fig. 7.

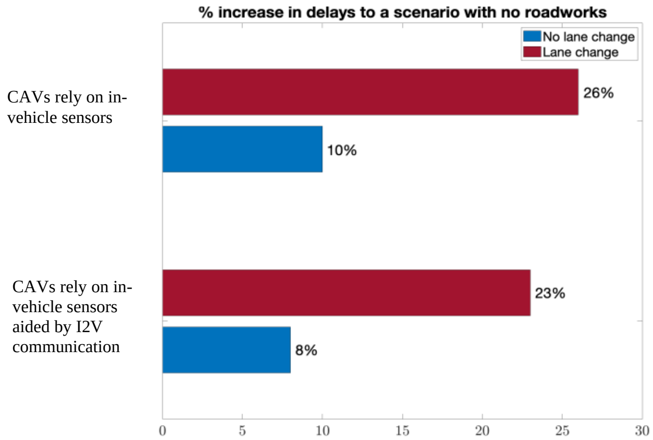

Fig. 7. Percentage increase in delays estimated with no roadworks scenario

As expected, Fig. 7. show that roadworks cause delays on the traffic network. Delay is 26% higher than baseline scenario when mandatory lane change is performed compared to the situation when the CAV maintained its trajectory within the same lane (i.e., 10% higher delays). Moreover, since the CAV was using only in-vehicle sensor data, in cases where the field-of-view of the CAV was blocked, the mandatory lane change was performed closer to roadworks which increases the delay due to surrounding traffic. Similar results are observed when using the fused data, delays increased by 23% when the CAV performed a mandatory lane change compared to a 8% increase in delay when lane changing manoeuvre did not happen.

C. Comparative Analysis

Comparing between both scenarios, a unanimous decrease throughout all KPIs were observed when the CAVs received the information pack in advance relative to the scenarios which vehicles solely relied on the in-vehicle sensor data only for perception and sensing. To further elaborate, a sharp 40% decrease of traffic conflicts and 3% reduction in delay are witnessed when CAV travels through roadworks with additional information of roadworks received compared to solely rely on in-vehicle sensors for mandatory lane change situations. Similarly, for scenarios without lane change manoeuvre, a percentage decrease of 12% and 2% in conflicts and delays respectively were achieved when the CAV received the information pack.

It is important to further elaborate the level of impact on the reduction of conflicts by sending out the information package to the CAV. This package contributes significantly towards traffic safety as it allows the CAV to plan the trajectory beforehand based on the dynamic map and by using the in-vehicle sensor data it was able to plan and reduce conflicts. Delays also decreased, despite the benefits accrued from the distribution of the information pack to the CAV on this KPI is lower. This is perhaps due to the short length of the testbed replicated within the simulation environment. Further testing was also performed to determine whether the mean conflicts, journey time and delays are the same in all the scenarios developed. A Kruskal-Wallis test was carried out and the results show that all three KPIs are statistically different.

The advantages of adopting a STC to send out the roadworks information package over using only in-vehicle sensor data to navigate through roadworks is clearly highlighted from the results obtained. This scenario resulted in the lowest number of conflicts, a shorter journey time and less delay.

Further testing was also performed to determine whether the mean conflicts, journey time and delays are the same in all the scenarios developed. The Kruskal-Wallis (KW) test evaluates the impact of modifications on the accuracy and precision of the simulation output. It yielded a substantial H statistic of 338.618, along with a p-value of 0, which decisively rejects the null hypothesis. Hence, this finding suggests that all three KPIs are statistically different and that the means of the results obtained after implementing the modifications were significantly different. The positive impact of these modifications is visually evident in Figure 6 and 7. To ensure simulation accuracy, we enhanced precision by averaging the results of 10 replications.

A closer look at Fig. 8 and 9 indicate that the results obtained from a single simulation exhibit greater fluctuations compared to the averaged results of 10 replications. These fluctuations can be attributed to the inherent randomness present in the system and the specific conditions encountered during each simulation run. However, by taking the average of multiple replications, a more stable and representative picture of the lane detection performance can be obtained. The standard deviation for delays across the 10 repetitions was found to be 0.768 seconds, reflecting the low variability in the amount of time CAVs experienced delays during the scenarios. Similarly, the standard deviation for TTC across the 10 different random seeds was 0.3403 seconds, indicating the low variability in TTC between the simulations.

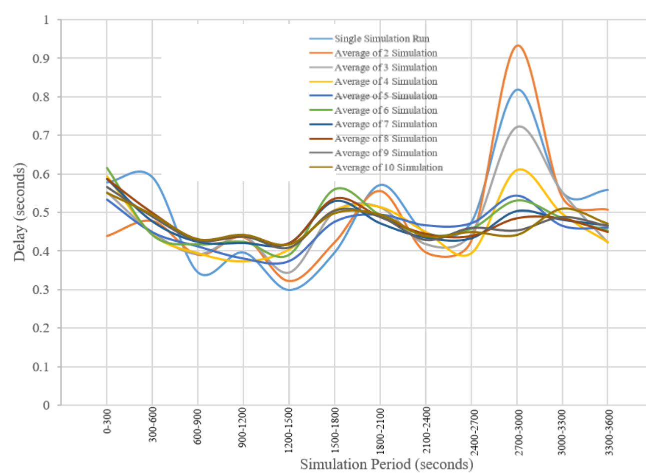

Fig. 8. Impact of replications on the average delay simulation results in normal traffic conditions (i.e., no roadworks)

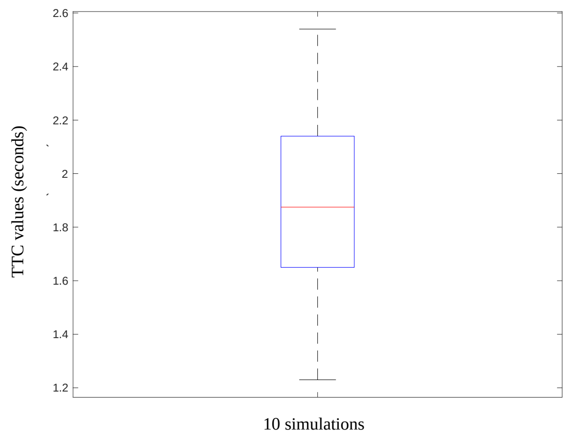

Fig. 9. The impact of replications on the average TTC simulation results in normal traffic conditions (i.e., no roadworks)

VI. Discussion

Navigating through complex traffic environments such as roadworks with mixed fleets is one of the key challenges faced by CAVs. At present there are no consistent operational procedures regarding how such vehicles can objectively interpret and react to rapidly changing situations within roadworks. Moreover, most of the existing guidance frameworks for CAV navigation adapt to an existing transportation framework. However, it is crucial to develop and implement more dynamic guidance frameworks with desirable features to accommodate the widespread deployment of CAVs in the future [55]. As a result, in this study, an integrated simulation framework was developed on a real-world controlled motorway facility in England to examine the impact of using in-vehicle sensor data and real-time information package sent out by STC to explore the implications of CAV operations during roadworks.

It was concluded that the existing level of infrastructure technology could mean that CAVs might encounter difficulties in navigating through sections of roadworks. This increases the chance that either a disengagement event would occur or that a CAV could encroach into a roadworks area. This is largely due to the limited sensing capability of CAVs in the presence of other moving objects (e.g., heavy goods vehicles, HGVs) which can block the line of sight. As such, a CAV approaching a lane closure in the left lane would not be able to detect if positioned behind a high-sided vehicle such as an HGV. This would cause the CAV to delay merging into the next lane which potentially increased the risk of a collision.

One method is to provide warning messages from the smart traffic control device to the CAV (I2V). However, there are no agreed standards or protocols for what the message should include from smart traffic control devices even though dissemination of such data in real-time is essential [55]. This research recommends an information package transmitted by STC to CAV via I2V with all the necessary information for the CAV to carry out an informed decision and safe manoeuvre related to a roadworks scenario. Nevertheless, proper and accurate infrastructure maps are still crucial for the desired functioning of many I2V applications. CAV installed map data might be comparable to the current navigation maps stored in GPS devices such as Garmin and TomTom navigators, and smartphone applications (e.g., WAZE and Google Maps) [80]. However, maps with more precise details which can help CAVs plan manoeuvres are crucial [18]. CAV maps need to be three-dimensional, including all objects on the road or on the roadside such as buildings, trees, roadside units, traffic signals/signs [81], and includes efficient lane-level digital maps to apply self-position estimation [18]. Moreover, one may argue that how could the High-Definition (HD) map be built in real-time in a dynamically changing operational environment such as roadworks? Construction companies can develop a digital twin model (i.e., a digital replica of a physical model of the roadworks environment) which is ‘dynamic’ meaning that any changes in the physical component (e.g., changing road layout, lane configurations via cones) are automatically captured in the digital model through the sensors installed in the real-world. The digital map can then be transferred to CAVs in real-time.

It is interesting to observe that the safety benefits are more significant (about a 40% reduction in traffic conflicts) than the improvements of traffic delays (about a 3% reduction) with the inclusion of the V2I communication from the STCs, irrespective of whether mandatory lane change has been taken place. The reason of less significant improvement in delay might be due to the limited length (650m) of the testbed used for simulation. Given this limitation, the travel time would not deviate significantly. It is important to note the driving behaviour used or assumed in the simulation analysis affects the results obtained [9]. The behaviour adopted in this study was following a conservative driving behaviour and longer following gaps. Comparable to results in the literature while this type of behaviour is usually cited for safety studies, mobility studies usually assume assertive following behaviour and shorter gaps [9]. This indicates that CAV benefits are sensitive to the assumed driving behaviour calling for more efforts that attempt to understand driver’s behaviour of CAVs.

An essential part to consider is the security of this data and procedures required to ensure the data is robust and accurate enough for the CAV to operate safely. The efficiency of the data transmission via V2I is highly dependent on the MPR of CAVs. To avoid communication congestion and confusion, messages should not be exchanged with vehicles on parallel roads and should be propagated in one direction [9]. However, it is known that as the MPR increases, communication congestion can still occur because of the multiple transmitters and receivers on the network and the delivery rate can be affected. Therefore, this requires further testing and validation.

This paper has reaffirmed the use of communication modules to inform roadworks situations as well as the implementation of HD maps which are pivotal for a safe trajectory generation. Studies have proved that I2V communication can improve the traffic safety by reducing the time to collision by more than 70% [82]. Furthermore, delay and emissions can be reduced by 46% and 33% respectively [83]. The CAV design is the prerequisite for trajectory generation, yet sensors might fail to interpret roadworks precisely in ever-changing road conditions. Further digging into the results, it is interesting to observe that the safety benefits are more significant (about a 40% reduction in traffic conflicts) than the improvements of traffic delays (about a 3% reduction) with the inclusion of the V2I communication from the STCs, irrespective of whether mandatory lane change has been taken place. The reason of less significant improvement in delay might be due to the limited length (650m) of the testbed used for simulation. Given this limitation, the travel time would not deviate significantly. However, key results of this study validate that improvements in safety and traffic efficiency are significant only if the communication modules and HD maps are in presence. Therefore, it can be summarised that the CAV design and specifications are just the enabler for the roadworks information and HD maps to be deployed whilst the CAVs design per se did not contribute significantly when approaching roadworks.

Additionally, although the microscopic simulator VISSIM is not equipped to capture human-CAV interactions, in the present study the interaction of human-vehicles was used to estimate conflicts (equation 3) based on the leader-follower vehicle type, speed and direction angle. For future work, fuel and energy consumptions could be employed as a key performance indicator (KPI) as they could assist in achieving net zero emissions in the transport sector.

VII. Conclusion

This paper developed collision-free trajectories for CAVs to safely navigate around roadworks at a motorway environment. An integrated simulation platform consisting of traffic, communication and vehicle autonomy simulators was developed and a simulation model of the controlled motorway segment was created, calibrated and validated by employing the data from a series of controlled experiments. This facilitated to test the performance of the trajectory planning algorithms in two primary scenarios: (1) when a CAV only utilised the data from in-vehicle sensors and (2) a CAV received additional data and information via a Smart Traffic Cone (STC) in advance regarding roadwork configurations (road and lane layouts) in their collision-free trajectory generation algorithms. From these two approaches, this research revealed the way in which CAVs could navigate through roadworks in a highway environment with the aim of improving safety and mobility by addressing potential conflicts while ensuring smooth traffic operations.

From the comparative analysis between the two scenarios, the results confirmed that traffic conflicts and traffic efficiency improve when CAV receives the information pack in advance compared to solely reliant on in-vehicle sensors. The results stay consistent irrespective of whether lane change maneuvers took place or not. Amongst all KPIs, the introduction of STC achieves the greatest safety benefits which a decrease up to 40% of number of traffic conflicts is recorded. In addition, delays are reduced by 3%. The scenarios examined in this research were based on two underlying concepts: (1) enhance mobility and (2) improve safety at roadworks.

The findings of this paper could provide useful insights to network operators about traffic conditions and road safety after the implementation of CAVs. For CAV manufacturers, the result can inspire the development of planning algorithms to better equip CAVs when approaching roadworks situations Highway authorities can also benefit by considering the deployment of the STC especially along roadworks, as to assist with the introduction of CAVs.

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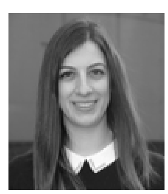

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