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Assessing Connected Vehicle's Response to Green Light Optimal Speed Advisory from Field Operational Test and Scaling Up

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What are the main factors related to road or service configuration influencing the response behaviour of connected vehicles? How does it evolve with respect to the Market Penetration Rate (MPR) of connected vehicles? Here are some questions raised by this paper with a focus made on Green Light Optimal Speed Advisory (GLOSA) strategy. Such a system, based on V2I communication, aims at providing speed advice/recommendations when approaching an intersection to adjust speed and enhance fuel consumption. The message is displayed on the Human Machine Interface (HMI) of the connected vehicles and a response is expected from the driver. This paper derives its interest in the response behaviour of the driver to HMI. It develops a two-stage methodology based on (i) Field Operational Test to collect realistic inputs (*e.g.*, response rate, delay, deceleration profile, etc.) and (ii) a simulated environment used for extending the findings to non-observed cases (*e.g.* higher MPR). Besides, the methodology that is well-fitted for generic evaluation and comparison of pilots sites' conclusions, one further contribution lies in the process to select the explaining factors. Factors are targeted among features of (i) the road configuration (*e.g.* number of lanes), (ii) the service configuration (*e.g.* activation distance), or (iii) the individual route choice and traffic conditions. Among others, it is highlighted that the activation distance plays a significant role in the response behaviour and, depending on the cycle duration, a short activation distance might be completely inefficient, while a true environmental impact requires high MPR.

Index Terms— GLOSA / eco-driving, Connected Vehicle, Field Operational Test, microscopic simulation, response behaviour, Regression.

I. INTRODUCTION

IN the last few decades, there has been a large-scale deployment of various sensors and data collection systems in the road traffic infrastructure. This has helped in the development of new technologies, such as Cooperative Intelligent Transport Systems (C-ITS), which has also transformed the vehicles' roles into mobile sensors, therefore creating a synergy between information and transportation physical domain [1]. This family of C-ITS services, enabled by vehicle-to-everything (V2X) communication, are aimed to have a positive impact on road traffic efficiency, environment, and safety aspects, once deployed in the real world.

One of the widely-researched C-ITS service is the Green Light Optimal Speed Advisory (GLOSA) *a.k.a.* the Eco-Cooperative Adaptive Cruise Control (Eco-CACC), provided to connected vehicles near signalized intersections [2]. This service delivers tailored advice to the vehicle in order to smoothly cross a traffic signal, with the primary objectives of improving safety, fuel efficiency and reducing emissions. It is achieved through a communication between the traffic signal and the on-board vehicle unit, which is performed by the SPAT (Signal Phases and Timing) messages broadcast to Connected Vehicles (CV) by Road Side Unit (RSU - through Dedicated Short Range Technology) or by Traffic Management System (TMS - through 3G/4G/5G technologies). Since its introduction as a concept in 2006 [3], there have been a significant number of contributions by researchers in terms of methodological formulations (*e.g.*, [4], [5], [6], etc.), eval-

uation in a wide variety of scenarios (*e.g.*, [7], [8], etc.), and optimization of the algorithm itself (*e.g.* [9], [10], [11], etc.). Researchers have primarily relied on simulation-based experiments (*e.g.* [12]), with only a few works reporting their findings on the basis of implementation from pilot studies (*e.g.* [13], [5]) or field operational tests (FOT) (*e.g.* [14], [15]). Hence, there is still a significant gap in research in developing and applying a methodological framework that evaluates the system impacts for a wide range of scenarios with due considerations of the realistic behaviours from the FOTs.

In the context of human-driven connected vehicles, only a few studies in literature have attempted to investigate driver attitude and behaviour towards GLOSA services. For example, Gajananan *et al.* [16] performed a multi-user driving simulator-based experiment and highlighted in brief that there are a few seconds of delay in the driver response which is dependent on the speed difference between the vehicle speed and the recommended speed. Olaverri-Monreal *et al.* [17] performed qualitative evaluation of the driving experience based on lab-controlled driving simulator experiments to understand how much it affected the drivers in terms of distraction, change in behaviour, satisfaction and perceived performance. The experiment concluded with a positive attitude and general acceptance towards the GLOSA service. These experiments were valuable to develop a qualitative understanding of the driver attitude towards GLOSA, in general, but were not useful, in principle, to evaluate the actual driver response, in terms of compliance rate, response behaviour, etc. Only one study [5] revealed certain modifications in driver behaviour from experiments conducted in the real world. 400 drivers were recruited in San Jose, California, USA to investigate

the change in the acceleration and deceleration profile of the vehicles equipped with the GLOSA service (active trip) as compared to the baseline or non-equipped vehicles (inactive trip). The study revealed that there are statistically significant differences in the profiles between the two cases with smoother performances for the active trips. Several researchers have performed sensitivity analysis with hypothetical data in traffic micro-simulation to show that the factors related to driver response have a considerable effect on the performances. Liao *et al.* [18] demonstrated that the driver compliance rate to GLOSA messages has a substantial impact on the vehicle emissions. Karoui *et al.* [12] performed similar simulation-based studies to show that increased driver reaction has a significant detrimental effect on the traffic and environmental efficiencies. These studies reveal both the distinct gap in literature and the importance in considering such driver-related factors in the evaluations of C-ITS services, in general, and GLOSA, in particular. There is also a major research gap in identifying the different factors that influence the response behaviour of such drivers.

Therefore, it has been aimed in this study to develop and apply a methodological framework that combines field data- and simulation- based analysis to realistically scale up and quantify the impacts of a particular C-ITS service. The three important contributions are: (i) identifying the factors that significantly influence the driver response to a GLOSA speed advice; (ii) extracting some features related to driver response (distribution of response time, average deceleration, and average speed compliance) from the real-world tests and incorporating them in a traffic micro-simulation framework; and (iii) producing realistic impacts on traffic and environmental efficiency for a wide range of scenarios by taking into account the driver response behaviour. The study has been carried out with reference to vehicles equipped with GLOSA service and the connected traffic signals in the metropolitan area of Bordeaux, France. Once some indications were obtained with respect to driver response, it was further attempted to incorporate the same in an integrated simulation environment to extend the results to generic situations and to scale up the assessed impacts. ARTERY [19] was used as the comprehensive simulation tool for performing I2V simulations based on ETSI ITS-G5 protocols through the coupling of a microscopic traffic simulator, SUMO [20], and a discrete events simulator, OMNET++ [21].

The rest of the manuscript is structured in the following four sections. The subsequent section provides an introduction to the methodology adopted in the present study, especially in terms of database development for performing the analysis of the response behaviour of the drivers and the simulation framework adopted for scaling up. The following section discusses the findings from the analysis and identifies the factors which contribute to variation in the driver responses. In the subsequent section, the aggregated response features are incorporated in the simulation framework for performing the scaling up and investigating the impacts of several parameters, *viz.*, market penetration rate, activation distance, etc. on the traffic efficiency. Finally, the major contributions and the future perspectives from the present study are highlighted in the

concluding section.

II. METHODOLOGY

The adopted methodology is composed of two main phases illustrated in Figure 1. The initial phase (in orange) is dedicated to the analysis of data resulting from Field Operational Test (FOT). It aims at featuring the driving behaviour of end-users (i.e. Connected drivers) according to the eco-driving instructions provided on the Human Machine Interface (HMI). The purpose of the second phase (in green) lies in the scaling-up process. It offers to generate Key Performance Indicators resulting from a simulated, controlled and reproducible environment. Some indicators highlighted during initial phase are integrated as parameters to feature the response behaviour of the connected vehicles in the simulation. The key steps are further described in the following subsections.

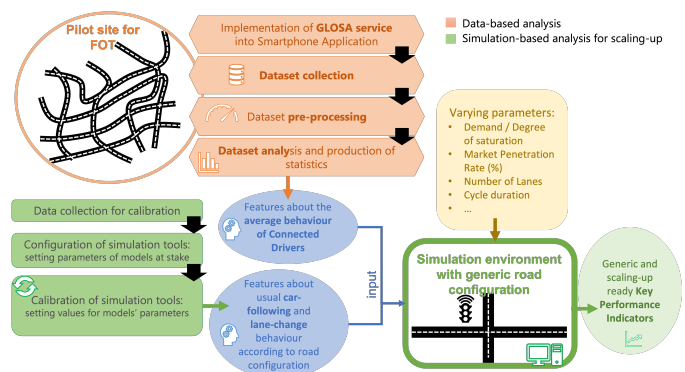


Fig. 1: The Two Phases Methodology

A. Database Development

The database has been generated from European project C-The-Difference (CTD) [22] thanks to a large-scale FOT which was aimed at assessing the impact of network-wide deployment of C-ITS services. A smartphone application has been developed that enabled to display some eco-driving instructions to drivers and generate log-data. Log-data have been passively and regularly collected within a database server. By overlapping log-data tables, some explaining factors can be intersected and evaluated. The application is built on sub-modules of GoogleMaps/Waze, with the objective of having a refined generation of the GPS position. As a result, no further processing was carried out to refine the GPS positions.

The data stored on the server results from the logs generated by the flow of exchanged data (see Figure 2a) during the communication between Traffic Management System (TMS) and connected vehicles (*i.e.* a driver equipped with an on-board smartphone). The communication between TMS and smartphone is only ensured by 3G/4G technology. Two types of data are logged:

- **the collection of messages (e.g. SPAT) emitted by the road manager:** On the pilot site, traffic lights are centralized and managed by TMS (GERTRUDE). For every equipped traffic light, SPAT messages are continuously computed within GERTRUDE's management

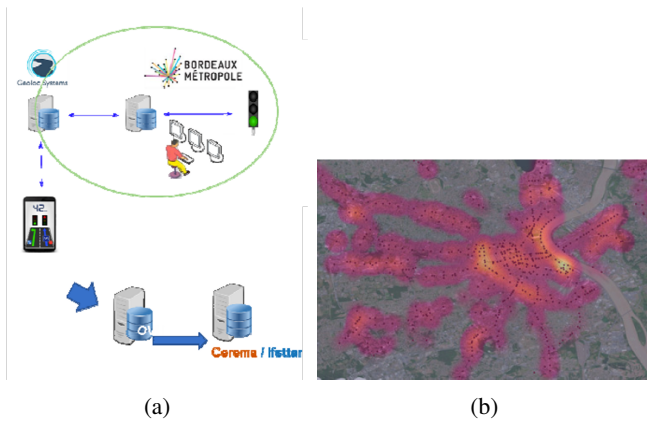


Fig. 2: (a) Exchanged data flow between TMS and connected vehicles (b) Heat-map of the spatial distribution of the GPS positions collected on the metropolitan area of Bordeaux

system according to management strategies. For pilot's needs, data contained in SPAT messages are duplicated on the server. It enables to store timestamped information about the current state for any equipped traffic light.

- the collection of information related to the smartphone when a use case is triggered:** Each smartphone equipped with the app continuously map-matches its GPS position and seeks for messages associated to its current zone. It enables the smartphone to request and collect any message relevant to its current location and the downstream intersection. According to the collected information, the smartphone continuously evaluates and computes the need to trigger one of the use cases under consideration. When a use case is triggered, usually a message is displayed on the HMI and a reaction of the driver is expected. Then, some log data are collected and forwarded to the server. These data are mainly resulting from the Cooperative Awareness Messages (CAM) regularly emitted by activated smartphones. For each use-case occurrence, data are collected from 30 seconds before to 30 seconds after the event. It enables to describe the vehicle's trajectory before, during and after the event. Indicators have been calculated and stored into a synthetic table according to use-case type. The relevant data include: (i) the current ID of the end-user/smartphone; (ii) the intersection ID; (iii) the timestamp; (iv) the timestamped ID of the event enabling to follow with time the actions on the HMI; (v) the timestamped ID of the actions applied on HMI; (*e.g.* first display of the message, update of the message, etc); (vi) the GPS position of the smartphone with a frequency of 1Hz; (vii) some features resulting from the GPS of the smartphone (*e.g.* current speed, current heading, etc); (viii) supplementary information about the origin of use case activation (message ID, zone ID, GLOSA advice, etc) and context information (*e.g.* message content, etc).

The smartphone application has been developed to evaluate a wide range of C-ITS services. In the current methodology, we focus on the drivers' response to the GLOSA use case. This

use case is triggered when an user enters an activation zone in the vicinity of equipped traffic light. Then, the following sequential process takes place:

- 1) detection by the smartphone application of the vehicle's entry into the zone by geo-matching;
- 2) recovery of the information on the traffic light cycles of the upcoming intersection
- 3) calculation of the instructions to be displayed: The displayed instruction vary according to the situations experimented by the driver. Five cases are identified:
 - *Eco-Stop (E)* for stopping the engine, when the current speed is lower than 2 kph and the time to green is greater than 7s;
 - *Go (G)*, when the vehicle is stopped in the queue;
 - *Pass (P)*, when the current speed of the driver enables him to cross the intersection during the green phase;
 - *Stop (S)*, when the current speed is lower than 2 kph, but the time to green is lower than 7s, or the computed speed advice is lower than 20 kph;
 - *Speed recommendation (V)*, when the smartphone can compute a speed recommendation higher than 20 kph to reach the stop-line at the beginning of next green phase.
- 4) display of the instructions on the HMI
- 5) optional: acknowledgement of the instructions by the driver
- 6) optional: interpretation and decision making by the driver
- 7) optional: driver action on vehicle controls (deceleration)

Steps 1 to 4 are automated and can be estimated to be less than two seconds. The evaluations made in the present study are concerned with steps 4 to 7, *i.e.*, from the time the instruction is displayed (and logged) on the HMI until a driver performs some action resulting in a significant slowdown. From the data collected, it is only possible to estimate this elapsed time, rounded to 1s, due to the temporal resolution of the Cooperative-Awareness Messages with reference to the position and speed information of the driver.

The database under study has been developed over 8 months on the metropolitan area of Bordeaux (France), where 580 intersections were managed via 4G, while 546 of them have been mapped for GLOSA use case (see Figure 2b). It results in 600 untrained drivers generating around 3 million GPS positions during the experiment. As the experiment is fully crowd-funded, the panel characteristics were unknown. Within the database, we can register around 30,469 GLOSA use cases. The study is focused on the drivers receiving a speed recommendation (around 22,198) and, especially, their adopted behaviour. Some intersection configurations (around 5%) were vulnerable to generate false-positive cases (*i.e.*, GLOSA is triggered when it should not be) due to grade-separated facility, like a road overpass, (vertical confusion) and/or a narrow crossroad, like a configuration with closely placed traffic signals for the mainline and merging traffic (horizontal confusion). With the available GPS accuracy, it was not possible to filter these cases effectively, except for removing vehicles

travelling with high speed and/or the suspicious intersections. In order to identify and filter them more accurately, it will be necessary to modify the cartography, to take into account the altitude parameter as well (for vertical confusion) and adopt a highly accurate positioning system (for horizontal confusion).

To enrich the database and refine the analysis, some land-use data have been integrated. This open-data are produced by the French Geographical Institute [23]. It gives access to geographical description of the road segments with features about the road type, the number of lanes, the free flow speed, the average speed, and the existence of bike or Public Transport lane. This dataset is geographically referenced by a multi-line string depicting the road segments. In order to merge the land-use data with the ones resulting from the data server, the GPS position of any first GLOSA message displayed on the HMI is map-matched with the geographical segment of the land-use data by applying the two steps: (i) a spatial request with a tolerance of 50m, which is performed on the geometry of the road and the position of the first GLOSA message; (ii) a request to match the intersection ID the two databases: the one of the GLOSA message and the one with road characteristics. It may be mentioned that due to the General Data Protection Regulation (GDPR) of the European region, it was not possible to obtain the socio-economic profiles and characteristics (*e.g.*, age, gender, experience, etc.) of the individual drivers which may have further enriched the analysis.

To evaluate the consistency of response behaviour over time, the CoopITS database resulting from C-ROADS project [1] has been used. The only major difference between both databases lies in the stakeholders and the period of implementation. Both database are generated on the metropolitan area of Bordeaux with the collection of the log-data resulting from a smartphone app. Both experimentation ensure the communication through 3G/4G and the implementation of the GLOSA algorithm has been developed by the same provider. Some differences occur in the logged indicators, but most of them are shared and enable to produce significant comparison. While the CTD database was generated during September 2017 – April 2018, the CoopITS database is more recent and has been generated on 5 months since February 2021.

B. Data Pre-Processing

Several filters were necessary to obtain the optimal conditions for evaluating the response behaviour and minimizing the effect of congestion or other masked phenomena. The specific behaviour of interest is to identify when there is a speed reduction after receiving the first speed advice which imply slowing down. The slowdown can result either from the use of the engine brake or from the use of the mechanical brake. In the case of Bordeaux, the terrain maybe considered to be flat, making it possible to retain the hypothesis of a perceptible slowdown during engine braking (versus sloping terrain). The response behaviour was, therefore, analysed after filtering the recorded events (trajectories):

- **Filter 0:** GLOSA Advice = ' V_a ': The case which indicates a slowdown with a speed advice.

- **Filter 1:** Duration of Trajectory ≥ 4 seconds available before the broadcast of first message: This is to characterize the driver profile prior to receiving a speed advice. The intention was to ensure that the trajectory upstream of the first advice is not too short while maintaining a sufficient size of the dataset. A sensitivity analysis revealed that, with 4 seconds an inflection appears in terms of eligible trajectories, while few changes are observed on the response rate and response time of the drivers beyond 4 seconds.
- **Filter 2:** Minimum message duration of ≥ 10 seconds: Majority of the trajectories, *i.e.*, 90%, are having a message duration in the range [10s , 60s]. A message duration of less than 10s is considered too short for obtaining a response as the instruction is provided when the driver is too close to the intersection.
- **Filter 3:** Vehicle speed at the time of first message broadcast ≥ 20 km/h: It directly results from the GLOSA algorithm since no speed instruction below 20 kph is provided on the HMI.
- **Filter 4:** Upstream slowdown $< - 3$ km/h between (time of first broadcast - 4 seconds) and (time of first broadcast): This is to ensure that the vehicle is not already in the process of slowing down before receiving first advice. The value results from a sensitivity analysis highlighting an inflection with regard to several aspects (*e.g.*, the total amount of eligible trajectories, the total amount of responses, etc).
- **Filter 5:** Speed after first message broadcast ≥ 10 km/h: It is aimed at removing the vehicles involved in queue or congestion between the emergence of the message on the HMI and the intersection. Since the lowest speed instruction provided is 20 kph, a speed of 10 kph is the threshold considered to highlight congested states. Such consideration is justified by a recent study [24] focusing on the relationship between driver's cognitive fatigue and driver's speed variability. For the present case, it can be derived that in the worse case the driver's speed might reach 10 kph for a tired and inattentive driver with the lowest speed instruction (20 kph).

C. Data Analysis

Once the database was filtered, the refined database with the eligible use-cases was employed to obtain the average response rate, the average speed compliance and the distributions of response time and deceleration performance of the connected drivers. After filtering, 1328 eligible use-cases were obtained from the CTD database and 130 eligible use-cases were obtained from the CoopITS database. On this filtered data, a response was registered, if:

- 1) A slowdown greater than 1 km/h/s is observed. This corresponds to a minimum observed deceleration rate of around 0.25 m/s/s for an approach speed of 40-50 km/h [25].
- 2) The slowdown is for a minimum duration of 3 seconds. In order to select this filter, the dataset was explored to observed the distribution of speed difference between

the initial speed of the vehicle and the speed advice. The 15-th percentile speed difference, was found to be 3 kph. So, considering a minimum deceleration of 1 km/h/s, we considered a minimum duration of 3s., and

- 3) The slowdown starts during the first 10 seconds of the message broadcast. Initially, the entire distribution of response time was observed without considering any cut-offs. It was observed that the distribution exhibits a long tail beyond 10s. However, they correspond to less than 15% of the cases. In perception-reaction time studies, researchers generally report the 85-th percentile value [26], which in the present case is 10s. Therefore, based on this consideration, a filter of maximum response time of 10s, for performing the analysis by excluding the outliers, was adopted.

Further, in order to develop additional insights and explain the variations in the response rate and the response behaviour of the connected driver, several factors were taken into consideration. The factors selected as the independent variables include aspects related to the road and traffic conditions, and the status of the user. These are as follows:

- Time of day (t_{peak}): This explains at what time of day the user was provided the speed instruction, and was classified as during the peak or off-peak period of the day. The peak hours were identified based on relating historical information with the timestamp on the CA messages generated by the vehicle. This variable was dummy-coded (0=off-peak hour).
- Number of lanes (N_b): This factor considers the number of available lanes in the direction of travel (ranging from 1 to 4).
- Average travel speed (Sp_{av}): This factor considers the daily average traffic speed on the particular road section (a continuous variable).
- driver route (Rou_{CV}): This factor includes whether the driver is moving through, or turning left or right at the intersection. This variable was dummy-coded with the through movement considered as the base level.
- Distance to stop-line at first speed advice (D_{SL}): This is the distance of the connected vehicle from the stop-line when the first speed advice was displayed on the HMI and was considered as a continuous variable, also considered as activation distance.
- Driving operation ($Accel$): This factor considers the aspect whether the driver was increasing speed (accelerating) before and/or just after receiving the first speed advice and was considered as a dummy variable (1=accelerating; 0 otherwise).
- Driving speed (Sp_{CV}): This is the speed of the vehicle (in kph) at the instant when speed advice was displayed on the HMI.
- Speed advice (Sp_{adv}): This is the advised speed (in kph) displayed on the HMI.
- Speed difference (Sp_{diff}): Instead of the previous two variables, the difference between the vehicle speed and advised speed (in kph) may also be considered as a single independent variable.

An attempt was made to observe the effects of different factors on the response rate ($Resp$) as the dependent variable (1=response; 0=no response). A logit model [27] was developed with the model specified in Eq. 2. Furthermore, multiple linear regression models [28] were developed to investigate the effects on response time (t_{resp}), deceleration ($Decel$), and speed compliance (Sp_{compl}) as continuous dependent variables with the model specifications as shown in Eqs. 3, 4 and 5 respectively. t_{resp} was defined as the time elapsed (s) from the time of display of the first speed advice to the time when the driver begins to reduce speed. $Decel$ is the average deceleration (m/s^2) that the driver performs while continuously and gradually reducing the speed after receiving the first speed advice. Sp_{compl} matches with the difference in the final speed (after slowdown, Sp_{CV}^{end}) and Sp_{CV} expressed as a fraction of Sp_{diff} as shown in Eq. 1.

$$Sp_{compl} = \frac{Sp_{CV} - Sp_{CV}^{end}}{Sp_{diff}} \quad (1)$$

$$Y_{Resp} = \alpha_{resp} + \beta_{t0} * t_{peak} + \beta_{nb0} * N_b + \beta_{spav0} * Sp_{av} + \beta_{r0} * Rou_{CV} + \beta_{d0} * D_{SL} + \beta_{acc0} * Accel + \beta_{spdiff0} * Sp_{diff} \quad (2)$$

$$t_{resp} = \alpha_t + \beta_{t1} * t_{peak} + \beta_{nb1} * N_b + \beta_{spav1} * Sp_{av} + \beta_{r1} * Rou_{CV} + \beta_{d1} * D_{SL} + \beta_{acc1} * Accel + \beta_{spdiff1} * Sp_{diff} \quad (3)$$

$$Decel = \alpha_{dec} + \beta_{t2} * t_{peak} + \beta_{nb2} * N_b + \beta_{spav2} * Sp_{av} + \beta_{r2} * Rou_{CV} + \beta_{d2} * D_{SL} + \beta_{acc2} * Accel + \beta_{spdiff2} * Sp_{diff} \quad (4)$$

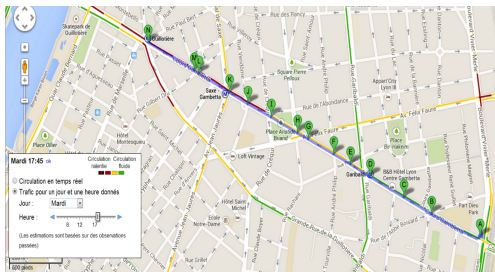
$$Sp_{compl} = \alpha_{compl} + \beta_{t3} * t_{peak} + \beta_{nb3} * N_b + \beta_{spav3} * Sp_{av} + \beta_{r3} * Rou_{CV} + \beta_{d3} * D_{SL} + \beta_{acc3} * Accel + \beta_{spdiff3} * Sp_{diff} \quad (5)$$

D. Scaling-up

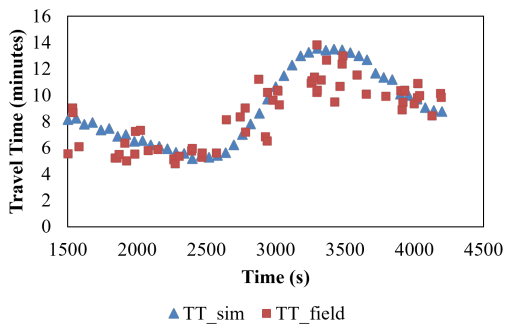
Once the response of the drivers were available from the FOT, the next stage was to incorporate this response behaviour in simulation tools to bring out the realistic impacts for more generic traffic, control conditions and at the network scale. The microscopic traffic simulator, SUMO [20], was selected to simulate the traffic operations. It is able to replicate the driving behaviour of a road user and its interactions with the surroundings. It is composed of several component layers which can interact with each other: the environment layer corresponds to the supply side with the features of the road network, the agents layer includes the driver, vehicle and road manager features, the sensor layer allows to collect information about the environment through various types of traffic sensors, and finally there is the communication layer where the agents can receive and disseminate messages

which is very important to replicate the connected vehicles. The communication layer results from a coupling between the traffic model and a communication model, OMNET++ [21], through a TCP-based client/server architecture, called TraCI. OMNET++, through the help of TraCI, can extract vehicle-state information from SUMO at each time-step and give instructions to alter the current vehicle state within the same time-step. The coupling is concretely operated within a framework, i.e., a set of OMNET++ modules respectively named Veins, INET and SimuLTE, which is overlaid to include a wide range of communication technologies. The resulting tool, ARTERY [19], offers the possibility to simulate vehicles equipped with ITS-G5 and LTE protocol stacks.

The first step was to check the performance of the traffic micro-simulator with the default values of the car following and lane-changing models to understand whether calibration was necessary. To achieve this, the traffic performance in terms of travel time was extracted during the peak hour for an urban arterial (Figure 3a) in the city of Lyon, France with a network of traffic signals. The traffic signal, road geometry, speed limit and traffic demand information were obtained and coded in the simulator. A comparison of the simulated and observed travel time during the peak period (Figure 3b) indicated statistically similar results with the root-mean squared error less than 10% which ensured that further model calibration was not necessary.



(a)



(b)

Fig. 3: (a) Urban Arterial in Lyon, France; (b) Simulated and Observed Travel Time

In the next step, a GLOSA algorithm, similar to the one implemented in the Bordeaux metropolitan network, was developed in the Artery simulation framework. The algorithm was further augmented to incorporate additional parameters related to the distribution of driver response time, average deceleration rate and the average speed compliance. This helped to have

a realistic representation of the driver's response to GLOSA messages. Finally, an experiment was designed to investigate the effect of different factors, that include:

- traffic factors, *viz.*, demand (in terms of degree of saturation): [0.50; 0.75; 0.90],
- market penetration rate (%): [0 (*i.e.*, baseline); 10; 30; 50; 75; 100],
- road and control factors, *viz.*: (i) number of lanes: [1; 2],(ii) cycle length (s): [60; 90],
- a factor related to operation of GLOSA, *viz.*, activation distance (m): [300; 500; 1000].

The key performance indicators (KPIs) are selected considering the focus on evaluating the impacts on traffic and environmental efficiency. For traffic efficiency, average stopped delay and average number of stops per vehicle are considered as the main KPIs. For evaluating environmental efficiency, the selected KPIs are average CO_2 , NO_x emissions, and fuel consumption per vehicle-km travelled. Similar KPIs have been selected in some recent studies related to GLOSA or eco-CACC services (*e.g.*, [11], [12]). PHEMLight emission model [29] integrated with SUMO has been used for estimating the pollutant emissions. It is an instantaneous vehicle emission model developed by the TU Graz and is pre-calibrated for the European vehicle fleet. For the sake of simplicity and uniformity, all the vehicles have been assumed to be passenger cars operating with Euro-IV gasoline.

III. FOT DATA ANALYSIS

This section is focused on the driver response behaviour of the connected vehicles as observed from FOT. In the first stage, an analysis was made to explore the factors responsible for initiating a response among the connected drivers and in the second stage the behaviour of the drivers who actually displayed a response were investigated in further detail. These are discussed in the following subsections.

A. Response Rate

An analysis of the C-The-Difference and CoopITS datasets revealed that about 70% of the eligible use-cases displayed a response to GLOSA speed advice in both the cases. Out of 1328 and 130 eligible use-cases for each dataset respectively, 933 and 91 users displayed a response. Pearson's Chi-square test was performed and chi-square statistic ($=0.0054$) and p-value ($=0.941$) shows that there is no statistically significant difference between the two datasets. This shows a consistent attitude by the connected drivers to both the smartphone applications in terms of response rate, when conditions enable to apply the recommendations. In order to develop further insights, binary logistic regression was carried out considering the response variable (1=response; 0=no response) with the model as specified in Eq. 2. It may be mentioned that the following models have been developed using the C-The-Difference database only as they provided sufficiently large sample size. A future scope may be to validate or refine the models using the more recent CoopITS database once sufficient data is available.

The model results are summarized in Table I. The results show that there is a significant impact of the driving operation ($Accel$) on the response rate. The drivers who were accelerating prior to a speed advice were observed to have a statistically higher response rate as compared to other drivers. The activation distance (D_{SL}) was also observed to have a significant impact on the response rate; the negative sign indicates that higher the activation distance, lower is the probability to display a response to GLOSA speed advice. On the other hand, higher the speed difference between the driver speed and the speed advice (Sp_{diff}), higher is the probability of a response. Other variables (e.g., t_{peak} , Sp_{av} , etc.) could not display any significant effect on the response rate.

TABLE I: Logit model estimates with the factors influencing $Resp$

Variable	Coefficient	S.E.	z	P> z	
Intercept	1.4566	0.409	3.565	0.000	
t_{peak}	-0.0559	0.217	-0.257	0.797	
Rou_{CV}	LT	-0.2368	0.197	-1.201	0.230
	RT	-0.0054	0.209	-0.026	0.979
N_b	-0.1357	0.125	-1.089	0.276	
Sp_{av}	-0.0035	0.006	-0.545	0.586	
D_{SL}	-0.0036	0.001	-4.835	0.000	
$Accel$	0.5612	0.145	3.862	0.000	
Sp_{diff}	0.0167	0.008	2.202	0.028	
No. of Observations = 1328					
Log-likelihood = -770.21					
Degrees of Freedom = 8					

While initially D_{SL} and Sp_{diff} were incorporated as continuous variables in the model, an attempt was further made to explore whether there is any non-linear effect of these variables on the dependent variable. Fig. 4 shows that there is a parabolic relationship of the two variables with the response rate. Therefore, the logit model was augmented by considering different levels for D_{SL} and Sp_{diff} and considering a D_{SL} value of 0-100 m and a Sp_{diff} value of 0-5 kph as the reference levels respectively. The levels were partitioned with equal intervals, e.g. 50 m in case of D_{SL} parameter, and 5 kph in case of Sp_{diff} parameter. Likelihood Ratio Test [30] was conducted to compare the model pairs with linear and non-linear specifications. Upon comparing the two models, we obtain Likelihood Ratio, $LR = 2(770.21 - 756.63) = 27.16$, with degrees of freedom = 3 (modified model adds 3 additional parameters), and critical value (at 0.05 significance level) = 7.815, which establishes that the modified model provides a statistically significant better fit.

The modified model provides further insights related to the dynamics of the driver response. Based on the results summarized in Table II, drivers were observed to be most responsive when the first speed advice is displayed between 200m and 150m from the stop line. Similarly, the response rate also maximises when the difference between Sp_{CV} and Sp_{adv} is between 20 and 10kph and decreases if the Sp_{diff} is higher or lower than this range. These findings are interesting as they tend to highlight that there may be an optimal activation distance and optimal range of speed where GLOSA advice may trigger more frequent responses among the connected drivers.

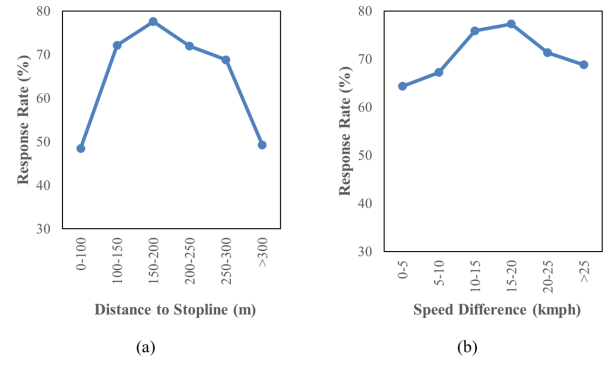


Fig. 4: Variations of Response Rate with (a) D_{SL} ; (b) Sp_{diff}

TABLE II: Modified Logit model estimates with the factors influencing $Resp$

Variable	Coefficient	S.E.	z	P> z	
Intercept	-0.6542	0.383	-1.709	0.088	
$Accel$	0.5286	0.148	3.582	0.000	
D_{SL}	300m	-0.0541	0.394	-0.137	0.891
	250m	0.7197	0.396	1.816	0.069
	200m	0.9203	0.376	2.450	0.014
	150m	1.2139	0.375	3.238	0.001
	100m	0.9219	0.380	2.425	0.015
Sp_{diff}	25kph	0.2313	0.245	0.943	0.346
	20kph	0.3355	0.233	1.438	0.150
	15kph	0.6177	0.216	2.857	0.004
	10kph	0.5315	0.192	2.768	0.006
	5kph	0.1828	0.175	1.046	0.296
No. of Observations = 1328					
Log-likelihood = -756.63					
Degrees of Freedom = 11					

B. Response Behaviour

The next task was to investigate the type of response displayed by the connected drivers in terms of response time, deceleration rate and speed compliance. Again, as can be observed from Fig. 5, for both smartphone applications a similar response was observed in terms of response time with a mean of around 5s and 4.7s and a standard deviation of about 2.5s in both cases. Welch's t-test was performed to compare mean response time and 2-sample K-S Test was performed to compare the distribution of response time. For the first test, the test statistic was 1.21 ($p=0.226$) and the second case, the test statistic was obtained as 0.08 ($p=0.594$). This shows that the mean and distribution of response time are statistically similar for the two datasets which emphasizes that both response rate and response behaviour are stable and similar across different applications. However, since the CoopITS database had very few observations, they were not used for subsequent analysis.

The response time was observed to follow a normal distribution (Fig. 6a) while the deceleration with an average value of $0.61m/s^2$ indicated closer similarity to a log-normal distribution (Fig. 6b). A similar deceleration distribution were also observed from the field operational tests conducted in San Jose, California [5]. In terms of speed compliance, a Sp_{compl} value of 0.75 was observed among the connected drivers. The aggregated response behaviour, viz., distribution of response

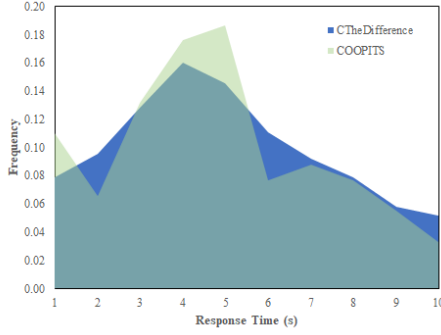


Fig. 5: Distribution of response time as observed by two GLOSA smartphone applications

time, the average deceleration and the average compliance rate were taken as direct inputs for the simulation-based analysis as response characteristics for the drivers of the connected vehicles.

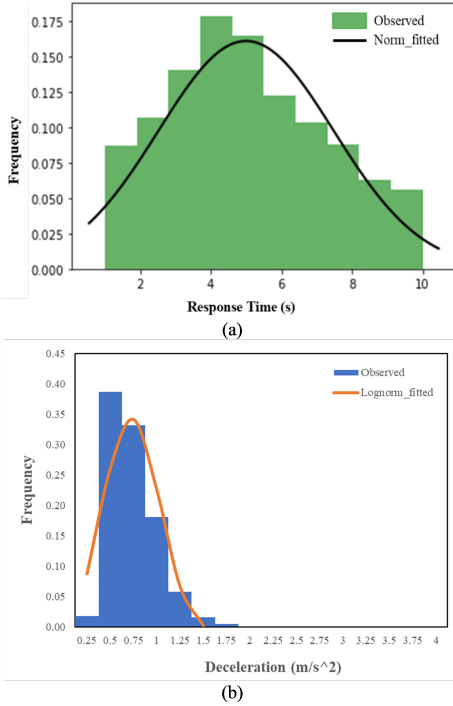


Fig. 6: (a) Response Time; (b) Deceleration

A deeper investigation revealed that the response behaviour changes with respect to different factors. In fact, Fig. 7a-d show the variations of response time with respect to different factors, such as D_{SL} , Sp_{CV} , Sp_{adv} and $Accel$. Therefore, multiple linear regression was adopted to explore the effect of different factors on each aspect of the response behaviour. Initially a correlation matrix was developed to check for collinearities between the independent variables and a strong correlation($=0.60$) was observed between Sp_{CV} and Sp_{adv} . Therefore, Sp_{diff} was selected instead and the correlation matrix is displayed in Fig. 7. The detailed findings with respect to each aspect of response behaviour are discussed in the following subsections.

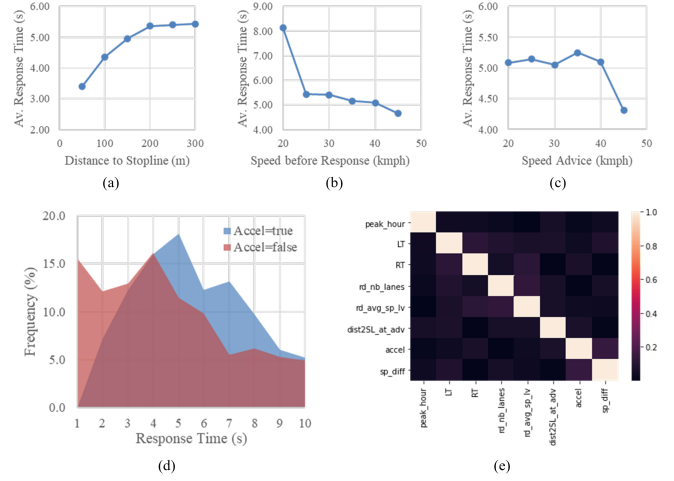


Fig. 7: (a) Variation of response time with D_{SL} ; (b) Variation of response time with Sp_{CV} ; (c) Variation of response time with Sp_{adv} ; (d) Variation of response time with $Accel$; (e) Correlation Matrix for selected independent variables

1) Response Time

An MLR (Multi-Linear Regression) model of response time based on Eq. 3 was first developed, taking into account the non-linear effect of D_{SL} and Sp_{diff} variables considering the observations made from the analysis of response rate. The results, as summarized in Table III, show that the response time, in general, increases with D_{SL} with certain variations. $Accel$ naturally shows a highly significant effect indicating that the vehicles, which are in acceleration at the time when the first speed advice is displayed, take a longer duration to respond to the message. The response time was observed to be significantly lower if the Sp_{diff} becomes higher than 20 kph.

TABLE III: Model estimates with the factors influencing response time

Variable	Coefficient	S.E.	t	P> t	
Intercept	3.4995	0.608	5.76	0.000	
$Accel$	0.9969	0.16	6.224	0.000	
D_{SL}	300m	1.6071	0.654	2.458	0.014
	250m	1.4983	0.634	2.365	0.018
	200m	1.6094	0.609	2.644	0.008
	150m	1.1652	0.603	1.933	0.054
	100m	0.6429	0.61	1.053	0.292
Sp_{diff}	25kph	-0.547	0.329	-1.664	0.096
	20kph	-0.5396	0.299	-1.804	0.072
	15kph	-0.2382	0.26	-0.917	0.36
	10kph	-0.1461	0.239	-0.612	0.541
	5kph	-0.2662	0.236	-1.128	0.26
No. of Observations = 933					
Log-likelihood = -226.5					
Degrees of Freedom = 11					

2) Average Deceleration

With respect to $Decel$, Eq. 4 was augmented to include the non-linear effects of D_{SL} and Sp_{diff} in a way similar to the analysis of t_{resp} . Table IV shows that the connected drivers appeared to perform a significantly stronger deceleration in

cases where they were accelerating during receipt of the first speed advice ($Accel=1$) and cases where the average speed level (Sp_{av}) of the road is higher. A gradual increase in the deceleration was observed with an increase in the speed difference between Sp_{CV} and Sp_{adv} . The analysis also revealed that the connected vehicles performed smoother decelerations if the D_{SL} is higher. Another interesting observation was that, during the peak hour, the connected vehicles performed stronger deceleration (around 90%CI), as compared to the other times of the day.

TABLE IV: Model estimates with the factors influencing deceleration

Variable	Coefficient	S.E.	t	P> t	
Intercept	0.4492	0.082	5.478	0.000	
t_{peak}	0.0506	0.032	1.586	0.113	
Sp_{av}	0.0026	0.001	2.764	0.006	
$Accel$	0.0424	0.018	2.365	0.018	
D_{SL}	300m	-0.1832	0.074	-2.466	0.014
	250m	-0.1372	0.072	-1.9	0.058
	200m	-0.0462	0.069	-0.666	0.506
	150m	-0.0019	0.069	-0.027	0.978
	100m	0.0478	0.07	0.687	0.492
Sp_{diff}	25kph	0.171	0.036	4.687	0.000
	20kph	0.0186	0.034	0.554	0.58
	15kph	0.0702	0.029	2.41	0.016
	10kph	0.0541	0.027	2.023	0.043
	5kph	0.0154	0.026	0.582	0.561
No. of Observations = 933					
Log-likelihood = -76.624					
Degrees of Freedom = 13					

3) Speed Compliance

An analysis of the Sp_{compl} based on Eq. 5 augmented with the level-based coding of D_{SL} and Sp_{diff} revealed statistically significant effects of several variables (Table V). It was interesting to note lower speed compliance levels for right turning vehicles ($Rou_{CV}=RT$) and with increase in the number of lanes (N_b) in the direction of travel. Higher flexibility of travel space with respect to lane availability apparently reduces the compliance to the speed advice. The speed compliance is also reduced for vehicles which are in a state of acceleration prior to receiving the speed advice. More significant speed compliances were observed when the D_{SL} is between 200-100m (as compared to the reference level of 0-100m) which again reveals the fact that drivers tend to show better acceptance to the speed advice when they are closer to the stop-line. The speed compliance gradually decreases with the increase in Sp_{diff} but then increases marginally if the Sp_{diff} is too high (greater than 25 kph).

IV. SCALING-UP

The aggregated response behaviour (response time distribution, average decelerate and average speed compliance) observed from the FOT were incorporated in the integrated SUMO and ARTERY simulation framework for scaling up. These are as follows:

- The response time was incorporated as a constrained normal distribution in the range of [0s;10s] with mean of 5s and standard deviation of 2.5s.
- The deceleration was considered as $0.6m/s^2$.
- The speed compliance rate was adopted as 0.75 (or 75%).

TABLE V: Model estimates with the factors influencing speed compliance

Variable	Coefficient	S.E.	t	P> t	
Intercept	0.9448	0.075	12.552	0.000	
Rou_{CV}	RT	-0.067	0.028	-2.385	0.017
N_b		-0.0348	0.018	-1.964	0.05
$Accel$		-0.0842	0.018	-4.806	0.000
D_{SL}	300m	0.0538	0.072	0.743	0.458
	250m	0.0394	0.07	0.56	0.576
	200m	0.093	0.068	1.373	0.17
	150m	0.1141	0.067	1.698	0.09
	100m	0.1252	0.068	1.843	0.066
Sp_{diff}	25kph	-0.3462	0.036	-9.722	0.000
	20kph	-0.4063	0.033	-12.406	0.000
	15kph	-0.2386	0.028	-8.403	0.000
	10kph	-0.1687	0.026	-6.465	0.000
	5kph	-0.0678	0.026	-2.625	0.009
No. of Observations = 933					
Log-likelihood = -52.970					
Degrees of Freedom = 13					

A. Impact of Activation Distance and MPR

The comprehensive impacts on traffic and environmental efficiencies are summarized in Fig. 8 which illustrates the percentage improvements in average number of stops and emissions with GLOSA speed advice over the baseline. With the incorporation of driver response time and the speed compliance rates, an activation distance of 300m appears to be too short to generate a considerable positive impact even at high market penetrations of CV, especially with long cycle duration (*i.e.*, 90s). With the increase in the activation distance to 500m, there is a considerable improvement in terms of traffic efficiency even at low MPR and the point of inflection can be observed around an MPR value of 30%. These observations are in line with Karoui *et al.* [12] where the benefit in the stopped time gain is deteriorated beyond MPR of 25% when a driver response time is taken into account. However, the improvement is less drastic when an activation distance of 1000m is considered. For example, for a 90s traffic cycle and at 0.75 degree of saturation on a single lane road, an activation distance of 300m provides only 3% improvement in stops at 30% MPR while, in comparison, about 62% and 75% improvements are observed for activation distances of 500m and 1000m respectively under similar conditions. Additionally, it may be observed that, at low traffic demands, there are significantly higher number of stops made by non-connected vehicles in lieu of the CVs at a market penetration of 30% or below. This shows that, under such conditions, the CVs are unable to influence the traffic stream, as a whole. In the same line, although the environmental efficiency of CVs are improved at all levels of market penetration, a benefit in terms of environmental efficiency for the entire traffic stream is observed only when the MPR exceeds 30%, with a further improvement if the activation distance is around 1000m. For example, upto an MPR of 30%, the environmental benefits are in the range of 3-5% which goes up to 10% at 50% MPR and more than 15% in a fully connected environment. Similar observations were also made by Gajanan *et al.* [16] where they suggested a penetration rate of more than 40% is necessary to achieve a significant reduction in CO_2 emissions.

The unequipped vehicles are likely to contribute to high traffic oscillations at low MPR and in denser traffic conditions, causing more frequent speed change and higher emissions [31]. Additionally, while the general trend is similar for CO_2 and NO_x emissions, the improvement is higher for the latter. For example, while there is a reduction of up to 5% in CO_2 emissions at 30% market penetrations of CV, the same is more than 15% in terms of NO_x emissions. With reference to increasing activation distance, the improvement in emission gain with respect to NO_x emissions is also higher as compared to CO_2 .

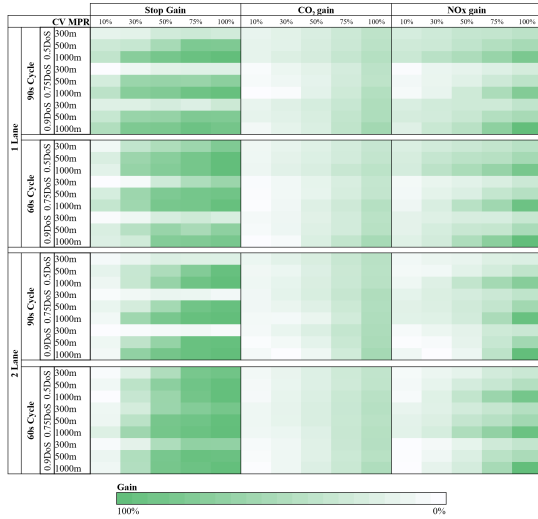


Fig. 8: Summary of Realistic Impacts of GLOSA on Traffic and Environment Performance

B. Impact of Cycle Length

Fig. 9 shows the evolution of the traffic and environmental performances with respect to two different traffic signal cycles of 90s and 60s. It clearly shows that the GLOSA speed advice can still be effective with an activation distance of 300m if there is a reduction in cycle length. This highlights the fact that where it is infeasible to provide a long activation distance, it may be necessary to consider reducing the cycle time to achieve some meaningful impact. Moreover, in terms of CO_2 emissions, while a more-or-less linear reduction is observed with respect to increasing MPR for 90s cycle time, there is a visible non-linear effect with 60s cycle lengths. This again shows that it is necessary to have a high market-penetration of connected vehicles in order to have a meaningful impact on emission reduction.

C. Impact of Road Geometry

Increase in the number of lanes indicates an opportunity for non-connected vehicles to overtake the connected vehicles when they comply to the GLOSA advice to reduce the speed. As a result, a reduced benefit is expected in traffic efficiency and the same can be observed in Fig. 10, especially at low degrees of saturation and low market penetration of CVs giving a higher opportunity for overtaking by the unequipped

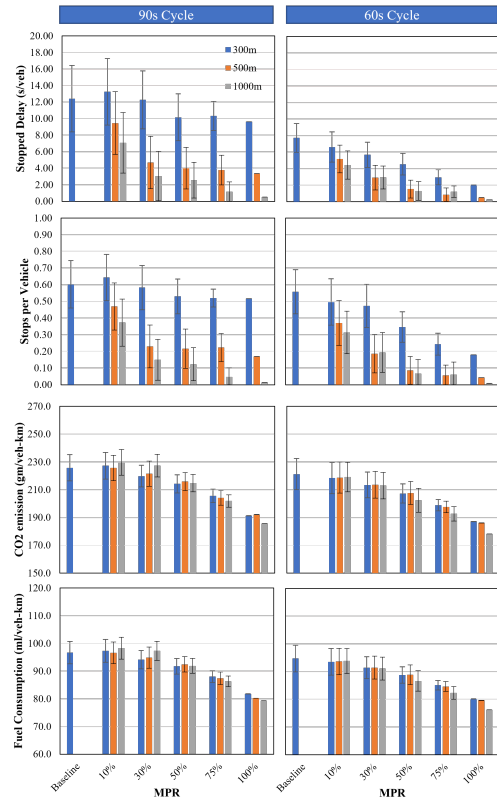


Fig. 9: Impact of Cycle Length on GLOSA Performance

vehicles. The impact becomes similar only at very high MPR and it also varies linearly for 2-lane roads without any visible inflection point as was observed for 1-lane. In terms of emissions also, there is a stronger reduction in the emissions with increase in MPR for single lane roads, although the average CO_2 emissions per vehicle-km travelled is lower for 2-lane roads (refer Fig. 8). Moreover, when there are more than one lane available, a shorter activation distance appears to be more effective as it provides lesser opportunity to overtake.

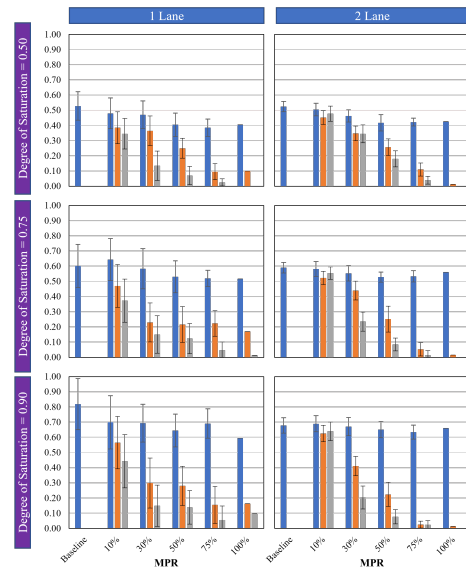


Fig. 10: Impact of Lane Availability on Number of Stops

V. CONCLUSIONS AND PERSPECTIVES

This paper is one of the first contributions to make some specific and meaningful observations related to the driver response behaviour of connected vehicles from the field operational tests of a C-ITS service, GLOSA. It was very interesting to bring out the variations in response rate, response time, deceleration and speed compliance behaviour. Significant impacts on driver response were observed with respect to several factors, the most important of which include the activation distance, the difference of the advised speed with the instantaneous speed of the driver and whether the driver was accelerating when the speed advice was displayed on the HMI.

The response rate was observed to generally decline and the response time was observed to increase with increase in activation distance. But at the same time, the speed compliance was improved and the drivers performed smoother deceleration with longer activation distances. This suggests that the activation distance should be neither too close to nor too far from the stop-line. On the other hand, the simulation results show that a short activation distance with long cycle length will significantly restrict the positive impacts of GLOSA service. Therefore, when short activation distances are maintained, the signal cycle lengths have to be adjusted accordingly to enhance the benefits in terms of traffic and environmental efficiencies.

If there is a high difference between the instantaneous and the advised speed, then there are less chances of drivers showing a response or adhering to the speed instructions by decelerating to the necessary speed. As a consequence, even if they show a response, they will be forced to come to a stop at the intersection. Therefore, the speed of the driver should be taken into account before offering a speed advice. In cases where the difference is too high (*e.g.*, higher than 20 kph), a speed advice should not be provided, rather the driver should only be provided an instruction to come to a gradual stop to avoid hard braking near the intersection. The drivers who are accelerating at the instant when the speed instruction was provided are more likely to show a response in terms of speed reduction, but the response time will be naturally higher in such cases. In a few cases, several other factors, such as time of the day, the number of lanes available in the direction of travel, etc. were also observed to have an effect on the driver response.

An interesting research direction will be to explore the refinement of GLOSA algorithm to provide an optimal speed advice by taking into account the driver response features and observe if it enhances the impacts on traffic flow performance.

The aggregated driver response features were incorporated in the simulation framework and is an important contribution to the existing scholarship to generate more realistic impacts for different scenarios. One of the most interesting aspects was to observe that with long traffic signal cycles, a short activation distance was more-or-less ineffective to bring out a substantial impact on the traffic efficiency. Therefore, where short activation distances cannot be avoided, it may be meaningful to reduce the cycle length to obtain more benefits from GLOSA service. Also in cases of multi-lane urban roads, a higher MPR

is necessary to achieve the same benefits as compared to the single-lane roads. In terms of environmental efficiency, high market penetration is necessary as well to achieve a significant emission reduction.

While some interesting observations have come out from the present work, it is still an open research question on how to more accurately predict a driver response to the speed instructions, and accordingly optimize GLOSA algorithm to achieve the maximum impact. Although, significant impacts were observed on the response behaviour with respect to several parameters, there were a lot of unexplained variations in the response variables which may be due to the individual behaviour of the driver, their socio-economic profiles, and real-time driving conditions. Therefore, in the future, with further sensorization of urban road spaces, there will be a scope to enrich the database with more relevant factors and improve the model performances.

Although the two database (C-The-Difference and CoopITS) display statistical similarity based on the aggregate response behaviour, further enrichment of the newer database may help to validate and refine the disaggregate models. Moreover, the simulation-based analysis in the present study takes into account only the aggregated response behaviour. Therefore, with improved empirical models, the disaggregate impacts of some individual parameters on the response behaviour can also be incorporated as a further refinement of the simulation analysis.

The present work has been focused on GLOSA or eco-driving use case for urban traffic environment with interrupted flow facilities. It will be interesting to apply a similar approach to observe and characterize the response behaviour from FOTs for other use-cases and traffic environments.

VI. ACKNOWLEDGMENTS

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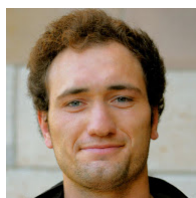
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