ARTICLE IN PRESS

JOURNAL OF TRAFFIC AND TRANSPORTATION ENGINEERING (ENGLISH EDITION) XXXX; XXX (XXX): XXX

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.keaipublishing.com/jtte

Original Research Paper

# Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions

*Giuseppina Pappalardo* [a,*], *Riccardo Caponetto* [b], *Rosario Varrica* [a], *Salvatore Cafiso* [a]

[a] *Department of Civil Engineering and Architecture, University of Catania, Catania 95125, Italy*

[b] *Department of Electrical, Electronic and Computer Engineering, University of Catania, Catania 95125, Italy*

HIGHLIGHTS

- Open on-road LSS test under various weather conditions such as dry, wet and rain.
- Generalized estimating equation to highlight correlation among observations.
- Average 3.9% fault probability of LSS with high variability in two-lane rural roads.
- Comparatively rain increases the fault probability by a factor of 2.75 than dry weather condition.
- Marking RLw and curvature 1/R are the most relevant road factors.

ARTICLE INFO

*Article history:*
Received 9 February 2021
Received in revised form
6 December 2021
Accepted 13 December 2021
Available online xxx

*Keywords:*
Lane support system
Physical infrastructure
Operational design domain
Weather condition

ABSTRACT

With the growing rate of automated vehicles (AVs) at the lower level of automation, the experimental tests are also in progress with vehicles at higher levels. In the absence of extended digital infrastructures and deployment of level 5 full automated vehicles, the physical infrastructure is required to maintain a fundamental role to enable their introduction in public roads. This paper focuses on lane support system (LSS) whose operational design domain (ODD) is strongly connected to the road characteristics and conditions. An experimental test was carried out with a state of the art, and LSS and advanced technologies were used for road monitoring on different roads under various environmental conditions including dry, wet pavements and rain. We applied the generalized estimation equation for logistic regression to account within-cluster homogeneity which is induced by repeated measures on the same road sections. Statistical models allow the identification of variables that are significant for the LSS fault probability among various effects of road features including marking, pavement distress, weather conditions, horizontal curvature, and cross section. Results pointed out the relevance of the wet retro-reflection of marking (RLw) and the horizontal curvature in the definition of ODD for LSS. Threshold values have been proposed for the tested LSS. Wet pavement doesn't affect the LSS performance when

* *Corresponding author*. Tel: +39 095 738 2215.
E-mail addresses: giusy.pap@dica.unict.it (G. Pappalardo), riccardo.caponetto@unict.it (R. Caponetto), varricaros@gmail.com (R. Varrica), dcafiso@unict.it (S. Cafiso).

Peer review under responsibility of Periodical Offices of Chang'an University.
https://doi.org/10.1016/j.jtte.2021.12.002

compared to the dry condition. Rain was shown to be critical even with very good road characteristics.



## 1. Introduction

According to the definition of the Society of Automotive Engineers (SAE International, 2018), there are 6 progressive stages of driving automaticity, from level 0 (L0, no automation) to level 5 (L5, full automation). At L1 and L2, the driver is in charge for the assisted driving task, and at higher levels (L3+) the automated vehicle (AV) can drive autonomously, but only at L5 the operational design domain (ODD) is assumed unlimited. The vehicle automation is expected to improve safety and mobility. Despite of the potential benefits, barriers to mass-market penetration remain, including the definition of the appropriate standards for liability and guidelines for autonomous vehicle certification (Fagnant and Kockelman, 2015). In 2022, the inclusion of advanced driving assistant systems (ADAS) at L1 and L2 will become mandatory for European vehicles to protect road users (European Commission, 2018). The lane support system (LSS) is one of the new compulsory safety ADAS for vehicles that will always be present in the new cars. Therefore, increasing share of vehicles in the traffic flow will be furnished with systems for the identification of lane markings (L1 and L2) and new standards for certification have already been proposed by the International Organization for Standardization (ISO) and by the European Standards Organization. In L2 ADAS, adaptive cruise control (ACC) in combination with LSS ensures vehicle positioning both on the roadway and in relation to other vehicles. For L2+ vehicles, a process belonging to the field of robotics is used for automated driving. In this process the "perception" and "localization" are stages of the dynamic driving task (DDT) whereas other processes like lane detection performed by LSS. LSS is used for centering the vehicle within the road lane. Therefore, for a safe operation, the ODD of LSS needs to be defined to ensure actual conditions monitoring and timely vehicle communication to control the availability of the automated DDT. For a certain AV system, ODD represents the set of driving conditions under which it is designed to work (SAE International, 2018). These driving conditions include weather conditions, road (and roadside) infrastructure components, and vehicle-related conditions such as speed and AV driving logics (Olstam et al., 2020).

In such type of framework, the ODD of LSS shows high interactions with the characteristics and conditions of the physical road infrastructure (Gruyer et al., 2017; NCHRP, 2020). Currently, roads are designed and maintained for drivers, only. Therefore, despite of the assumed technological readiness, considerable uncertainty still exists regarding the needs of LSS vision systems in to "read" the road, as highlighted by recent state of the art reports (ERTRAC, 2019; Marr et al., 2020). In this perspective, the paper describes the experimental set-up that was specifically designed and data collection with high accuracy equipment. The methodological statistical approach was selected to identify road characteristics and variable weather conditions that defines the ODD of LSS system with data collected in repeated runs. In the framework of the present state of the art, the paper contributes to identify the road infrastructure components of ODD considering other than marking quality also road geometry features and pavement conditions.

The paper is organized in the following sections.

- Overview of the technologies used in LSS to highlight the links between system features and road infrastructure.
- State of the art and gaps in the knowledge about operational design domain for LSS.
- Experimental design and data collection in selected road and environmental conditions using a mobile laboratory specifically equipped for the study.
- Statistical analysis of data and models to identify factors and inter-correlation among road and weather conditions.
- Results and discussion.
- Conclusions.

## 2. Technological frameworks

The sensory components of automated driving require an automated vehicle to collect and process multiple data before making decisions. Fully automated driving at L4, L5 requires a wide set of sensors consisting of camera, radar, laser imaging detection and ranging (LIDAR), Global Navigation Satellite System (GNSS) and connectivity equipment. To acquire the accuracy required for level 3+, AVs need a precision navigation system that can locate the vehicle accurately within a matter of centimeters. Sensor data (radar, LIDAR, GNSS and cameras) used for object identification, detection and interpretation of horizontal and vertical signs, can be associated with high definition maps (HD map) to allow for navigation. HD maps for self-driving vehicles are considerably more detailed than a conventional map requiring high computation power as it requires the continuous updating of the three-dimensional vision of the environment. Due to the high deployment costs of digital infrastructures, especially in the secondary rural road network, the availability of connectivity and HD maps will be delayed. In this framework, when the interpretation of the road infrastructure is not supported by connectivity (V2X) and digital infrastructures, the reading of road markings, signs and traffic signals is mainly done by means of camera-based artificial vision.

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

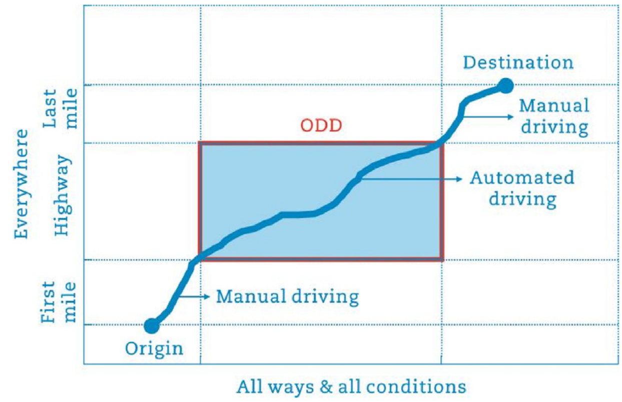



**Fig. 1 – Example of limited ODD and transition in the DDT (Alkim, 2017).**

Machine vision for AVs involves cameras and sensors that feed digital data to the signal processor, which runs complex AI algorithms to provide input for driving control (Gruyer et al., 2017). Mono and stereocameras (Cafiso et al., 2017), can provide an accurate assessment of speed and distance, as well as the detection of obstacles and moving objects. The LSS operation consists of several phases, such as image capture of markings, identification of image properties, lane detection and tracking (Chen et al., 2020). Each LSS uses its own proprietary AI algorithms for detecting lane markings. However, technologies are similar (Narote et al., 2018). Currently, camera systems use complementary metal oxide semiconductor (CMOS), image sensors having a resolution of up to two megapixels to adapt quickly to diverse light situations. No color-accurate signal is generally required, as only the direct raw data of the image sensor is used with color filter to provide a higher light intensity (e.g., signal-to-noise ratio (SNR) = 1 for 1 millilux (mlx)). For marking detection, the main issue in the digital image is the contrast between the pixels of the pavement marking and the road (NHTSA, 2017). The impact of road geometry to the algorithm's performance to detect road markings is related to the viewing geometry that defines distance to the target area and viewing angle with respect to horizontal positioning (Kluge and Lakshmanan, 1995).

Because of the common and well-established vision technology, selected road features have been identified to define the ODD of LSSs. Road marking characteristics, pavement and environmental conditions affect pixel intensity and contrast ratio, road geometry (horizontal and vertical alignment, cross section) define the field of view of camera for lane marking detection. As the design speed is of concern, the frame rate is set usually at high frequencies (e.g., 30–60 frame/s) to operate up to 180 km/h certified by OEMs in standard dry and daylight conditions (Mobileye, 2019).

## 3. LSS operational design domain

According to SAE, the operational design domain (ODD) is defined as the "operating conditions under which a given driving automation system or feature is specifically designed to function including, not limited to environmental, geographical, and time-of-day restrictions, and the requisite presence or absence of certain traffic roadway characteristics" (SAE International, 2018). The AV can perform safely only within its ODD (Olstam et al., 2020). It is worth mentioning that only for level 5 is the ODD assumed to be "unlimited" in SAE J3016. Therefore, for a given ADAS, the ODD and corresponding SAE level should be clearly defined by the manufacturer. In situations where the AV is outside of its ODD (Fig. 1), the vehicle should transit to a minimal risk condition (NHTSA, 2017). The transition needs to be clearly identified and timely recognized by the AV at L3 and L4 or communicated to the driver at L2 and L3 to avoid critical safety concerns during the fallback of the automatic driving task (De Winter et al., 2014; Vlakveld et al., 2015).

The international organizations have defined standard test conditions to certify the systems (Table 1).

Table 1 shows as the testing conditions are not representative of the real-world environment (e.g., light and weather) and road characteristics. Moreover, some factors are not defined (N.D.), have a qualitative definition (e.g., marking quality) or are set at only favorable values (e.g., lane width > 3.5 m, radius of curve (*R*) > 250 m) not always available in the secondary rural road network.

Austroads technical report AP-T347-19 (Austroads, 2019) provided a widespread literature evaluation complemented by consultations with industry stakeholders. Results confirmed that all referenced testing of vehicle capabilities for LSSs require that this testing occurs only in the most favorable conditions. Marking characteristics of luminosity ratio for day conditions and retro-reflectivity in night conditions appear the matter most investigated. Conclusions associated to LSSs emphasized that the results offered by in-field testing remain still limited.

Farah et al. (2018) provided a literature review on infrastructure for automated vehicles. It was found that there is a limited data about road infrastructure as compared to digital infrastructure. A research review promoted by EuroRAP and Euro NCAP (Lawson, 2018) identified and classified low/medium and high severity factors affecting the performance of LSS.

- High severity factors: road surface condition such as wet or icy, marking characteristics and maintenance conditions.
- Medium severity factors: road gradient, road curvature and boundaries between multiple lanes.
- Low severity factors: lane width (too narrow or too wide) and visibility (e.g., foggy conditions).

Austroads project documents the outcomes of a literature analysis and on-road and off-road evaluations of data focusing specifically on implications of pavement markings for machine vision (Marr et al., 2020). The main results were as follows.

- A minimum 3:1 contrast ratio between markings and the pavement surface is generally supported by machine-vision systems.
- Many of the design standards for markings meet or exceed machine-vision requirements.

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

**Table 1 – Standards for the test of the systems.**

| Road & environmental factor | ISO 17361:2017 (International Organization for Standardization, 2017) | European new car assessment program (European New Car Assessment Program, 2018) | EU standard (European Commission, 2012) |
|---|---|---|---|
| Road surface | Dry and flat surface of asphalt or concrete | Dry, flat and level paved surface, no irregularities including cracks or manhole covers within 3 m laterally or 30 m longitudinally of the test area | Flat, dry asphalt or concrete surface |
| Temperature | Between 10 °C and 30 °C | Between 5 °C and 40 °C | Between 0 °C and 45 °C |
| Visibility | Good horizontal visibility exceeding 1 km, daylight with illumination more than 2000 lx and no shadows | Good horizontal visibility exceeding 1 km and no precipitation | Visibility conditions that allow safe driving at the required test speed |
| Lane marking type | N.D. | Lane markings that continue at least 20 m beyond the testing vehicle. line width ranging from 100 to 250 mm | According to national standards in EU countries. Line width ranging from 100 to 300 mm |
| Lane marking quality | Good condition, according to the relevant national standard | RL > 150 mcd/lx/m$^2$, RLw > 35 mcd/lx/m$^2$ | Good condition and of a material conforming to the standard in the member states |
| Lane width | N.D. | Between 3.5 and 3.7 m | Greater than 3.5 m |
| Verge | N.D. | A verge from 0.2 to 0.3 m wide | N.D. |
| Speed | N.D. | N.D. | 65 km/h |
| Radius of curve | $R$ > 500 m for Class I; $R$ > 250 m for Class II | N.D. | $R$ > 250 m |

Note: N.D. indicates not defined; RL indicates marking retroreflectance in dry condition; RLw indicates marking retroreflectance in wet condition.

- Lane widths (either too narrow or too wide) may reduce machine vision's capability to detect lane markings.
- Daytime conditions generally make lane detection less effective than at night.
- Wet pavements have different impacts on LSS. With minimal ambient lighting (e.g., rural roads) the contrast ratio can be even improved due to reduced specular diffusion.

Project 20–102, task 6 road markings for machine vision (Pike, 2019), noted contents are shown as follows.

- Edge lines and lane lines show a similar performance.
- Roadway lighting minimally affects nighttime performance.
- Daytime conditions are in general more difficult than nighttime conditions, especially on a wet day because of the reflective glare.
- The effect of speed is minimal (up to 104 km/h).
- For daytime dry conditions, a luminance coefficient in diffuse lighting conditions (Qd) of more than 100 mcd/lx/m$^2$ seems to be suitable.
- A difference of > 25 mcd between markings and the pavement surface is required.

The European Union Road Federation (European Union Road Federation, 2018), suggests a minimum marking reflectance RL in dry conditions of 150 mcd/lx/m$^2$ and a minimum width of 150 mm for visible road markings. For wet and rainy conditions, the minimum level of performance of the marking in wet conditions (RLw) has been proposed at 35 mcd/lx/m$^2$.

Adverse weather conditions, such as fog or rain, are well documented scenarios that are problematic for vision-based detection systems (Chen et al., 2020; Gopalan et al., 2012).

To best of our knowledge, marking quality is the road factor that mainly attract the researchers and road agencies, instead a limited number of studies have considered the effects of road geometry (e.g., horizontal alignment, cross section). Nitsche et al. (2014) led a qualitative research based on literature review and stakeholders' consultation. The primary factors were identified in quality of lane markings, poor visibility due to bad weather, and irregular or damaged road edges or curbs. Low curve radius was of medium importance. Morsink et al. (2016) hypothesized that the radii of road curves could be reduced, due to the greater reliability of automated vehicles, but minimum thresholds were not defined.

Simulation studies focusing on detection algorithms showed that errors are prone to occur when the curve radius is narrow, and the lane width is high. An increase of LSS failure probability to 6% compared to 1.5% in ideal straight road alignment has been reported. The horizontal alignment was qualitatively classified as straight or curved sections (Deng and Wu, 2018).

A systematic review of current findings on lane marking was carried out by Babić et al. (2020), one of the conclusions was that curves are critical sections for LSS, but only tangents are still involved in the test procedure.

Reddy et al. (2020) in a field test, found that the highest lane-keeping performance was observed on tangents and the least on left curves. No quantitative values of curve radii were reported. Few in field experimental studies have

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

(a) (b)

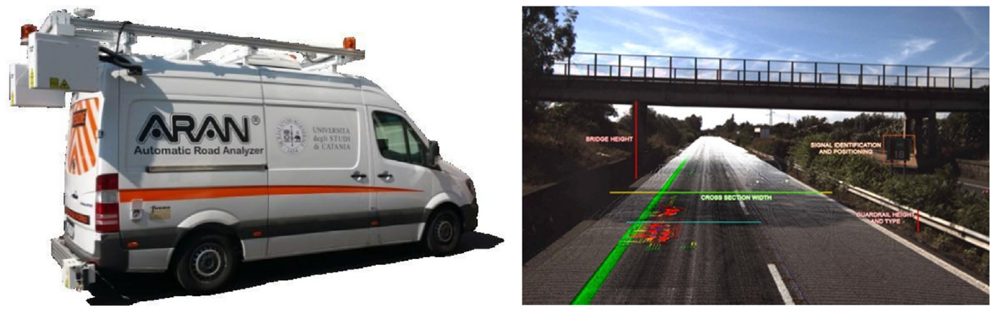



**Fig. 2 – Data can be surveyed with ARAN from different sensors installed on board. (a) ARAN 9000. (b) Data from ARAN 9000.**

analyzed quantitative effect of the horizontal alignment on the LSS performance in detail. García et al. (2020) identified a correlation between system disengagement with speed and curve radius during test carried out in dry and day conditions. In the same environmental conditions, Cafiso et al. reported that curvature radius and marking coefficient Qd are the most relevant road factors in explain the LSS fault probability (Cafiso and Pappalardo, 2020), thresholds of Qd > 150 mcd/m$^2$/lx and R > 140 m have been identified for the day and dry testing conditions (Pappalardo et al., 2021).

Recently, the Automated Vehicle Safety Consortium (AVSC, 2020) has proposed a best practice for defining the ODD. The testing parameters that are appropriate to this study, such as lane width, verge width, climate conditions and horizontal alignment, are specified.

This background clarifies that, even if road factors affecting the ODD of LSS have been identified, the main research focus is on marking characteristics. Therefore, some questions are still open concerning the relevance of road geometry features and the combined effects of different road characteristics and conditions which define the LSS real world operation.

More specifically, the paper contributes to identify the road infrastructure components of ODD for LSSs by considering other than marking quality (reflectivity parameters). This research also highlights road geometry (cross-section and horizontal alignment) and pavement conditions (dry, wet, cracking) with experimental data and a modeling approach which is able to handle the combined set of conditions.

## 4. Experimental data collection

### 4.1. *Experimental study design*

Experimental studies in open roads allow ADAS to be exposed to a wide variety of conditions that would not be fully feasible in closed-loop testing and are difficult to model in simulation. However, open-road as compared to closed-track testing might have some disadvantages related to the control over the ODD conditions, the difficulty of replication in different locations and repeatability in iterate tests (Thorn et al., 2018). Furthermore, the issues of safety and legal responsibility must be settled.

To address the controllability, replicability, and repeatability issues, in the experimental setup we applied a longitudinal approach, using repeated runs in designated sections of two-lane rural roads with traffic volume and physical settings that were correctly monitored by the mobile laboratory during the test. As detailed below, uncontrolled events have been identified and data cleaned from the sample. Moreover, to solve safety and legal constraints, during the test the LSS system was in operation but without control or feedback to the driver. The instrumentation required for the in-field experiment and the data collection and coding are defined below.

### 4.2. *Instrumentation*

To gather the information needed for LSS and ODD performance evaluation, a variety of equipment was employed. The Automatic Road Analyzer (ARAN) is one of the most advanced mobile laboratories for road asset survey (Cafiso et al., 2019b). ARAN 9000 (Fig. 2) is able to collect data and accurately evaluate the geometric characteristics of the road and the inventory of road asset (e.g., typology and geometric features of marking, sign, barriers, access). Using the laser cracking measurement system (LCMS), it is possible to automatically detect and classify the distresses on the pavement surface (Cafiso et al., 2019a). For the objectives of the research, we considered only linear extension of longitudinal cracks with medium/high severity width greater than 10 mm (ASTM, 2011).

Pavement marking quality has been gauged with the support of a portable retroreflectometer (Fig. 3). Pavement marking were classified according to the EU standard for "road marking materials - road marking performance for road users and test method" (British Standards Institution, 1998), which states the next parameters.

- Luminance coefficient in diffuse lighting conditions (Qd): measure of visibility of the road markings as perceived by drivers of motor vehicles in conditions of diffuse lighting (daylight or artificial light) at a distance of 30 m.
- Marking reflectance RL in dry conditions: measure of visibility of road markings in dry conditions, as perceived by drivers, at night at 30 m with the aid of artificial lighting provided by the headlamps of their vehicles.

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

**Fig. 3 – Survey of the marking retroreflectance in dry (RL, Qd) and wet conditions (RLw).**

- Marking RLw: measure of visibility of road markings acquired in the same testing condition as for RL while 1 min after the surface is flooded with water (wet pavement).

The ARAN was coupled with a Mobileye 6.0 system (Fig. 4), which uses a digital camera and AI algorithms for providing driving assistance in lane keeping, forward and pedestrian warnings (Mobileye, 2019).

LSS output from Mobileye has been collected at high frequency (60 frames per second, fps) and synchronized with ARAN and road data via the standard CAN protocol by building an Arduino platform and software codes. More specifically, depending on the actual lane marking detection, two conditions are available and used in the study, marking detected (coded as LSS = 0) or marking not detected (coded as LSS = 1).

### 4.3. *Data collection and coding*

The experiment was carried out in two-lane rural roads in daylight under various weather conditions (dry, wet and rain) (Fig. 5). Wet pavement conditions refer to the presence of a thin film of water with light or no rain (equivalent to the RLw testing conditions). Two-lane rural road was selected because it offers more constrained conditions than primary rural roads both in terms of road characteristics (e.g., minimum curve radius, lane and shoulder widths) and maintenance (e.g., marking and pavement distress). In urban environment LSS performance is less reliable because of the complex traffic and infrastructure conditions and less effective due to the lower running speeds. That is the reason because, usually LSS is automatically switched off at speed lower than 40–60 km/h.

The road stretches for a total extension of about 30 km have been selected to cover a wide range of values of the road characteristics to be included in the analysis.

All data were associated with homogeneous sections of variable length between 20 and 50 m, having a constant value for each variable considered in the experiment. To record reliable LSS exits and fault conditions with potential hazard to the driver assistance, the minimum and maximum section lengths with a travel time between 1 and 6 s have been identified. As the Mobileye data are concerned, the positive lane detection (i.e., LSS = 0) and the negative condition of failure in the detection (i.e., LSS = 1) have been associated to each sample section in different conditions of dry and wet pavement or rain. Other factors, out of the experiment set up (e.g., parked vehicles, edge pavement drop off), which can create artefacts have been detected reviewing the video recording of an auxiliary front camera (Fig. 6) and removed from the database. Only data collected without closing forward vehicles have been included in the dataset. The time gap of the vehicle in front (if present) is detected by the forward warning of Mobileye (Fig. 4). A minimum gap of 1.0 s was set as threshold to guarantee a suitable field of view for mark detection by LSS. The LSS data used in the study refer mainly to free flow conditions with a running speed in the range 50–71 km/h limited only by the road geometry and posted speeds.

After the data cleaning the dataset was composed by 1608 samples, collected in 667 road sections with an overall length of 26.2 km without repetition of measures in the same environmental conditions (dry, wet, rain). The road sample is composed by 334 curved units with radius ranging between 73 and 880 m. Summary statistics of the variables in the database are described in Tables 2 and 3, and the frequency distributions showed in Fig. 7. Sample size and data variability may be considered representative of two-lane rural roads. Table 4 displays the Pearson product moment correlations of each pair of continuous variables. All the explanatory variables are not correlated except for Qd with RL, that show only a moderate correlation (0.339). Therefore, they were all included in the statistical modeling.

## 5. Regression modelling

The purpose of study was to evaluate the operational failure mechanism for LSS under complex real-world conditions of road and weather factors. With the objective of relating the probability of system fault described by a dichotomous variable (i.e., LSS = 0, 1) to one or more covariates, the logistic regression is a suitable statistical model. Tests were conducted with multiple runs on the same sections of two-lane rural roads in diverse weather conditions, i.e., dry, wet, and rain. Repeated observations can be interdependent, as nested tests in the same road section are likely to function similarly than tests in different sections. Therefore, the testing experiment efficient for estimating the system performance, posed conditions for model-based statistical inference. More specifically in an ordinary logistic regression model the responses for each observation are considered independent of each other while this assumption is violated in multilevel longitudinal studies (Laird and Ware, 1982).

Adopting a logit model fitted with generalized estimation equations (GEE) to estimate the regression parameters, allows to overcome the absence of a closed-form joint likelihood function as in the standard logistic models (Liang and Zeger, 1986).

A GEE is a method based on quasi-likelihood estimation for longitudinal marginal models that allows a valid interpretation of the regression coefficients ($\beta$) in Eq. (2) and standard

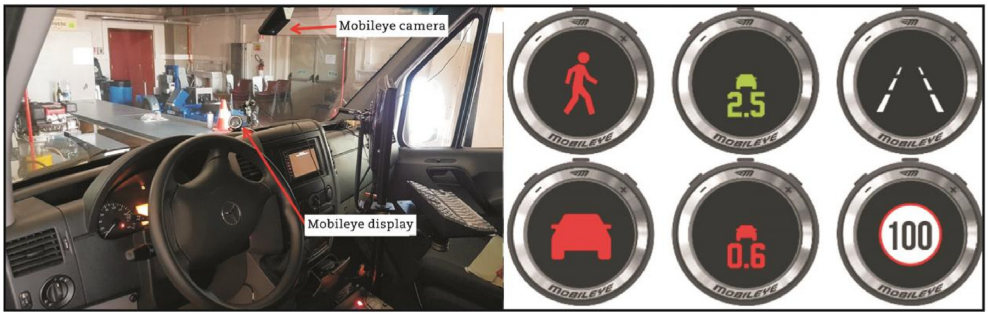



**Fig. 4 – Mobileye 6-Series.**

errors of the estimates, by implicitly considering the correlation (Liang and Zeger, 1986).

The LSS response is a binary dependent variable $Y_{it}$, which takes the value of either 0 or 1 in the section $i$ at test $t$ ($t = 1, 2, 3$) and the GEE logit assumes the similar model as the standard logistic regression.

$$Y_{it} \sim \text{Bernoulli}\ (y_{it}|\pi_{it}) = \pi_{it}^{y_{it}}(1-\pi_{it})^{1-y_{it}} \tag{1}$$

The systematic component $\pi_{it}$ is given by

$$\pi_{it} = \frac{1}{1+\exp(-(\beta_0+\beta_k x_{k(it)}))} \tag{2}$$

where $x_{k(it)}$ is the vector of $k$ explanatory variables for section $i$ at test $t$ and $\beta_0$, $\beta_k$ is the vector of coefficients to be estimated. $\pi_{it}$ is interpreted as the probability of the dependent variable Y equaling a success rather than a failure.

GEE models need three conditions, the mean function $\pi_{it}$ and the variance function given by the variance of the Bernoulli stochastic component, like in standard logistic. Moreover, the correlations within each section $i$ in the repeated measures $t$ are displayed by defining the structure of a $3 \times 3$ "working" correlation matrix. Note that the model assumes correlations within section "i" but independence across sections. Even if the correlation structure is incorrectly specified, GEE models provide consistent estimates of the parameters and consistent estimates of the standard errors may be found via a robust estimator (Liang and Zeger, 1986). More specifically, GEE for logistic regression was applied in SPSS (SPSS 25.0.0) for a two-level random model, where the first (lower) level defined by the test repetitions ($t = 1, 2, 3$) in the different weather conditions (dry/wet/rain) and the second (higher) level represented by the inspection units ($i = 1, 2, \cdots, 667$), each of which was characterized by site specific road factors (curvature, marking coefficients Qd, RL, RLw, verge width, pavement cracking). Correlation matrix was defined as "independent" and we applied the Huber/White/sandwich robust estimator which can provide a consistent estimate of the covariance (Bressoux, 2010), if the number of units is relatively large and the number of repeated tests is relatively small, as in the present study.

## 6. Results

The total sample consisted of 1608 tests, clustered in 667 units, characterized by 6 factors at L2 (Qd, RL, RLw, $1/R$, long crack, verge width) and by 3 repeated measures in different weather conditions at L1 (dry, wet, rain). We fit three multilevel logistic regression model forms. The first one was the null model (model 1) which contained no environmental or section characteristics i.e., an intercept-only model. In such a way, it incorporated only section-specific random effects to model between-section variation in system faults. The simple model 1 with no predictors is useful to estimate the fault probability in the overall test runs and the goodness of fit, estimated by the quasi-likelihood under independence model criterion (QICC) that can be used for comparison with the other models with more explanatory variables. The second model (model 2) included only the weather test factors, to estimate their effects when sharing the identical section average conditions. The third model (model 3) included both weather factors and road section characteristics significant at 95th level of confidence.


**Fig. 5 – Various weather conditions during the experiment. (a) Dry condition. (b) Wet condition. (c) Rain condition.**

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

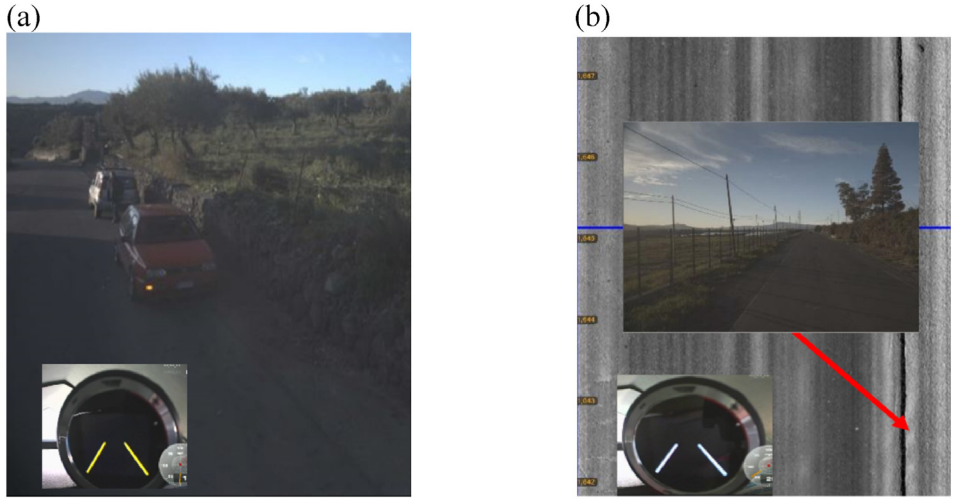


**Fig. 6 – Data cleaning Mobileye screen. (a) Missing marking detection due to parked vehicles (false positive). (b) Road edge detected as marking (false negative).**

The results of the GEE for two-level logistic regression of the intercept-only model 1 are shown in Table 5.

The multivariate logistic model 2 (Table 6) and model 3 (Table 7) were then developed with the significant factors to assess their simultaneous effect on the dependent variable.

The Wald $\chi^2$ test was used to fix the significance of individual $\beta$ coefficients, and a backward selection method, with a significance level of 5%, was applied in model 3 to select only significant variables (Blanchet et al., 2008). In model 2, which consists of only weather-related testing conditions (Table 6), the overall significance of the explanatory variable was associated with the odds of a fault in the system at 10% significance level (P-value = 0.101). In the model 3, which included both test and section characteristics, 3 of the 6 road factors (i.e., longitudinal crack, Qd and verge width) showed a P-value higher than 0.05 and therefore were removed in the backward selection, whereas the weather condition remained significant (Table 7).

For model 3, the last column in Table 7 also shows the standardized coefficient and odds ratio. Since the variables are measured in different units, these continuous variables have been standardized to compare the relative influence of different predictors. Unlike ordinary regression, for which there is a unique definition for the standardized coefficient, in logistic regression it is not possible to define a standardized coefficient. However, there is a small difference in meaning if we are interested only in the ranking order of the magnitude of the influence of the predictors on the dependent variable (Menard, 2004). The procedure suggested by Menard is to standardize both the predictors and the dependent variable resulting in the standardized coefficient $\beta^*_k$:

$$\beta^*_k = \beta_k S_{k(x)} \Big/ \left(\pi/\sqrt{3}\right) \tag{3}$$

where $\beta_k$ is the unstandardized logistic regression coefficient of the predictor $x$ (Eq. (3)), $S_{k(x)}$ is the sample standard deviation of the predictor $k(x)$, $\pi/\sqrt{3}$ is the standard deviation of the standard logistic distribution.

The usual goodness of fit statistics based on the log-likelihood estimation, cannot be computed in GEEs. Therefore, the corrected QICC was used to compare different sets of model terms. The criterion states that the lower the QICC value the better the model. The goodness of fit results for all the models are reported in Table 8.

The highest value of QICC in the intercept-only model 1 in Table 8, shows that the addition of the predictor variables significantly reduces the deviance as compared to a model containing only a constant term and they are thus useful for predicting the probability of the studied outcome. Only weather factors at L1 in model 2 have not improved the goodness of fit that is significantly better in model 3 when road factors are considered to explain the LSS fault probability.

**Table 2 – Summary statistics: continuous variables.**

| Variable | Number of samples | Minimum | Maximum | Mean | Standard deviation |
|---|---|---|---|---|---|
| 1/R ($m^{-1}$) | 1608 | 0 | 0.01364 | 0.002374 | 0.0029232 |
| RL ($mcd/m^2/lx$) | 1608 | 30 | 429 | 216.54 | 73.888 |
| RLw ($mcd/m^2/lx$) | 1608 | 0 | 118 | 88.29 | 21.218 |
| Qd ($mcd/m^2/lx$) | 1608 | 30 | 223 | 178.01 | 31.249 |
| Longitudinal crack (m) | 1608 | 0 | 37.972 | 0.391542 | 2.72337 |

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

**Table 3 – Summary statistics: categorical variables.**

| Variable | Category | | |
|---|---|---|---|
| LWD | ON = 1 | OFF = 0 | |
| Frequency (%) | 97.1 | 2.9 | |
| Verge width (cm) | <20 | 20–30 | >30 |
| Frequency (%) | 37.3 | 31.4 | 30.8 |
| Weather | Dry | Wet | Rain |
| Frequency (%) | 39.4 | 28.2 | 32.5 |

## 7. Discussion

Coefficients and confidence intervals estimated in the three models can be further analyzed to gain information about the LSS fault probability.

The coefficients in Tables 6 and 7 are more prone to estimate the relevance of the explanatory variables rather than specific threshold values. Moreover, it is important to note that in multilevel logistic regression the interpretation of the coefficients and odds ratios for the individual variables is conditional on both the within and inter-cluster covariates (Liang and Zeger, 1986).

### 7.1. Model 1

In model 1 with only intercept, we can better estimate the average and confidence interval of the LSS fault probability in the overall test runs. In the null the estimated intercept was −3.503, whereas the estimated standard error was 0.1488. Thus, on average the system fault probability was

$$\exp(-3.503) / (1+\exp(-3.503)) = 2.9\% \tag{4}$$

The 95% probability interval for the LSS fault would lies in the interval 2.2%–3.9%.

### 7.2. Model 2

In model 2 with only L1 variable, the weather reference condition was set to "dry". The significant criterion for the weather-related variable was satisfied only at a 10% confidence level, especially for the low significance of the wet conditions ($P$-value = 0.861) in explain a change in LSS fault probability from the dry pavement condition. The odds ratio of the estimated rain coefficient shows an average increase of 1.81 in the probability of LSS fault when compared to the dry condition at 8% level of confidence.

It is noteworthy that the overall $P$-value = 0.101 of the weather coefficient estimates was acceptable, but higher than the most robust acceptance level of 0.05. This means that the effects of inter-cluster variations of the road characteristics can be expected relevant like the within-cluster weather factor. Therefore, the role played by the weather condition needs to be investigated in more detail by using the model 3, whereas the inter-cluster level of road factors is also considered.

### 7.3. Model 3

The results in Table 7 show that curvature $1/R$ and marking parameters RL and RLw significantly affect the probability of the system fault. No significant effects are caused by the

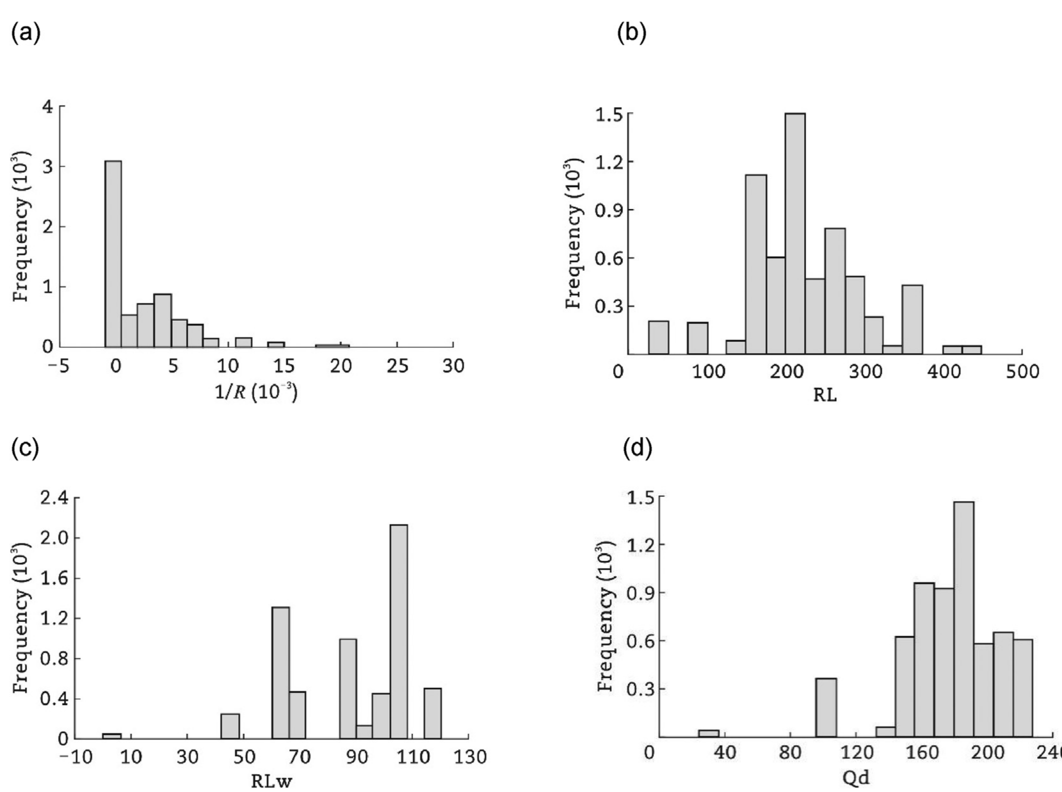



**Fig. 7 – Frequency distribution of continuous variables. (a) 1/R. (b) RL. (c) RLw. (d) Qd.**

**Table 4 – Correlation matrix: explanatory variables.**

| Variable | RL | RLw | Qd | Longitudinal |
|---|---|---|---|---|
| 1/R | 0.0635 | 0.0391 | 0.0343 | −0.0829 |
| RL | 1.0000 | −0.0663 | 0.3390 | −0.0584 |
| RLw | | 1.0000 | 0.2650 | −0.0634 |
| Qd | | | 1.0000 | −0.0657 |
| Longitudinal crack | | | | 1.0000 |

luminance coefficient Qd, the extension of longitudinal crack and the verge width, given that the P-values of all these covariates were identified greater than 0.05 and the variable excluded during the backward procedure. Weather variable is also significant at 5% level of confidence.

In model 3, for each variable included in the models the odds ratio of the standardized coefficients, reported in Table 7, represents the percentage increase in the odds of an outcome for an increase of one standard deviation in the variable $x_i$. A one standard deviation change is a reasonably substantial change typically encompassing approximately 10% of the total range of the independent variable. Indeed, for the categorical variable, the odds ratio represents the percentage increase with respect to the reference condition in the model (i.e., dry).

A comparison of the value of the odds ratio among the variables shows that curvature 1/R and rain may give the highest increase in fault probability with values of 1.26 and 2.75, respectively. Effects statistically significant are also associated to RLw (odds ratio = 0.65, P-value = 0) and RL (odds ratio = 0.81, P-value = 0.004), but not to the wet condition when compared to the dry ones (P-value = 0.623).

In logit models, for analyzing the relevance of covariates (numerical and categorical) with a different range of variation, even standardized odds ratios are difficult to compare. A method suggested in the literature recommends analyzing the increase in goodness-of-fit (g.o.f.) when each variable is added to a model that already contains all the other variables (Gromping, 2006). We applied a procedure similar to the computation of the McFadden's pseudo-$R^2$ (McFadden, 1972) to estimate the proportion reduction in the g.o.f. allocated by each variable when excluded from the model by using QICC as g.o.f. measure.

$$\text{Pseudo-}R_k^2 = 1 - \text{QICC}_k/\text{QICC}_0 \tag{5}$$

where $\text{QICC}_0$ is the g.o.f. of a model with no predictors, $\text{QICC}_k$ is the g.o.f. for the model being estimated without the covariate $k$.

**Table 5 – Intercept-only model parameter estimates.**

| Parameter | $\beta_0$ | Standard error | 95% Wald confidence interval | | Hypothesis test | | |
|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | Wald Chi-square | df | P-value |
| Intercept | −3.503 | 0.1488 | −3.795 | −3.211 | 553.867 | 1 | 0 |

**Table 6 – Multilevel logistic Model 2 parameter estimates.**

| Parameter | $\beta$ | Standard error | 95% Wald confidence interval | | Odds ratio | Hypothesis test | | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | | Wald Chi-square | df | P-value |
| Intercept | −3.718 | 0.2613 | −4.231 | −3.206 | | 202.487 | 1 | 0.000 |
| D/W/R | | | | | | 4.577 | 2 | 0.101 |
| D/W/R = wet | −0.073 | 0.4150 | −0.886 | 0.741 | 0.93 | 0.031 | 1 | 0.861 |
| D/W/R = rain | 0.595 | 0.3419 | −0.075 | 1.265 | 1.81 | 3.028 | 1 | 0.082 |
| D/W/R = dry | 0[a] | | | | | | | |

Note: [a] means this value sets to zero because this parameter is redundant; D/W/R means dry/wet/rain.

**Table 7 – Multilevel logistic full model 3 parameter estimates.**

| Parameter | $\beta$ | Standard error | 95% Wald confidence interval | | Hypothesis test | | | Standardized $\beta$* (odds ratio) |
|---|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | Wald Chi-square | df | P-value | |
| Intercept | −0.518 | 0.6256 | −1.744 | 0.708 | 0.685 | 1 | 0.408 | |
| D/W/R | | | | | 10.448 | 2 | 0.005 | |
| D/W/R = wet | 0.184 | 0.3748 | −0.550 | 0.919 | 0.241 | 1 | 0.623 | (1.2) |
| D/W/R = rain | 1.013 | 0.3200 | 0.386 | 1.640 | 10.016 | 1 | 0.002 | (2.75) |
| D/W/R = dry | 0[a] | | | | | | | |
| 1/R | 143.479 | 47.696 | 49.996 | 236.963 | 9.049 | 1 | 0.003 | 0.23 (1.26) |
| RL | −0.005 | 0.0016 | −0.008 | −0.002 | 8.438 | 1 | 0.004 | −0.21 (0.81) |
| RLw | −0.036 | 0.0070 | −0.050 | −0.022 | 26.396 | 1 | 0.000 | −0.42 (0.65) |
| Scale | 1 | | | | | | | |

Note: [a] means this value sets to zero because this parameter is redundant; D/W/R means dry/wet/rain.

**Table 8 – QICC goodness of fit.**

| Model | Model 1 only intercept | Model 2 L1 | Model 3 L1 & L2 |
|---|---|---|---|
| QICC | 426.677 | 426.349 | 384.864 |

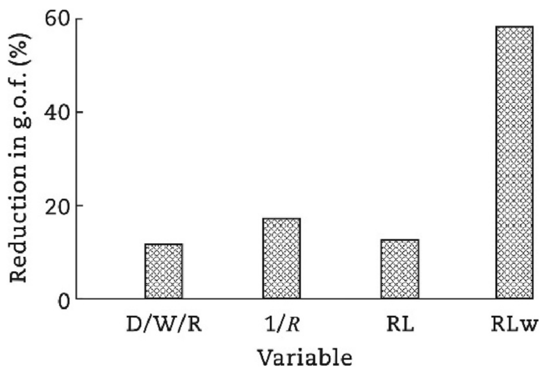



**Fig. 8 – Relative importance of covariates in model 3.**

The graphical output in Fig. 8 shows the incremental impact of each variable in model 3. Marking RLw is the most important variable in explaining the variability of the LSS fault probability.

Curvature 1/*R* plays a more limited role in the g.o.f. of the model, but as represented by the value of the odds ratio previously discussed, it can cause the largest increase in the fault probability, as well.

Therefore, the variability of fault probability with curve radius for different values of marking quality and weather conditions was further analyzed by drawn $\pi_{it}$ (Eq. (2)) versus 1/*R* for different values of the other covariates in model 3. Results are showed in Fig. 9 and threshold values of 10% and 5% are drawn as reference for medium and high-risk thresholds of LSS performance (Reddy et al., 2020).

It is evident that a value of RLw = 35 and RL = 150, for marking quality, as suggested by European Commission (2012) and Euro NCAP (European New Car Assessment Program, 2018) is adequate to guarantee a fault probability less than 10% in dry and wet conditions only in straight alignment. Minimum values of RLw = 50 (RW3-EN 1436) and RL = 150 (R3-EN 1436) can provide an acceptable risk of fault in wet and dry pavement and for curve radius higher than 200 m. In road curves with $R < 150$ m the LSS is not able to provide acceptable detection also with very good pavement marking. Rain conditions remain challenging for LSS requiring very high marking standards (eg., RL = 150 and RLw = 75) while always limited by the curvature radius.

## 8. Conclusions

Lack of digital infrastructure's extended availability and the deployment of AVs at L5, the ODD need to be remained limited for AVs. The characteristics and conditions of physical road infrastructure will play a fundamental role in enabling their safe introduction.

The results of the present study complement existing knowledge that is focusing on pavement marking characteristics in the definition of ODD for LSSs. Results offer the added value of a real-world experiments where different factors can occur simultaneously. The testing procedure on 26.2 km of two-lane rural roads with repeated measures was an efficient way for collecting data to analyze LSS performance in different road characteristics and environmental conditions. Still, some posed issues on the applicability of the conventional statistical inference, because repeated observations are interdependent. Therefore, we applied the GEE multilevel logistic models to increase the precision of the estimates and to better handle within-cluster and inter-cluster correlations.

Statistical models allowed the identification of the statistically significant road and environmental factors affecting the fault probability of the LSS tested in the experiment. However, the importance of the identified factors for the ODD can be generalized to other systems due to the similarities in the technology of LSS based on computer vision.

With reference to the tested system, the mean fault probability was estimated at 3.9% with 95% level of

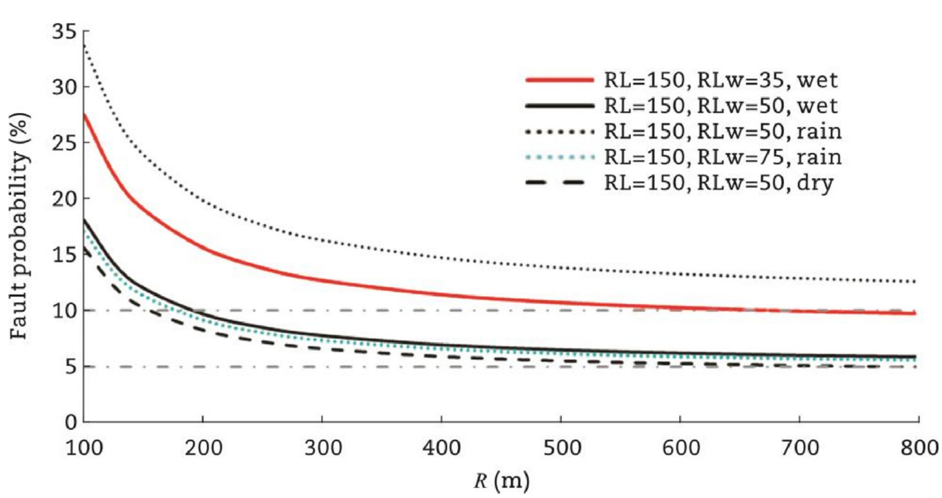



**Fig. 9 – LSS fault probability.**

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002

confidence, under average road section characteristics and weather conditions during the test, showing high performance of LSS. Results also highlights good performance in two-lane rural roads that are more challenging than motorway and primary roads for their geometric and maintenance characteristics. When only the weather conditions were considered, model 2 presented a lower statistical significance at 90% for the coefficient estimates, showing that only the rain condition can explain a variation in the LSS fault probability and that the inter-cluster variations in road characteristics can be meaningful as well. Therefore, as final step in the analysis, all the available co-variables have been considered in the model 3. The results showed that RLw, *R* and rain are the most significant and contributing factors in the LSS fault probability. LSS performance in wet pavement was not significant different from that in dry conditions, confirming the contrast ratio is not affected by the presence of a thin film of water.

Noteworthy are some results that should be emphasized in the perspective of preparing roads for AVs. The horizontal curvature needs increased consideration, because sharp curves are sites where the support of LSS for keeping the lane is more important and recurrent in the secondary roads and specific sites, such as intersections, interchanges, and roadwork areas. That the quality of marking is a basic requirement was confirmed. The control parameters and reference conditions can be like those usually considered in the present standards for human vision to guarantee a suitable contrast ratio with the pavement surface, but LSS based marking detection and tracking is more sensible to artefacts (e.g., bad maintenance, dirt, glare, traffic congestions, parked vehicles, pavement edges, and etc.).

For a safe and wide introduction of AVs in public roads the ODD must be clearly defined with a shared responsibility between public sector and OEMs. Road agencies can be called to maintain at good standards the infrastructure conditions while further technological development of LSSs is needed to extend the ODD to cope with the geometric feature and maintenance conditions of the existing roads. The factors limiting the ODD for LSSs must include rain. Good pavement surface maintenance can avoid ponding to limit the risk of thin water films, but also with medium rain intensity, like in the experiment conditions, the issue is difficult to handle. Therefore, monitoring of rain intensity and communication coverage at a very small geographical scale (e.g., 2 km) is required to identify and communicate in advance about the occurrence of critical weather conditions to AVs (including fog and snow). The research revealed the relevance of the combined effect of several factors (e.g., curvature and marking vs. weather) and the opportunity of including real-world conditions in the testing and certification of the system.

## Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

## Acknowledgments

The authors acknowledge the support of Mr. Alessandro Finicelli of AutoBynet in coding the data from the Mobileye system. This work has been partially financed by "Astro Database" Project of the University of Catania.

## List of acronyms

| | |
|---|---|
| ADAS | Automated driving assistance system |
| AI | Artificial intelligence |
| ARAN | Automatic road analyzer |
| AV | Automated vehicle |
| CAV | Connected and automated vehicles |
| CI | Confidence interval |
| CMOS | Complementary metal oxide semiconductor |
| DDT | Dynamic driving task |
| GEE | Generalized estimating equation |
| GNSS | Global Navigation Satellite System |
| LIDAR | Light detection and ranging |
| LCMS | Laser cracking measurement system |
| LSS | Lane support system |
| ODD | Operational design domain |
| OEM | Original equipment manufacturer |
| QICC | Quasi-likelihood under independence model criterion |
| V2X | Vehicle-to-everything |

## REFERENCES

Alkim, T., 2017. Connected and automated driving in The Netherlands—Challenge, experience and declaration. Road Vehicle Automation 4, 25–31.

ASTM, 2011. Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys. D6433–11. ASTM International, West Conshohocken.

Austroads, 2019. Infrastructure Changes to Support Automated Vehicles on Rural and Metropolitan Highways and Freeways: Audit Specification (Module 1). Available at: https://austroads.com.au/publications/connected-and-automated-vehicles/ap-r606-19 (Accessed 15 September 2021).

Automated Vehicle Safety Consortium (AVSC), 2020. AVSC Best Practice for Describing an Operational Design Domain: Conceptual Framework and Lexicon. Standard AVSC00002202004. Available at: https://avsc.sae-itc.org/principles-02-5471WV-44074RU.html?respondentID=25427355#our-work (Accessed 15 September 2021).

Babić, D., Fiolic, M., Babić, D., et al., 2020. Road markings and their impact on driver behaviour and road safety: a systematic review of current findings. Journal of Advanced Transportation 2020 (1), 1–19.

Blanchet, F.G., Legendre, P., Borcard, D., 2008. Forward selection of explanatory variables. Ecology 89 (9), 2623–2632.

Bressoux, P., 2010. Modélisation statistique appliquée aux sciences sociales. Population 64 (1), 244–247.

British Standards Institution (BSI), 1998. Road Marking Materials-Road Marking Performance for Road Users and Test Methods. BS EN 1436:1998. BSI, London.

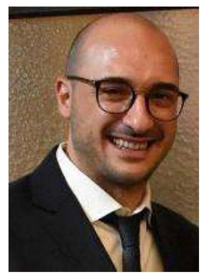
Cafiso, S., Di Graziano, A., Goulias, D.G., et al., 2019a. Distress and profile data analysis for condition assessment in pavement

management systems. International Journal of Pavement Research and Technology 12 (5), 527–536.
Cafiso, S., Di Graziano, A., Pappalardo, G., 2017. In-vehicle stereo vision system for identification of traffic conflicts between bus and pedestrian. Journal of Traffic and Transportation Engineering (English Edition 4 (1), 3–13.
Cafiso, S., Di Graziano, A., Pappalardo, G., 2019b. A collaborative system to manage information sources improving transport infrastructure data knowledge. Journal of Engineering and Technological Sciences 51 (6), 855–868.
Cafiso, S., Pappalardo, G., 2020. Safety effectiveness and performance of lane support systems for driving assistance and automation experimental test and logistic regression for rare events. Accident Analysis and Prevention 148, 105791.
Chen, W., Wang, W., Wang, K., et al., 2020. Lane departure warning systems and lane line detection methods based on image processing and semantic segmentation: a review. Journal of Traffic and Transportation Engineering (English Edition) 7 (6), 748–774.
Deng, G., Wu, Y., 2018. Double lane line edge detection method based on constraint conditions hough transform. In: 17th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), Wuxi, 2018.
De Winter, J.C.F., Happe, R., Martens, M.H., et al., 2014. Effects of adaptive cruise control and highly automated driving on workload and situation awareness: a review of the empirical evidence. Transportation Research Part F: Traffic Psychology and Behaviour 27 (part B), 196–217.
European Commission, 2012. Regulation (EC) No 661/2009 of the European Parliament and of the Council as Regards Type-Approval Requirements for the Installation of Lane Departure Warning Systems in Motor Vehicles. Available at: https://op.europa.eu/en/publication-detail/-/publication/59c0adba-4994-4e24-87a9-3601d888d9f3 (Accessed 15 September 2021).
European Road Transport Research Advisory Council (ERTRAC), 2019. Connected Automated Driving Roadmap. Version: 8. Available at: https://www.ertrac.org/uploads/documentsearch/id57/ERTRAC-CAD-Roadmap-2019.pdf (Accessed 29 October 2020).
European Commission, 2018. Strategic Action Plan on Road Safety. COM (2018) p. 293 Final. Available at: https://eur-lex.europa.eu/resource.html?uri=cellar%3A0e8b694e-59b5-11e8-ab41-01aa75ed71a1.0003.02/DOC_2&format=PDF (Accessed 29 October 2020).
European New Car Assessment Program (Euro NCAP), 2018. European New Car Assessment Program Test Protocol – Lane Support Systems. Available at: https://cdn.euroncap.com/media/41770/euro-ncap-lss-test-protocol-v202.201811091311328900.pdf (Accessed 18 September 2021).
European Union Road Federation (ERF), 2018. Marking the Way Towards a Safer Future. An ERF Position Paper on How Road Markings Can Make our Road Safer. Available at: http://erf.be/wp-content/uploads/2018/07/ERF-Paper-on-Road-Markings_release_v2.pdf (Accessed 20 October 2020).
Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice 77, 167–181.
Farah, H., Erkens, S.M.J.G., Alkim, T., et al., 2018. Infrastructure for automated and connected driving: state of the art and future research directions. Road Vehicle Automation 4, 187–197.
García, A., Camacho-Torregrosa, F.J., Baez, P.V.P., 2020. Examining the effect of road horizontal alignment on the speed of semiautomated vehicles. Accident Analysis and Prevention 146, 105732.
Gopalan, R., Hong, T., Shneier, M., et al., 2012. A learning approach towards detection and tracking of lane markings. IEEE Transactions on Intelligent Transportation Systems 13 (3), 1088–1098.
Gromping, U., 2006. Relative Importance for linear regression in R: the package relaimpo. Journal of Statistical Software 17 (1), 1–27.
Gruyer, D., Magnier, V., Hamdi, K., et al., 2017. Perception, information processing and modeling: critical stages for autonomous driving applications. Annual Reviews in Control 44, 323–341.
International Organization for Standardization (ISO), 2017. Intelligent Transport Systems–Lane Departure Warning Systems–Performance Requirements and Test Procedures. ISO 17361: 2017. ISO, Geneva.
Kluge, K., Lakshmanan, S., 1995. A deformable template approach to lane detection. In: Intelligent Vehicles' 95 Symposium. Detroit, 1995.
Laird, N.M., Ware, J.H., 1982. Random-effects models for longitudinal data. Biometrics 38 (4), 963–974.
Lawson, S., 2018. Roads that Cars Can Read – Report III, Tackling the Transition to Automated Vehicles, European Road Assessment Program (EuroRAP) and European New Car Assessment Program (EuroNCAP). Available at: https://www.irap.org/2018/06/new-report-tackles-the-transition-to-automated-vehicles-on-roads-that-cars-can-read/ (Accessed 22 October 2020).
Liang, K.Y., Zeger, S.L., 1986. Longitudinal data analysis using generalized linear models. Biometrika 42, 121–130.
Marr, J., Benjamin, S., Zhang, A., 2020. Infrastructure Implications of Pavement Markings for Machine Vision. AP-R633-20. Publication no, ISBN 978-1-922382-25-2. Available at: https://austroads.com.au/publications/connected-and-automated-vehicles/ap-r633-20 (Accessed 15 September 2021).
McFadden, D., 1972. Conditional Logit Analysis of Qualitative Choice Behavior. Institute of Urban and Regional Development, Berkeley.
Menard, S., 2004. Six approaches to calculating standardized logistic regression coefficients. The American Statistician 58 (3), 218–223.
Mobileye, 2019. Going Visual: Why Recording a Collision Isn't the Solution. Available at: https://static.mobileye.com/website/us/fleets/files/Going%20Visual.pdf (Accessed 6 October 2020).
Morsink, P., Klem, E., Wilmink, I., et al., 2016. Zelfrijdende Auto's: Ontwikkelagenda ZRA en Wegontwerp. Tho Haskoningdhv Nederland B.V., Amsterdam.
Narote, S.P., Bhujbal, P.N., Narote, A.S., et al., 2018. A review of recent advances in lane detection and departure warning system. Pattern Recognition 73, 216–234.
National Cooperative Highway Research Program (NCHRP), 2020. Infrastructure Enablers for Automated Vehicles and Shared Mobility. NCHRP Project 20–113F. NCHRP, Washington DC.
National Highway Traffic Safety Administration (NHTSA), 2017. Automated Driving Systems 2.0: A Vision for Safety. NHTSA, Washinton DC.
Nitsche, P., Mocanu, I., Reinthaler, M., 2014. Requirements on tomorrow's road infrastructure for highly automated driving. In: 2014 International Conference on Connected Vehicles and Expo. ICCVE), Vienna, 2014.
Olstam, J., Johansson, F., Alessandrini, A., et al., 2020. An approach for handling uncertainties related to behaviour

and vehicle mixes in traffic simulation experiments with automated vehicles. Journal of Advanced Transportation 2020, 1–17.
Pappalardo, G., Cafiso, S., Di Graziano, A., et al., 2021. Decision tree method to analyze the performance of lane support systems. Sustainability 13 (2), 846.
Pike, A., 2019. NCHRP 20-102. Impacts of Connected Vehicles and Automated Vehicles on State and Local Transportation Agencies. Available at: https://apps.trb.org/cmsfeed/TRBNetProjectDisplay.asp?ProjectID=4004 (Accessed 22 October 2020).
Reddy, A., Farah, H., Huang, Y., et al., 2020. Operational design domain requirements for improved performance of lane assistance systems: a field test study in The Netherlands. IEEE Open Journal of Intelligent Transportation Systems 1, 237–252.
SAE International, 2018. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-road Motor Vehicles. SAE International, Warrendale.
Thorn, E., Kimmel, S., Chaka, M., 2018. A Framework for Automated Driving System Testable Cases and Scenarios. NHTSA, Washington DC.
Vlakveld, W., Vissers, L., Hulleman, K., et al., 2015. An Empirical Exploration of the Impact of Transition of Control on Situation Awareness for Potential Hazards. SWOV Institute for Road Safety Research, The Hague.

**Giuseppina Pappalardo** received the PhD in engineering of road infrastructures at University of Catania, in 2004. Since 2004, she has been PostDoc at the Department of Civil Engineering and Architecture. Her current research focuses on road safety, especially for vulnerable users, and on road asset management. Her research products include more of 70 published papers in international journals and conference proceedings. She is member of National and International committees (e.g., PIARC, TRB).

**Riccardo Caponetto** received the master's degree in electronic engineering and the PhD degree from the University of Catania, Catania, in 1991 and 1994, respectively. Since 1994, he has been a researcher with STMicroelectronics. From 1995 to 1998, he was a professor of industrial robotics with the University of Messina, Italy and at present associate professor at University of Catania. His current research interests include systems modeling and control, fractional order systems, and soft computing techniques.



**Rosario Varrica** received the master's degree in civil engineering from the University of Catania, Catania, in 2019. He is working as engineer in a construction company that deals with the design and construction of public works.

**Salvatore Cafiso** is a full professor of highway engineering at the University of Catania. He is affiliated with the Department of Civil Engineering and Architecture. Member of committees of international associations (e.g., TRB, PIARC) and of editorial boards of some international journals. Research interests include pavement design and maintenance, road geometric design and transportation safety with participation in several national and international projects. He is the author of more than 200 scientific publications and several presentations at international conferences. He is currently studying the role of the physical road infrastructure in the era of smart roads and autonomous vehicles.

Please cite this article as: Pappalardo, G et al., Assessing the operational design domain of lane support system for automated vehicles in different weather and road conditions, Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2021.12.002