Identifying and testing the Operational Design Domain factors of Lane Keeping System at horizontal curves using PreScan

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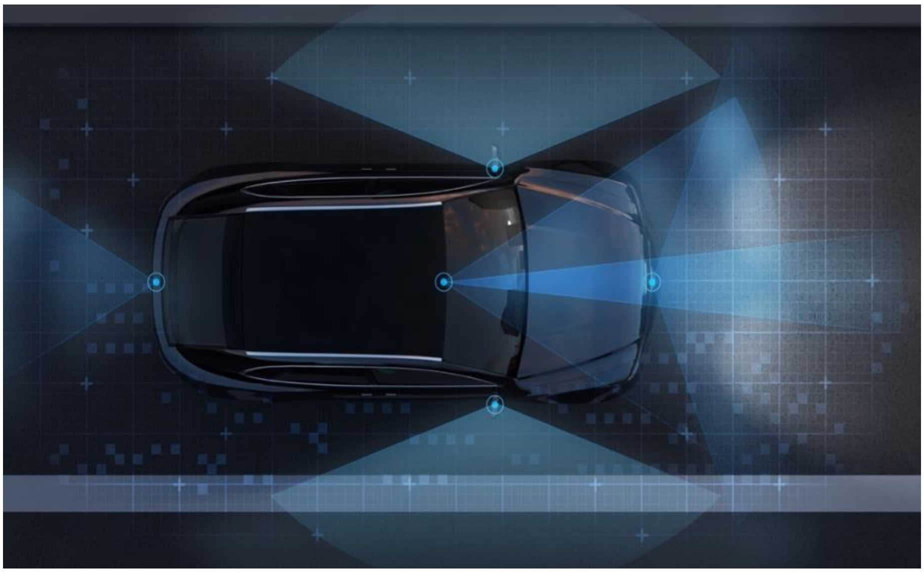
to obtain the degree of

Master of Science in Civil Engineering: Transport and Planning

Delft University of Technology

To be defended publicly on March 30, 2022



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Acknowledgements

This thesis marks the end of my journey as a master's student in Transport & Planning at TU Delft. It has been a wonderful and surreal 2.5 years that has taught me many different things and has brought me one step closer to becoming a transport professional. This was possible thanks to the constant support I received from all the people around me.

First and foremost, I would like to thank my committee members for guiding me throughout the thesis period. Thank you, Bart, for the constant support you gave during every obstacle I faced. I am very grateful for having you on my committee. You always inspired me to take a step back and think from a greater perspective. Despite your busy schedule, I'm thankful for your quick and valuable response, without which I would've overlooked certain aspects of my thesis. The frequent meetings with Haneen are what kept me driven throughout the entire thesis period. Thank you Haneen, for the kind words and support you provided during the times in need. Your guidance has inspired me to become more confident in my capabilities and has helped me become more independent. Thank you, Meng, for providing feedback to me at every milestone even after moving away from Delft. I appreciate your time and effort in supporting my journey. Narayana and Freddy have been the most involved in this journey. Thank you, Narayana, for your guidance and feedback, and for constantly checking in on me. I would also like to thank Freddy who has been part of this journey from even before the thesis started. You have been the constant pillar of support in my thesis and your insights were very valuable in making my thesis more complete. I also appreciate the ease I could approach you and for figuring out the specifics in moments of confusion with me, especially during the last leg of my thesis. I am really glad you were part of this journey. I would like to thank Enguerrand for sharing his expertise from the industry which was very useful in shaping my research better. I would also like to extend my gratitude to Alessandro from Siemens for helping me with any issues that came up in the simulation and to Arjen, Pieter, Alex and Sean from Siemens, the very few who I had the chance to meet during these Covid times for welcoming me so warmly at the office.

I am indebted to my family, for being the backbone to completing my master's at TU Delft. Amma and Acha, your constant support in trying times are what helped me push through. Thank you, Bro man, and Achu Chechi for your belief and optimism in me. I wouldn't have achieved this without the gentle encouragement and everlasting faith you have in me. Thank you, Lakeshmi, for being the constant in my life, and both Sreeja chechi and Prasad chettan, for supporting me through thick and thin. To Shehab and Ananya, my best friends in Delft who are like my second family; I'm very thankful to you Ananya for never making me feel alone in this whole journey and thank you Shehab for always being there for me no matter what. I don't know what I would do without you two. I am also thankful to Abhi, who always made sure I am feeling well and for feeding me the amazing food he cooks. I also want to thank Ocean's 13 peeps (Rameen, Kavya, Akarsh, Dani, Appi) and the Saturday Dinners group (Sameer, Shriya, Ritika, Rucha, Aishu) for filling the awful times of the pandemic with happiness and smiles. The same goes for my best mates from T&P, Raunaq and Aswin, who were always there for anything and everything throughout this journey. I would like to thank Anton, who motivated me to step out of my house during the pandemic for grabbing a coffee, going for walks or working at the University. I would also like to extend my gratitude to Gayathri and Zack, for feeding me and making sure I was healthy amidst sleepless nights. I would also like to thank people away from Delft but still supported me virtually – Rohit, Sapna, Nabil, Sushant, Shehar, Surbhi, Dhachu and Keethu. I also thank the Malayali community here in Delft (Gary, Jitin, Sreeja, Mahesh, Govind, Gopal, Aadil, Arjun) who always made me feel homely in the many gatherings we had. Finally, I am thankful to Ramya aunty, for the constant support and well wishes throughout this journey.

Thank you all for helping me realize this dream and I'm super excited to move on to the next phase of my life. I hope my accomplishments from this research would be useful to the researchers and professionals in this field.

Neeraj Kumar
Delft, March 2022

Table of Contents

List of Figures

List of Tables

Executive summary

Introduction

The European Commission has mandated the presence of some advanced safety features in all vehicles sold in the EU from 2022 onwards. Vehicle manufacturers are competing to be at the frontline of this technology. However, since the technology is still maturing, there have been reports of fatalities that involve vehicles equipped with these features. The main objective of such advanced driver assistance systems (ADAS) is to remove the human error factor in driving and aims to reduce the severity of the crashes, if not completely prevent it. One such ADAS feature prevalent in the market now is the lane-keeping system or lane assistance system. There are many vehicles already operational in the market with these systems equipped, with gaining focus on higher levels of vehicle automation. Despite the ADAS targeted to improve road safety, there are many limitations of this technology that has to be addressed. The systems are developed to function in certain conditions and has limitations. Hence it is important to understand them. Therefore, this research focuses on the lane-keeping system and uses simulation to understand the system limitations associated with it.

The specific operating conditions defined by the original equipment manufacturer (OEM) in which the system or the ADAS feature is designed to function is known as the operational design domain (ODD) of the system. There are six levels of vehicle automation categorized by the Society for Automotive Engineers (SAE), ranging from no-automation (level 0) to full automation (level 5). Each of these SAE levels will have a different ODD definition that mainly includes infrastructural, environmental, geographic, operational constraints. The system might malfunction or disengage in driving situations outside its ODD, and a fallback sequence will be initiated to bring the vehicle to a safe stop. However, in the same level of vehicle autonomy, each OEM specifies the ODD differently. As a result of the different OEMs competing to be at the forefront of the autonomous vehicle market, a wide range of proprietary ODD definitions exists. Level 2 vehicle that has ADAS features like lane-keeping system equipped requires a human driver to monitor the driving environment at all times. The driver's only source of information about the ODD of the vehicle is the publicly available vehicle instruction manual, but on closer inspection, some of the ODD boundaries of the system are not explained very clearly in them. For example, the boundary conditions for the radius of curvature of the road is described as ‘sharp curves’ in 3 out of the 5 OEM manuals and also as ‘winding roads’ in 2 out of the 5 OEM manuals. However, what radius value classifies as a sharp curve is missing. Similarly, for lane width, 3 out of the 5 OEM manuals mentions that the system cannot function at narrow lane widths, but the exact lane width is not provided. Hence, bringing all these different ODD definitions by the OEMs under one umbrella is of paramount importance and is currently being attempted by regulatory organisations.

A standard way of testing the impact of the different ODD attributes on the performance of a lane-keeping system is still absent. A cost and time-efficient way to tackle this problem is by using simulation to simulate the different driving situations to find the dependency of the different ODD attributes on the ODD definition. However, there is no standard ODD definition format that can be used to test the ODD in a simulation environment. Therefore, this research aims to fill this by providing a conceptual framework and a method to assess the ODD boundaries of a lane-keeping system using simulation. This would then be beneficial to researchers, policymakers, OEMs to refine the ODD and to test the effect of the relevant ODD attributes on the performance of the system. This research objective is achieved using the following main research question:

"How to assess the ODD boundaries of vehicles equipped with Lane-Keeping System at horizontal curves using PreScan?"

This research focuses on testing the ODD compliance of the lane-keeping system at a horizontal curve. The simulation software used in this study is Simcentre Prescan owned by Siemens. The outcome of this thesis is the learnings about the impact of the tested ODD attributes on the lane-keeping performance and it can be used in Prescan to assess the ODD of more already built test cases in Prescan.

Research method

To answer the formulated research question, this study followed a sequence of three phases, namely the exploratory phase, development phase and simulation phase.

The exploratory phase included an initial investigation of the ODD standards, academic literature and OEM manuals to gather the ODD attributes relevant to the lane-keeping system and the associated ODD boundary conditions. This exploratory phase also included learning about the simulation capabilities of Prescan. The vehicle speed, the radius of curvature of the curve, lane width and weather conditions were the ODD attributes tested in this research. Test vehicle speeds of 100 km/h, 110 km/h, 120 km/h, 130 km/h and 140 km/h were tested at curve radii of 750 m, 900 m, 1200 m, and lane widths of 2.6 m, 2.75 m, 3.0 m, 3.25 m, 3.5 m and 3.6 m. A design speed of 120 km/h was used in the design of experiments and based on that; the minimum curve radius of 750 m was chosen from the Rijkswaterstaat guidelines. The tested speeds are based on the speed range provided in the OEM manuals. The lane widths values tested were chosen based on existing literature on lane-keeping performance. The weather conditions tested in this study were fog, heavy rain, extreme rain, heavy snow and extreme snow.

The development phase brings together all the findings from the exploratory phase to develop the use cases on Prescan. A 0.3 m acceptable lateral offset value is termed as the 'Offset threshold value' in this study. This value was chosen based on the 0.3 m criterion used in a previous driver behaviour study to flag lane wandering events and lane changes. This classification involves assigning binary values 1 and 0 to the 'Performance' metric proposed in this study; 1 means the test vehicle is within the offset threshold value and 0 means the test vehicle is deviating beyond the offset threshold value. This performance metric was integrated into the developed use cases. While developing the test cases, one attribute was varied at a time and the other attributes were kept constant. This was done to check the level of impact each of these attributes has on the lane-keeping performance of the test vehicle. Since none of the ODD attributes in a test case changes value during the run time, an initial ODD assessment is done that will hold for a specific test case throughout the test run.

Finally, in the simulation phase, the developed test cases were run, the data collected was analysed and conclusions were formed. The lateral offset data for every timestep is measured from all the test cases run in Prescan. This data is then filtered, compiled and analysed to assess the effect of the tested ODD attributes on the lane-keeping performance. The mean lateral offset, maximum lateral offset and the proposed 'Exposure' metric were used in the analysis. The exposure metric is the ratio of the simulation time in which the test vehicle was within the offset threshold value based on the performance metric and the total simulation time for which the vehicle was driving on the curve. The results from the performance assessment are compared with the initial ODD assessment, and conclusions were drawn.

Results and conclusions

The test cases are classified into two, namely with precipitation and without precipitation. The test cases without precipitation are compared with each other to identify the impact of change in any one of the ODD attributes on the performance and then reflect on the initial ODD assessment of the test case. For the test cases with precipitation, they are compared with the sunny weather condition. The initial ODD assessment of the test cases with and without precipitation are compared with the results obtained from the performance assessment. Figure A and Figure B show the variation in mean lateral offset and maximum lateral offset of all the test cases without precipitation. As for the test cases with precipitation, the weather variations did not show much effect on the lane-keeping performance and hence no conclusive evidence could be extracted from it.

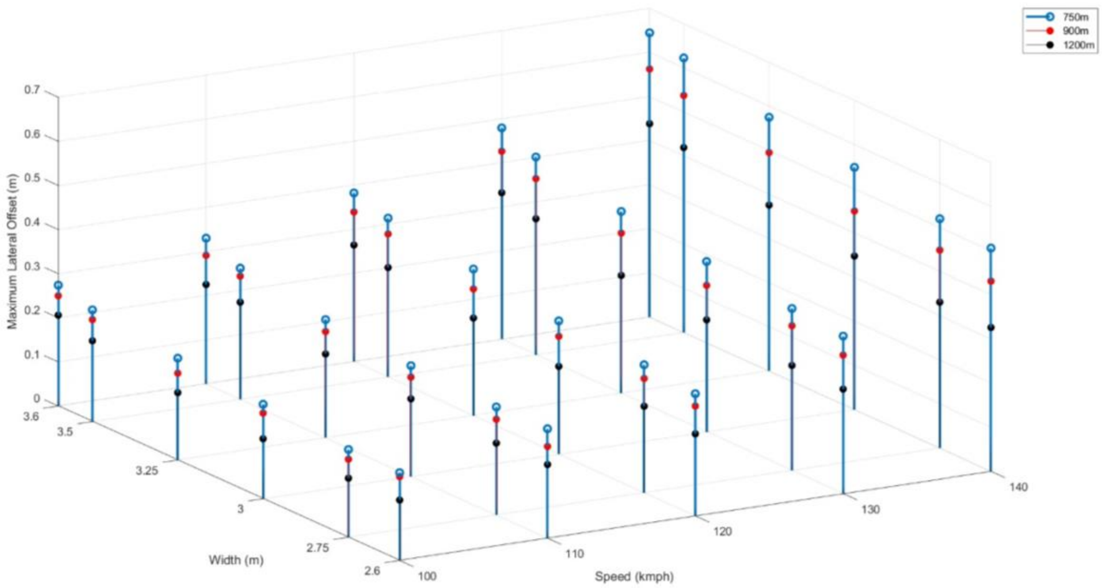

Figure A: Maximum lateral offset variations of test cases without precipitation

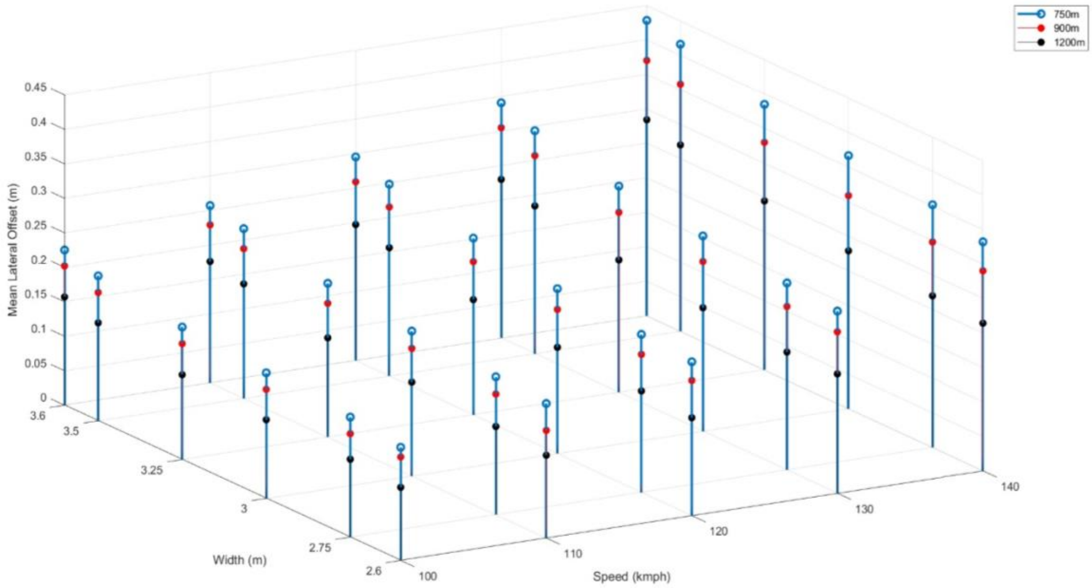

Figure B: Mean lateral offset variations of test cases without precipitation

All the test cases without precipitation at 100 km/h were found to be within the offset threshold value of 0.3 m for all lane width and radii of curvature tested. This means that if the upper ODD boundary for speed is set at 100 km/h, then all the test cases are fully within the offset threshold value. The upper boundary of speed increases to 110 km/h if the upper ODD boundary of lane width is set at 3.5 m because all test cases of the vehicle moving at 110 km/h have a lateral offset within 0.3 m for all lane widths less than 3.5 m. Similarly, if the vehicle has to move at 120 km/h, then only the test cases with the radius of curvature of 1200 m were fully within the offset threshold. All the test cases of 1200 m radius curve at 120 km/h in all lane width variations are completely within the 0.3 m offset threshold. Similarly, if the vehicle has to move at 120 km/h at a 750 m radius of the curve, then the lane width that ensures higher lane-keeping performance narrows down to 2.6 m to 2.75 m. This type of correlation between the ODD attributes makes it hard to concretely define a specific ODD boundary.

A higher exposure value is indicative of better lane-keeping performance and a lower value of exposure is indicative of poorer lane-keeping performance. It was found that higher speeds have higher exposure values in narrow lane width compared to wider lane widths for curve radii 750 m and 900 m. In the 1200 m radius of curve test cases, there is a decrease in the exposure value at 2.6 m and 3.6 m lane width compared to the other lane width. For curve radii 750 m and 900 m, an increase in lane width results in a higher exposure value. This may be because, at a higher radius, the effect of lane width variation becomes more prominent. For the same lane width and radius, increasing speed results in lower exposure. Similarly, for the same lane width and speed, an increase in radius of curvature results in higher exposure. From all the test cases, a lane width of 2.6 m has the highest exposure value and lowest mean lateral offset and maximum lateral offset within the same radius of curvature or speed. This is surprising since the OEM manuals mention narrow lane widths as outside ODD and do not mention wide lanes as an ODD limitation. It was also found that while exiting the curve, there was a deviation nature towards the opposing lane shown by the test vehicle. Within the same radius and speed, this deviation nature was found in higher lane widths and minimal in narrow lane width.

From the test cases that include weather variations, it was found that the impact of weather was negligible. The only notable differences found were the swerving nature at narrow lane width conditions and large deviations during extreme snow weather. The test vehicle was observed to be swerving heavily between the lane centre and the right lane marking in all-weather variations with a 2.6 m lane width. At 3.6 m lane width, the swerving is lesser, and the weather conditions do not seem to impact the lateral offset variations compared with the sunny weather conditions. Fog and rain conditions were expected to have a higher impact on the vehicle's lane-keeping performance, but surprisingly it had less effect.

It can be concluded from this research that there is a strong interdependency between the ODD attributes tested. This can lead to a possibility that the ODD definition may not exactly be a straightforward set of specific values in the form of a table, but instead can be dynamic considering this interdependency. It was also observed that some test cases classified inside ODD from the initial ODD assessment had poor lane-keeping performance and vice-versa. The lowest effect on the exposure was shown by weather variations. This can be because of the unreliable weather presets in Prescan because results from on-road experiments show a higher impact of weather conditions on the lane-keeping performance. It can also be because of any underlying factors at play inside the controller. Therefore, based on the impact of the tested ODD attributes, speed, radius of curvature and lane width can be classified as critical ODD attributes. Another observation from the test cases was the ability of the test vehicle to move at higher speeds in narrow lane widths with good lane-keeping performance compared to wider lane widths. This falls in line with findings from previous literature and will require validation. If narrow lane width does indeed ensure higher lane-keeping performance, then more lanes can be added to the roadway and it can facilitate higher capacity. The research approach of this study is used to develop a conceptual framework to assess the ODD boundaries of an ADAS feature in a simulation environment, as shown in Figure C.

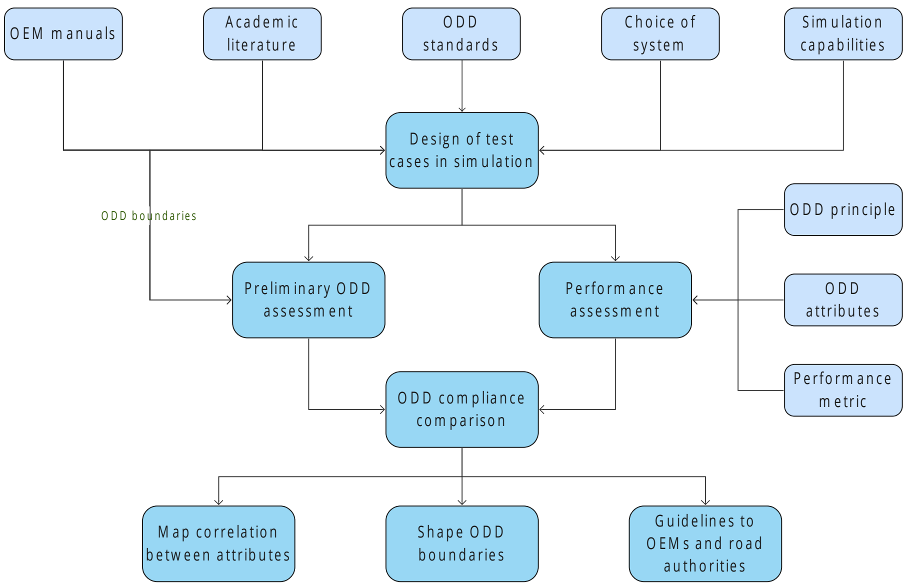

Figure C: Proposed framework to assess the ODD of an ADAS feature in simulation

Limitations and recommendations

This study has some limitations due to the choices and assumptions made. The lane-keeping system's ODD is not just restricted to the speed, lane width, the radius of curvature and weather variations alone. Hence, further studies are required to test more ODD attributes to gain further insight into ODD boundary conditions. The major limitation posed by this study is the omission of superelevation in the test cases due to the restrictions of the simulation software used. In terms of realism, superelevation is very important in the design of the experiments. However, the trends reported in this study is still expected to hold since the impact of including superelevation will affect all the test cases. Further investigation by including the effect of friction and superelevation will be very useful. The same research approach can be used on the same or another simulation environment to check if the trends are still visible. The biggest drawback in simulation studies is the combinatorial explosion, which limits this research as well. From all the combinations of values assigned to the chosen ODD attributes in this study, a total of 540 test cases could've been tested. However, only 130 cases were possible to test in this research. The Simcentre Prescan360 framework does provide a time and cost-effective way to address this problem. However, it was not implemented in this study. An initial peak in the lateral offset was observed in all test cases, which can be attributed to the lack of V2I communication or GPS sensor equipped on the test vehicle. The test vehicle was observed to deviate to the right side excessively while entering the curve. This behaviour might be because of the lack of superelevation at the curve, or due to the lack of V2I communication or GPS since the test vehicle cannot anticipate the curve segment until it reaches the curve.

From a scientific perspective, the ODD assessment conclusions from this study can be compared with on-road experiments. With more attributes tested, a higher level of detail can be achieved regarding the ODD boundary conditions and the degree of correlation between the different ODD attributes must be mapped out as well. The framework proposed by this research can be used to perform a similar ODD assessment on lane-keeping systems on other simulation platforms or for other ADAS features. Realism can be increased for the simulations by using OpenStreetMap or other means of testing real-life driving situations. ODD attributes like time of day, road surface conditions, headway, condition of lane marking, driving in shadows, would be interesting directions for future research.

From a practical perspective, the OEMs can use the results from this study and the framework to test the ODD boundary conditions and better define the OEM manuals. it is recommended to have open communication between the developer of the system, policymakers and road authorities. Furthermore, the OEM is advised to communicate the ODD boundaries of the system more clearly to the drivers to prevent accidents. If the ODD is defined by the OEMs, it would be useful for researchers and drivers to know how the ODD boundary conditions were tested and the principle behind it. The road authorities can also use this information to adapt the existing infrastructure for ensuring safety for vehicles equipped with lane-keeping systems. It can also be used by Siemens to fine-tune the lane-keeping algorithm and enhance the lane-keeping functionality. The ODD assessment approach used in this study can be used to test and gather data for the many use cases that are already built on Prescan with a lane-keeping system.

1. Introduction

1.35 million people die every year due to road crashes (WHO, 2018), many of which are caused by human error. As per the National Highway Traffic Safety Administration (NHTSA), more than 90% of collisions are associated with human error, like distraction, fatigue and emotional driving (Singh, 2015). Autonomous vehicle (AV) technology removes this human factor in driving and aims to reduce the severity and amount of such crashes. It has been shown that the introduction of vehicle automation can increase the capacity of roads and intersections since AVs travel with shorter headways due to the improved safety that it provides (Kamal et al., 2015). Additionally, AVs have shown a positive influence on the traffic flow efficiency based on indicators like capacity, capacity drop and traffic stability (Hoogendoorn et al., 2014). AVs have also proven to increase the mobility of people with limited mobility like the disabled and elderly population (Truong et al., 2017), and also increases fuel efficiency, resulting in lower emissions (Milakis et al., 2017). Consequently, the European Commission has mandated the presence of some advanced safety features in all vehicles sold in the EU from 2022 onwards (European Commission, 2018). This will contribute to the EU's 'Vision Zero' project that aims at reducing road deaths to almost zero by the year 2050. Along with the safety of people, the EU mandate will also help drivers to gradually get used to the Automated Driving System (ADS). This will in return increase the public trust and acceptance of AV, eventually transitioning to fully autonomous driving.

1.1. Background

Vehicle manufacturers are competing to be at the frontline of this technology. However, there have been multiple incidents in the past few years that involved fatalities while driving an autonomous vehicle. One of the noteworthy fatal accidents that made the news is a Tesla with an 'Autopilot' system speeding up and steering into a concrete barrier[1]. It was reported that the vehicle was operating under conditions it couldn't handle and that the driver was distracted. NHTSA has reported 11 crashes involving Tesla Autopilot, with 17 injuries and one death in these 11 crashes. The Tesla 'Autopilot' functionality is an advanced driver-assistance system (ADAS) designed to keep the vehicle in its lane and at a safe distance from vehicles in front of it. Despite the name, the system is designed for assisting the driver and expects the driver to be ready to intervene at all times. Another fatal accident that was reported involved an Uber test vehicle operating in self-drive mode, and it hit a pedestrian crossing the street with a bicycle[2]. Although the vehicle had a human safety backup driver in the driver's seat with the ability to take over control in case of an emergency, it was shown that the backup driver was visually distracted. The investigation found the cause of the accident to be due to the inattention of the backup driver. Hence, the safety of commercial AVs is an ongoing debate. This shows a need to identify the limitations of the systems' functionality and the need to evaluate the use of such systems in different driving situations. Additionally, drivers must also be aware of the actual capabilities of the AV and the limitations of the system in use.

[1] https://www.theguardian.com/technology/2018/jun/07/tesla-fatal-crash-silicon-valley-autopilot-mode-report
[2] https://www.nytimes.com/2018/03/19/technology/uber-driverless-fatality.html

Each Original Equipment Manufacturer (OEM) are developing their own autonomous system that is designed to work in specific geographic, environmental, operational, or infrastructural conditions. These dimensions within which the system is designed to function is known as Operational Design Domain (ODD). OEMs are trying to implement their own ODD for ADS that promises hands-free driving or highly autonomous driving. Examples of such systems are the Cadillac SuperCruise system, the General Motors driver monitoring system, Nissan ProPilot system, iNext, and so on. Google-owned Waymo became the first service provider to offer robotaxi rides to the general public in Arizona[3]. Recently, Tesla has said to offer 'full self-driving' feature to private vehicle owners on a subscription basis[4]. Additionally, companies are partnering together to push the AV technology forward, like Ford and Qualcomm, Cruise (owned by General Motors), Honda and Microsoft. Amazon recently acquired the autonomous vehicle start-up called Zoox[5] to also be a competitor in this arena. Apple Inc. has announced that they are planning to develop their own autonomous vehicle by 2024[6]. These recent developments in the market are pointing towards achieving the dream of fully autonomous vehicles on the road.

Different OEMs competing against each other to be the leading brand in AV technology results in a wide variety of defined ODD. Each OEM specifies the ODD differently in the same level of automation, resulting in a mismatch in the expected capabilities by the driver and actual capabilities of the system defined in the OEM manual (Farah et al., 2021). Due to this, questions arise like 'What happens when the AVs encounters a situation outside of its ODD?' or 'Are the failures outside the ODD permitted as long as the failure response is safe?'. There is no accepted standard of ODD that applies to all AVs equally. Additionally, the boundaries of existing ODDs are still unclear as well. For instance, in the owner's manual of a Tesla Model S, under the LKAS system, it says that the system may not function properly in sharp curves, which is an ODD boundary of the system. However, they don't specify what radius of the curve can be considered as a sharp curve. Similar cases exist in most of the owner's manuals of other AVs with other factors as well. Often the drivers are not aware of the ODD designed for the vehicle they are driving and are not informed whether the different real-life driving situations are within the ODD of the vehicle or not. Ensuring proper knowledge of the system by the driver and awareness is crucial for AV development (Eboli et al., 2017). Furthermore, there is no standard ODD definition format that can be used to test the ODD in a simulation environment.

1.2. Problem definition

Currently, there is no exact form of measurement to assess the ODD of any ADS system or ADAS features like lane-keeping system, adaptive cruise control, lane departure warning system, autonomous emergency braking system, etc. Having such a quantified ODD measurement would be useful in collaboration between the OEM and the other stakeholders to

[3] https://arstechnica.com/cars/2020/10/waymo-finally-launches-an-actual-public-driverless-taxiservice/
[4] https://www.businessinsider.com.au/tesla-autopilot-full-self-driving-subscription-early-2021-elon-musk-2020-12
[5] https://www.forbes.com/sites/tomtaulli/2020/06/27/amazon-buys-zoox-why-self-driving-technology-is-existential/
[6] https://www.theguardian.com/technology/2020/dec/22/apple-plans-self-driving-car-in-2024-with-next-level-battery-technology

improve the system and the infrastructure, and for widespread use of safe AV technology. However, due to the competition in the AV market between the different OEMs, such ODD assessment reports are not publicly available which hinders the modifications required in the system or the infrastructure for better safety. Since the system is designed to perform within its ODD, and the current road infrastructure was designed for human drivers, it is imperative to test the ODD boundaries of the system in the different driving conditions that an AV might encounter. The driving conditions are dependent on the different factors related to the infrastructure, environmental conditions, system constraints, operational constraints, and more. This dynamic driving environment made of different combinations between these factors makes it very difficult to define the ODD and to measure it, as shown in Figure 1.

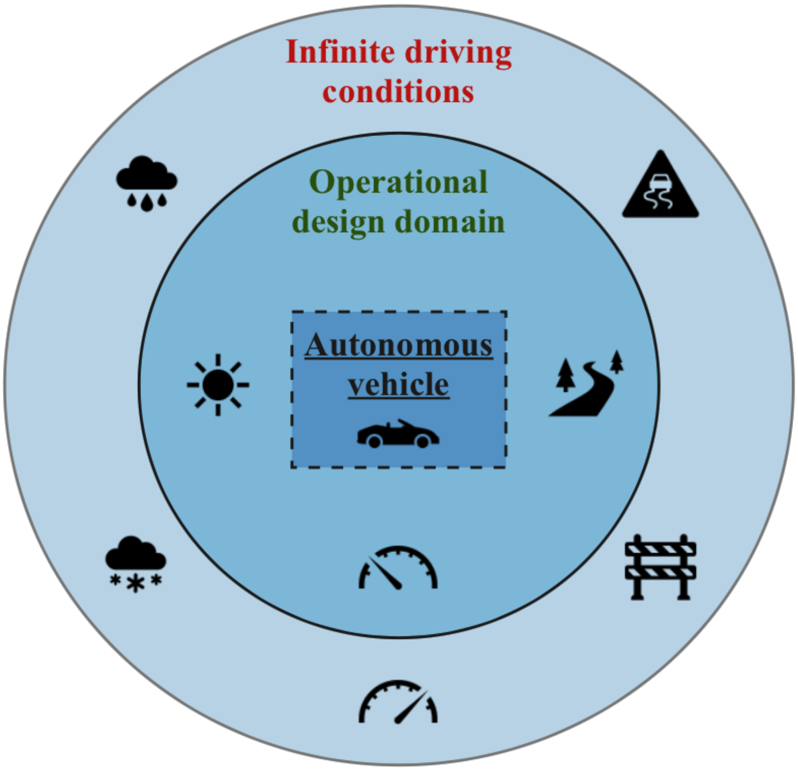

Figure 1: ODD challenges for autonomous vehicles

1.3. Research Objective

The goal of this research is to identify the attributes relevant to the ODD definition of a specific ADS feature chosen to classify developed test cases into either inside or outside the ODD. This can then be used to compare with results from a performance metric to test the ODD boundaries of that specific feature of the test vehicle using simulation. The developed metric would then be beneficial to OEMs to test the ODD of their system and as a long-term objective, be beneficial for drivers to be constantly informed about the ODD boundaries during various driving situations.

The ODD assessment metric will be able to test the effect of relevant road, vehicle and environmental characteristics on the performance of the lane-keeping system using the simulation software Prescan. This ODD assessment approach will be able to check whether the test case classification within or outside the ODD boundary is valid based on the performance of the lane-keeping system. Since this is a fairly new topic of investigation and is getting more and more prominence lately, a conceptual framework will also be proposed that can guide future researchers as a roadmap on how to assess the ODD boundaries of an ADS using simulation.

1.4. Research Approach

This research aims to answer the research questions by defining scenarios for a specific selected ADS system and simulating it in PreScan. For that, the different capabilities of the software are first explored and the characteristics relevant to the ODD definition are identified, along with finding the ODD attributes relevant to the ADS system from literature and OEM manuals. Using this, the use cases are defined, and the test cases are prepared. The test cases will then be run to extract the results and then analysis of the results will be done. This performance results from the test cases will then be compared with the initial ODD assessment done on the test cases. The research approach used in this study is shown in Figure 2. The whole approach was utilized for creating a framework for testing the ODD boundaries of a lane-keeping system using simulation.

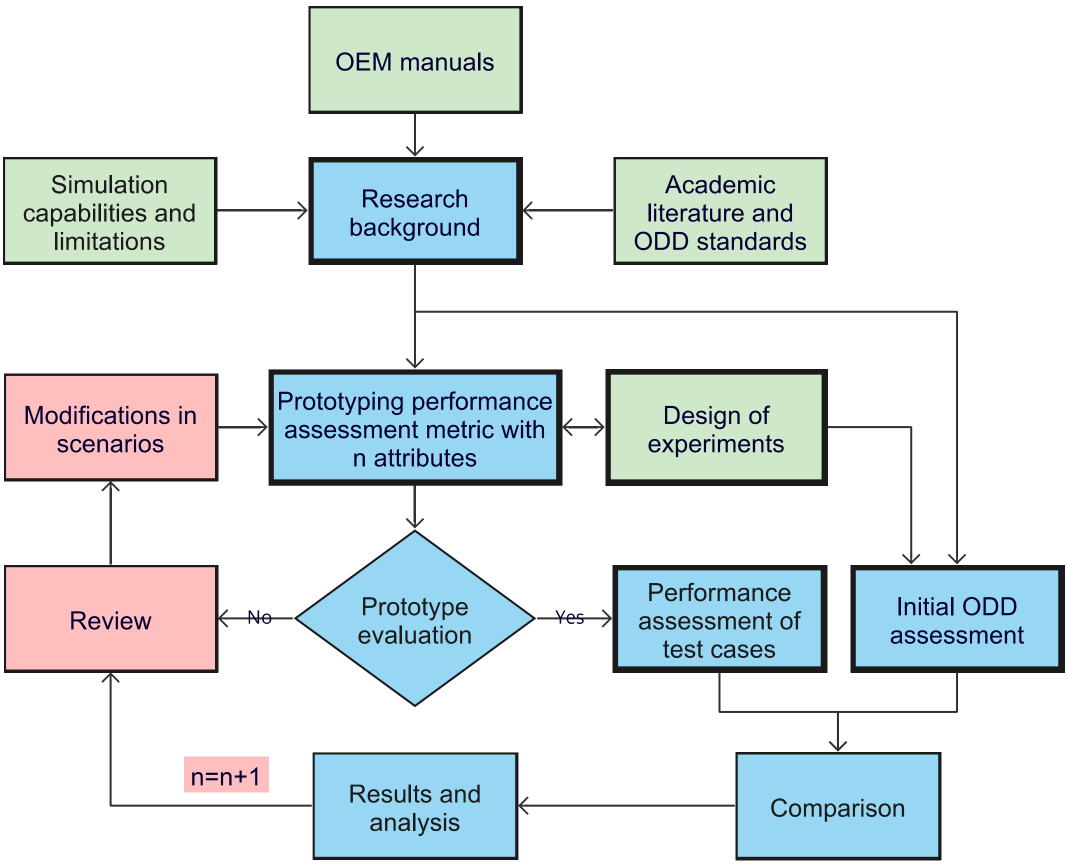

Figure 2: Research approach used in the study

1.5. Research Scope

The scope of this research is limited to the ODD of a lane-keeping system feature of an ADS at a horizontal curve. The type of curve (left or right) is not a considered factor in the study. The research does not take into account the human behavioural factor of driving or the fallback sequence of the system when it leaves its ODD. The interaction with other road users is also outside the scope of this research since the sole focus of this study is to understand the effect of the different ODD factors identified on the system in different driving scenarios. The effect of factors like tire condition, lane marking condition, the nighttime driving condition is also not investigated. Additionally, the research does not involve creating or modifying the sensor algorithm of the lane-keeping system, but only uses the algorithm that was already being used or available in Prescan provided by Siemens. Finally, this study does not aim to provide a new ODD definition or to provide a standard ODD definition for a lane-keeping system, but instead will focus on the ODD boundary assessment of the lane-keeping system in simulation.

1.6. Research Outline

The main findings from the literature review are discussed in Chapter 2, followed by the findings from reviewing the OEM manuals in Chapter 3. The research gaps and research questions are presented in Chapter 4. This is followed by the research methodology in Chapter 5 and the results from the analysis are then presented in Chapter 6. The discussion of results and formed conclusions are described in Chapter 7. Finally, the recommendations, reflection and future studies of this research are detailed in Chapter 8.

2. Literature Review

This chapter aims to discuss the findings from the literature review done on the research topic. Both academic literature and industrial documents were used for this. The sources used were Google Scholar, Researchgate, Elsevier, Sciencedirect, Transportation Research Record, among many others. These sources were used to find peer-reviewed journal papers, articles, reports, conference publications, and priority was given to the latest sources (2010 onwards).

To find the relevant literature to the research topic more effectively, a review of the bibliography of the relevant sources and theses was done in order to narrow down the search. This process is called snowballing and it was done throughout the literature review phase. Several keywords were used (by itself or in combination) to limit the search for literature. Some of these keywords are Operational design domain, Lane keeping system, ADS, Sensors, Simulation, Autonomous vehicles, Self-driving, Scenarios, Connected and automated driving. These were used to refine the literature at the earlier stage and then further filtering was done by reviewing the title and abstract of the gathered literature.

The main objective of the literature review is to provide state of the art of ODD definition so far from academic literature, ODD standards and OEM manuals, and to also identify relevant attributes to the ODD definition. These identified attributes would then be used to create the test scenarios for the simulation. It was found that there is only very limited research published on the topic of ODD, and that there is no universally accepted ODD standard yet. Furthermore, the ODD definitions provided on the OEM manuals are not clear enough in certain aspects.

2.1. General

With the advent of AVs, there has been immense research that focuses on identifying factors important for its safety and testing the performance of the system. Geyer et al. (2014) proposed a unified ontology that includes terms like ego vehicle, scenery, scene, scenario, etc. and ordered it into test and use case catalogues. This can be used for a structured representation of ODD. This was further specified into a two part ontology that consists of road structure by Czarnecki where the first one focuses on road structure (Czarnecki, 2018a), and the second one on road users and environmental conditions (Czarnecki, 2018b, p. 2). The road structure ontology includes factors like road type, road surface, road geometry, cross-section design, which can be used to define the ODD for an ADS. The second one covers road users (vehicles and pedestrians) and environmental conditions, that include atmospheric, lighting and road conditions. Colwell et al. (2018) suggested that models based on this ontology can be used as a reference to create an ODD.

The concept of static ODD and dynamic ODD was also introduced by Seppelt et al. (2017) where the identified conditions and elements were classified into the two categories. Static ODD includes the set of roadway and environmental conditions with a fixed location, whereas dynamic ODD contains the set of roadway and environmental conditions for which on-board sensing is necessary to identify state changes with respect to time. The study also examined the human considerations in the form of a questionnaire study that tested the knowledge of Tesla owners' knowledge of the AutoPilot functionality. According to the categorisation by Seppelt et al. (2017), the ontology proposed by Geyer et al. (2014) is static in nature.

The study done by Wittmann et al. (2015) uses the term 'functional boundary', which is similar to the ODD concept and highlights the need to monitor the functional boundary for safety purposes. The term is similar to ODD in the sense that the boundary defined is identical to the domain that can be defined. Identifying the relevant boundaries pertaining to all the factors/conditions of the ODD is a challenge because the AV itself is a complex system that runs through a complex environment with different variables. The functional boundary defined by Wittmann et al. is a combination of static environment, traffic dynamics, environmental conditions, vehicle state and passenger actions. Each of this element consists of multiple factors to be taken into consideration while defining the boundary. Wittmann et al. has highlighted in their study that for safe operation, the monitoring of functional boundary is required.

These studies provide different ways of categorisation of the relevant factors for defining the functional boundary or ODD, and studies what an ODD should consist of. The complexity of defining a complete ODD of an AV, let alone a single ADAS feature is clearly hard. However, there is neither a standard way to define the ODD, nor a formal method to test the ODD and the safety and risk associated with it.

2.2. Automated vehicles

2.2.1 Levels of automation

There exist an international standard by The Society of Automotive Engineers (SAE) (NHTSA, 2016) which defines AV from Level 0 (full control by the human driver) to Level 5 (full control by the vehicle), as shown in Table 1.

Table 1: SAE levels of Driving Automation

Level	Name	Dynamic Driving Task (DDT)		Fallback	ODD
		Sustained Lateral & Longitudinal Vehicle Motion Control	Object and Event Detection and Response		
0	No Driving Automation	Driver	Driver	Driver	N/A
1	Driver Assistance	Driver and System	Driver	Driver	Limited
2	Partial Driving Automation	System	Driver	Driver	Limited
3	Conditional Driving Automation	System	System	Driver	Limited

4	High Driving Automation	System	System	System	Limited
5	Full Driving Automation	System	System	System	Unlimited

From Table 1 it can be understood that the ODD is limited to specific driving conditions except for level 5 which has unlimited ODD, which indicates that the system can perform all driver-manageable driving tasks in every on-road driving situations. This means that level 5 ADS promise the same mobility that a human driver can provide (Colwell et al., 2018). The functions of the driver and system, and the features of the different levels is shown in Figure 3.

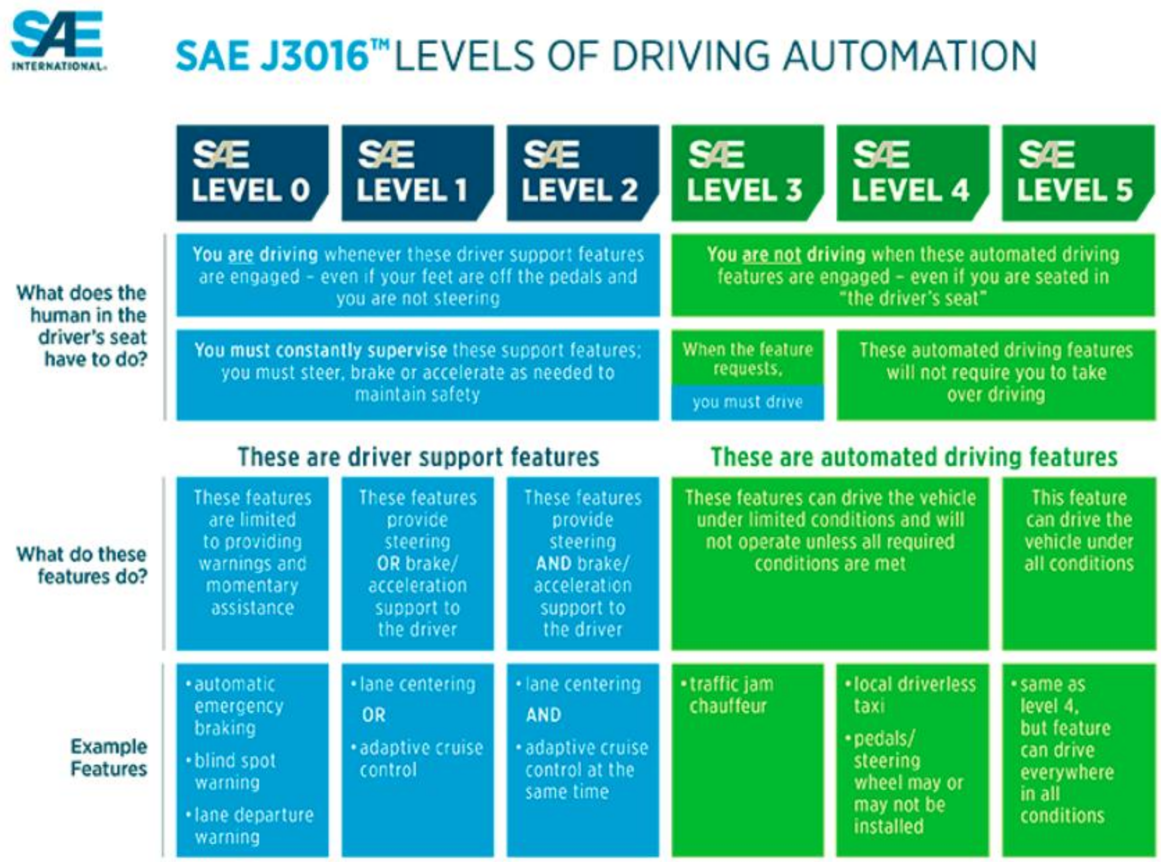

Figure 3: SAE levels of driving automation and functions

Driving automation refers to both ADAS and ADS. As per SAE definition, Levels 1 and 2 are called Driver Support Systems and Levels 3 to 5 are identified as ADS. However, levels 1 and 2 are more commonly referred to as ADAS. The purpose of ADAS features on an AV is to support human drivers, whereas an ADS can ultimately be able to operate without a human driver.

As the name suggests, in Level 0 the driver performs all longitudinal and lateral tasks like steering and acceleration. The driver is completely in control, although the system can give some warning like lane departure or collision alerts. At Level 1, the system can control the speed or steering of the vehicle, but not both simultaneously. Adaptive cruise control is an example for this level of autonomy where a set speed and safe distance between the car ahead is maintained by automatically applying the brake and throttle. At Level 2, the vehicle takes over the two primary driving functions of lateral and longitudinal control. For example, having adaptive cruise control with lane keeping would require both the function and the system does that. However, the driver still has to be ready to take-over control in case the system cannot handle the driving situation. At Level 3 autonomy, the vehicle can monitor its surroundings and can change lanes or accelerate past a slower vehicle by controlling the steering, throttle and brake. The driver has to stay alert to take back control when the vehicle initiates it. An example feature of this is the traffic jam assist or highway autopilot which can be operated on highways or when the traffic is slow. In Level 4, more highly complex driving situations can be handled by the system itself. The driver can relax during driving situations that previous levels cannot manoeuvre, like construction sites or lane closures. The driver still has the option to manually takeover. However, since the ODD of Level 4 ADS is still limited, there can still be driving situations that the system cannot handle. In these situations, the vehicle prompts the driver to take back control, but if it receives no response, the vehicle brings itself to stop safely. Google Waymo is currently operating driverless taxi services in specific areas in the USA. Finally, Level 5 autonomy requires no human attention and no fallback ready driver to take over either. However, most of the current commercial AV only include Level 1 and Level 2 autonomy where human drivers are assisted by driver assistance features and partial automation is provided. This means that the driver may be requested to take control of the vehicle in certain conditions outside the system's ODD.

The Vienna Convention of 1968 did not allow the large-scale use of higher levels of autonomy features on public roads with the exception of Germany. This is a direct consequence of lack of standardization and validation techniques (Takács et al., 2018). One of the major milestones towards deployments of ADS was the amendments to the 1968 Vienna convention in 2016 that allows automated driving technologies transferring driving tasks to the vehicle in traffic, given these technologies adhere to the United Nations vehicle regulations or if it can be overridden by the driver. As a result, the amendment allows ADS functionalities in AVs, provided that a driver is present and can take control of the vehicle (UNECE, 2016).

During ODD violation when the ADS is outside the designed functional boundary, level 4 or level 5 ADS responds by automatically performing the DDT, whereas from level 1 to level 3 ADS, the system requests manual control takeover from a fallback-ready user. The purpose of a DDT is to achieve a 'minimum risk condition' or 'safe state', which is dependent on the driving situation (Reschka & Maurer, 2015). When the system's capability to monitor the driving environment is compromised, the DDT fallback sequence ensures the safety of the driver with minimal effect on the traffic state. An example DDT fallback sequence can be a pullover manoeuvre to the side of the road or braking to avoid an emergency hazard. The roles of the user and the ADS for each SAE level of driving automation is shown in Figure 4 (Daimler, 2019).

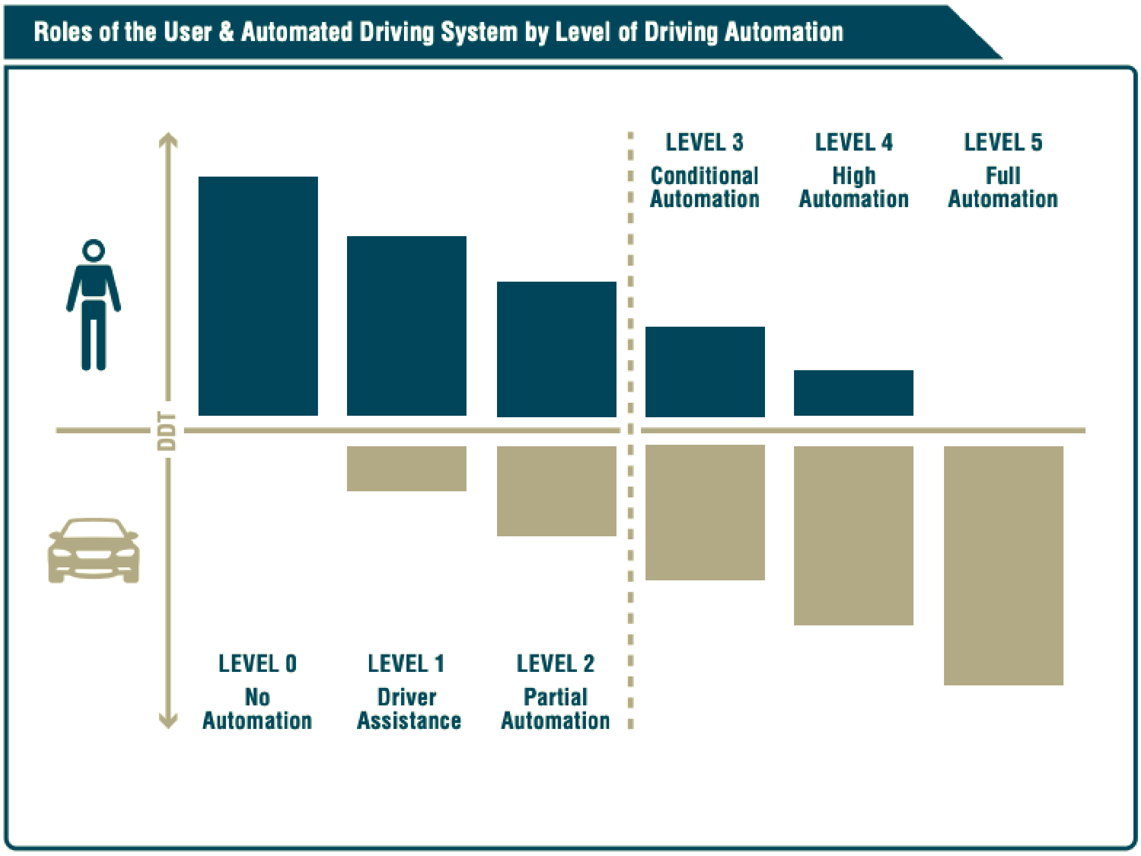

Figure 4: Roles of driver and system in SAE levels

The ADS of the vehicle must be aware of the impending ODD exit and alerts the driver for the driver to takeover. If the takeover request isn't fulfilled, the system will initiate the DDT to achieve a minimal risk condition. For the driver, it would be more comfortable if the frequency of this takeover request is less. The elimination of this transfer situations for the control of vehicle between ADS and driver is important. Hence the continuity and length of the ODD plays an important role (Kulmala et al., 2019).

The process of AV approaching an ODD exit is illustrated by SAE (SAE, 2018) is shown in Figure 5.

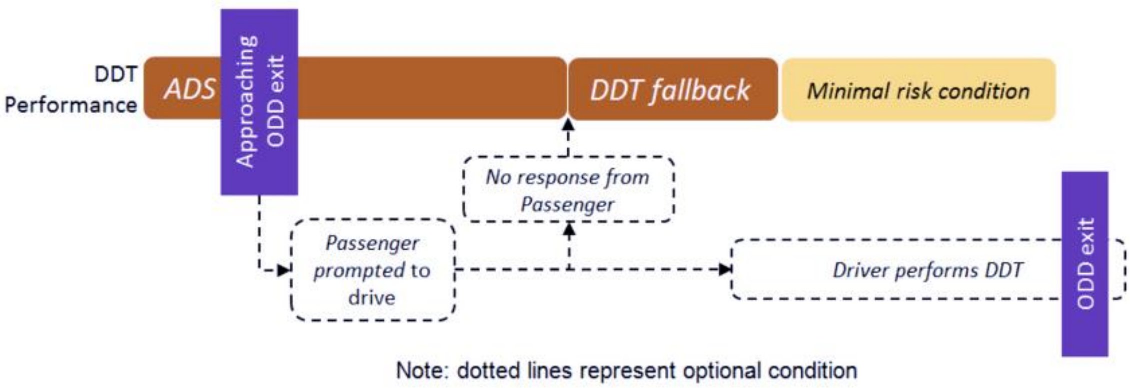

Figure 5: Performance of AV when approaching ODD exit

2.2.2 ADS in vehicles

ADS on a vehicle is capable to perform driving tasks and monitoring the driving environment (NHTSA, 2016). The human driver does not have to pay much attention in the driving circumstances that ADS assists with as long as the driving situation is within the ODD of the system. It provides various benefits that include better efficiency, safety and reduction of workload (Kalra, 2017). Driver support systems, as the name suggests, supports the driver by providing warnings, assisting in driving function and automating some driving functions. ADS replace the human driver decision making to eliminate possible human error and helps to provide a better assisted control over the vehicle (Piao & M Mcdonald, 2008). ADS cannot completely prevent the accidents from happening, but instead can reduce the severity of the accident and can better protect the drivers from some of the human factors and errors that are the cause of most of the traffic accidents (Ziebinski et al., 2017). Some of the ADS features present on vehicles in the market now are Adaptive Cruise Control (ACC), Blind-spot monitoring (BSM), Autonomous Emergency Braking System (AEBS), Lane Departure Warning System (LDW), Lane Keeping Assist (LKA), Pre-crash systems, Parking Assistance system and Forward Collision Warning (FCW).

These systems are in place to increase the overall road safety and driving comfort. Shaout et al. (2011) has provided state of the art for many of these systems and have provided an elaborate description of the benefits and drawbacks of each of these systems. ACC helps reduce driver fatigue by allowing the driver to rest their foot from the gas pedal on long drives. It also enhances fuel economy by maintaining a constant speed when the system is activated. It uses lasers or radar to match the speed of the vehicle in front. Only systems paired with an AEBS system can automatically slow down or stop when the car ahead brakes. ACC reduces the number of brake and switch operation required of the driver (Yadav & Szpytko, 2017). This reduces the burden on the driver. The system is very helpful during foggy or poor weather conditions, when the driver is not able to judge the distance between the preceding vehicles effectively. Most OEMs have their own exclusive names for ACC, like ‘Distronic Plus’ by Mercedes, ‘Active Safe’ by Porsche or ‘Traffic Jam Assist’ by Volkswagen, which is an extension of ACC that is effective in congestion as well.

Blind-spot monitoring system uses sensors mounted on side mirrors or rear bumper to detect vehicles approaching from adjacent lanes. Not only active sensors like LIDAR or ultrasound but also passive sensors have been used for blind spot detection (Kim et al., 2017). The study proposed an algorithm instead of the appearance-based feature to discriminate approaching headlights from background noise in the sensors, which was successfully implemented in simulation. The system is useful in situations where the driver is about to change lanes and the system detects a vehicle next to you. The system will then provide warnings and takes control of steering and brakes to avoid collision. Different OEMs have different names for blind-spot monitoring system, like ‘Side Assist’ by Audi, ‘Active blind spot detection’ by BMW or ‘Blind spot warning’ by Nissan. A side by side comparison of the conditions under which the system may not function is shown in Table 2.

Table 2: The comparison of boundary conditions of blind-spot monitoring system between BMW, Audi and Nissan

BMW (Radar)	Audi (Radar)	Nissan (Camera sensor)
When vehicle approaching faster than your own	If passing a vehicle with relative speed greater than 15 km/h	If vehicle approaching rapidly from behind
Speed below approximately 30 km/h or 50 km/h	Speed below 30 km/h	Speed below 32 km/h
Heavy fog, rain or snowfall	Poor weather conditions like heavy rain, snow, mist or fog	Sudden light changes like sunrise, sunset, tunnel, bridge
Tight curves or narrow lanes	Narrow lanes, wide lanes, driving at edge of lane, tight curves, slope on roadway	Wider or narrow lanes than standard lane width
If bumper is dirty or iced up		Wet roadway

From 2022, the EU have mandated all new cars and light vehicles to be equipped with AEBS. It reduces the risk of rear-end crashes by 38% at low speed (Fildes et al., 2015). While the reduction of traffic accidents is expected because of the widespread use of the system, concerns regarding many drivers using the system without proper understanding of the trigger conditions (TCs) have arisen (Mimura et al., 2020). In this study done by Mimura et. al., the trigger conditions are classified into 17 types which are taken from the manufacturer website, and broadly into two categories, namely 'do not work properly' and 'work accidently'. AEBS consists of camera and radar sensors that builds an internal model of the car environment and assesses whether emergency action is required to prevent an accident (Kopetz & Poledna, 2013). The system warns the driver with auditory warnings first, and then applies warning brake if there's no response. If there's still no response, the system applies full brakes to avoid collision. AEBS also provides brake assist to provide the additional braking force required to avoid a collision. However, combining this with the human driver's control can sometimes be the cause of an accident.

Lane support or monitoring systems like LDW and LKA assist the driver by giving warnings or taking control before imminent accident for increased safety. Both the technologies are beneficial for bettering the safety for vehicle occupants and road users. LDW continuously monitors the position of the vehicle to be within the lane markers (Narote et al., 2018) and provides warning when it steers dangerously away from the lane markers. LKA on the other hand, can automatically steer the vehicle to the pre-determined location using steering control and differential braking (Chen et al., 2018). The system alerts can be visual, auditory or vibration on steering wheel. Most systems use cameras, laser sensors mounted in the front of the vehicle or infrared to recognize the lane markings to judge when to provide the warning or to steer. Different OEMs market this system in their vehicles under different names. There are limited studies regarding the environmental and road condition effects on LDW and LKA performance. Mansor et al. (2020) suggests a new test protocol for assessing the performance of LDW and LKA systems. The system in the study was designed to activate at a speed of 65 km/h. For all the on-road test scenarios, the test vehicle successfully provided warning and automatic correction in both dry and wet conditions. However, to assess large number of driving situations that an AV can encounter, traditional testing methods will not be able to keep up. In simulated environments however, thousands of simulated scenarios can be evaluated autonomously, saving time and cost (Huang et al., 2016).

Precrash systems can detect and alert the driver to imminent accidents. The system uses radar or laser sensors to detect vehicles and alert the driver. It can even tension the seatbelts and charge the brakes to prepare for imminent collision. The different OEMs, like earlier, has different names and consists of different phases within the implementation of the system, but consists of more or less the same functionalities. The park assist system helps the driver to maneuver the vehicle into parking spaces. It uses radar to find the parallel, diagonal or perpendicular parking spots (Shaout et al., 2011).

The OEMs does not completely educate the customers in two main aspects: real function of the system and capability of the system to perform the function (Lesemann, 2008). The study done by Lesemann have compiled the then existing ICT-based systems into a roadmap, as shown in Figure 6 and it shows that the systems are becoming more complex with single functionalities getting combines into single features which are complex sensor integration. The drivers being uncertain or assuming that the satisfactory conditions for the system of one OEM will work for another is something that has to be addressed. This obvious need of a commonality or standardization will promote quick and intuitive understanding in drivers.

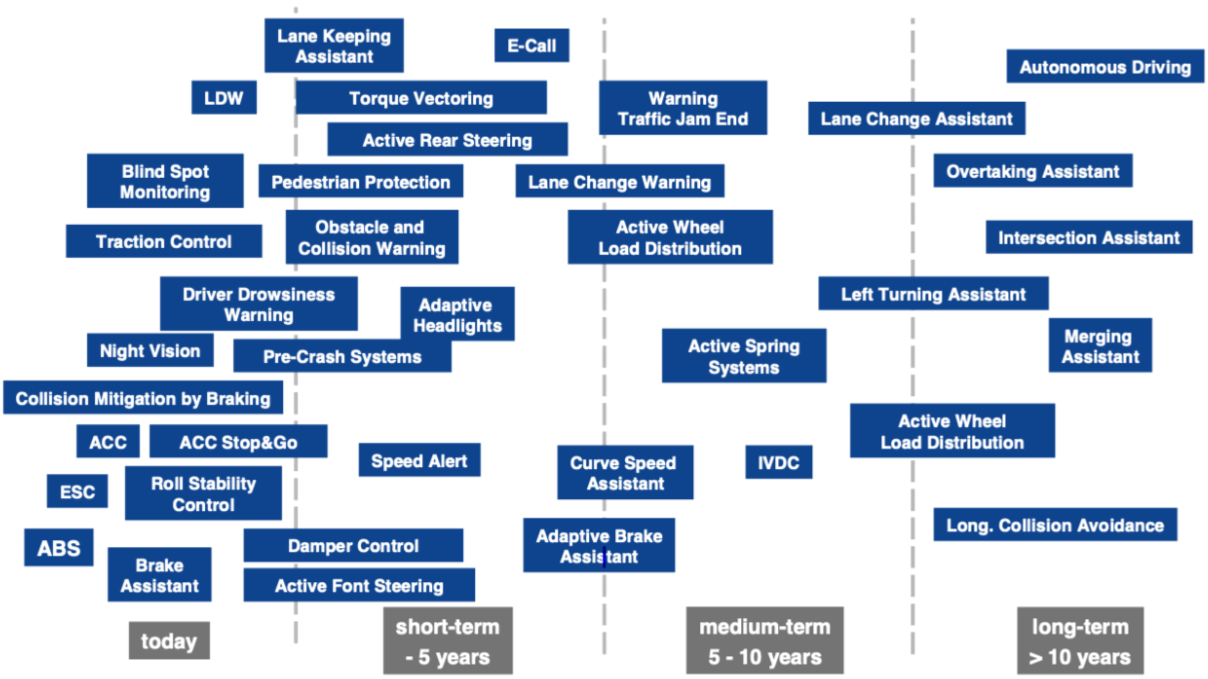

Figure 6: Roadmap of ICT-based safety systems (Lesemann, 2008)

The most concerning aspect here is that similar systems are given different names by the different OEMs, with very minor operational differences like the phases or buttons involved, but all providing the same functionality. This lack of standard or coherency can lead to much misinterpretation, like the Tesla naming its driver assistance systems as ‘Autopilot’ or ‘Full

Self Driving (FSD)' when it actually is not fully autonomous. Such a mismatch between the real capabilities of the system defined in the manual and the driver's understanding of the system (Farah et al., 2021) can lead to dangerous driving situations. Hagl & Kouabenan (2020) concludes from their research on drivers' perception of road risk and risky driving behaviours that it is of paramount importance to make drivers understand that ADS are not fool proof. They advise not to exaggerate the capabilities of the system for the sake of marketing purposes. Further studies and training session are very much needed for safer ADS implementation.

A study done by Dickie & Boyle (2009) on the drivers' understanding of ACC limitations shows that ACC is being misused in the case of partial driving automation because users expect it to perform effectively in situations when it actually cannot. This can have a negative impact on the safety benefit of such ADS features. However, the findings also show that with prolonged use, the drivers become more aware of the limitations that ACC pose and this in indicative that the drivers can be trained over time to properly and safely use the ACC system.

2.2.3 Sensors

The sensor technologies used for each of the ADS systems is mentioned in the previous section. Depending on the required functionality, the system will use a different combination of a set of sensors. There are mainly 4 types of sensor technologies used in AVs, namely radar, lidar, vision and infrared (IR).

1. Radar: It uses high frequency electromagnetic waves to measure the distance and speed. Commonly used radar systems operate at 24 GHz and at 76/77 GHz.

2. Lidar: Light Detection And Ranging (LIDAR) is a laser-based sensor. The laser increases the field of view and the resolution of lidar/radar sensors. It helps to identify road users and obstacles in the field of view.

3. Vision: It uses one or more digital video cameras for road detection and on-road object detection. Road detection includes lane line marking detection and road surface detection. This helps in lane position or object mapping in the vehicle path (Pendleton et al., 2017).

4. Infrared: It uses an IR LED and detector to measure the distance and map the roadway characteristics. This helps in object recognition and can detect objects in less visibility conditions

These sensors can be broadly classified into two types; sensors that can detect longitudinal or lateral proximity objects, and sensors that can detect roadway or in-vehicle attributes for the stability of the vehicle. For instance, a BSM system require detection of short-range rear proximity objects and these can be detected by IR, vision, short range radar or laserscanner technologies. Figure 7 from the study done by Lesemann (2008) shows the various sensor technologies and the respective ranges.

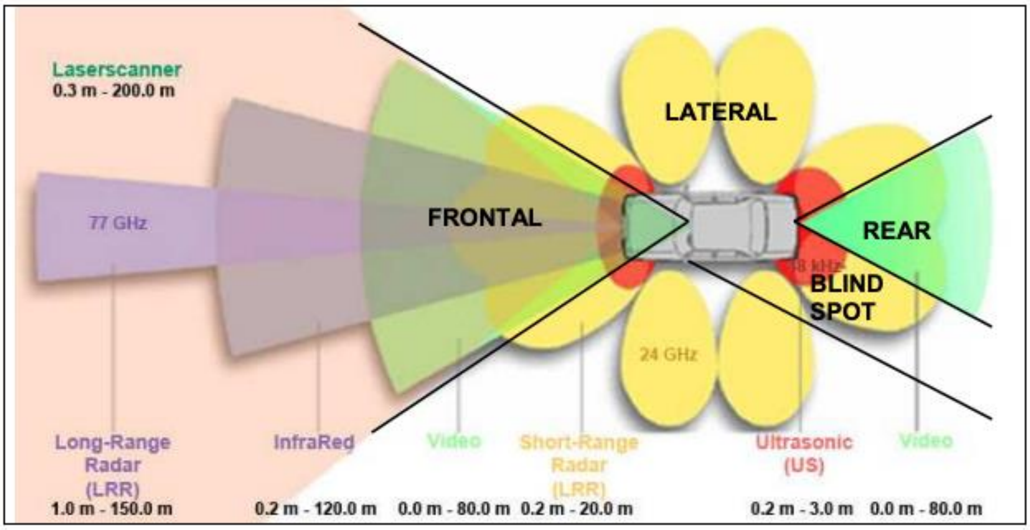

Figure 7: Sensor technologies and their ranges (Lesemann, 2008)

The most commonly used sensor for lane keeping systems is the camera sensor. Xing et al., (2018) studied about the two common approaches used for lane detection in vision-based LKS, namely conventional computer vision and novel deep learning. The computer vision-based algorithm that uses image processing for lane tracking has more computational efficiency than the deep learning-based algorithm that trains the deep neural network for lane detection. However, it was reported that the computer vision-based algorithm is unable to detect the lane markings in difficult driving situations like curves.

There are other sensors like wheel speed sensor, yaw rate sensor, acceleration sensor, steering wheel angle sensor used by OEMs in some systems. Currently, radar sensors are widely used for obstacle detection (Piao & M Mcdonald, 2008) and compared to IR or vision, radar sensors perform equally well during day and night, in most weather conditions. But a large angular reach and resolution is one of the major issues with radar-based sensors (Agogino et al., 2000) and so it lacks the resolving power to observe lane marking (Bar Hillel et al., 2014). However, compared to radar, lidar has a better angular reach and resolution. Despite that, lidar based sensors are sensitive to weather conditions that can reduce the range and can detect pseudo objects due to the road spray. The effectiveness of the sensor depends on the operative range of the sensor uses and the road/weather conditions, and therefore the application of such systems are limited (Piao & M Mcdonald, 2008).

Camera sensor can provide mono or stereo vision. The camera can map the objects ahead of the vehicle and measure the distance between the object and the vehicle. Additionally, the camera can detect the state of the motion, whether the object is stationary or is moving. Furthermore, stereo camera can be used for different ADS features like the Traffic Sign Assist (TSA) (Ziebinski et al., 2017). TSA can recognize and extract important information from traffic signs, like the speed limit, and communicates to the driver. For ACC and AEBS, the camera sensor measures the distance to the leading vehicle to avoid rear-end collisions. Similarly, for LKA and for LDW, camera is used to map the lane markings and provide the driver with warnings to change the lanes.

While cameras capture image and video data that is labelled by data analysts and interpreted by machine learning, radar and lidar provide further detail into the vehicle surrounding that can ensure more robustness in detecting and avoiding obstacles on the road. This becomes especially important in driving situations with lower visibility, like during bad weather conditions or during nighttime. However, radar sensors are relatively expensive compared to camera, and the data processing requires significant computing power from the vehicle. Tesla had recently announced that all their vehicles will be moving towards a vision only system and removed radar sensor, claiming that a vision-only system is all that is needed for full autonomy. A summary of the view angles and the maximum operational distance for the sensors is shown in Table 3 (Ziebinski et al., 2017).

Table 3: Summary of sensor view areas

	Video (front)	Infrared	Short-range Radar	Long-range Radar
View angle [deg]	50	40	80	20
Max. distance [m]	80	120	20	150

2.3. Operational Design Domain (ODD)

The problem arises when each of these OEMs manufacture their own vehicles without a common or standard ODD. There will be driving situations where high levels of automations can be granted, and in other complex situations where the ODD of the vehicle ends and the vehicle handover the control to the driver or perform a minimum risk maneuver (MRM). The ODD defined can be very specific, like a low speed public street or a single fixed route. Similarly, there is a plethora of ODD definitions in existing literature, with several visions of what the purpose of the ODD should be (Gyllenhammar et al., 2020). However, it is acknowledged that the safety of ADS depends on the list of all the attributes/conditions that the AV might encounter, i.e. the ODD of the system.

2.3.1 Standards and definitions

SAE defines the term ODD as “the operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics” (SAE, 2018). In other words, ODD defines the domain over which the automated vehicle (AV) can operate safely (Colwell et al., 2018). It defines the operating environment that the system is defined for. By definition, the ODD for Level 5 AVs is unlimited, because the vehicle is fully automated and is equipped to encounter any kind of scenario. However, for levels 1 to 4 the ODD is limited, and it is characteristic to the system, which is subject to changes depending on the OEM.

ISO 21448:2019 defines ODD as the specific conditions under which a given driving automation system is designed to function (ISO, 2019). These conditions can be spatial, temporal, legal or environmental. This standard provides specific guidance on defining the safety of an ADS system or feature for its intended functionality. The guidance is on the applicable design, verification and validation measures to achieve safety of the intended functionality (SOTIF), which is defined as the absence of unreasonable risk due to hazard resulting from functional insufficiencies of the intended functionality. The standard is intended for ADS or emergency intervention systems for which proper situational awareness is critical to safety.

UL4600 released by Underwriters Laboratories (UL), an accredited standards developer in the USA and Canada, defines ODD as the set of environments and situations the system is intended to operate within (UL, 2019). This includes not only direct environmental conditions and geographic restrictions, but also a characterization of a set of objects, events, and other conditions that will occur within the environment.

BSI PAS 1883:2020 released by the British Standards Institution (BSI) defines ODD as the operating conditions under which a given driving automation system or feature thereof is specifically designed to function safely (BSI, 2020). This includes but not limited to the environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics. The taxonomy provided in the standard with the ODD attributes is shown in Figure 8.

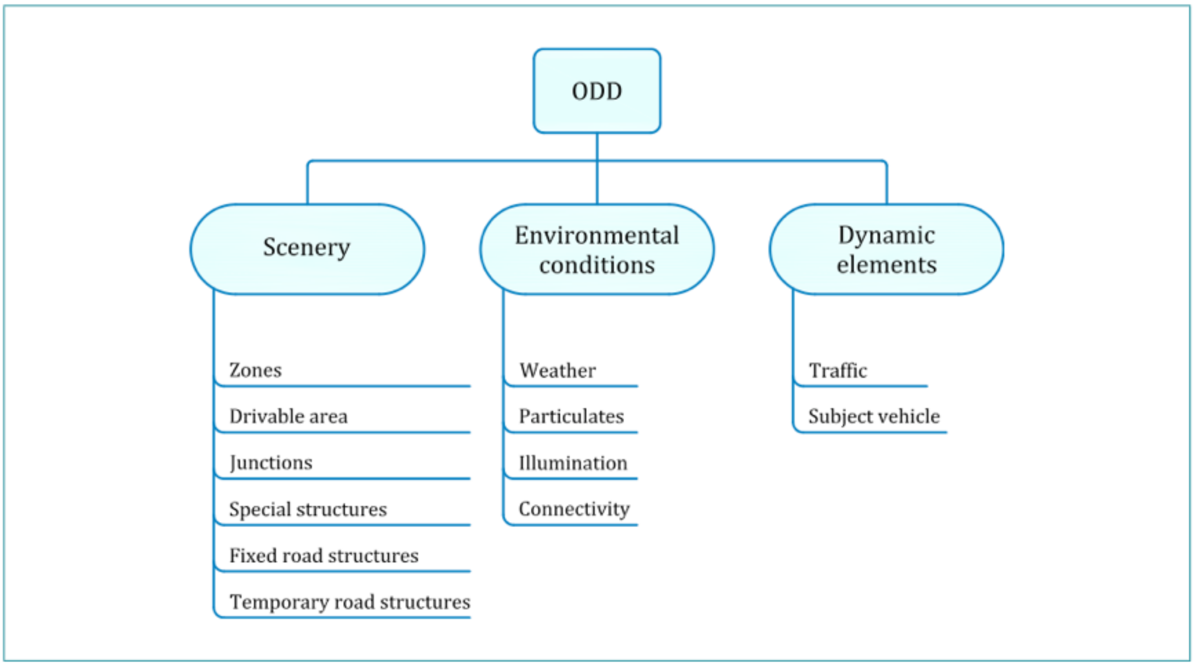

Figure 8: BSI PAS 1883:2020 taxonomy for ODD attributes

The industry program of SAE called The Automated Vehicle Safety Consortium (AVSC) provides a best practice document for describing an ODD for SAE Level 4 vehicles. It provides a conceptual framework and a lexicon that can be used by developers and OEMs to describe their ODD and to communicate this to the users (SAE, 2020). The elements in this lexicon are weather-related environmental conditions, road surface conditions, roadway infrastructure, operational constraints, road users, non-static roadside objects, and connectivity. These variables have sub-classification that entails a detailed description of an ODD definition. This best practice provides a sample ODD definition, both in a tabular and descriptive format. However, the thresholds of many of these used parameters in the ODD definition is not present. Nevertheless, the main objective of this best practice document was to establish commonly defined terms related to ODD and recommending a framework in which they can be applied, which was successful.

The U. S. Department of Transportation (USDOT) definition of ODD indicates that the ODD should be identified by the manufacturer (USDOT, 2018). Example ODD categories are provided in the Federal guidance report. OEMs are encouraged to define the ODD in their vehicles tested or deployed and document the process and procedure for assessment, testing and validation of the ADS functionality with the prescribed ODD. As per the report, an ODD describes the specific operating domains in which an ADS feature is designed to function with respect to roadway types, geographic area, speed range, lighting conditions, weather conditions and other operational constraints (NHTSA, 2017). The ODD will likely vary for each ADS feature, even if there are more than one ADS feature on a vehicle. The testing framework proposed in the report considers the potential range of ODDs and its potential test cases, using an ODD taxonomy that organized the different ODD elements identified through literature. The proposed taxonomy is shown in Figure 9.

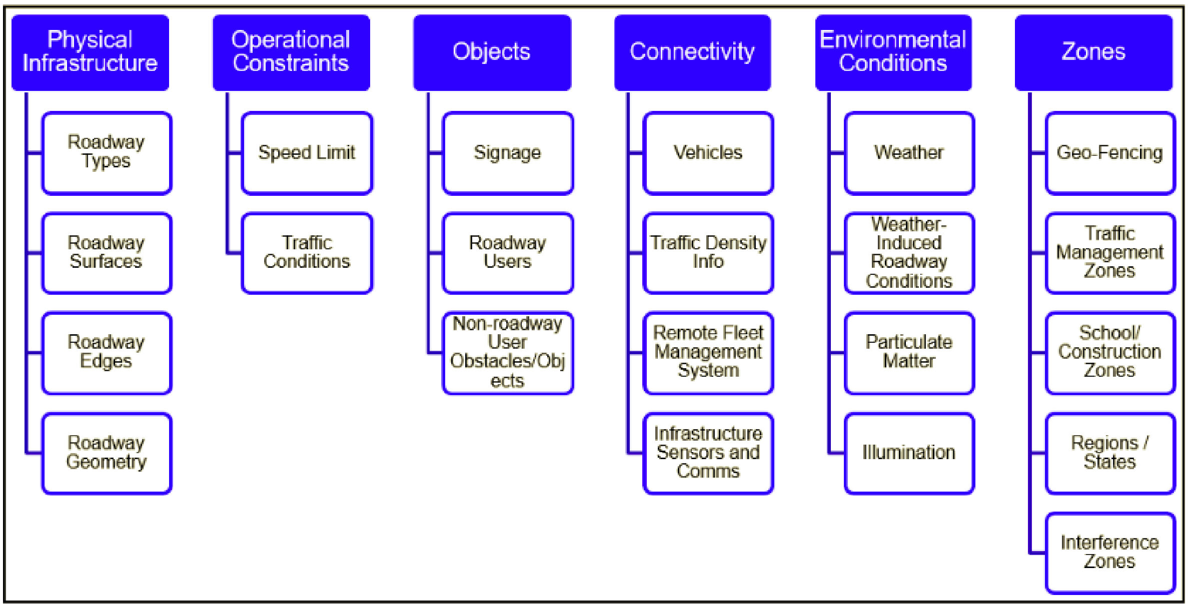

Figure 9: NHTSA taxonomy for ODD attributes (NHTSA, 2017)

Similar to the SAE classification, there exists a classification called Infrastructure Support for Automated Driving (ISAD) by Carreras et al. (2018) which represents the infrastructure support level to the AVs in levels A, B, C, D, E; A represents highest infrastructural support level and E represents the lowest level. Erhart et al. (2020) uses this classification on the Austrian motorway network for a systematic evaluation of road section where infrastructural upgrades can close certain information gaps that can help the vehicle's perception and adapt to driving situations. However, the study assumes the ISAD classification to be static, but in reality, for AVs to adapt to situations on road, the classification has to be dynamic.

2.3.2 Ongoing projects

There have been very few studies on the effectiveness of the ODD of different OEMs and even fewer research to define ODD elaborately. Currently, each OEM are building their own proprietary ODD and a future where such data is shared between companies seems very far away because there isn’t much incentive to do otherwise. Hence, a standardization has become the need of the hour. This need of standards has urged many national and international standardization bodies attempting to standardize the ODD concept. One such standardization is being done by ASAM through the project called OpenODD (ASAM, 2020). There are other standardization activities done that addresses the needs of the industry, but there still exists the gap in the industry for an ODD definition format for simulation. This is where ASAM OpenODD aims to step in for representation of this abstract ODD specification in a more well defined and standard manner that enables machines to interpret and perform analysis. This would then be a standard format which is both human readable and machine readable.

There is ISO TS 5083 which is under development which provides guidance on safety of an ADS system in its design and verification stage (ISO, 2021b). The standard aims to provide a guidance to developing and validating an AV equipped with ADS. It is intended for SAE level 3 and 4 road vehicles, including trucks and buses. Another ongoing project is the ISO/AWI 34503 which deals with the taxonomy for ODD of ADS (ISO, 2021a). This taxonomy in development will be complimented with a high-level definition format that is intended to be used by regulators and non-coders.

There is the UNECE WP.29, the world forum for harmonization of vehicle regulations, which has already embarked on regulations for ADS with significant involvement from the UK (UNECE, 2021). Although this defines the safety and environmental performance requisites for all kind of vehicles like cars, vans, trucks, buses, powered two-wheelers and even non-road mobile machineries, it aims to improve global vehicle safety and the framework in development is intended to decrease environmental pollution and energy consumption.

2.3.3 ODD attributes

Common factors affecting the ODD are the time of day, weather, road features and vehicle characteristics. Studies done by Koopman & Fratrik (2019) and Kulmala et al. (2019) in Finland lists out the many attributes related to physical and digital infrastructure that can have an effect on the ODD.

Koopman & Fratrik (2019) provides a comprehensive list of criteria, organized into eight categories that should at least be included in an ODD. There is a significant knowledge gap in the current understanding of ODD in terms of the attributes that can have an impact on the ODD and the level of importance of the attribute in the ODD definition. Filling this gap will increase knowledge not just about the ODD definition itself, but also the sensor capabilities, the developments and the impacts on AVs, paving the way to Highly Autonomous Vehicles (HAV). They also emphasize on other domain constraints that can be difficult to enumerate without significant experience. Another important aspect that is mentioned is the system's inherent equipment limitation that can impact the ODD, like the minimum illumination required by the camera sensor. The list of ODD factors that is compiled in their research is shown in Table 4.

Table 4: ODD attributes by Koopman & Fratrik (2019)

ODD characteristic	Attribute
Operational terrain, vehicle surroundings and projected vehicle path	Slope, camber, curvature, banking, coefficient of friction, road roughness, air density
Operational infrastructure	Navigation aids, traffic management devices, special road rule, vehicle to infrastructure availability
Environmental/weather conditions and sensor interference	Surface and air temperature, wind, visibility, precipitation, icing, lighting, glare
Rules of interaction	Traffic laws, social norms, customary signaling and negotiation procedures with other agents (human and autonomous)
Communication (including machine to machine and human interaction)	Modes, bandwidth, latency, stability, availability, reliability
Infrastructure data availability, correctness, level of detail and temporary deviations	Construction zones, temporary traffic rules during emergencies, traffic jams
Expected distributions of operational state space elements	Toll booths, police traffic stops

One of the deliverables of the MANTRA project by Conference of European Director of Roads (CEDR) provides a list of relevant ODD attributes and a sample ODD for a Level-4 highway pilot (Ulrich et al., 2020). The work package 4 of project MANTRA analyzes the correlation between the automated functions and the infrastructure. The expected impacts to infrastructure from the need for the required ODD for the safe deployment of automated vehicles are addressed, which can further improve the ODD coverage of the automated functions. The MANTRA project uses ODD attribute list proposed by Kulmala et al. (2019).

Kulmala et al. (2019) research from Finland as part of the European Union – European Innovation Partnership (EU-EIP) project studies the impacts and economic feasibility of automated driving and provides a roadmap and action plan. One of the main focus of the research is understanding the ODD requirements of Level 3 and Level 4 ADS like highway chauffeur and highway autopilot for passenger vehicles, buses, shuttles and freight vehicles. Since there is no standard ODD specification that could've been used for the study because it is up to the OEMs to specify the ODD of the respective ADS. For this purpose, a list of attributes was developed in the study with its respective infrastructure and state characterization, as shown in Table 5.

Table 5: ODD attributes proposed by Kulmala et al. (2019)

ODD attribute	Physical/Digital infrastructure	Static/Dynamic
Road	Physical	Static
Speed range	Physical	Static
Shoulder or kerb	Physical	Static
Road markings	Physical	Static
Traffic signs	Physical	Static
Road furniture	Physical	Static
Traffic	-	Dynamic
Time	-	Dynamic
Weather conditions	-	Dynamic
HD map	Digital	Static
Satellite positioning	Digital	Static
Communication	Digital	Static
Information system	Digital	Static

However, there are some limitations in improving the ODD coverage and extending it because of the dependency on the capabilities of the sensors and software that the OEMs use to develop the ADS. Based on pilot studies, desktop analysis, expert interviews and workshops, the ODD requirements for the following five driving functionality use cases were chosen in the MANTRA project.

- Highway autopilot including highway convoy (L4)
- Highly automated (freight) vehicles on dedicated roads (L4)
- Automated PRT (Public Rapid Transit)/shuttles in mixed traffic (L4)
- Commercial driverless vehicles (L4) as taxi services
- Driverless maintenance and road works vehicles (L4)

Since the OEM is responsible for specifying the ODD for its ADS and there is no universally accepted ODD specifications or list of attributes that can be used, the ODD specification for each of these use cases was assumed from publicly available reports, documents and discussions. The sample ODD requirements for Level-4 highway autopilot used in these studies is shown in Figure 10.

Highway autopilot incl highway convoy	
Road	Motorway or similar dual carriageways with separated driving directions, only on line sections not including toll plazas, ramps or intersections, but containing straight driving on weaving sections
Speed range	Up to 130 km/h; some systems do not work below 30-40 km/h; no restrictions 2030-
Shoulder or kerb	Safe stopping for a minimal risk condition requires a wide paved shoulder available for this purpose and not used for, e.g. hard-shoulder running. Safe refuges or shoulder areas similar to bus stops could be made available in case of narrow shoulders at intervals of e.g. 500 m on each carriageway
Road markings	Minimum quality of solid or dotted lines painted on the pavement if accurate lateral positioning is based on a camera detecting the location of the lane borders, and if the lines indicate traffic management information (e.g. no overtaking or lane change)
Traffic signs	Needed for vehicle to react to traffic control indicated by traffic signs along its trajectory to select appropriate speed or to take other required action. The sign content can be accessible via cloud, or tags and/or beacons attached to the sign [or as data inside the vehicle system (not necessarily in a cloud). could be just downloaded i.e. each time the car starts and then stored in the vehicle.]
Road furniture	Wireless radio beacons or physical landmarks possibly with sensor reflectors to support and increase positioning accuracy for AD vehicles. This is most valuable in tunnels and in totally open areas with no fixed objects nearby, or on sections with high likelihood of poor road weather conditions; or when some objects in the environment interfere with the vehicle's sensors.
Traffic	Not in incident situations with people on roadway, or other safety information cases like road work zones
Time	No specific requirements
Weather conditions	All conditions except for heavy rain or snowing, or road covered with thick layer of snow or water, or in some cases sun glare, heavy fog, or darkness without lighting, 2030- only most severe restrictions apply such as floods, thick snow, etc.
HD map	HD Map of minimum quality needed if the lane identification and accurate lateral lane positioning solution is based on satellite positioning with 3D HD map matching.
Satellite positioning	Needed if the road position, lane identification and accurate lateral lane positioning solution is based on satellite positioning with 3D HD map matching. Satellite positioning accuracy is supported by land stations (e.g. RTK) and possibly also by landmarks on problem sections (tunnels, forests, ...) and conditions (weather).
Communi-cation	Needed for end of queue, lane change, and merge situations for negotiations among vehicles and for maintaining a local dynamic map. Short latency V2V communication is a necessity for highway convoy. V2I communication can be used to receive traffic management information in addition to real-time information.
Information system	Real-time traffic information on incidents, roadworks, events, congestion and other disturbances (SRTI) on the road ahead are needed for tactical decisions on route choice, lane selection and safe speed choice. Digital rules and regulations as well as a geofencing database are also

Figure 10: ODD requirements for Level-4 highway autopilot (Kulmala et al., 2019)

A study done by Gietelink (2007) investigates methods that can be used to study the impact of the possible disturbances and faults that can impact the ADAS. Environmental and ambient conditions like temperature, rain, snow, light, vibration, electro mechanic disturbances and fog are listed as few of these disturbances. Additionally, the driver is also mentioned as an important source of disturbances, like ignorance, distraction, panicking and over-reacting. Since it is difficult to quantify the influence of these psychological driving attributes on the system, they were excluded from the research.

The research done by Seppelt et al. (2017) describes that the operational conditions (the ODD) of different ADS features vary based on factors such as vehicle's position within a lane, road curvature, lane marking number and quality, lead vehicle presence and behaviour, road type, and location of road features (such as tunnels, construction zones, tollbooths or intersections). The review done by this study also mentions the concern about the driver's use of ADS features due to potential misunderstanding of role distinctions complicated with a confusing array of ODD.

2.3.4 ODD assessment

The study done by Gyllenhammar et al. (2020) proposes a set of four strategies for the ADS to remain in its ODD by using use cases as a convenient strategy to map the different operating conditions. Using permutation and combinations on the different factors in driving (like geographical area, weather condition, road condition, lighting condition, speed of the vehicle, etc.), a variety of ODDs can be defined. The set of four strategies is proposed to ensure that the ADS does not encounter an ODD exit while activated rather than monitoring the ODD during runtime. The Farah et al. (2021) developed an analysis method to assess the ODD for LKA. A field test was conducted with different road types and conditions to check the performance of the LKA system for different ODD classification (inside the ODD, outside the ODD, not in or out). The experiment resulted in finding a mismatch between the ODD specified by the OEM in the manual and by the driver in all test situations. In many situations where the system is not intended to work (outside ODD) and situations where the system may or may not perform adequately, drivers thought it was within the ODD; meaning the driver relied on the system where the driving situation was clearly not within the ODD. Such mismatches must be addressed by the OEMs by informing or warning the driver that the vehicle is outside the ODD. Each OEM specifies the ODD differently in the same level of automation, resulting in a mismatch in the expected capabilities by the driver and actual capabilities of the system defined in the OEM manual. This showed that drivers' awareness of the system capabilities of AV is not sufficient and must be increased.

The different OEMs or vehicle manufacturers have developed their own automated driving use cases based on their own sensor choice, connectivity, positioning options, and other factors concerning the ODD that are available to them in the most economically feasible way. The only influence on these choices is from the local, national and global regulatory frameworks (Ulrich et al., 2020). It was also pointed out that in the SAE J3016 group, the ODD is specific to the specific individual ADS feature and can only be defined by the OEM, based on the technological capacities and limitations of the system (Aigner et al., 2019).

Additionally, most drivers do not read the manuals provided by the OEMs (Khastgir et al., 2018). Hence the gap between the driver's knowledge about the system and the actual capabilities grow even wider. The driving simulation study done by Khastgir et al. (2018) shines even more light into this need of making the driver aware of the system's true capabilities. The authors found that after introducing the participants of the simulator study with the knowledge about the actual capabilities and limitations of the system, the trust in the system increased as compared to when no knowledge was provided about the system. It can be argued that the results from this simulation environment cannot be directly transferred into the real world. Studying the evaluation of this trust in real-world is still ongoing. However, assessing the limitations of ODD as defined by OEMs can be effectively done by simulations than field test because it is a safer environment and is cost efficient. Additionally, a wide variety of scenarios can be tested in simulation which would be difficult to implement in real-life scenario.

A recent recommended practice from SAE (NHTSA, 2016) presents the need to monitor ODD at runtime. This is done to check whether the ADS encounter only situations that it was designed to handle safely. When the ADS leave the ODD or is about to leave the ODD, it initiates a DDT fallback to achieve minimal risk condition. Until Level 3 ADS Systems, the DDT fallback is human intervention, and for Levels 4 and 5 it is executed by the ADS itself.

If an ADS is expected to detect whether it has left its ODD, then the system must be equipped to monitor the ODD at runtime to detect the possible ODD exits (Colwell et al., 2018). This study proposes an approach to achieve maximum functionality during system failures by modifying a runtime representation of the ODD based on the system capabilities. This study on the restriction of ODD based on current system capabilities is termed as Restricted Operational Domain (ROD). The research focuses on ROD and continuous monitoring of the safe domain. The proposed approach would therefore allow an ADS to continue to operate within a safe domain during changing system capabilities.

The approach for validation of AV safety before deployment proposed by Koopman & Wagner (2018) includes multiple levels of simulation and testing. The approach puts focus on assessing the system, checking for design faults in the system and a run-time monitoring approach to manage the identified risks. Koopman and Wagner argues that HAVs has to be deployed before the technology is fully mature, in a way that continuous improvement can be done based on the approach suggested. However, many ethical issues arise on implementing imperfect technology. The authors also address the fact that this approach will yield a process of iterative improvement. The study states that at a higher level of automation, the concept of ODD will assume that the AV won't encounter a situation it cannot handle due to its highly reliable ODD or it will reliably detect that it is in a situation outside the ODD and will initiate failure response sequence. However, in reality, driving situations can be outside the ODD without being detected by the system due to the gaps in understanding the full scope of ODD definition or the gaps due to ignoring relevant ODD constraints by different OEMs.

2.3.5 ODD boundaries

García & Camacho-Torregrosa (2020) conducted on-road pilot tests for lane keeping systems where the test vehicle was run on different lane widths ranging between 2.28 m to 3.80 m. It was found that the lane keeping system cannot function on lane widths less than or equal to 2.50 m. It was also concluded that the system can always operate on lane widths greater than or equal to 2.75 m. Although the field test showed that the lane keeping system can operate in lane widths less than 2.5 m, it was reasoned that the lane widths cannot be reduces even further with the current stage of vehicle automation technology.

The study done by García et al. (2020) by testing a Level 2 vehicle on different horizontal curves established a strong relationship between the maximum speed the system can attain and the curve geometry. This new maximum speed was termed as ‘automated speed’, which is found to be lower than the design speed and operating speed in many cases. It was also clear from the study that there was a strong relationship between the speed and the disengagements. Additionally, the system performance couldn’t be tested at higher speeds above the speed limit, and at curves sharper than 170 m for speeds as low as 50 km/h. The study concluded that the automated speed is lower than the design speed for curves sharper than 550 m.

The field tests done by Reddy et al. (2020) identified the factors that affects the lane keeping performance and also investigated the effect of vehicle speed and visibility conditions on the lane keeping performance. The identified factors were lane width, type of curve, weather conditions, lighting conditions and speed. The highest lane keeping performance was observed on lane widths that are wider than 2.50 m. Similarly, only speeds higher that 90 km/h resulted in low lane keeping performance. It was also reported that curves are critical sections where the lane assistance systems might fail.

Mecheri et al. (2017) tested the different lane width variations in a driving simulator experiment. It was reported that there is no significant in-lane position difference in different lane width variations and it was attributed to the driver penalty of risk of running into oncoming traffic or lane departure. An average offset value of 34 cm toward the edge line was reported for all the four lane widths tested (2.75 m, 3.0 m, 3.25 m, 3.50 m).

The master thesis by Chaudhary (2021) on the infrastructure assessment for ODD of lane keeping system found that the test vehicle speeds of above 80 km/h resulted in better lane detection. Two test vehicles were used in the study’s experiment. It was also found that wet road conditions severely lowered the lane detection performance. It was also reported that the lane detection performance is significantly less during daytime compared to nighttime. Additionally, the test vehicle could not detect lanes of lane widths below 3 m. It was concluded in the study that the lane positioning performance was affected by lane width, lane marking type, curved sections, weather and lighting conditions for both the test vehicles.

The study done by Ghasemzadeh & Ahmed (2017) aimed to use available naturalistic driving studies data to better understand how the driver adjust their driving behaviour to compensate for increased risk from reduced visibility. The research focused on drivers’ lane keeping ability in heavy rain and slippery road conditions. A criterion of ±0.3 m was kept to flag lane wandering events in the data. Continuous lane offset greater than this threshold value was considered as a full lane change. The standard deviation of lane position (SDLP) was defined in this study on a binary level; if the average SDLP is within 0.5 m, the lane keeping performance was considered acceptable, and if it was above 0.5 m, it was considered unreliable.

Additionally, it was also reported that heavy rain conditions have a statistically positive relation with the SDLP.

2.4. Simulation

2.4.1 Advantages and disadvantages of simulation

Autonomous driving systems, as mentioned earlier, are becoming increasingly complex. Testing these systems before deployment and fine tuning them to increase efficiency is very important. Other than on-road testing, an effective method is virtual simulation. The advantage of simulation is that the testing is fairly simple, low-cost and easy to reproduce (Huang et al., 2016). Despite on-road testing being highly representative, it is limited to a lot of critical scenarios that the vehicle can encounter, along with the time and cost associated with it. Simulation on the other hand can evaluate the system efficiency of multiple driving situations in a short time. However, the reliability and accuracy are dependent on the models used in the simulation. The main edge that simulation has over on-road testing is that it allows testing of scenarios that are otherwise highly regulated on public roads due to safety concerns (Yurtsever et al., 2020).

Test cases and scenarios require a combination of ODD elements to describe a driving condition. Situations like 'concrete surface with a light mist' or 'hilly road with a specific elevation' is hard to re-create in test facilities and it may need new infrastructure to support testing (Thorn et al., 2018). ODD elements like weather is difficult to quantify and re-create, although on-road testing and functional safety design practices can be used to address such elements. A list of advantages of using simulation for testing provided by Thorn et al. (2018) is shown below:

- Controllability: can control many aspects of a single test
- Predictability: can be designed to run as specified and so there is less uncertainty about how the test will run
- Repeatability: allows multiple execution of the same test in the same way, with same inputs and initial conditions
- Scalability: allows generation of large number and type of scenarios
- Efficiency: can include a temporal component, which can be used to speed up the simulation in real time so that many tests can be run in the very short time as compared to on-road testing

The ASAM simulation guide about standardization for highly automated driving (ASAM, 2021) provides a comparison of physical testing on proving grounds and virtual testing in simulation. The comparison is shown in Table 6.

Table 6: Comparison between physical testing and simulation testing

Physical testing on proving ground	Virtual testing in simulation
• Requires test drivers • Requires test vehicles • Need large dedicated areas for proving grounds • Relies on weather conditions for certain use cases • Expensive form of testing	• Allows parallel testing • Able to create scenarios that focus on the test objectives • Enables to perform a greater number of tests in the same amount of time • Allows to replicate tests • Helps to define test focus for physical test sites

The above factors depend upon the nature of the simulation software used. The simulation can be either stochastic or deterministic. If the simulation is stochastic in nature, it can account for a certain level of unpredictability or randomness. Multiple runs with same conditions can give different outcomes. Since stochastic models are derived from probabilistic theory, the results of two simulations ran with the same input parameters should give two different outcomes because it includes random and unpredictable behaviour. Whereas simulation software that are deterministic in nature contain no random variables or randomness, and therefore will provide the same outcomes for the same set of input values assigned in multiple runs. In that sense, deterministic models are predictable.

Raju & Farah (2021) studied the different traffic microsimulation platforms available and their importance in modeling connected and automated vehicles (CAV). The research discusses the ongoing research attempts in CAV microsimulation and the limitations of the present CAV microsimulation studies. The study mentions that despite the many advantages of the microsimulation platforms, there are limitations as well. Since the simulation models requires calibration, in which some cases the microscopic data isn't readily available, certain assumptions are made. The effect of these assumptions gets reflected on the simulation outcomes as well. Additionally, another reported drawback is the simulation's processing factor, where in some microsimulation platforms it falls to a single core in the computer processor. This may not work very well with heavy traffic flow conditions, leading to the simulation crashing.

One of the main limitations of simulation testing is combinatorial explosion. This happens in testing when a test object can be described by a number of parameters, each with a range of possible values. Hence, every combination of these parametric values would be a potential use case. Consequently, it becomes unfeasible to test every possible combination of the parameters (Grindal, 2007). There are combination strategies that helps identify a subset of all the combinations based on coverage, therefore enabling the objective evaluation of the selected combinations.

2.4.2 Simulation software

Virtual simulation is an efficient way of testing complex self-driving systems, with full access to ground truth data and performance evaluation, with a wide variety of scenarios (Dosovitskiy et al., 2017). There are many simulation softwares that can be used for this purpose. Some of them include CarCraft and SurfelGAN used by Google Waymo, Webviz and The Matrix used by Cruise, and DataViz used by Uber. Most of these are proprietary tools, but there are other softwares like PreScan, Vissim, Carla, SUMO, USARSim, etc. The latter two software have been reported to lack the detail in testing, especially in driving environment (Huang et al., 2016).

Carla is an open-source simulator which is used for the validation of ADAS. It is based on Python and C++. Vehicles, buildings, weather conditions, etc. are available on the open digital assets that Carla provides. CARLA is most suited for end to end testing of unique functionalities that AV offer such as perception, mapping, localization, and vehicle control because of many built-in automated features they support (Kaur et al., 2021).

PreScan is a simulation software which follows a systematic physics-based approach for ADAS and AV system simulation. It uses MATLAB/Simulink internally for modelling the physics and motion behaviour of vehicles and pedestrians. PreScan has different libraries such as road infrastructure, weather conditions ,vehicles (also called actors) to create the scenarios. PreScan is better equipped to model dynamic movements of AV, whereas Vissim can be used to model interactions better. Prescan is a nanoscopic simulation platform that includes detailed physics-based vehicle models, the associated sensors and external programming interface like MATLAB/Simulink/C++ for detailed tracking and control of the actor during the simulation runtime. This study is not focused on interactions between users and is more particularly focused on the system functionality. PreScan provides better detailed simulations for ADAS (Kaur et al., 2021), with higher resolution than Carla. Therefore, PreScan would be ideal for this study.

The main steps or subdivisions used in PreScan is building the scenario, modelling the sensor systems, adding the control system algorithms, followed by executing the experiment, and visualization with a PreScan window called VisViewer that allows multiple perspectives such as top view or diagonal view. In the study done by Ortega et. al. (Ortega et al., 2020), the results showed that the elements modeled in the PreScan, such as the road infrastructure, sensors, and actors or vehicles, could be used in real-time scenarios. It also supports real-time data and GPS vehicle data recording, which can then be replayed later on. This is very helpful for situations which are otherwise not easy to simulate with synthetic data.

2.5. Summary

The ODD has been defined on a broader sense by many of the standardization organisations. There are few studies that provide a taxonomy for classification of the attributes relevant to the ODD definition. However, there is very limited research done on identifying the ODD boundary conditions for the different vehicle, infrastructural and environmental attributes. A cost and time efficient way to tackle this problem is using simulation to simulate the different driving situations to find the dependency of the different attributes on the ODD definition. Even so, the relevant attributes of the ODD definition are dependant on the ADS feature and there is no standard way to test the boundaries in simulation. There is a lot of research on the lane keeping system and level 2 AVs, and that can be because such vehicles are on the road now and there are reports of problems associated with it. However, the ODD aspect of the lane keeping system is not explored much. Therefore, it is imperative to expand the current understanding of the ODD and to identify which factor has an effect on the system and to what level it impacts the ODD.

3. Review of OEM manuals

The lane keeping system section from five OEM manuals were investigated. The ODD descriptions mentioned in these manuals are compiled into a table as shown in Table 7. The factors that affect the performance of the system are categorized into the list of attributes shown in the table. As per the OEMs, descriptions presented in the table under each attribute are the conditions that the vehicle may not detect the lane markings, affects the system performance or suspend the system in such cases. This table is used to get an overall idea of how the OEMs define the ODD in the OEM manual and is not intended for comparison between each other since the system's capabilities are different.

Table 7: Findings from OEM manuals

OEM Attribute	**Cadillac**	**Honda**	**Volvo**	**Nissan**	**Tesla**
Speed	Below 60 km/h, above 180 km/h	Below 72 km/h, above 145 km/h	Below 65 km/h, above 200 km/h	Below 60 km/h	Below 64 km/h, above 145 km/h
Weather	Poor weather	Fog, rain, snow	Winter	Fog, rain, snow	Heavy rain, snow, fog
Visibility	Poor visibility		Bad weather with reduced visibility		
Headway	Close vehicle in front	Close vehicle in front		Close vehicle in front	Vehicle in front
Light variations	Tunnels, sun shines directly into camera	Tunnels, dawn, dusk, light reflected on roadway		Sunrise or sunset, tunnel, under a bridge	
Shadow	Driving in shadows	Driving in shadows			Shadow on lane markers
Road condition		Low contrast; rough, bumpy or unpaved; snowy or wet	Poor road surfaces	Slippery, uneven, ice or snow on roads,	
Lane marking	Poor lane marking	Narrow, wide or changing		Multiple lane markers	
Road gradient	Banked roads	Hilly road or crest of hill			
Curves	Sharp curves	Sharp curves		Sharp curves or winding roads	Winding roads

Road type				Outside freeways or highways	
Lanes	2-lane roads	Double lines	Narrow lane width	Narrow lane width	Narrow roads

The blank cells in the table indicates that the attribute is not mentioned in the limitations of the OEM manual's lane keeping system section or in the sensor limitations. It can be seen that for the feature or functionality offered, there are different set of operating conditions across the five OEMs. For the same attribute itself, there are different ranges that the OEM has defined for the system. For instance, the speed range or the weather conditions. Cadillac has mentioned poor weather as the outside ODD condition, but the exact conditions is missing. Similarly, for headway, it is mentioned in four out of the five OEM manuals that a close vehicle in front can affect the system performance. The exact value of headway is not specified. The same applies for the radius of the curve as well, where the OEMs have only mentioned sharp curves as the outside ODD condition. However, what defines a sharp curve for a specific OEM manual is not clear. Despite the ODD boundaries being vague, the OEMs expect the drivers to always have the ODD boundaries in mind while driving. It is also noteworthy that all the attributes except speed and headway in the table is static in nature while testing in simulation. In other words, only the speed and headway can change during a simulation run as the other attributes are environmental and infrastructural conditions in the simulation. This must be taken into account while performing the ODD assessment in simulation.

4. Research Gaps and Questions

4.1. Research Gaps

The research gaps found from the literature review are:

(i) The different ODD definitions that exist across the literature does not provide a concrete set of ODD boundaries. Most of the ODD standards only provide a taxonomy to define the ODD. However, some ODD standards take operational constraints into account whereas some others don't. A similar trend is seen across the different OEMs as well. Moreover, there exist different ODD definitions in the OEM manuals for the same system or level of autonomy, with some OEMs providing very little information about the system and not providing the ODD boundaries itself. The OEMs not adhering to any standard ODD definition format or taxonomies provided makes it hard to compare the lane-keeping performance of two different vehicles as there is no single standard ODD framework that the ODD definition has to follow. This disparity in ODD creates a knowledge gap and can lead to a misunderstanding of the impact of certain attributes relevant to the ODD due to the lack of standardization.

(ii) The knowledge gap that exists between the driver's understanding of the vehicle capabilities of staying within ODD or not and the actual capability of the system to stay within the ODD. Current systems do not provide a warning when the vehicle is approaching an ODD exit condition. The only source of knowledge about the ODD boundaries for the driver is from the OEM manuals which do not explain the ODD boundary conditions clearly enough to interpret them. This leads to an additional trust in the system by the driver in driving conditions that may not be within the ODD.

(iii) The absence of a framework to assess the ODD of ADAS features in a simulation environment restricts learning more about the characteristic and underlying information about the relevant ODD attributes.

(iv) The OEM manuals define the ODD boundary of the radius of a curve as 'sharp' and lane width as 'narrow or wide lanes'. These boundary conditions are insufficient and report from the literature review shows different values for the ODD boundaries for the same system.

The first and second gaps will not be addressed by this study. However, the research done here can be used to identify the relevant features necessary for standardization in the future and to bridge the driver's understanding and the actual capability of the system. The third gap is aimed to be filled by creating a suitable framework to assess the ODD boundaries in the simulation environment. The fourth gap is aimed to be solved by mapping the different attributes relevant to the ODD into use cases in PreScan and simulating it to identify the ODD boundaries of the chosen attributes.

4.2. Research Questions

To achieve the research objective, this study aims to answer the following main research question:

"How to assess the ODD boundaries of vehicles equipped with Lane Keeping System at horizontal curves using PreScan?"

This can be answered by splitting the main question into sub research questions, as follows:

SQ1. How is the ODD of lane-keeping systems defined in the literature and the various OEM manuals so far? **(Chapter 2)**

SQ2. What are the different road or vehicle characteristics, or environmental conditions widely factored to the ODD boundary of the lane-keeping system? **(Chapter 2 and Chapter 3)**

SQ3. What are the simulation capabilities of PreScan to test the ODD boundaries of the lane-keeping system? **(Chapter 5)**

SQ4. How can the ODD boundaries of an ADAS feature like lane-keeping system be tested in a simulation environment? **(Chapter 5)**

SQ5. What are the test cases required to test the ODD boundaries for a test vehicle equipped with a lane-keeping system? **(Chapter 6 and Chapter 7)**

SQ6. How does the test vehicle's ODD compliance from the built test cases compare to the ODD boundaries of the attributes found from the literature and OEM manuals? **(Chapter 7)**

5. Research Methodology

The research follows mainly three phases as illustrated in Figure 11.

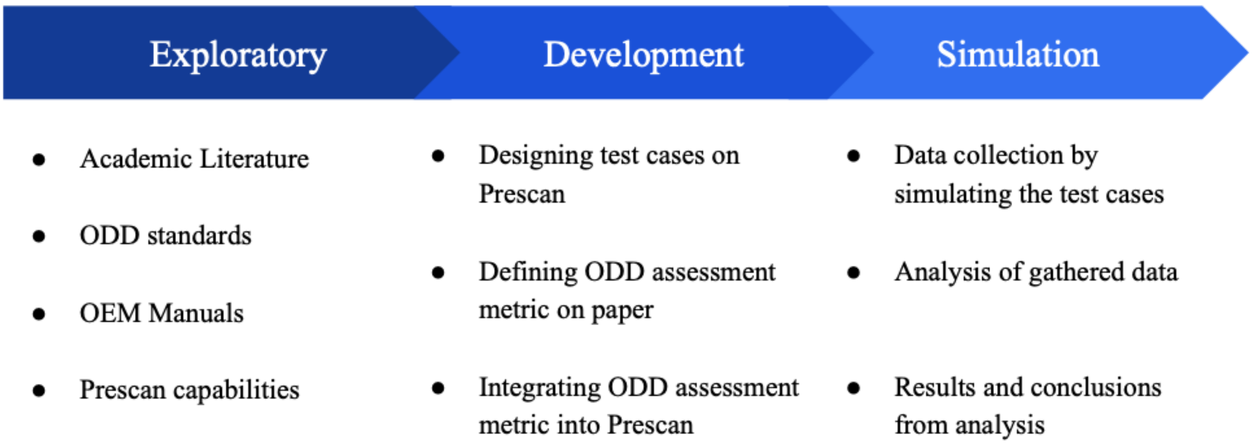

Figure 11: Research sequence followed

The exploratory phase includes the state of the art where the current ODD definitions and relevant ODD attributes are identified from academic literature, standards, and OEM manuals. Along with that, the simulation capabilities of Prescan are also investigated to understand which attributes can be tested in PreScan and therefore included in the scenarios for testing.

The development phase brings together all the findings from the exploratory phase to develop the test scenarios/use cases to be tested based on the chosen ADAS feature to be tested. A set of test cases are created from the developed use case. A test case is defined as an instantiation of the use cases in the simulation. In other words, it is the set of combinations of values assigned to the attributed used in the use case. Based on the ODD definitions found in the exploratory phase, the developed test cases are classified as either inside the ODD or outside the ODD. The ODD boundaries are also identified from the exploratory phase, which is used for the development of the use cases. Alongside this, the performance metric is created on MATLAB and then integrated into Prescan.

Finally, the simulation phase involves simulating the developed use cases, analyzing and reporting the results. A cyclical approach is used here, wherein every successive cycle, the realism of the use cases is improved, and more attributes are added. An initial ODD assessment is done before running each test case and classification of either inside or outside the ODD is followed. After the simulation run, the performance assessment result of the test case is compared with the initial ODD assessment. This approach would check if the performance of the lane-keeping system is factored in the ODD definition. A test case that is classified as inside the ODD is expected to have good lane-keeping performance, and an outside ODD test case is expected to have poor lane-keeping performance. This is checked using the performance metric and exposure metric introduced in this study and will be described later in this section. The workflow and the back end of PreScan are detailed in Appendix A: Prescan.

5.1. Choices and assumptions

Based on the findings from the exploratory phase, the lane-keeping system was chosen as the ADAS feature to be tested in this study. This system was chosen due to the availability of resources in Prescan based on the lane-keeping system. Additionally, there are not many studies in the literature that has tested this system in simulation with the different attributes. There was also the plan to expand to other functionalities/features, but due to time restrictions, it was not possible. The OEM manuals that were investigated for identifying the relevant ODD attributes for the lane-keeping systems are listed below with the name they have mentioned for their respective lane-keeping system:

- Cadillac Escalade: Lane keep assist
- Honda Clarity: Lane keeping assist system
- Volvo S90: Lane keeping aid
- Nissan Leaf: Intelligent lane intervention
- Tesla Model S: Lane assist

The chosen test vehicle on Prescan was the Mazda RX8. This was one of the most used test vehicles in Prescan for demo experiments. In addition, for this research, the model of the vehicle is not very relevant since the focus is more on the system performance and that depends solely on the sensors equipped. The only difference if another model of vehicle is used will be the dimensions of the vehicle. First, a default lane keeping algorithm that brings the test vehicle to the lane centre purely based on the intended trajectory of the vehicle was implemented by equipping the test vehicle with a lane marker sensor by Prescan. However, this was too simplistic and full of errors. This sensor did not appear to be affected by weather conditions and also showed a strong swerving nature between the lane markings. Four out of the five OEM manuals that were investigated used a camera sensor for the lane-keeping system. Hence, a camera sensor was equipped on the test vehicle for more realistic simulation runs. The lane-keeping algorithm was provided by Siemens for which the camera sensor connects to the Simulink end and tries to bring the test vehicle to the lane centre for the entire path.

5.2. Simulation setup

The dimensions of the test vehicle are 4.43 m x 1.86 m x 1.31 m. The simulation runs with a time step of 0.05 seconds. At each time step, the deviation from the lane centre is measured, known as the lateral position or the lateral offset. The right-hand coordinate system is used, where the distance towards the right is positive and towards the left is negative, as shown in Figure 12. The lateral offset data of each time step is recorded and the data points of the test vehicle at the curve section is filtered out.

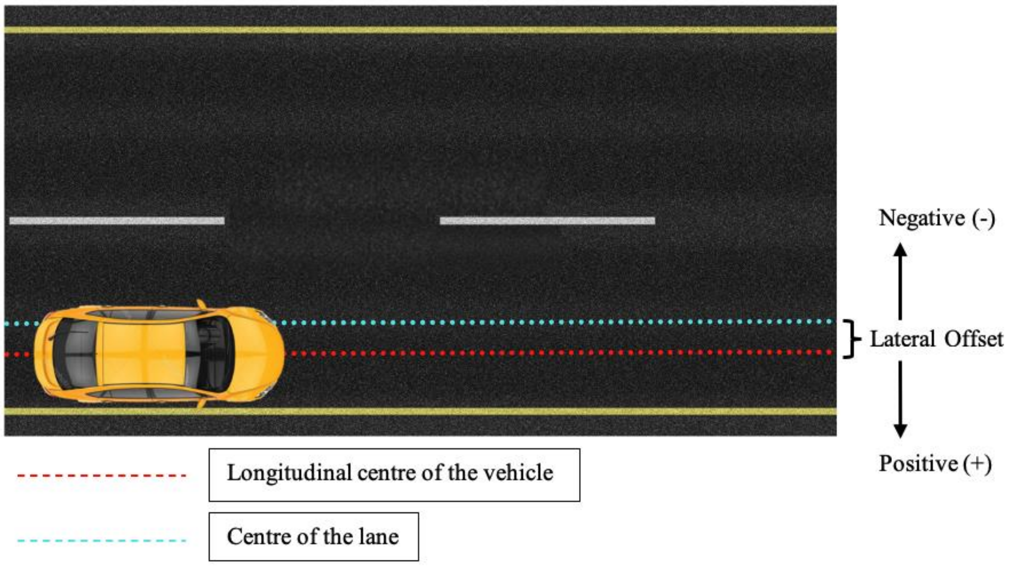

Figure 12: Measurement of lateral offset

5.2.1. Environmental conditions

Prescan allows testing of precipitation conditions like fog, rain and snow. The preset levels of rain and snow available to test in Prescan are shown in Table 8 and Table 9 respectively.

Table 8: Available levels of rain in Prescan

Level of precipitation	Velocity of rain (m/s)	Diameter of particle (mm)
Drizzle	-1.0	0.77
Very light rain	-3.2	0.77
Light rain	-3.8	0.93
Moderate rain	-4.2	1.06
Heavy rain	-4.7	1.23
Very heavy rain	-5.6	1.57
Extreme rain	-6.6	2.03

Table 9: Available levels of snow in Prescan

Level of precipitation	Velocity of snow (m/s)	Diameter of particle (mm)
Light snow	-1.0	2.5
Moderate snow	-1.0	5.0
Heavy snow	-1.0	10.0
Extreme snow	-1.0	20.0

The quality of the shadow created by the sun on objects can be tested in Prescan on a scale of low, medium and high. However, this is not taken into account in this study because including shadow as an attribute would inherently add shadows of the test vehicle in the use case.

Consequently, this would require adding the position of the sun as well in the design of experiments. However, due to the limitation of combinatorial explosion, the effect of shadow was given the lowest priority and hence the sun shadow setting is always set to low.

5.2.2. Vehicle dynamics

Prescan provides a 'Simple Dynamics' model to easily simulate the vehicle dynamics behaviour. There are two available vehicle dynamics options, namely 'simple 2D' and 'simple 3D'. Simple 2D vehicle dynamics refers to a model that is capable of simulating a test vehicle's longitudinal, lateral and roll motion. This is used on Prescan's 2D roads, i.e. flat roads. A simple 3D vehicle dynamics model can simulate the test vehicle's longitudinal, lateral, vertical, pitch and roll motion, and includes the suspensions model as well. It's used on Prescan's 3D roads, i.e. roads with a height profile or banking.

When the test vehicle has to steer, the vehicle dynamics model converts the angle into a wheel's rotation angle using a steering factor. This is used to calculate the lateral forces generated by the tyres. There is a simple model in Prescan that takes the slip angle into account, i.e. it takes the deformation of the tyre into account. The equilibrium of these lateral forces and the inertial force results in a yaw moment, which is then applied to the vehicle's centre of gravity and generates a yaw angle. This yaw angle is applied to the steering and makes the test vehicle steer.

There is the path follower block in Simulink that translates a trajectory (consists of the path and speed profile) into steering angle input for the vehicle dynamics Simulink block. The system keeps the test vehicle aligned with the lane centre by applying a steering correction to the test vehicle whenever it deviates from it.

5.2.3. Sensor properties

A camera sensor is equipped on the test vehicle. The camera sensor has a minimum detection range of 0.1 m and a maximum detection range of 250 m. The position and orientation of the camera on the test vehicle are shown in Figure 13. Prescan allows the implementation of monovision or stereo vision configuration. A monovision camera is equipped on the test vehicle. The frame rate of the camera is 20 fps and has a focal length of 7.5 mm. The control algorithm associated with the camera sensor is lane centering in nature and tries to bring the test vehicle to the centre of the lane of the intended trajectory. The controller is triggered immediately when the test vehicle deviates from the lane centre. In such situations with deviation, the distance error between the lane centre and the actual trajectory is calculated at a timestep and is fed into the vehicle dynamics as a steering angle to bring the vehicle back to the lane centre. It is a linear control system where the distance error is proportional to the steering angle. Therefore, the system will be one timestep behind where the prediction is made from the values of the previous timestep. Figure 14 shows what the camera sensor sees in the simulation.

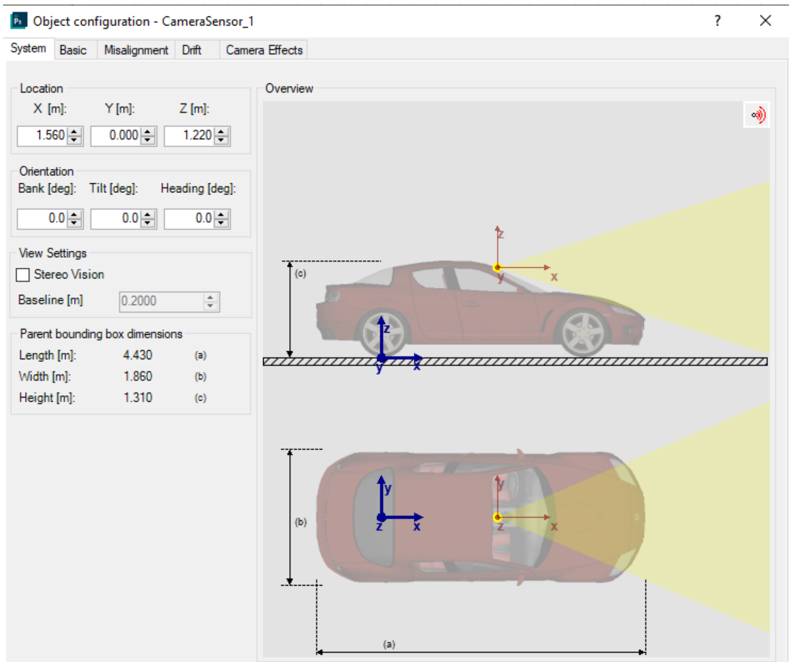

Figure 13: Camera sensor position on the test vehicle

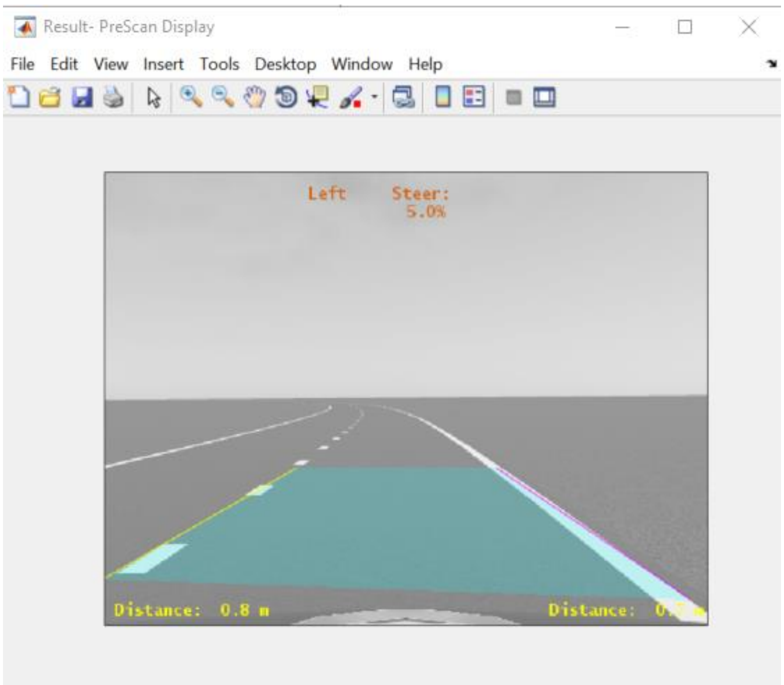

Figure 14: Camera sensor view

5.2.4. Infrastructure

The test vehicle follows the Netherlands' rule of right-hand traffic. All the test cases involve the test vehicle taking a left curve, and right curves aren't used since the impact of the type of curve is not the focus of this research. For experiments during nighttime, there are no streetlamps provided for the roads. Hence the only source of light is the vehicle headlights and the fog lamps. Although superelevation is possible on Prescan, it is not possible to provide superelevation at a curve without elevating the roadway with a ramp segment provided in

Prescan (see Figure 15). If this is done, then the curve will be elevated, and the vehicle has to climb uphill before every curve and downhill after the curve. Since it is not very realistic to elevate the road segment at every curve and it’s not possible to predict the effect it might have on the sensor, the superelevation is not provided at curve segments for this research.

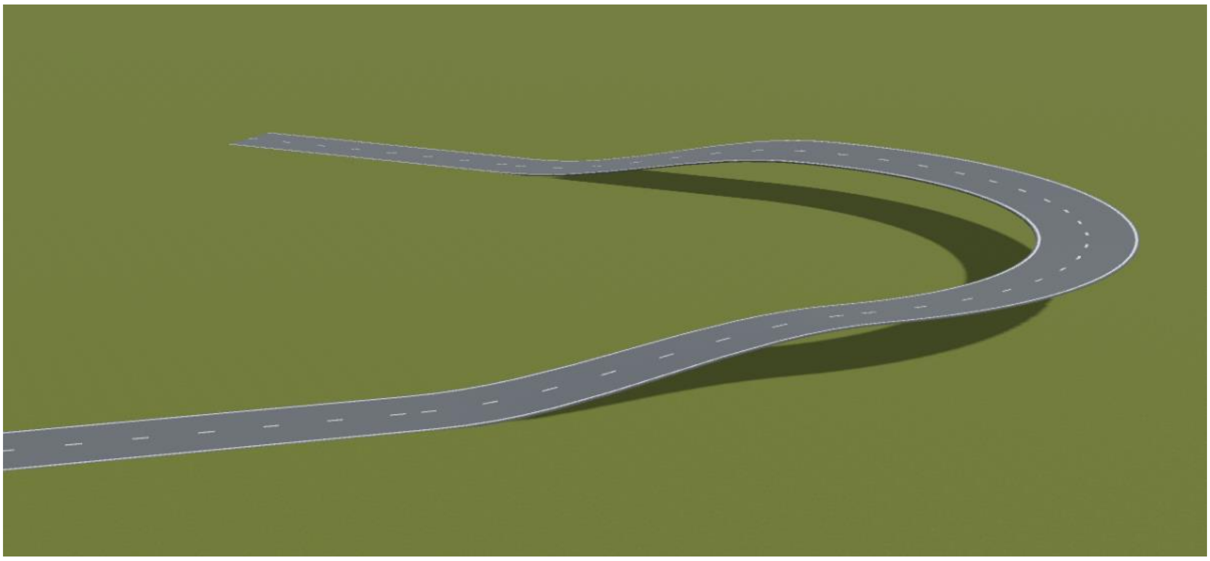

Figure 15: Banking of roads in Prescan

5.3. Initial ODD assumption

The sample ODD of the attributes tested is developed based on the findings from the literature review and is shown in Table 10. It is assumed before running the use cases that these driving situations are inside ODD. The ODD boundary conditions for speed and weather conditions are acquired from the OEM manuals. The boundary conditions of lane width are found from literature and for the radius of curvature, the Rijkswaterstaat guidelines are used. This is then compared with the results after the simulation runs.

Table 10: Sample inside ODD conditions from the literature

Attribute	Boundary conditions
Speed	60 km/h to 140 km/h
Lane width	Greater than or equal to 2.75 m
Weather conditions	Sunny and light precipitation
Radius of curvature	Greater than or equal to 750 m

An example driving situation that is within the ODD of its lane-keeping system based on this sample ODD would be *the test vehicle moving at a speed of 100 km/h in a lane of 3.5 m width during the daytime without any precipitation at a curve of 750 m radius*.

5.4. Performance metric

Since most of the attributes chosen are static like the infrastructure and environmental conditions, it is difficult to assess the ODD of the test vehicle during run time. Moreover, Prescan does not allow the extraction of the infrastructural details from the graphical user interface (GUI) to the Simulink end. Therefore, an initial assumption of the ODD boundaries of the test vehicle is formulated before running the test cases. A performance assessment of the test cases is done after running the test cases using the 'performance assessment' metric introduced, the mean lateral offset and the maximum lateral offset of each test case. The assessment metric will be a function of the lateral offset of the test vehicle, which is compared to the acceptable lateral offset threshold of 0.3 m, which was obtained from section 2.3.5 of the literature review. This performance assessment metric is then used to calculate the 'exposure' of each test case, which is the ratio of the simulation time for which the test vehicle was within the 0.3 m lateral offset and the total simulation time when the vehicle was at the curve. The results from the lane-keeping performance are finally compared with the initial ODD assessment done of the test cases. During the simulation run of a test case, speed and lateral offset are the only values that can change values. However, since each test case has the test vehicle moving at a constant speed, the lateral offset is the only dynamic value. The 0.3 m value used in the metric will be termed as the 'Offset threshold value' in this study.

The metric integrated into Prescan on the Simulink end tests the lateral offset of the test vehicle at each time step. The lane-keeping performance assessment equation is shown in Equation 1, where 'u_i' is the speed of the test vehicle in km/h at the timestep i, 'lateral $offset_i$' is the lateral offset of the test vehicle at timestep i and 'performance' is the binary variable that returns the value 1 if the test vehicle deviates more than the 0.3 m offset threshold value, and 0 if the test vehicle is well within the 0.3 m offset threshold value.

$$Performance = \begin{cases} \mathbf{1}, if(lateral\ offset_i \leq 0.3\ m) \\ \mathbf{0}, otherwise \end{cases}$$

Equation 1: Performance assessment metric equation

This equation will be applied iteratively at each time step i for the whole simulation run. This equation can essentially map all the static attributes identified that are relevant to the ODD. Since the ODD boundary of speed is explicitly mentioned in the OEM manuals, it is assumed that the speed range has a particular effect on the lane-keeping performance of the system.

5.5. Design of Experiments

The use cases were built based on the minimum arc length and minimum horizontal curve radius guidelines by Rijkswaterstaat as shown in Table 11 and Figure 16, and based on the ODD attributes identified from the exploratory phase.

Table 11: Rijkswaterstaat guidelines for minimum arc length

Lane type	Design speed (km/h)	Minimum arc length (m)
Main road	120	100
Non-main road on base of design speed	90	75
	70	60
	50	40

situation	minimum curve radius per design speed for non-main runways 120 km/h*	90 km/h	70 km/h	50 km/h
counter cant	4,000 m	N/A**	N/A**	N/A**
2.5% cant	1,500 m	700 m	350 m	N/A***
3.0% cant	1,350 m	630 m	315 m	N/A***
3.5% cant	1,200 m	560 m	N/A***	N/A***
4.0% cant	1,050 m	490 m	N/A***	N/A***
4.5% cant	900 m	420 m	N/A***	N/A***
5.0% cant	750 m	350 m	180 m	85 m
5.5% cant		340 m	175 m	85 m
6.0% cant		330 m	170 m	85 m
6.5% cant			165 m	80 m
7.0% cant			160 m	80 m

* Design speed 120 km/h only applies to parallel runways with a large proportion of long-distance traffic, which therefore play an important role in the network.

** For arcs with a design speed of 90 km/h, 70 km/h and 50 km/h, no counter cant applied.

Figure 16: Rijkswaterstaat guidelines for minimum horizontal curve radius

A design speed of 120 km/h is considered for the use cases since the recent UN regulation for Automated Lane-Keeping System (ALKS) allows vehicles equipped with the lane-keeping system only on motorways and expressways without any interactions with pedestrians or cyclists (UNECE, 2021). For a design speed of 120 km/h, the minimum length of the horizontal curve is 100 m. The curve length used in all the use cases is 300 m. The same curve length is used in all the use cases so that for all the test cases with the same speed, the vehicle will enter and leave the curve at the same time. This would be beneficial in comparing the data between the different test cases. Assuming a 5 per cent superelevation in the Rijkswaterstaat guidelines for minimum horizontal curve radius, the minimum curve radius is 750 m. Hence the curves 750 m, 900 m and 1200 m are chosen for the testing. Five values of speed are taken for each use case, namely the design speed, two values of speed above and below design speed. Therefore, the speed values used for testing are 100 km/h, 110 km/h ,120 km/h, 130 km/h and 140 km/h. As for the lane width, since the lane width has an impact on the performance of the system, the values between 2.5 metres to 4 metres at steps of 0.25 metres are tested (eg: 2.5 m, 2.75 m, 3.0 m). However, the simulation does not work for lane widths less than 2.6 m and greater than 3.7 m. Also, for 3.7 m lane width, in most of the test cases, the vehicle was either going outside the roadway and entering back, or the simulation wasn't working. Hence 3.7 m was omitted from the simulation. So, the lane width values tested in the use cases are 2.6 m, 2.75 m, 3.0 m, 3.25 m, 3.5 m, and 3.6 m. Rain and snow weather conditions are tested, along with fog conditions. For both rain and snow, heavy and extreme levels for each weather condition according to Table 8 and Table 9 are tested. All combinations of driving speed, the radius of curve and lane width are tested. Due to the limitation of combinatorial explosion, the impact of weather is only tested for a limited set of use cases.

The level of abstraction for the design of use cases was inspired by the approach used by Project Pegasus (Steininger, 2019), as shown in Figure 17.

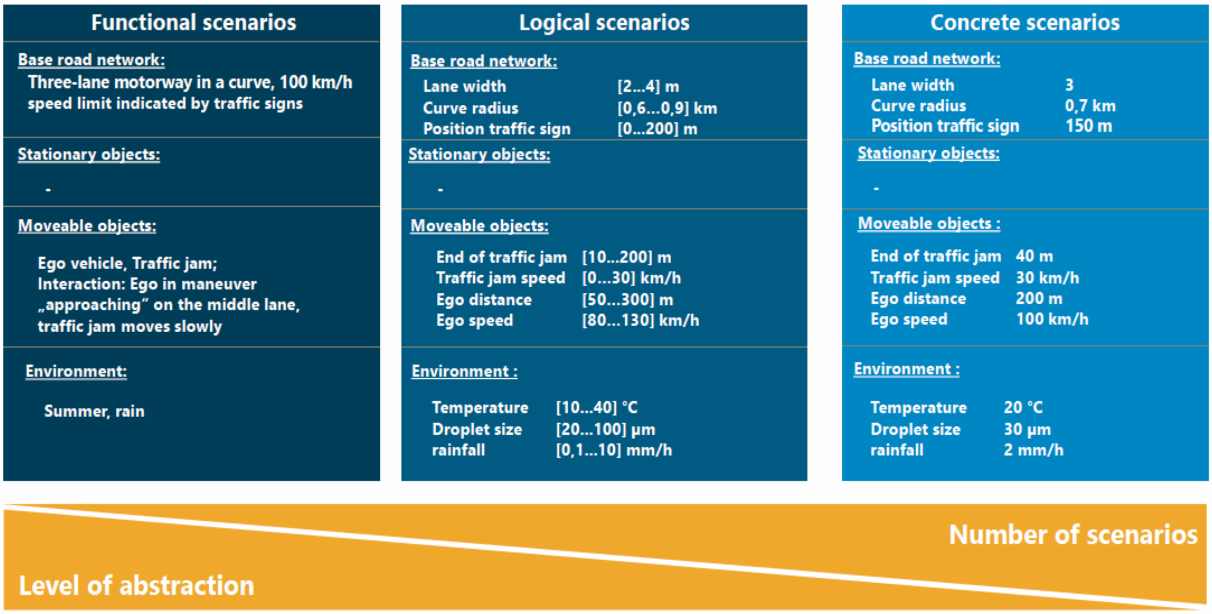

Figure 17: Level of abstraction for scenarios by Project Pegasus (Steininger, 2019)

The same level of abstraction is applied to this study as well, and the respective use case, value range for test cases and a sample test case are shown in Table 12. The functional scenario is the same as a use case that describes the driving situation. The logical scenario describes the range of values that can be assigned to the attributes used in the use case. The concrete scenario is the test case which has the specific values assigned to chosen attributes in the use case.

Table 12: Level of abstraction for scenarios

Use case	Value range for test cases	Test case (example)
Test vehicle at a curve of design speed 120 km/h	Radius of curve (m): [750, 900, 1200]	Test vehicle moving at a constant speed of 140 km/h at a curve of radius 750 m in a motorway of design speed 120 km/h and lane width of 3.5 m in light rain weather condition.
	Test speed (km/h): [100, 110, 120, 130, 140]	
	Lane width (m): [2.6, 2.75, 3.0, 3.25, 3.5, 3.6]	
	Precipitation: [Dry, Fog, Heavy rain, Extreme rain, Heavy snow, Extreme snow]	

Since Prescan is a physics-based simulation platform and deterministic in nature, there is no need to have multiple runs for the same set of values. Hence, the test cases are run only once with the set of combinations of values from the attributes chosen.

Without taking precipitation into account, all the combinations of the radius of the curve, test vehicle speed and lane width are tested; a total of 90 test cases. As for precipitation, all the combinations aren't considered, but instead just to see the impact of weather conditions on the other attributes, only lane widths 2.6 m and 3.6 m, and speeds 100 km/h and 120 km/h are tested for horizontal curve radii of 750 m and 900 m with the weather conditions fog, rain and snow. Since there are 2 levels of precipitation each in rain and snow, another 40 test cases are run for the weather variations. Therefore, a total of 130 test cases are done in this study.

5.6. Analysis

The lateral offset data extracted from the simulation runs at each time step is analysed to understand the impact of the chosen ODD attributes on the performance of the lane-keeping system equipped on the test vehicle. The 'mean lateral offset' is calculated by averaging the lateral offsets of all the data points of the vehicle at the curve segment (see Equation 2). The limits 'm' and 'n' in the equation are the timesteps at which the test vehicle enters and leaves the curve respectively. The 'maximum lateral offset' values are also extracted for each test case as shown in Equation 3.

$$Mean\ lateral\ offset = \frac{\sum_{i=m}^{n} lateral\ offset_i}{n - m}$$

Equation 2: Mean lateral offset equation

$$Maximum\ lateral\ offset = \max_{i=m\ to\ n}(lateral\ offset_i)$$

Equation 3: Maximum lateral offset equation

The lateral offset data from each timestep is converted into a 'Performance' value using Equation 1 based on the acceptable lateral offset value of 0.3 m. This data is then converted into time for which the vehicle was within the acceptable lateral offset and time for which the vehicle was outside the acceptable lateral offset at the curve segment. An 'exposure' metric is introduced to compare the different test cases since speed is one of the ODD attributes tested and the test vehicle takes different times at the curve for different speeds in each simulation run. The formula for calculating 'exposure' is shown in Equation 4. From the analysis of this performance data, the critical and non-critical ODD attributes are aimed to be found and the performance of each test case is compared against the initial ODD boundary assessment.

$$Exposure = \frac{simulation\ time\ when\ the\ lateral\ offset\ of\ ego\ vehicle\ is\ within\ 0.3\ m}{simulation\ time\ when\ the\ vehicle\ is\ at\ the\ curve}$$

Equation 4: Exposure metric equation

The simulation data is reported in two sets, first of the test cases without any precipitation and then the data of the test cases with precipitation. The mean lateral offset data, the maximum lateral offset data and the exposure data is reported for all the test cases. The complete dataset is presented in Appendix B: Simulation Data.

The analysis is also done separately for the test cases without any precipitation first and then for the test cases with precipitation. For the test cases without precipitation, the three attributes tested in the collected dataset is the speed of the vehicle, the radius of curvature and the lane width. The impact of the variation of the three attributes is observed one at a time. One of the attributes is varied and the other two are kept constant. The effect of the change in that attribute is observed and reported. Similarly, the variations of the other two attributes are looked at separately and the impact is reported. For example, the impact of the variation in speed is observed for the same lane width and radius of curvature, as illustrated in Figure 18.

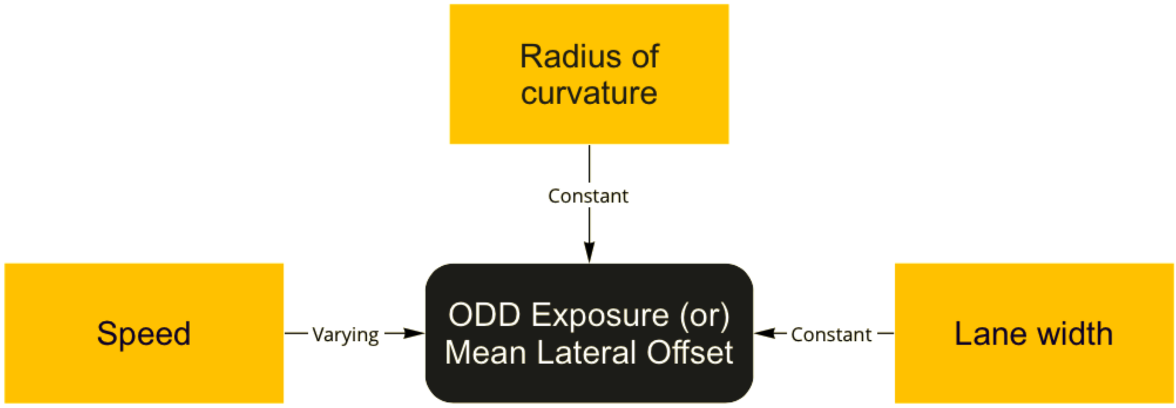

Figure 18: Example analysis iteration

For the simulation data with precipitation, a similar approach is used to check the effect of weather, speed change, lane width change and radius of curvature change separately. For both sets of data, the lateral offset for each test case is plotted along the simulation time and is shown in Appendix C: Lateral offset variations.

6. Analysis

The simulation runs are done in two sets, the first set without precipitation and the second set with precipitation. After running the test cases, the mean and maximum lateral offset values in metres at the curve segment for each test case is compiled into a single table and the exposure data are also compiled into another table for comparison.

In the case of test cases with precipitation, only the test cases with wider lane width and higher speed have a maximum lateral offset more than the offset threshold value of 0.3 m, and for the test case of a vehicle at 120 km/h at 2.6 m lane width for 750 m radius curve. The other test cases will give exposure values of 1 because it's within the offset threshold throughout the simulation run. The mean lateral offsets for all these test cases are well within 0.3 m.

6.1. Test cases without precipitation

One attribute is varied at a time and then the change in exposure or mean lateral offset is observed. The maximum lateral offset is not chosen for comparison here because due to the lack of vehicle to infrastructure communication (V2I) in the simulation as the vehicle is not expecting the curve and because of that, there is an initial spike in the lateral offset value. There is an initial peak visible for all the lane width variations and this can be attributed to the lack of V2I communication. For example, Figure 19 shows the lateral offset variations for the different lane widths for a vehicle speed of 140 km/h and a radius of the curve of 750 m.

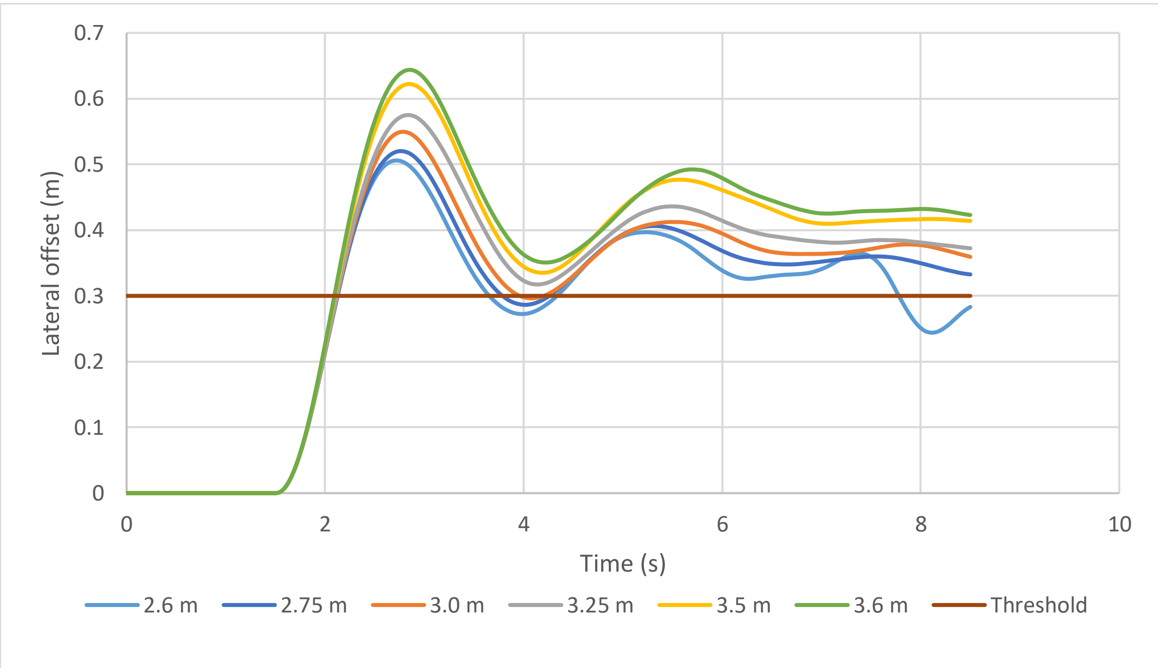

Figure 19: Lateral offset variation for different lane widths in 140 km/h and 750 m radius condition

6.1.1. Mean lateral offset comparison

The comparison of the mean lateral offset is done based on two sets of bar charts. The first set of bar charts comprises the lateral offset variations for the three different radii tested in three separate charts. Each chart consists of the mean lateral offset values for varying speed and lane widths. The second set of bar charts maps the variation in the radius of curvature and lane width for a specific speed. Figure 20, Figure 21 and Figure 22 shows the mean lateral offset variations for radii 750 m, 900 m and 1200 m respectively.

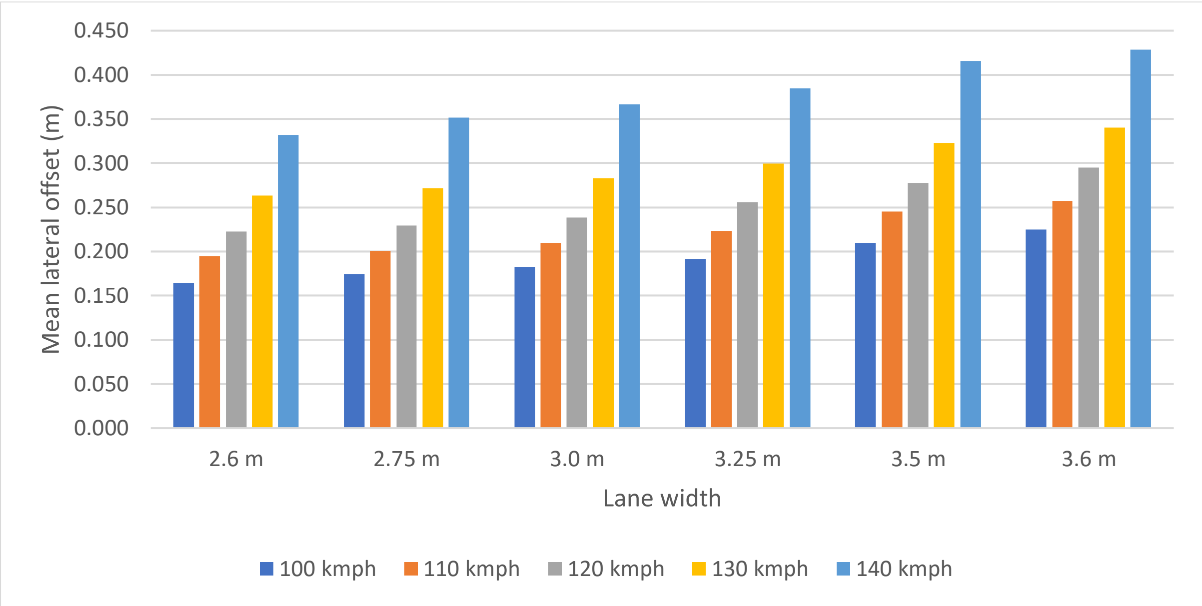

Figure 20: Mean lateral offset variations for 750 m radius curve

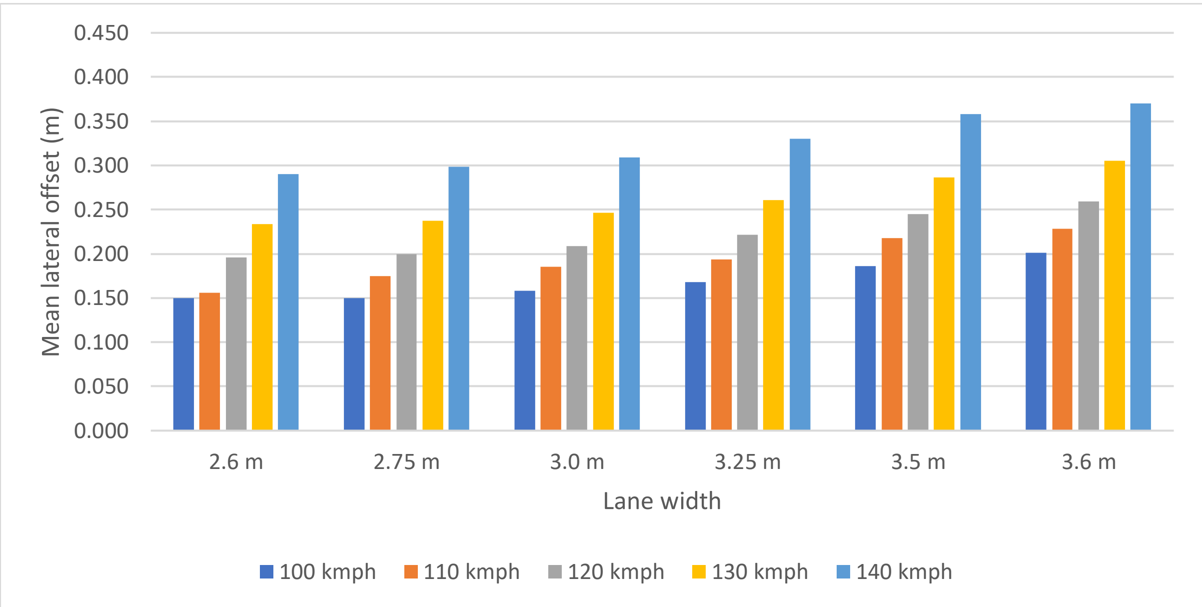

Figure 21: Mean lateral offset variations for 900 m radius curve

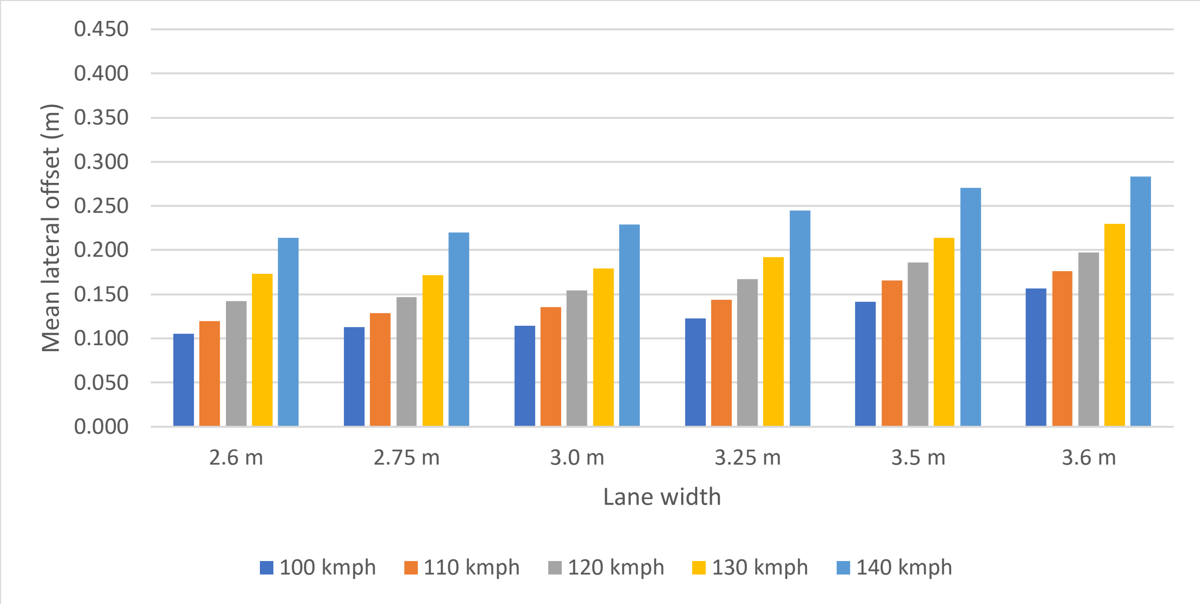

Figure 22: Mean lateral offset variations for 1200 m radius curve

It can be seen from these three figures that there is a positive correlation between the mean lateral offset and lane width. For the same speed (the dark blue bar), as lane width increases, the mean lateral offset increases as well. Similarly, for the same lane width, as speed increases, the mean lateral offset increases at a higher rate. The variations along different radii for 100 km/h, 120 km/h and 140 km/h are shown in Figure 23, Figure 24 and Figure 25 respectively.

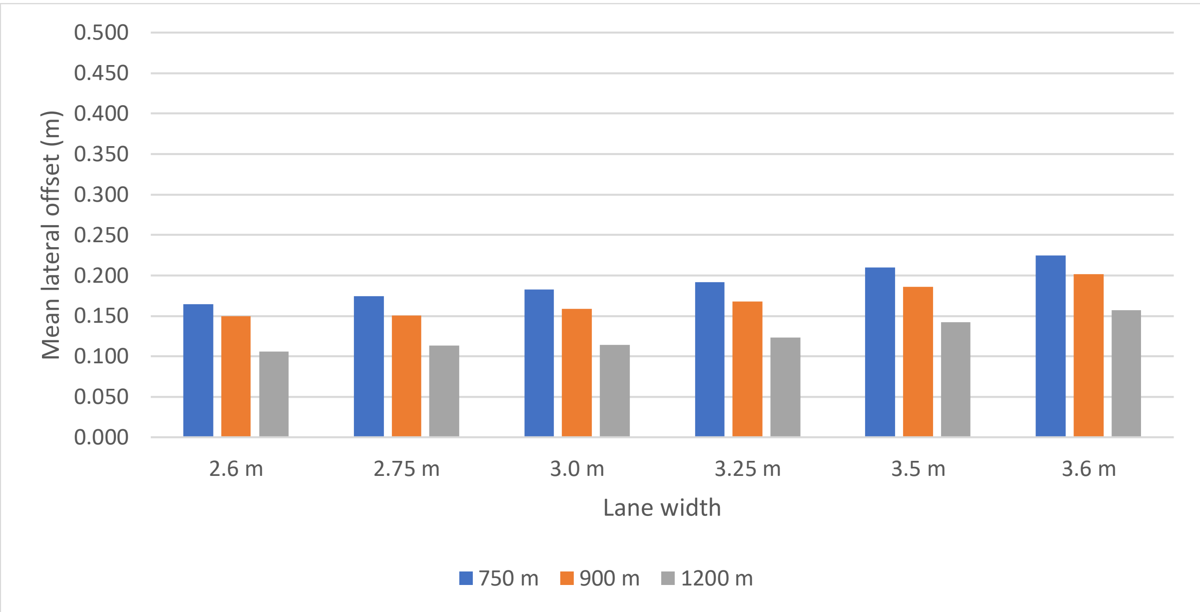

Figure 23: Mean lateral offset variation for 100 km/h

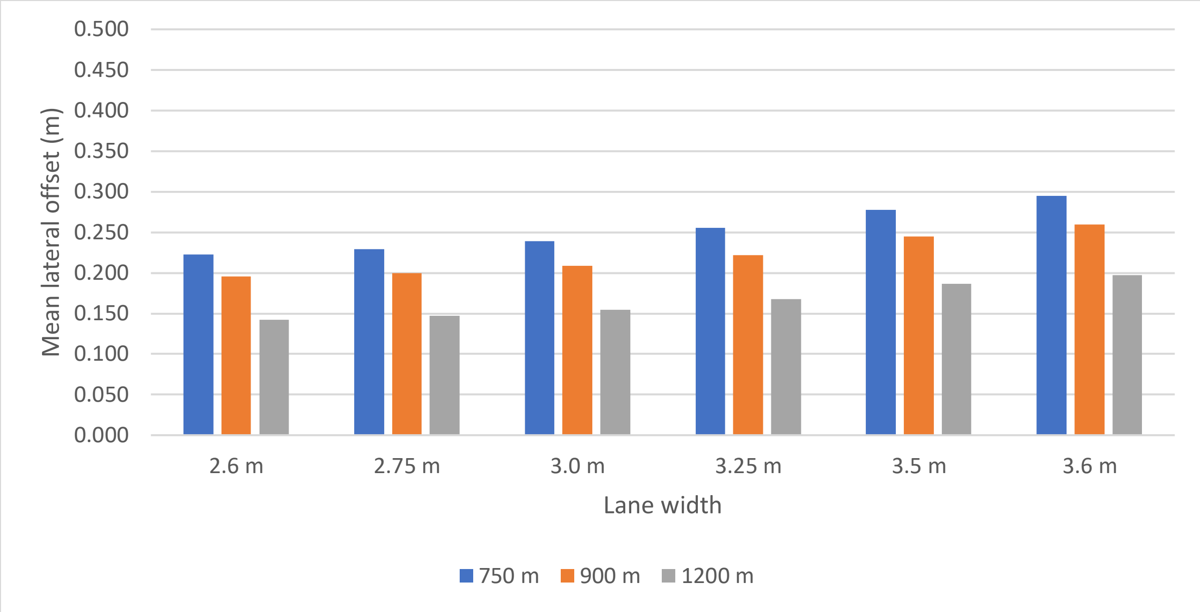

Figure 24: Mean lateral offset variations for 120 km/h

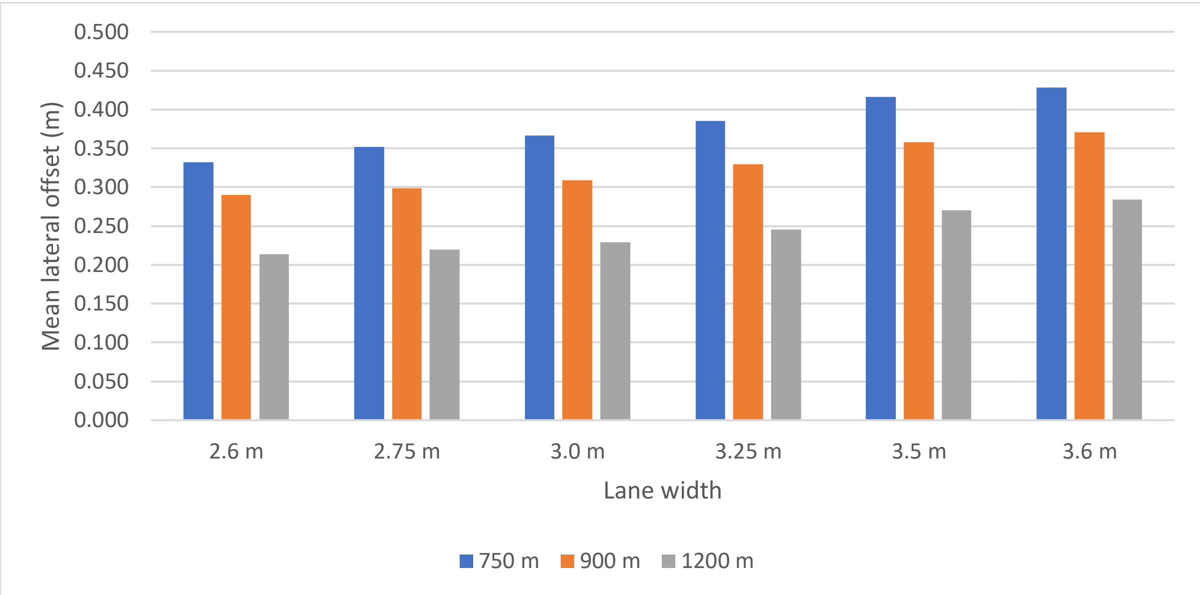

Figure 25: Mean lateral offset variations for 140 km/h

From these three figures, the effect of change in radius of curvature is visible. A higher radius of curvature has lower mean lateral offset values across all lane widths and speeds, and as established before, increasing lane width has a positive correlation with the mean lateral offset.

6.1.2. Exposure comparison

The exposure metric is beneficial to encompass the effect of the changes in the attributes from an ODD perspective and is used to map similar graphs to better understand the nature of impact each of these attributes has on the ODD. This can be utilized to compare the different test cases that are defined inside or outside from the initial ODD assessment using the performance assessment implemented. Figure 26, Figure 27 and Figure 28 shows the exposure comparison for lane width variations and speed variations at a constant radius of 750 m, 900 m and 1200 m respectively.

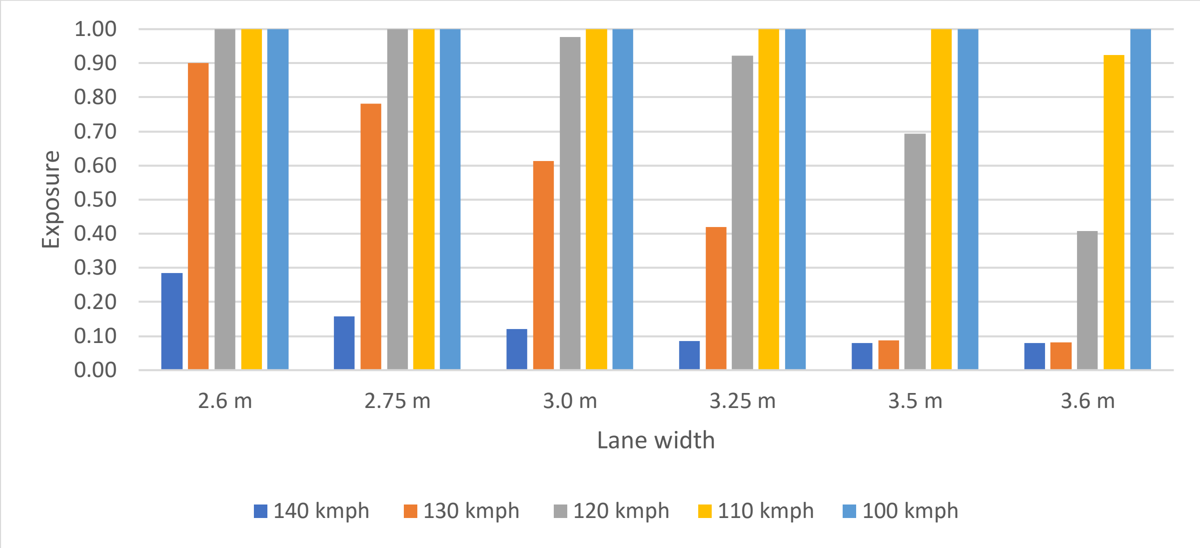

Figure 26: Exposure data comparison between different lane widths and speeds for test cases of 750 m radius curve

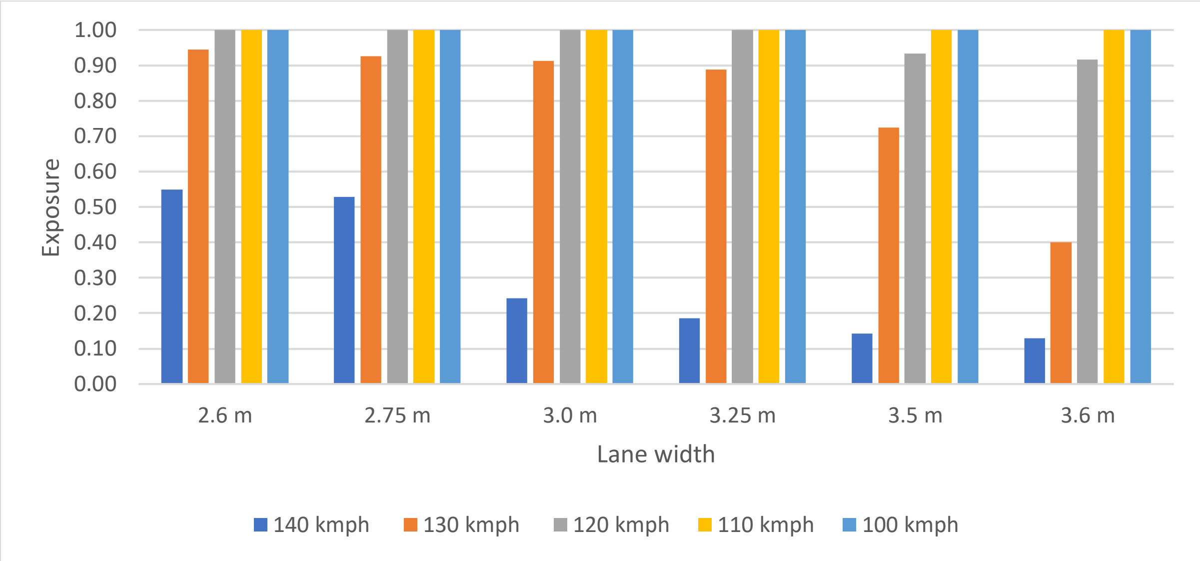

Figure 27: Exposure data comparison between different lane widths and speeds for test cases of 900 m radius curve

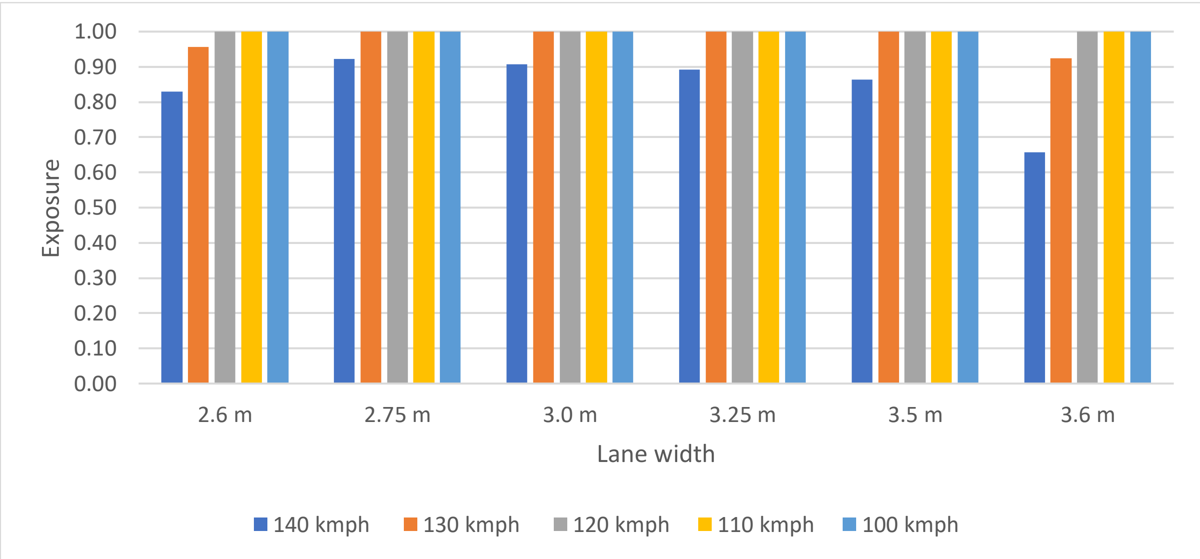

Figure 28: Exposure data comparison between different lane widths and speeds for test cases of 1200 m radius curve

From Figure 26 and Figure 27, it can be seen that the exposure value is higher at lower speed and lower lane width for 750 m and 900 m radii. As speed increases, the exposure value decreases and as lane width increases, the exposure value decreases. In Figure 28, it can be seen that at 1200 m radius, the exposure values are 1 for speed 100 km/h, 110 km/h and 120 km/h. For 130 km/h, the exposure value is 1 between 2.75 and 3.5 m lane width and is less than 1 at 2.6 m lane width and 3.6 m lane width. A similar dip in the exposure at 2.6 m and 3.6 m can be seen for 140 km/h as well. This trend is seen only for the 1200 m radius and not for the other two radii. Similarly, the exposure comparison along the different radii for a constant speed of 100 km/h, 110 km/h, 120 km/h, 130 km/h and 140 km/h are shown in Figure 29, Figure 30, Figure 31, Figure 32, Figure 33 respectively.

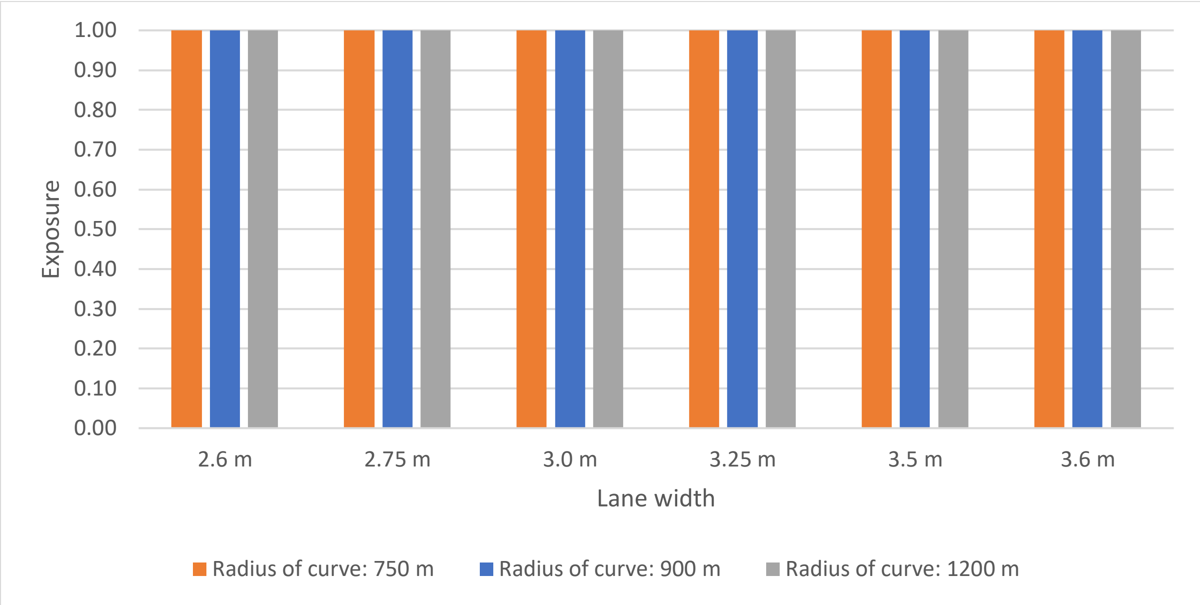

Figure 29: Exposure data comparison between different lane widths and radii for test cases of 100 km/h

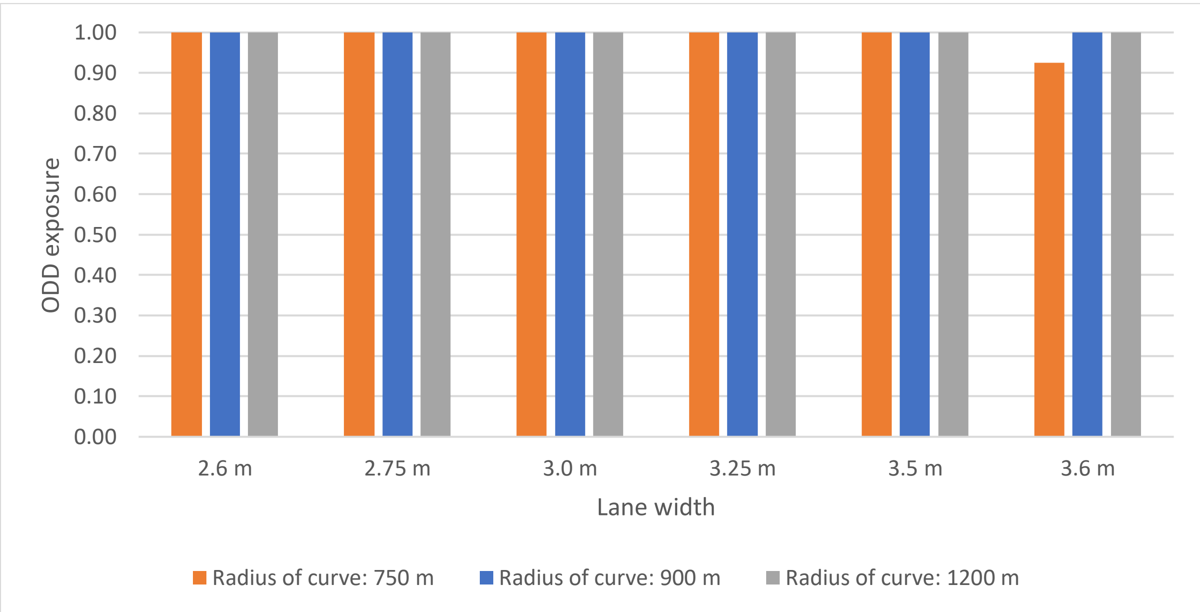

Figure 30: Exposure data comparison between different lane widths and radii for test cases of 110 km/h

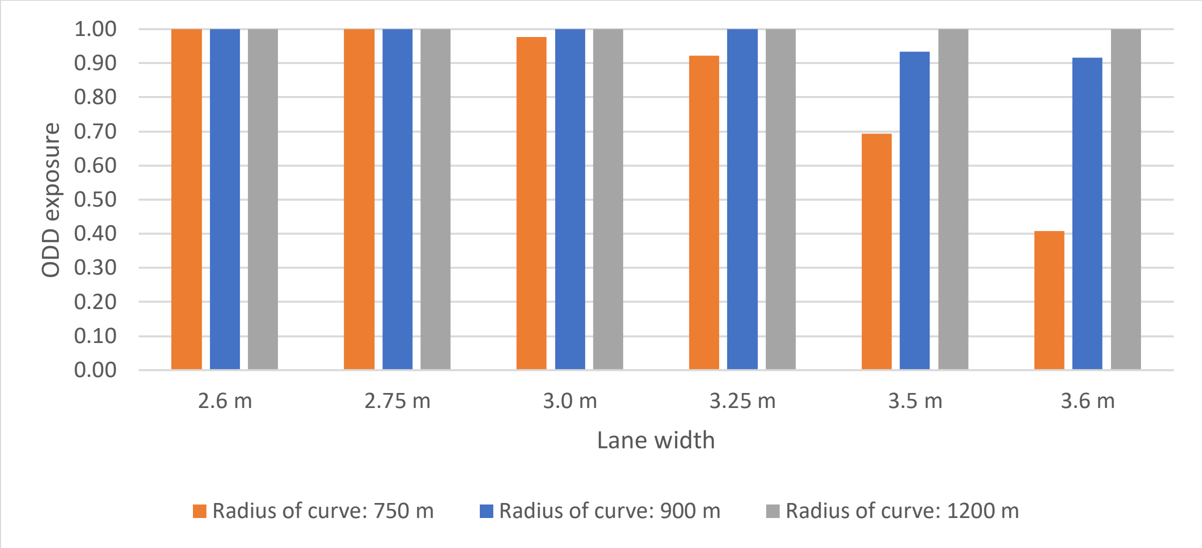

Figure 31: Exposure data comparison between different lane widths and radii for test cases of 120 km/h

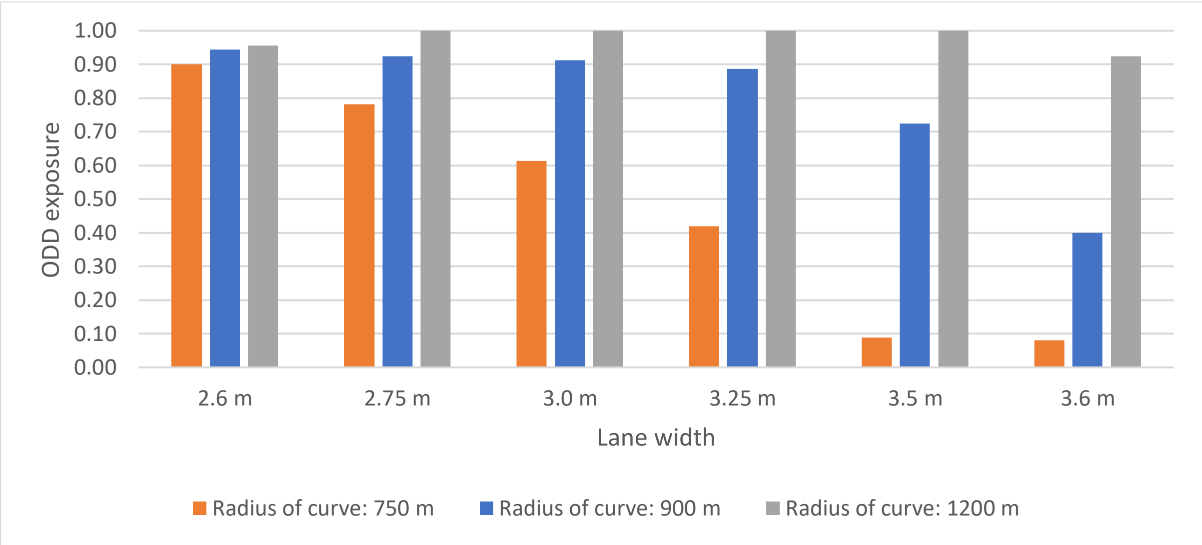

Figure 32: Exposure data comparison between different lane widths and radii for test cases of 130 km/h

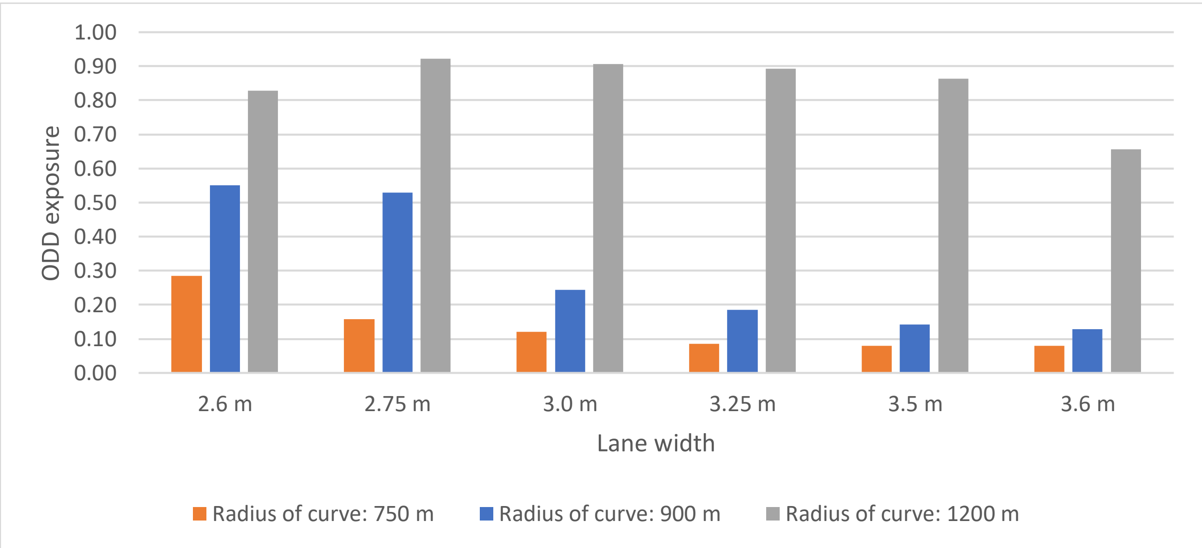

Figure 33: Exposure data comparison between different lane widths and radii for test cases of 140 km/h

From Figure 29, it can be seen that the exposure value is 1 for all the test cases, meaning that the vehicle is within the lateral offset threshold for the entire curve section. This is the ideal case of how the test vehicle is expected to perform in all the driving situations. The decreasing trend on the exposure value as lane width increases can be seen in all these figures for radii 750 m and 900 m. As seen in Figure 28, the dip in exposure value at narrow and wide lane width for 1200 m radius can be seen in these cases as well at speeds 130 km/h and 140 km/h (in Figure 32 and Figure 33 respectively). When comparing the radii, a higher radius result in a higher exposure value, especially at higher lane width and higher speeds. It can be that at a higher radius, the impact of lane width variations become more pronounced.

6.2. Test cases with precipitation

In the test cases with precipitation, the variation in lateral offset for the different weather conditions is generated for a 900 m radius curve. Figure 34 and Figure 35 shows the weather variations for a lane width of 2.6 m at speeds 100 km/h and 120 km/h respectively.

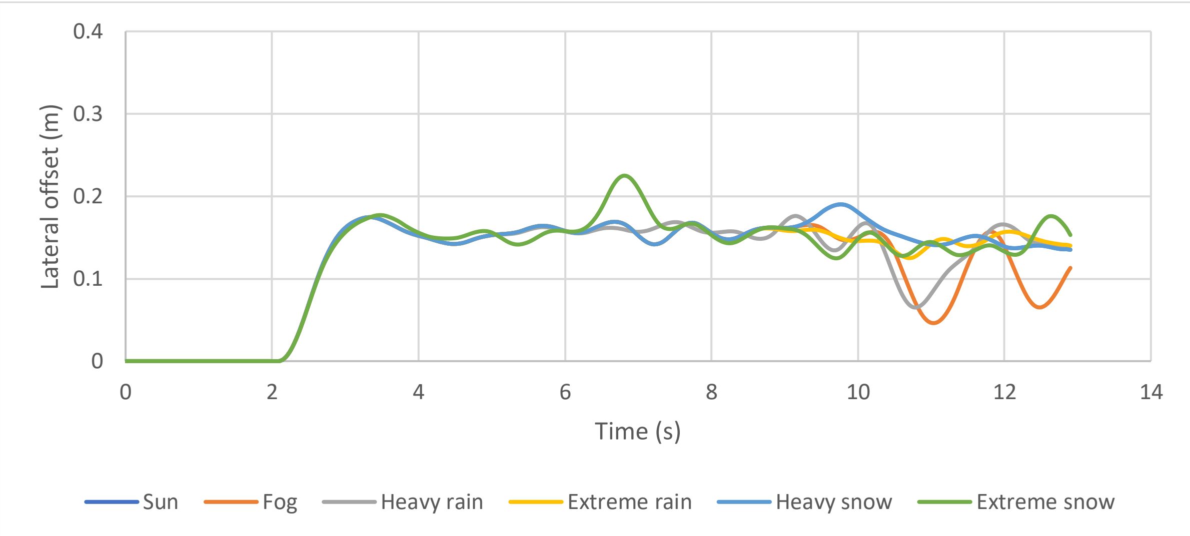

Figure 34: Lateral offset variation for different weather conditions at 2.6 m lane width, 900 m radius and 100 km/h

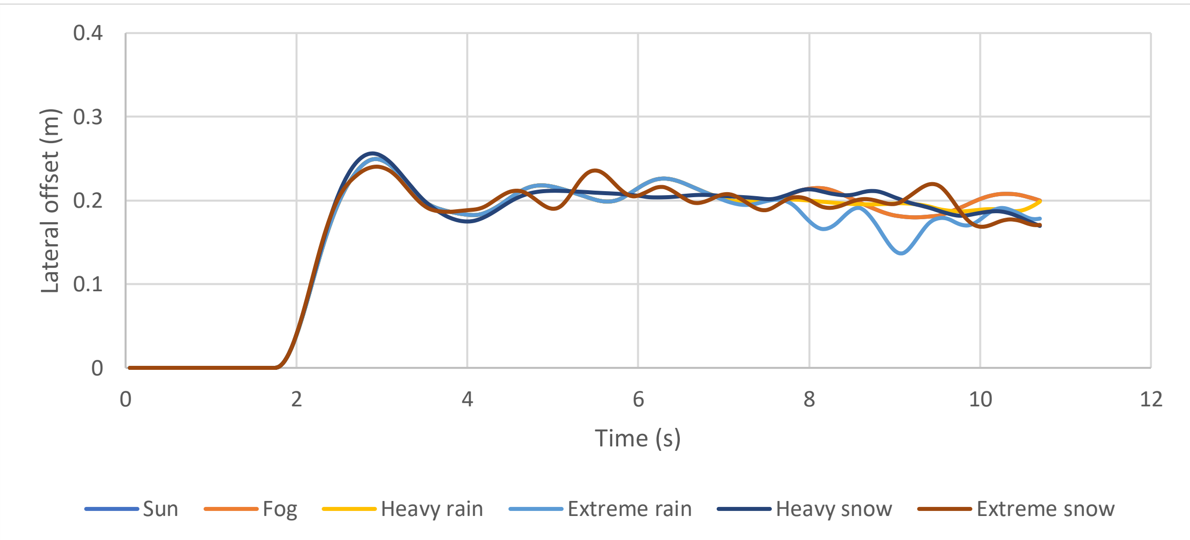

Figure 35: Lateral offset variation for different weather conditions at 2.6 m lane width, 900 m radius and 120 km/h

Similarly, Figure 36 and Figure 37 shows the weather variations for a lane width of 3.6 m at speeds 100 km/h and 120 km/h respectively. The lateral offset variations for all the simulation runs are shown in

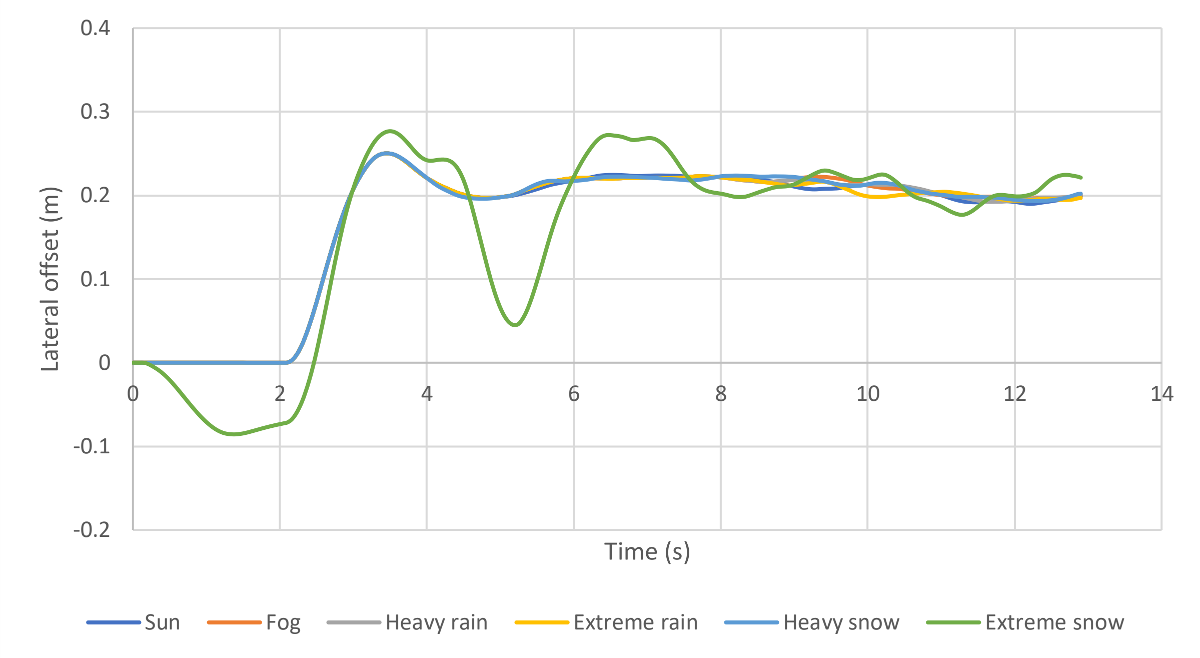

Figure 36: Lateral offset variation for different weather conditions at 3.6 m lane width, 900 m radius and 100 km/h

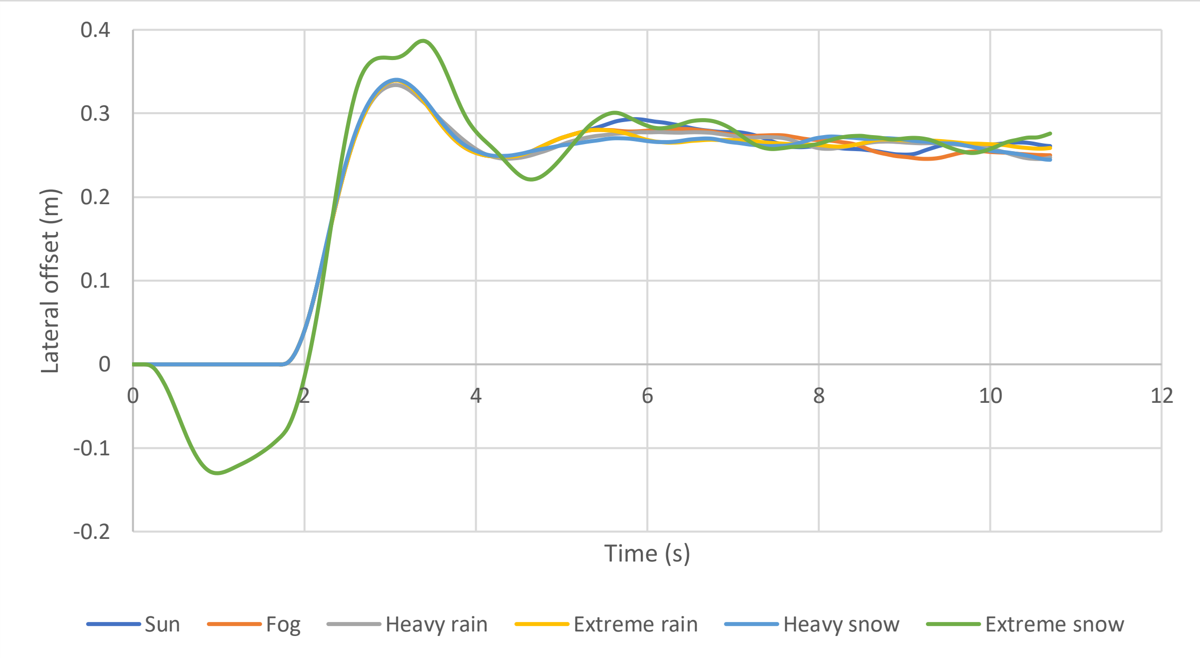

Figure 37: Lateral offset variation for different weather conditions at 3.6 m lane width, 900 m radius and 120 km/h

It can be seen from these figures that there is a swerving nature between the right lane marking and the lane centre by the vehicle at narrow lane width (2.6 m) as compared to the wider lane width (3.6 m) for both speeds. Extreme snow weather shows a high deviation from the baseline sunny weather condition at higher lane width compared to narrow lane width condition. All the other weather conditions do not vary much from the baseline condition. When comparing the mean lateral offset and maximum lateral offset data, the same pattern can be seen. The same set of graphs are generated for 750 m radius and a similar trend can be seen for a lower radius as well. Figure 38 and Figure 39 shows test cases with a constant lane of 2.6 m and speeds of 100 km/h and 120 km/h respectively, and Figure 40 and Figure 41 for a constant lane width of 3.6 m and speeds of 100 km/h and 120 km/h respectively. The mean lateral offset and maximum lateral offset is not seen to vary heavily with weather variations as compared to the other attributes in this case.

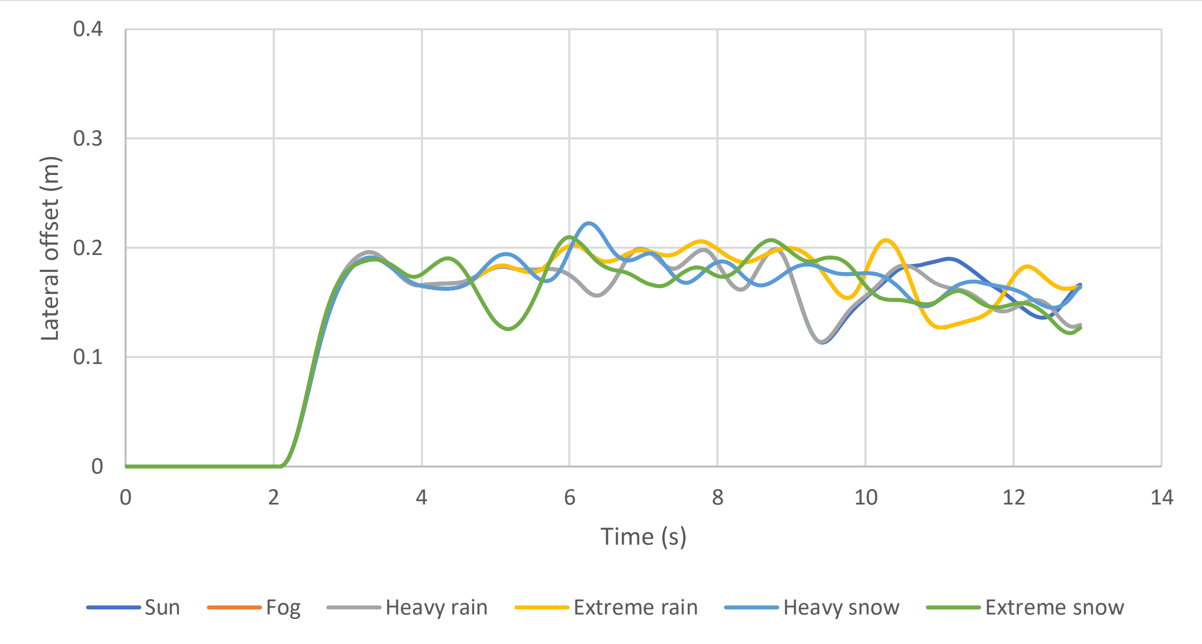

Figure 38: Lateral offset variation for different weather conditions at 2.6 m lane width, 750 m radius and 100 km/h

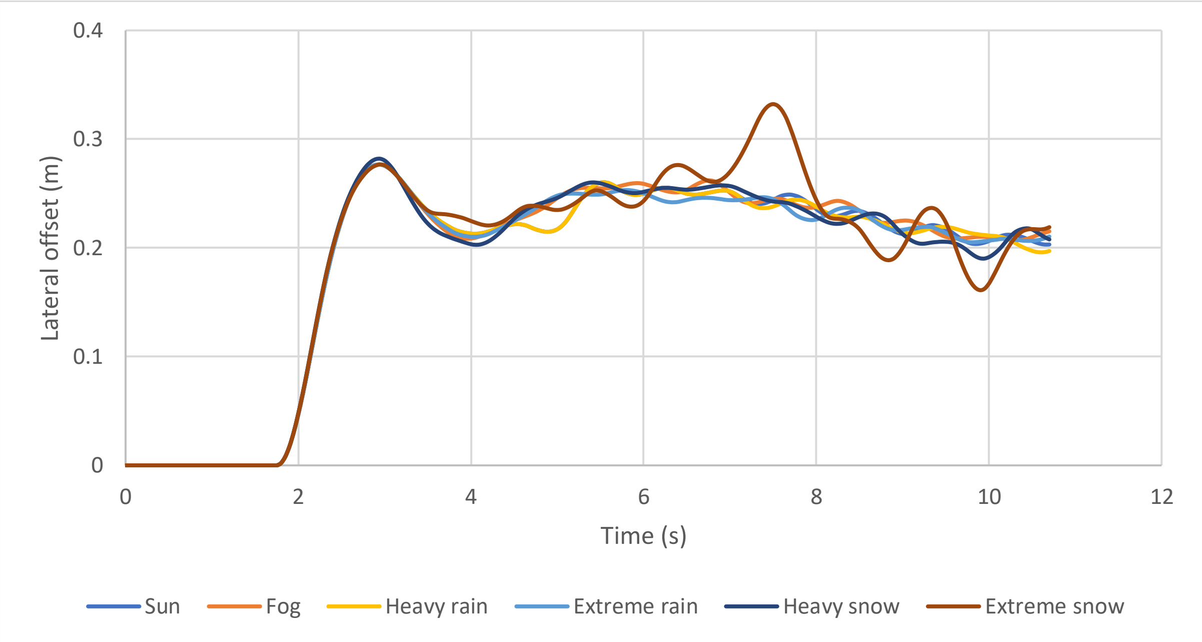

Figure 39: Lateral offset variation for different weather conditions at 2.6 m lane width, 750 m radius and 120 km/h

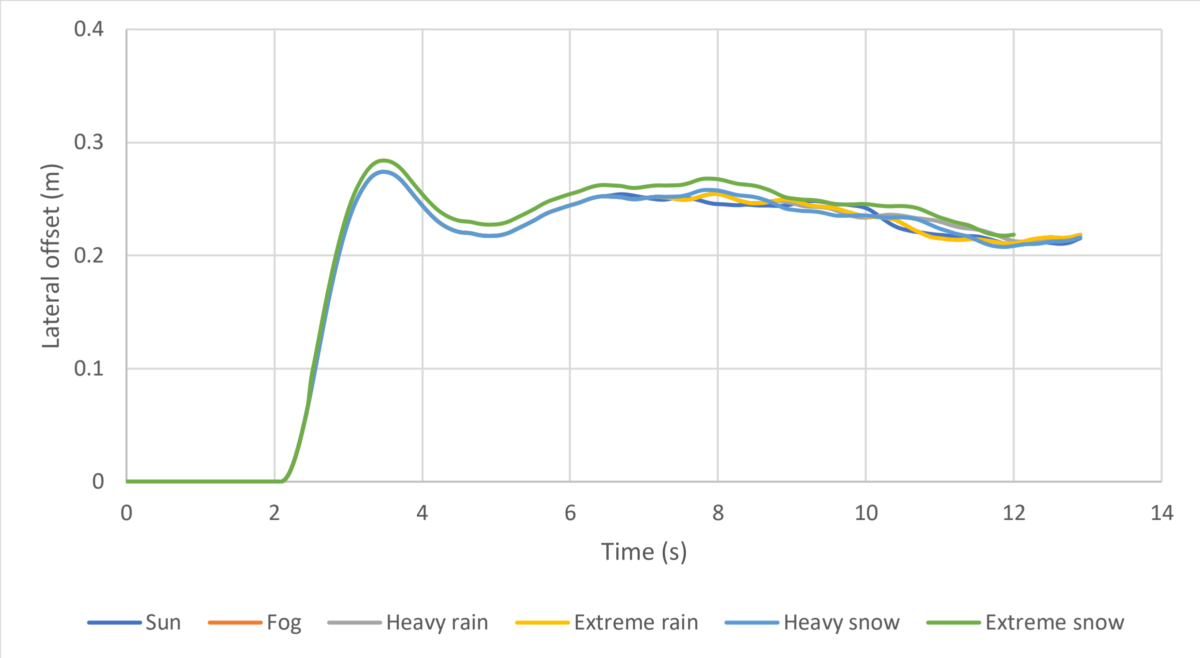

Figure 40: Lateral offset variation for different weather conditions at 3.6 m lane width, 750 m radius and 100 km/h

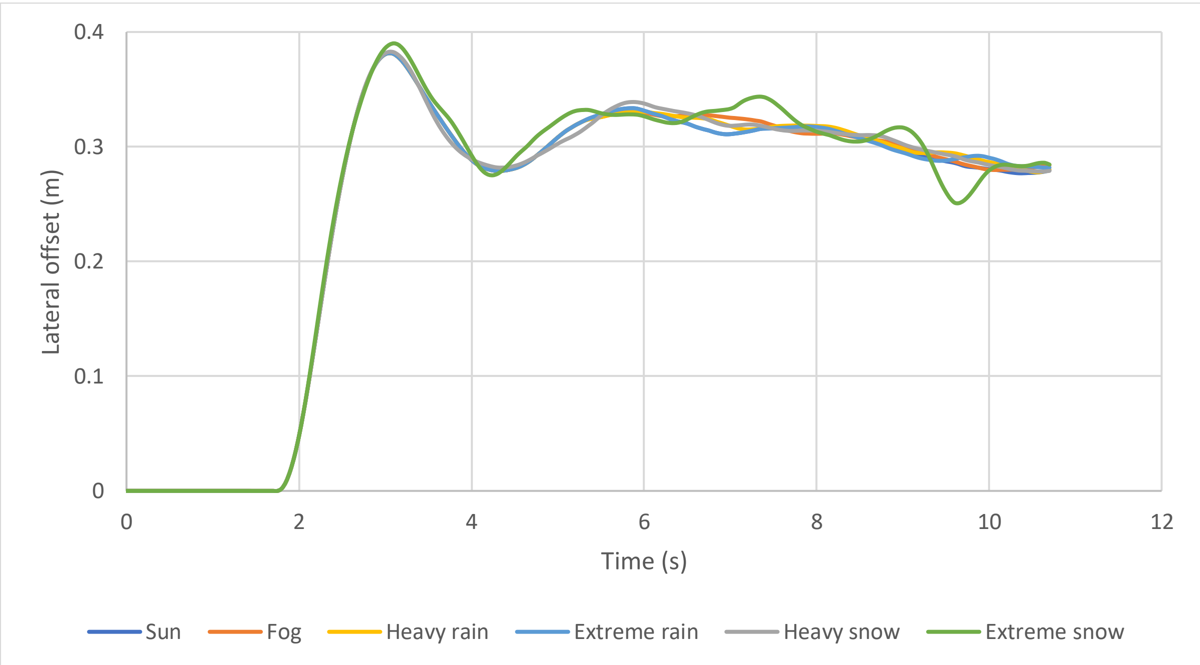

Figure 41: Lateral offset variation for different weather conditions at 3.6 m lane width, 750 m radius and 120 km/h

6.3. Performance assessment

As mentioned in Equation 1, the lateral offset value is compared with the offset threshold value of 0.3 m and based on that comparison, a binary value is assigned to the exposure metric; 1 meaning within the offset threshold value and 0 meaning outside the offset threshold value. This is plotted against the time and the assessment is illustrated. Example illustration of two test cases is shown in Figure 42 and Figure 43**.** The deviation of the vehicle beyond the offset threshold value at the beginning of the curve can be due to the lack of V2I communication as mentioned earlier.

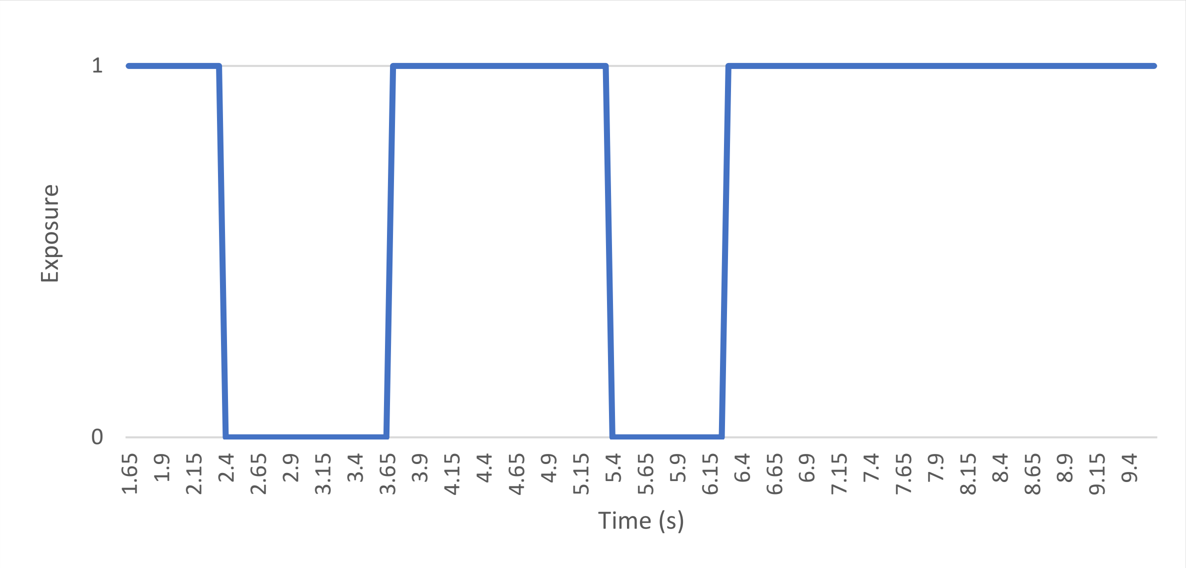

Figure 42: Performance assessment of vehicle moving at 130 km/h at a curve of radius 900 m and 3.5 m lane width

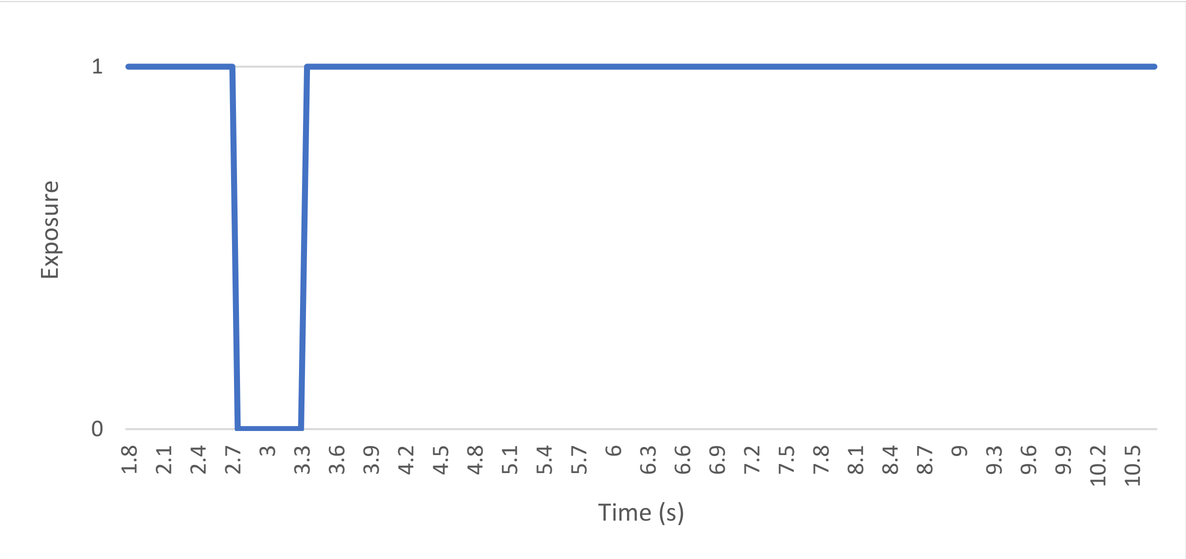

Figure 43: Performance assessment of vehicle moving at 120 km/h at a curve of radius 900 m and 3.5 m lane width

Comparing Figure 42 and Figure 43, the only difference in the tested attributes between these two test cases is the speed. It can be seen that a decrease in speed results in a reduction of the number of deviation flags from two in for 130 km/h to one for 120 km/h, for the same lane width and radius of curvature. In addition, the duration for which the vehicle was outside the acceptable lateral offset reduces with a decrease in speed. The test case in Figure 44 shows the assessment for vehicle moving at 120 km/h at a curve of radius 750 m and 3.5 m lane width.

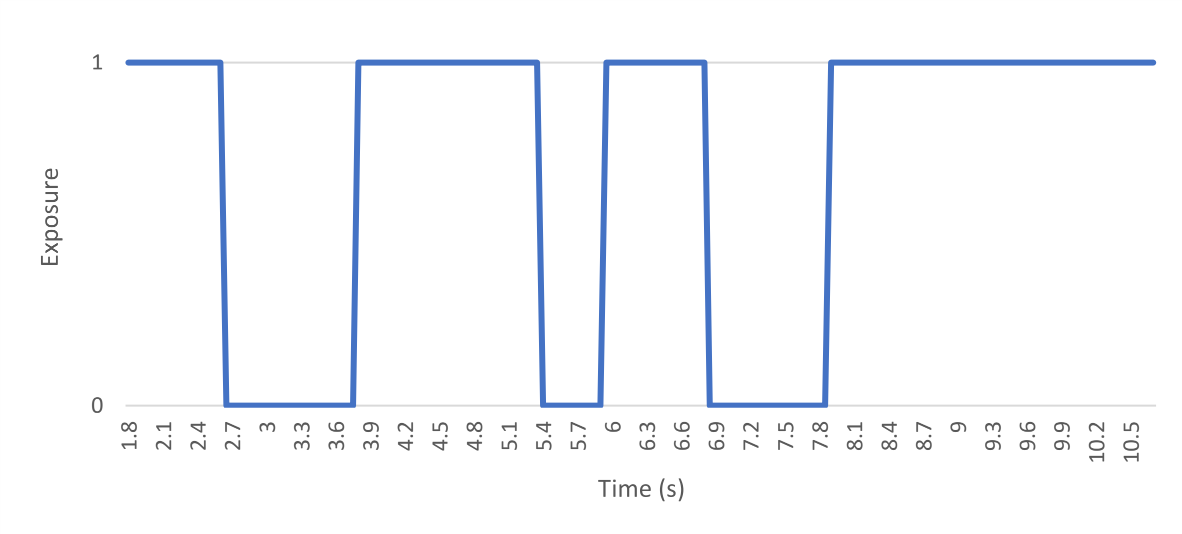

Figure 44: Performance assessment of vehicle moving at 120 km/h at a curve of radius 750 m and 3.5 m lane width

The difference between test cases shown in Figure 43 and Figure 44 is the decrease in the radius of curvature. The curve being sharper with the same lane width and speed conditions results in an increase from one ODD exit to three ODD exits. The test case shown in Figure 45 shows the ODD assessment of vehicle moving at 120 km/h at a curve of 750 m radius and 3.25 m lane width.

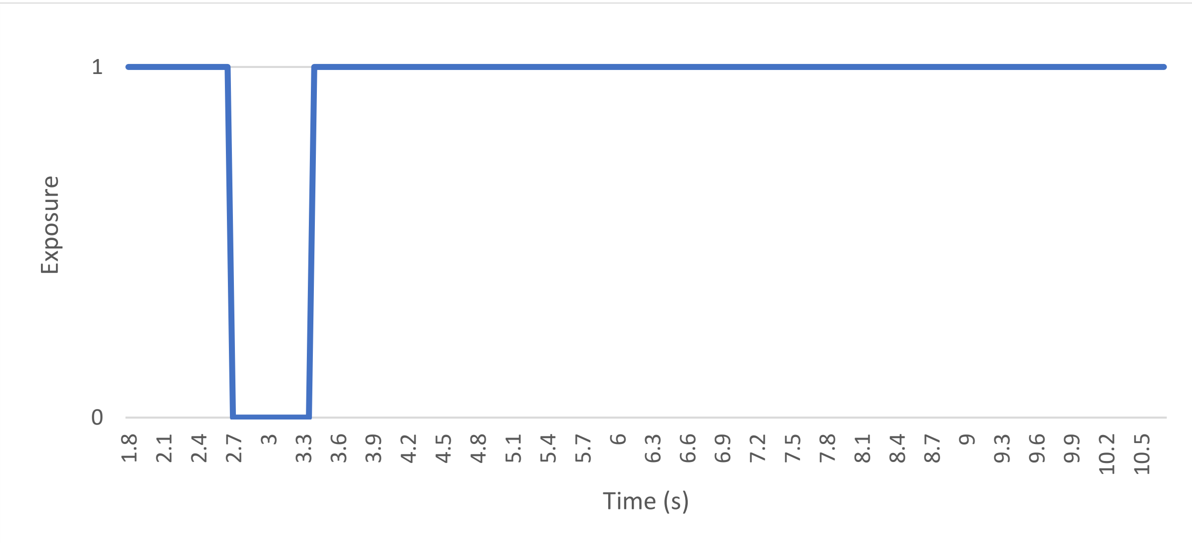

Figure 45: Performance assessment of vehicle moving at 120 km/h at a curve of radius 750 m and 3.25 m lane width

Figure 44 and Figure 45 depicts the test cases with the same radius of 750 m and speed 120 km/h, with the only difference being the lane width decreases from 3.5 m to 3.25 m. This change of lane width becoming narrower decreases the number of deviations beyond the offset threshold from three to one. It can be hypothesized from these results that geometric factors like lane width and radius of curvature have a higher impact on the performance compared to speed and weather conditions.

The binary values of each time step across the different lane widths are averaged to gain more insights on the location and nature of the vehicle deviation from the lane centre at a specific curve. These values are then plotted similarly to the performance assessment graphs as shown in Figure 46 and Figure 47 for test cases of 750 m – 120 km/h combination and 900 m – 120 km/h combination respectively. Comparing these two can provide more clarity on the effect of radius on the performance for the same speed of 120 km/h. Figure 48 shows a similar graph for the 900 m – 130 km/h combination. A value of 1 indicates that for all the lane widths at a specific timestep, the lateral offset is within the offset threshold and 0 means the lateral offset for all the lane widths is beyond the offset threshold at a specific timestep. A value of 0.5 at a specific timestep implies 3 out of the 6 lane widths tested are within the offset threshold and the remaining 3 are outside the threshold at the specific timestep. In other words, when the value is 0.5, there is an equal probability of deviating outside the threshold and being within the threshold among the different lane widths. A value higher than 0.5 implies a higher probability of staying within the threshold among the different lane widths and a value lower than 0.5 is indicative of a higher probability of deviating outside the threshold among the different lane widths.

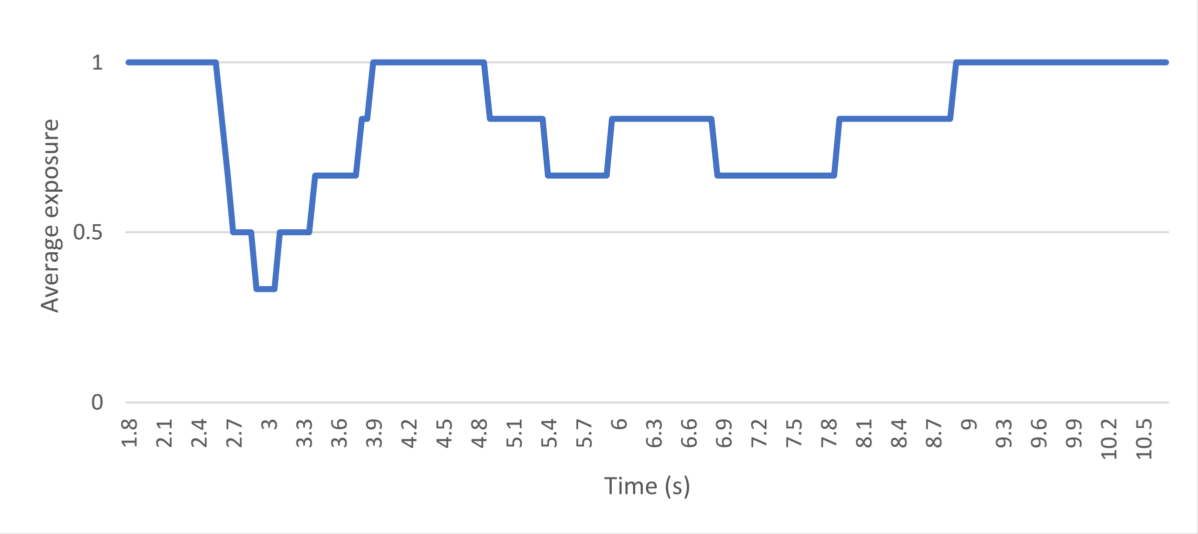

Figure 46: Assessment average across different lane widths for 750 m radius and 120 km/h

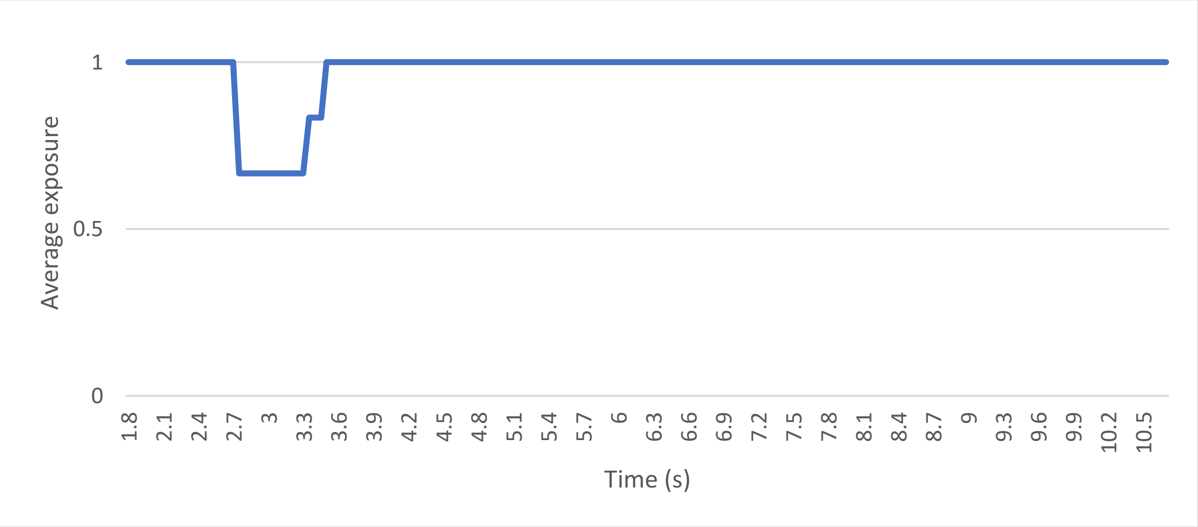

Figure 47: Assessment average across different lane widths for 900 m radius and 120 km/h

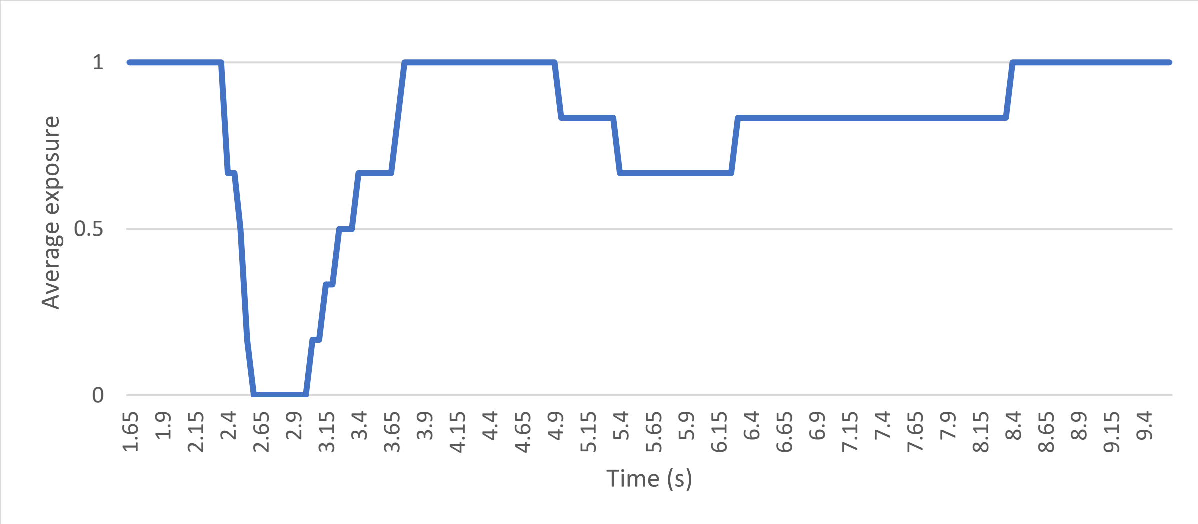

Figure 48: Average across different lane widths for 900 m radius and 130 km/h

It can be seen from these figures that the decrease in the radius of the curve leads to more deviations higher than the threshold. The closer the plot is to the X-axis, the higher the frequency of the exit across the different lane widths. It can also be seen that for a higher radius, the amplitude of the deviating beyond the threshold decreases, meaning the exit becomes less frequent. A similar trend was observed when the radius increases to 1200 m as well. When comparing Figure 47 and Figure 48, it is also observed that an increase in speed leads to more deviations beyond the threshold for the test cases with the same radius. The results from the data analysis are shown in the following 3D plots. These plots are a compilation of the mean lateral offset, maximum lateral offset and exposure data for all the test cases without precipitation and will be used as a reference to form the conclusions. Figure 49 and Figure 50 shows the maximum lateral offset and mean lateral offset for all the test cases without precipitation.

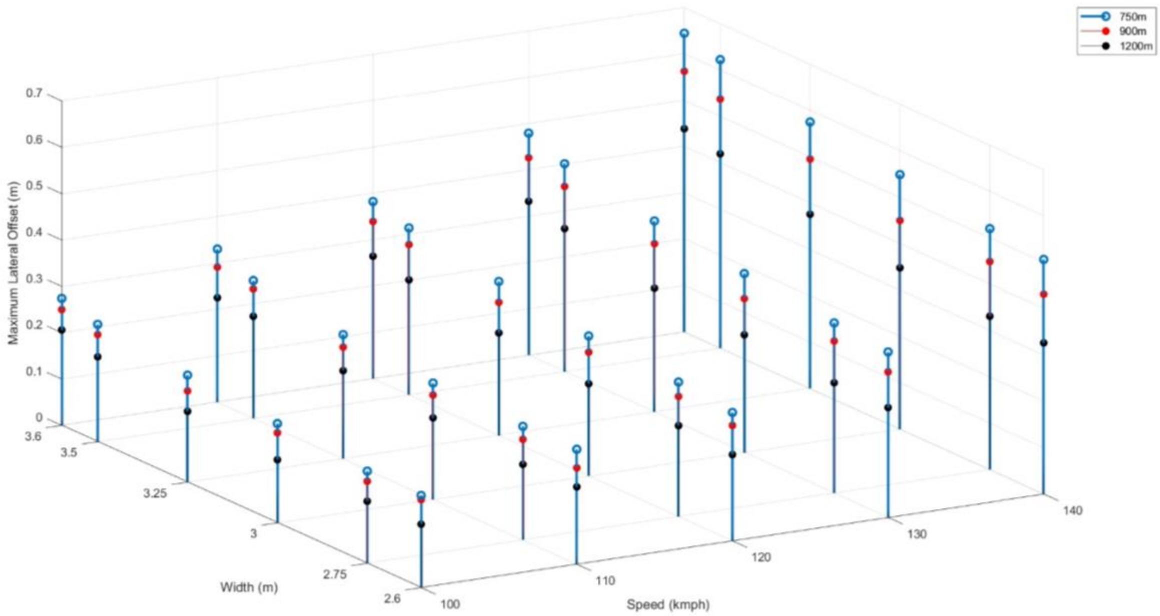

Figure 49: Maximum lateral offset variations of test cases without precipitation

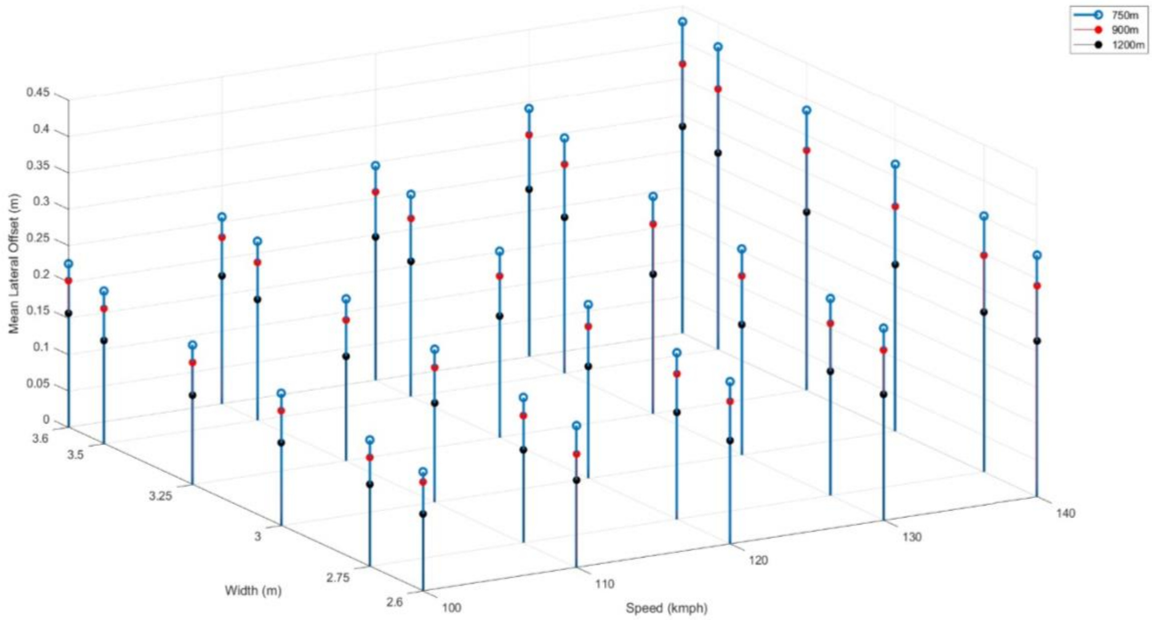

Figure 50: Mean lateral offset variations of test cases without precipitation

Figure 51, Figure 52 and Figure 53 depicts the exposure variations for the different speed and lane width changes for each of the radius tested, namely 750 m, 900 m and 1200 m.

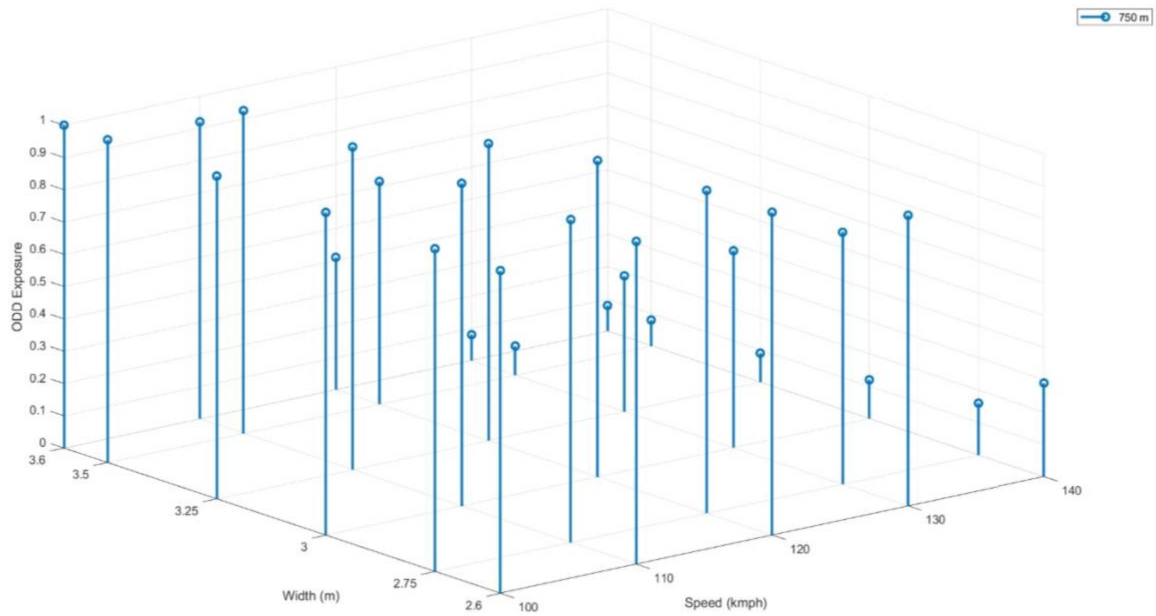

Figure 51: Exposure variations of all the test cases of radius 750 m without precipitation

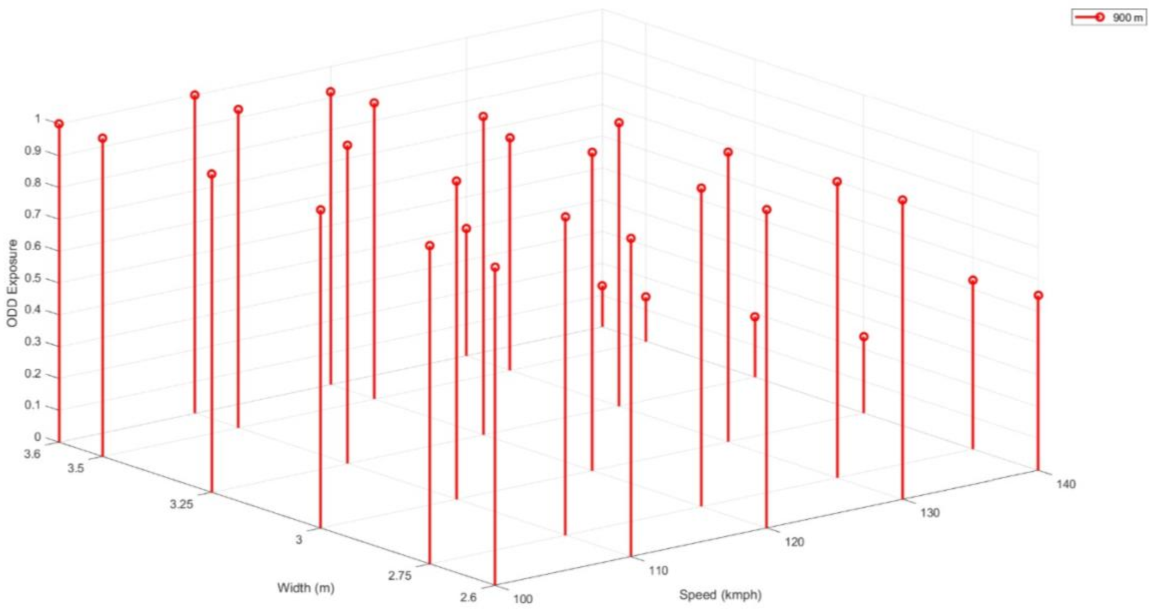

Figure 52: Exposure variations of all the test cases of radius 900 m without precipitation

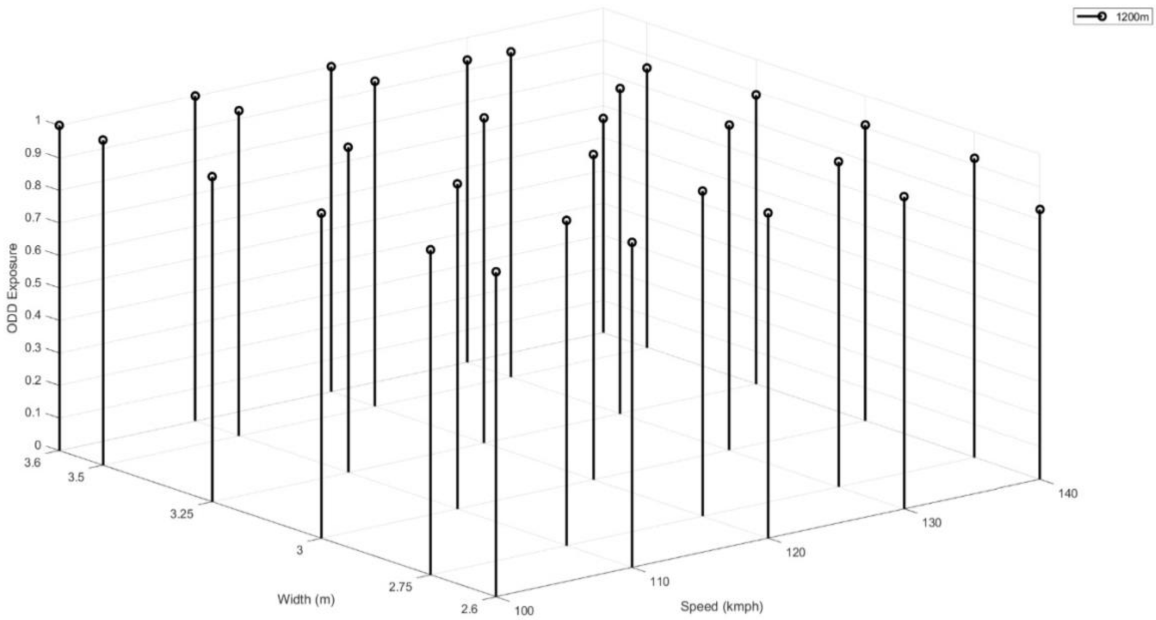

Figure 53: Exposure variations of all the test cases of radius 1200 m without precipitation

The initial ODD assessment of the test cases with and without precipitation is shown in Table 13 and Table 14 respectively. Each cell in the table is a test case and the colors green and red are indicative of the ODD presence of the test cases; green meaning inside the ODD and red meaning outside the ODD respectively. The term ODD presence can be defined as the ODD state of the vehicle in a test case. Since none of the attributes in the test case change value during the run time, this initial ODD assessment will hold for a specific test case throughout the test run.

Table 13: Initial ODD assessment of the test cases without precipitation

Radius of curve	Lane width	Speed				
		140 km/h	130 km/h	120 km/h	110 km/h	100 km/h
750 m	2.6 m					
	2.75 m					
	3 m					
	3.25 m					
	3.5 m					
	3.6 m					
900 m	2.6 m					
	2.75 m					
	3 m					
	3.25 m					
	3.5 m					
	3.6 m					
1200 m	2.6 m					
	2.75 m					
	3 m					
	3.25 m					
	3.5 m					
	3.6 m					

Table 14: Initial ODD assessment of the test cases with precipitation

Speed	Radius of curve	Lane width	Weather conditions					
			Sunny	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	750 m	2.6 m						
		3.6 m						
	900 m	2.6 m						
		3.6 m						
120 km/h	750 m	2.6 m						
		3.6 m						
	900 m	2.6 m						
		3.6 m						

Now the exposure data collected is filled into a similar table (see Table 15 and Table 16), with values closer to 1 indicative that the test case was mostly within the lateral offset threshold, and closer to 0 meaning that the test case was mostly outside the lateral offset threshold. This is then compared with the initial ODD assessment to see how the performance of a system when the test case is inside or outside the ODD.

Table 15: Performance assessment of test cases without precipitation

Radius of curve	Lane width	Speed				
		140 km/h	130 km/h	120 km/h	110 km/h	100 km/h
750 m	2.6 m	0.29	0.9	1	1	1
	2.75 m	0.16	0.78	1	1	1
	3 m	0.12	0.61	0.98	1	1
	3.25 m	0.09	0.42	0.92	1	1
	3.5 m	0.08	0.09	0.69	1	1
	3.6 m	0.08	0.08	0.41	0.92	1
900 m	2.6 m	0.55	0.94	1	1	1
	2.75 m	0.53	0.93	1	1	1
	3 m	0.24	0.91	1	1	1
	3.25 m	0.19	0.89	1	1	1
	3.5 m	0.14	0.73	0.93	1	1
	3.6 m	0.13	0.4	0.92	1	1
1200 m	2.6 m	0.83	0.96	1	1	1
	2.75 m	0.92	1	1	1	1
	3 m	0.91	1	1	1	1
	3.25 m	0.89	1	1	1	1
	3.5 m	0.86	1	1	1	1
	3.6 m	0.66	0.93	1	1	1

Table 16: Performance assessment of test cases with precipitation

Speed	Radius of curve	Lane width	Weather conditions					
			Sunny	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	750 m	2.6 m	1	1	1	1	1	1
		3.6 m	1	1	1	1	1	1
	900 m	2.6 m	1	1	1	1	1	1
		3.6 m	1	1	1	1	1	1
120 km/h	750 m	2.6 m	1	1	1	1	1	0.94
		3.6 m	0.41	0.39	0.4	0.42	0.4	0.34
	900 m	2.6 m	1	1	1	1	1	1
		3.6 m	0.92	0.92	0.91	0.92	0.91	0.84

Comparing Table 13 and Table 15 shows that many of the test cases that are classified as inside the ODD in the initial ODD assessment are not completely within the lateral offset threshold, with some test cases with exposure values closer to 0. This means that some test cases that are classified as inside ODD (for instance, the test cases with a speed of 130 km/h or the test cases with a higher lane width of 3.6 m) shows poor lane-keeping performance. It is also worth mentioning that some test cases defined as outside the ODD (test cases with a lane width of 2.6 m) shows better lane-keeping performance than the ones defined inside the ODD. This is surprising because as per the OEM manuals, driving in situations outside the ODD can lead to malfunctioning of the system. Similarly, Table 14 and Table 16 shows that although most of the test cases are classified as outside the ODD in the initial ODD assessment for test cases with precipitation, the performance assessment in these test cases shows that most of the test cases are well within the lateral offset threshold. This shows that test cases defined outside ODD do show good lane-keeping performance. For test cases with a 750 m radius, 3.6 m lane width and speed of 120 km/h, the performance is less. Therefore, test cases classified as inside the ODD need not have good lane-keeping performance and test cases classified as outside the ODD does show good lane-keeping performance. This means the ODD definition itself required much more attention from a performance aspect. Performance assessment can be the key to bringing more clarity into the ODD definition since it is difficult to capture the ODD boundaries of environmental or infrastructural ODD attributes that are missing from the OEM manuals. The lane-keeping performance is important in the ODD definition because it can be a safety concern if ignored. For instance, a driving situation that's inside the ODD with poor lane tracking performance can lead to the vehicle steering into the opposing lane. Therefore, including the performance assessment also in the ODD assessment would be a good start in defining the ODD in a better manner.

7. Discussion and Conclusions

7.1. Overview

The European Commission has mandated the requirement of advanced safety features in all vehicles sold in the EU from 2022 onwards (European Commission, 2018). This will help drivers get gradually used to ADS, eventually transitioning to fully autonomous driving in the distant future. There are more vehicles on road now equipped with lane-keeping systems and other driver assistance systems due to the added benefit of safety. One such ADAS feature is the lane-keeping system which has plenty of performance evaluation research being done on it but lacks research from an ODD perspective in simulation. As for the ODD definition, there are many ODD taxonomies present in academic literature for the classification of ODD attributes. These are recommended to be used by OEMs to classify their ODD definition of the system for effective comparison between the same ADAS feature offered by two different OEMs. However, this is not seen to be done by the OEMs and causes a disparity between the ODD definitions, leading to misunderstanding or misinterpretation of the defined ODD. The OEMs do not exactly specify the ODD boundaries in publicly available instruction manuals of the vehicles. The conditions where the system cannot function properly are very vaguely mentioned. Furthermore, the different OEMs provides the same ADAS feature with different names with differently defined ODD boundaries. Bringing these ODD definitions of all these OEMs under one umbrella is currently being attempted by policymakers and regulatory organisations. A standard way of testing the impact of the different ODD attributes on the performance of a lane-keeping system is still absent. Therefore, this research aims to provide a method to assess the ODD boundaries of a lane-keeping system using simulation and is intended to be used by researchers, policymakers and OEMs to refine the ODD and to test the effect of the ODD attributes on the performance of the system.

This research attempts to understand the current ODD definitions and provides a framework to apply this methodology in future ODD related studies. An initial ODD investigation is done to define the sample ODD of the system to be tested in simulation (using Prescan) and a preliminary ODD assessment of the test cases is done. Then a performance assessment of the test cases based on the 0.3 m acceptable lateral offset value is done to test the performance of the developed test cases. This would then be used to check the lane-keeping performance of the classified inside or outside ODD test cases. Since the ODD boundaries of ambient conditions are not readily available, the performance assessment would be useful to test the impact on the test cases developed by the different ODD attributes. This approach is extended to suggest an exposure metric to compare the different test cases investigated in this research. The use cases were defined based on the initial investigation and the lateral offset data is measured from all the test cases run in Prescan. This data was filtered, compiled and analysed to assess the effect of the attributes on the lane-keeping performance.

This chapter discusses the conclusions of the results reported in the previous chapter and reflects on the research approach used and on the literature findings. Finally, the limitations of this research are also discussed.

7.2. Answers to research questions

The main research question was "How to assess the ODD boundaries of vehicles equipped with Lane-Keeping System at horizontal curves using PreScan?". The following sub-sections answer the six sub-research questions one by one.

1. How is the ODD of lane-keeping systems defined in the literature and the various OEM manuals so far?

There are very limited ODD definitions specific to the lane-keeping system available in the literature. There are ODD definitions provided by standardization organisations on a broader level, but research on ODD boundaries is very limited. When the chosen OEM manuals were explored, the ODD definition available there was also limited. The OEMs have described the driving situations where the performance of the lane-keeping system might be affected, but the boundary conditions are not described in detail. Additionally, the same lane-keeping feature offered by the different OEMs has different ODD limitations with different names. This can be attributed to the control algorithm that the OEM uses. However, there are many aspects of the ODD that is left out in the OEM manuals. Details like warnings, display options, turning on and off are mentioned in detail in the OEM manuals, but the crucial information about the system's performance limitation is often mentioned very ambiguously. Furthermore, there is a lack of clarity on the underlying principle used by the OEMs while defining the ODD and hinders the refinement of the ODD gravely. These aspects of missing knowledge of the ODD from the available sources is indicative that the road authorities and drivers are not aware of the exact capability and limitation of the system. Therefore, the exact situations where the systems can perform properly is unclear.

There are projects like ASAM OpenODD that does attempt to bring a single ODD definition format that can be used by all OEMs which are both machine and human-readable. The new proposed format can enable easy knowledge transfer between the involved parties with ODD descriptions that are exchangeable, comparable and processable. This facilitates efficient communication between the parties involved like the road authority, policymaker, development engineer, simulation engineer, data scientist. Defining and exchanging information in a standard format can result in a common understanding of the ODD definition. This would especially be beneficial in situations like when a city can describe the ODD for its infrastructure in the standard format and makes it available to the OEMs. The OEMs can use this description to test and match the system/vehicle within the defined ODD to check if the vehicle can be allowed to drive in that city. Additionally, this testing would benefit from assessing the performance of the system, be it in terms of safety, lane marking adherence, fuel efficiency or any other aspect.

2. What are the different road or vehicle characteristics, or environmental conditions widely factored to the ODD boundary of lane-keeping system?

The ODD attributes relevant to the lane-keeping system found from the literature review and the OEM manuals are shown in Table 17.

Table 17: ODD attributes from literature and OEM manuals

Type of attribute	List of attributes
Environmental conditions	Weather, illumination, shadows, particulates,
Infrastructural attributes	Radius of curvature, lane width, type of roadway, type of lane marking, lane marking condition, roadway surface condition, roadway geometry, road gradient
Dynamic attributes	Speed, headway

3. What are the simulation capabilities of Prescan to test the ODD boundaries of lane keeping system?

Prescan offers a wide variety of functionalities to test the different ODD attributes. Since Prescan is a physics-based simulation platform and deterministic, it cannot map uncertainty in the test cases. The many available sensors can enable quick and efficient testing of ADS or ADAS features in Prescan. One of the major limitations of simulation, in general, is the combinatorial explosion. The greater number of ODD attributes that have to be tested on Prescan and the higher the range of values associated with it makes it more complex since the correlation between all the attributes becomes difficult to map. This is because of the sheer number of test cases that have to be tested when there are more ODD attributes to test. Prescan in itself does not address the combinatorial explosion issue, but a verification & validation framework called ‘Prescan360’ that uses Simcentre Prescan and Simcentre HEEDS together allows testing of a large number of test cases in very less time. The framework is illustrated in Figure 54.

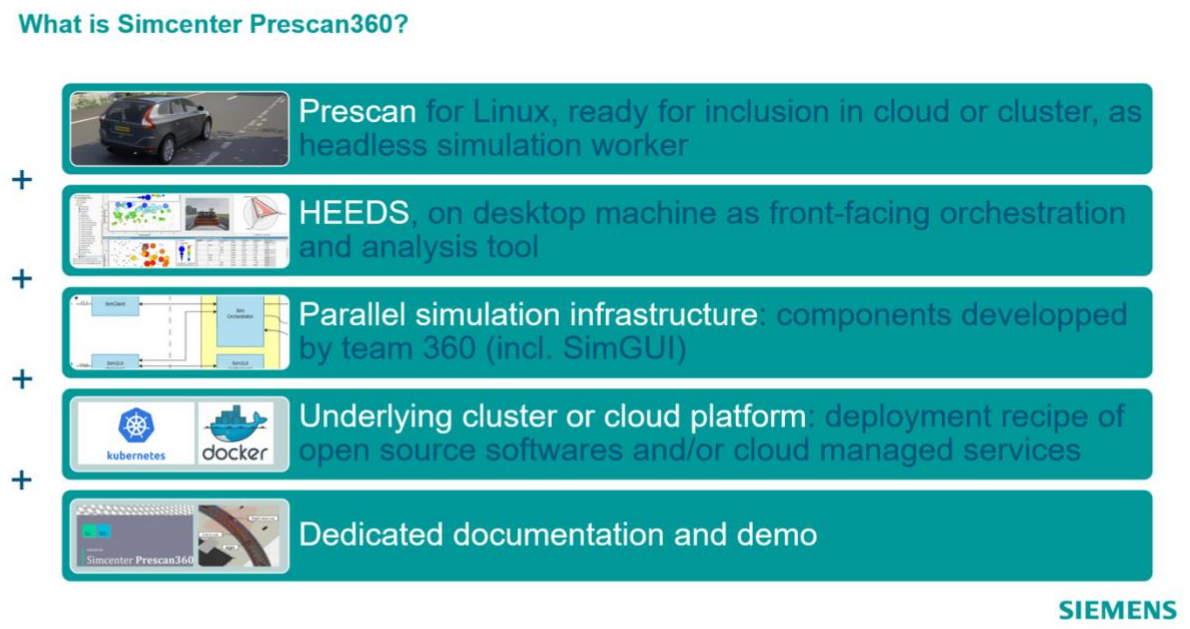

Figure 54: Simcentre Prescan360 framework

Prescan360 not only provides the solution to the combinatorial explosion but also gives access to massively parallelized simulations on cluster or cloud. HEEDS is a software that automates and accelerates the process by finding design configurations that best satisfy the requirements. Therefore, HEEDS provide the test cases sampling smartness essential for smart experimental design to overcome combinatorial explosion. However, Prescan360 and HEEDS were not utilised in this study. Moreover, the main advantage of Prescan is the range of available sensors. Although the idealized sensors in Prescan do not represent any actual sensors, these can provide much background information from the simulation environment that cannot be acquired from on-road testing or driving simulators.

4. How can the ODD boundaries of an ADAS feature like lane-keeping system be tested in a simulation environment?

The research approach used in this study can be utilised to test the ODD boundaries of a different ADAS feature in the same or different simulation environment. This performance assessment of the test cases can encompass most of the ambient conditions using the performance and exposure metrics, making it effective to compare the different test cases. However, it can depend on the type of attributes to be tested. In case more dynamic attributes are to be tested, the performance metric has to be adapted accordingly. For instance, if headway is also included in developing the test cases, then using only the offset threshold value of 0.3 m won't be sufficient. This is because a minimum headway is required between two test vehicles for perceived safety. In such cases, the headway can also be a function of the speed and therefore using a performance assessment similar to this study would be beneficial in capturing the exact ODD boundary of an attribute like headway. The framework proposed in this research (see Figure 55) can be applied to test the ODD boundaries of an ADAS in a simulation environment.

5. What are the test cases required to test the ODD boundaries for a test vehicle equipped with lane-keeping system in Prescan?

The test cases developed in this study is based on the findings from the literature review, OEM manuals and the understanding of the simulation capabilities of Prescan. The development of the test cases mostly depended on the attributes that has to be tested. The ODD attributes tested in this research are static and the value does not change during the simulation run. Therefore, the ODD presence of the test cases is either inside or outside the ODD throughout the run. The boundary conditions required to perform the initial ODD assessment are not easily available and they were extracted from different sources. The ODD boundaries of speed range and weather conditions were taken from the OEM manuals, the lane width boundary was taken from literature, and the radius of curve boundary was taken from the design guidelines. The boundary values provided in the ODD definitions of OEM manuals are very limited. For example, defining ODD boundary situations like a narrow road or sharp curve makes it very hard to define concrete test cases that are inside the ODD. This is why other sources like literature and design guidelines were also utilized to extract ODD boundary conditions for the lane-keeping system. The lack of clarity in the existing ODD boundaries and the absence of a standard ODD definition restricts ODD based test case generation. Due to this reason, a performance assessment is used to check the lane-keeping performance of the vehicle in the test cases based on an acceptable lateral offset value of 0.3 m. The combinations of the different values assigned to the attributes have to be tested to find the correlation between the ODD attributes in the test case and the results of the performance assessment can then be used to reflect on the initial ODD assessment done. These combinations were created based on the design guidelines and the ODD boundary conditions found in literature and OEM manuals. A total of 130 test cases were tested in this research surrounding the speed of the vehicle, radius of curvature, lane width and weather conditions. The major setback here was the issue of combinatorial explosion. For context, if all the combinations of speed, the radius of curvature, lane width and weather variations were to be tested, a total of 540 test cases need to be generated. Therefore, for weather variations, just two values of each attribute are tested to check how the variation in the attribute with weather variations impact the ODD compliance.

6. How does the test vehicle's ODD compliance from the built test cases compare to the ODD boundaries of the attributes found from the literature and OEM manuals?

An initial ODD boundaries assumption for the lane-keeping system was made based on findings from the literature and OEM manuals for the chosen attributes. These boundaries can hold if there are no other ODD attributes in play that can affect ODD compliance. Since this research combines the effects of the four ODD attributes chosen, the resulting ODD boundaries after the analysis is aimed to be described. As this research tests the different speed values, the time at the curve changes for the different speeds. Hence the exposure metric was introduced to test the lane-keeping performance of the vehicle in the different test cases. The test cases with weather conditions have a maximum lateral offset higher than 0.3 m when the vehicle moves at a higher speed at wider lanes. In the case of weather conditions like extreme rain and extreme snow, although the vehicle was well within the 0.3 lateral offset value in most of the test cases, there is a heavy when the lane width is narrow. Additionally, at a lane width of 2.6 m, there is a swerving nature observed between the lane centre and the right lane marking by the vehicle in all the weather conditions. However, for a lane width of 3.6 m, the swerving nature is less prominent, and it appears that the weather conditions do not heavily impact the lateral offset. Fog and rain conditions were expected to have a higher impact on the vehicle's lane-keeping performance, but surprisingly it had less effect.

From the performance assessment, the upper boundary for speed is suggested to be 100 km/h because all test cases of vehicles moving at 100 km/h were within the 0.3 m offset threshold value the entire time for all the test cases. If the upper ODD boundary of lane width is 3.5 m, then the upper boundary of speed increases to 110 km/h because all test cases of the vehicle moving at 110 km/h have the lateral offset within 0.3 m for all lane widths less than 3.5 m. Since the curve is designed for speeds of 120 km/h and if a speed of less than 120 km/h results in poor lane-keeping performance (lateral offset greater than 0.3 m), then the value of the other ODD attributes in that test case might be outside the system's ODD. For instance, at a 750 m radius curve, for lane widths 2.6 m and 2.75 m, the vehicle is completely within the offset threshold of 0.3 m when moving at a maximum speed of 120 km/h. When the lane width of this curve increases to 3.0 m, 3.25 m or 3.5 m, the maximum speed it can achieve while completely staying within a 0.3 m lateral offset becomes 110 km/h. Similarly, for a 3.6 m lane width, the maximum speed comes down to 100 km/h. Assuming that the vehicle must be able to move at the design speed of 120 km/h, based on the performance assessment, the ODD boundary of the radius of curvature becomes 1200 m since all test cases of 1200 m radius curve at speed of 120 km/h in all lane width variations are completely within the 0.3 m lateral offset throughout the simulation run. If the vehicle has to move at 120 km/h at a curve of radius 900 m, then lane widths between 2.6 m and 3.25 m are the ODD boundary conditions. Similarly, if the vehicle has to move at 120 km/h at a 750 m radius curve, then the boundary conditions for lane width reduces to 2.6 m to 2.75 m. This correlation between the attributes makes it hard to concretely define the ODD boundary. The ODD boundary for speed defined by the OEM manual (like 140 km/h) may hold for a certain set of driving conditions that is unknown to the drivers. Furthermore, the underlying principle for which the OEMs design the ODD boundaries (like perceived safety, fuel efficiency, lane-keeping performance, fault tolerance, etc.) is unavailable to the public. This lack of clarity or transparency is a huge barrier in testing the ODD boundaries.

Higher speeds have higher exposure values in narrow lane width compared to wider lane widths for curve radii of 750 m and 900 m. For the 1200 m radius of the curve, there is a decrease in exposure at 2.6 m and 3.6 m lane width compared to the other lane widths, whereas for curve radii of 750 m and 900 m, an increase in lane width results in higher exposure value. This can be because at a higher radius, the effect of lane width variations becomes more prominent. For test cases with the same lane width and radius, an increase in speed results in lower exposure. It is noteworthy that the upper boundary of the ODD range for speed provided by the OEMs is around 140 km/h to 160 km/h. The lane-keeping performance of the system becomes less even at speeds of 140 kmph. Hence, speeds higher than that is expected to result in even lesser lane-keeping performance.

Finally, for the test cases with the same lane width and speed, an increase in radius results in higher exposure. From all the test cases simulated, it can be concluded that a lane width of 2.6 m performs better in terms of the exposure value and because of the lowest mean and maximum lateral offset value within the same radius group. This is surprising because the OEM manuals classify narrow lane widths as outside ODD explicitly in the OEM manuals and do not mention wider lanes as an ODD limitation. It was also seen that the test vehicle tends to deviate into the opposite lane when leaving the curve for certain test cases; for instance, in the test case of 3.6 m lane width at 750 m radius, when the vehicle is moving at 120 km/h. However, for lane widths like 2.6 m and 2.75 m at a 750 m radius, the vehicle stayed well within the lane markings when exiting the curve, even at a speed of 120 km/h. Since the sole focus of this study is the performance of the lane-keeping system and the interaction in ODD attributes at the curve segment, the deviation at the end of the curve segment was not further investigated.

In the initial plan, lane widths ranging from 2.5 m to 4.0 m was to be tested in this study. However, only lane width values between 2.59 m and 3.7 m were possible for testing speeds of 140 km/h. In the initial testing, it was found that for a radius of 750 m, the maximum speed of the test vehicle was 50 km/h for lane widths of 2.5 m and 4.0 m. Since these speeds are not in the range of values planned to test in this research, lane widths that couldn't attain speeds of 140 km/h were omitted.

It can be concluded that there is an interdependency between the ODD attributes tested in this research. Therefore, there is a possibility that the ODD definition may not exactly be a specific set of values in a lookup table, but instead can be dynamic considering this interdependency. Furthermore, it was also found that geometric factors like lane width and radius of curvature have a higher impact on the exposure, compared to speed and weather conditions. The weather was found to have the lowest effect on the performance.

From the analysis of averaging exposure over the different lane widths, it is observed that sharper curves lead to more deviations beyond the offset threshold of 0.3 m. Additionally, as the radius increases, the frequency of such exits decreases over the lane widths. It was also seen that an increase in speed leads to a higher frequency of the exits within the test cases of the same radius.

Based on the analysis done, the attributes tested in this research can be classified into critical and non-critical attributes, where the former has a higher level of importance in the ODD definition than the latter. The ODD attributes like speed, the radius of curvature and lane width can be classified as critical attributes due to the correlation they have in the performance assessment. Whereas, the weather variations were not reported to have a higher level of impact on the exposure compared to the other three attributes. The level of impact of the weather condition on the lane-keeping performance observed in this study is quite contrary to findings from previous research. This can either be because the control algorithm in Prescan is very good and may not be representative of a controller in real life, or because the weather presets provided in Prescan is not accurate enough. Extreme weather conditions like dense fog that completely obstructs the lane markings were tested to see if the weather affects the controller in Prescan. When the droplet size and intensity of fog were manually changed and tested in Prescan, it did have a significant impact on the lane-keeping performance. Hence, the weather variations provided as presets in Prescan labelled heavy and extreme is not very reliable and requires further refinement. Therefore, no conclusions can be drawn about the impact of weather conditions based on the available data.

Having the sub-research questions answered, it is now possible to answer the main research question:

"How to assess the ODD boundaries of vehicles equipped with Lane-Keeping System at horizontal curves using PreScan?"

The answer to the main research question of this research is the implementation of the proposed framework shown in Figure 55 used in this study by using the exposure metric to assess the impact of the ODD attributes on the lane-keeping performance. The ODD boundaries and the correlation between the identified ODD attributes are clearer by implementing this framework in Prescan on test vehicles equipped with a lane-keeping system at horizontal curves. The results from this approach essentially provide more insight into the ODD boundaries and their assessment.

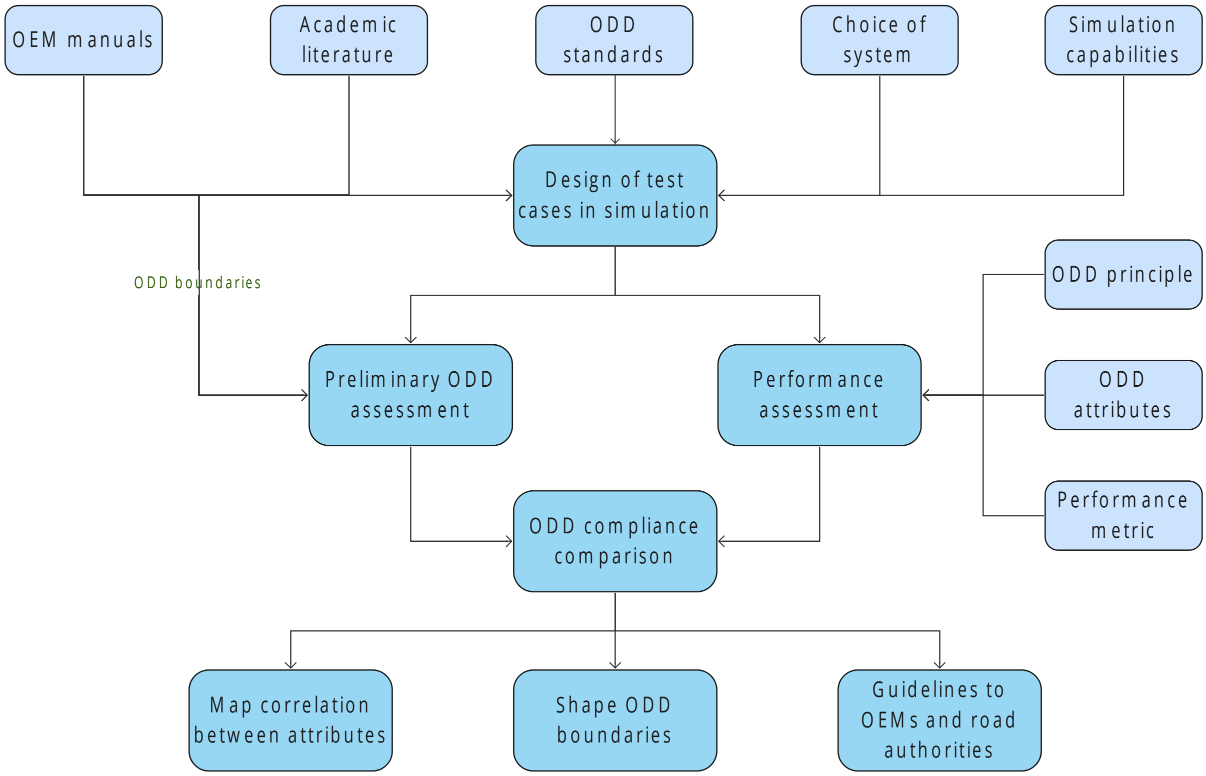

Figure 55: Conceptual framework to test the ODD boundary of ADAS in simulation

The main requirements of this approach are the initial exploration of ODD definitions of lane-keeping systems to find the attributes relevant to the system. These attributes are then filtered out based on the simulation capabilities of the simulation software. The use cases are built based on the filtered attributes and the values to be assigned for each test case are found from literature and OEM manuals. The classification of inside ODD and outside ODD is done based on the ODD boundaries identified from the exploratory phase. This is then compared to the performance assessment results from the simulation run of the test cases. Such a comparison helps identify the effect of each attribute on the ODD definition itself and the correlation between them. This methodology enables researchers and vehicle manufacturers to test the different ODD boundaries in a system's ODD definition and assess whether an ODD classification of a driving situation based on the ODD definition is complete or not. The approach used in this study is converted into a conceptual framework that can be used for the ODD assessment of any ADAS feature or ADS as shown in Figure 55.

From the results, it is seen that the performance aspect is not factored in the ODD definition and taking performance also into account will be useful for better defining the ODD boundaries. It is clear from the comparison between the initial ODD assessment and the performance assessment results that some test cases defined outside ODD has good lane-keeping performance and some test cases that are defined inside ODD has poor lane-keeping performance. This means that the ODD boundary definitions are incomplete and require further shaping. The reason behind it can be the lack of ODD boundary descriptions of all tested attributes in one place. The ODD boundaries were taken from design guidelines, OEM manuals and literature for the different ODD attributes since the OEM manuals did not contain all the necessary information. Additionally, the principle or basis behind the OEM's ODD definition is unavailable and understanding that would be very beneficial for the ODD assessment of the test cases.

7.3. Final Remarks

There is plenty of research that performs a performance evaluation of the lane-keeping system in on-road conditions and simulation. However, there are very limited simulation studies that test the lane-keeping system performance from an ODD perspective. This research aims to fill that gap by providing a framework that enables researchers to test the ODD of lane-keeping systems or other ADAS features. The effect of ODD attributes and the impact of the correlation between the attributes on the ODD boundaries are investigated, which can help researchers and OEMs to improve the ODD boundaries of the lane-keeping system. The study also takes into account the design factors, which can aid policymakers and road authorities in the future while designing roads for vehicles equipped with lane-keeping systems. Siemens can use the performance metric developed as a plugin to test the different use cases and gain insights on the ODD of the vehicle tested using the approach from this study. Moreover, ODD is gaining much traction lately and as the future of autonomous vehicles is coming closer, ODD must be given importance now more than ever.

There is a wide range of names assigned to lane-keeping systems by different OEMs with very limited information provided about the ODD. With the limited amount of knowledge available, the ODD must be experimentally tested by the road authorities or researchers to better understand the system's capabilities and limitations. There is no warning system in the vehicle that alerts the driver about the vehicle leaving the ODD or coming close to the ODD boundary. Combining ODD assessment and performance assessment as done in this study would help to be aware of when a system leaves the ODD in different driving situations. However, there should be efficient knowledge transfer between the involved stakeholders, like the OEMs, road authorities, traffic agencies. Such a collaboration can help upgrade both the road infrastructure and the driving system for compliance with a standard ODD definition. In addition, policymakers can clearly specify the road infrastructure characteristics and OEM system requirements to complement each other for safer and more efficient traffic movement. One of the major challenges faced by the OEMs (especially in the European Union) would be to satisfy the infrastructure requirements of different countries within the EU due to different regulations. This can be resolved by ensuring a level of homogeneity in the infrastructure across the countries. An alternate solution would be to digitalize the road infrastructure and share it with the OEMs so that they can test the system with the provided data. Once the system is tested and validated with the data on a simulation environment like in this study, the vehicle would be ready for the infrastructure and can ultimately minimize the ODD exits. This can only be done with a massive collaboration with the different partners in the industry, research organizations and government bodies. ODD requirement/sharing policies must come into effect more as international regulations rather than providing suggestions or taxonomies.

Since lane-keeping systems function with the underlying objective of staying within the lane markings by detecting them via sensors, it can be concluded that there is a direct relationship between the system and the road infrastructure that it uses. However, there is a knowledge gap between the OEMs that design the system for specific infrastructure conditions and the road authorities who provide the infrastructure. Specific details concerning the infrastructure conditions like the lane marking contrast or pavement friction would be used while testing the system by the OEM. The road authorities would have to ensure certain standards that the OEMs use in the built infrastructure, or the OEMs have to test their systems in the most realistic driving situations possible. Given that a model of a vehicle will release in different countries with different design guidelines, traffic composition and policies, the best way to test the system is using simulation. With efficient communication about the ODD between the OEMs and the road authorities, the testing of the system can become quicker, paving the way to higher levels of autonomy in vehicles. The ODD requirements of a specific system must be standard and should be communicated to the road authorities. This way, the road authorities would be well prepared to ensure road safety with these systems equipped in the vehicles before launching the vehicles in the market. Additionally, this can work the other way as well. The road authorities can provide the ODD definitions offered in a city or a highway and the OEM can then test the system in that ODD before launching it. The system can be tested using the approach mentioned in this study. Furthermore, in a complete ODD definition with more attributes, a single attribute being outside its ODD boundary would classify that driving situation as outside the ODD. However, the system might still be able to perform well, as shown in this study. Therefore, the proposed performance metric would be useful to further refine the ODD and it can be investigated to see whether the ODD exit of just one attribute results in system malfunction. In addition, the classification proposed in this study to separate ODD attributes as critical and non-critical would be beneficial for this objective.

It was seen from this study that lower lane width allows a higher speed of the test vehicle, along with better capability to map the lane-markings. This finding requires further validation. If this is validated, then based on it, the speed limits of the roads can be increased coupled with narrowing the lanes. Such a change can result in higher capacity and a chance to provide additional lanes. However, the vehicles need to communicate with each other with high precision regarding the vehicle position for safe movements of the vehicles. When the V2X (Vehicle-to-everything) communication technology is more advanced in the future, the proposed design change can indeed be a possibility. The perceived safety can be a problem since human drivers are still part of the loop. If lane narrowing becomes a possibility, then providing a dedicated lane for vehicles equipped with such systems can be a safer alternative in such a scenario to separate conventional vehicles from automated vehicles.

7.4. Reflection on the state of the art

While comparing the boundary conditions of the ODD attributes tested in this study against literature, some differences are noteworthy. The most interesting aspect is the ODD boundary for lane width. The on-road pilot tests for lane-keeping systems done by García & Camacho-Torregrosa (2020) found that the lane-keeping system cannot function on lane widths less than or equal to 2.50 m and that the system can always operate on lane widths greater than or equal to 2.75 m. The field tests done by Reddy et al. (2020) observed the highest lane-keeping performance on lane widths that are wider than 2.50 m. Similarly, only speeds higher than 90 km/h resulted in low lane-keeping performance. The study done by Chaudhary (2021) on the infrastructure assessment for ODD of lane-keeping system found that the test vehicle speeds of above 80 km/h resulted in better lane detection. However, the test vehicle could not detect lane widths below 3 m. From this study, it was found that the lane-keeping system cannot function at a lane width lower than 2.6 m or higher than 3.6 m. In addition, the system performance for the different lane widths is dependent on the speed of the vehicle and the radius of curvature. Test vehicle speed of 100 km/h was found to be completely inside the offset threshold of 0.3 m for all lane widths and radius of curvature tested. Furthermore, the test vehicle speed of 110 km/h was found to be within the offset threshold for all radii of curvature tested with lane width between 2.6 m and 3.5 m. The study done by (Hayeri et al., 2015) indicates that the lane width could be reduced given that the lane-keeping systems guarantee the vehicle staying within the lanes. This is in line with the results from this study that the test vehicle at lower lane width is showing higher lane-keeping performance compared to wider lanes. It is also noteworthy that the OEM manuals specify narrow lane widths as the ODD boundaries in the OEM manuals. However, the results from this study prove that wider lane widths like 3.6 m might also be an ODD boundary based on the performance.

García et al. (2020) concluded from testing a Level 2 vehicle on different horizontal curves that there is a strong relationship between the maximum speed the system can attain and the curve geometry. It was concluded in the study that there was a strong relationship between speed and disengagements. It was also found that the proposed 'automated speed' is lower than the design speed for curves sharper than 550 m. The research done in this thesis further establishes these correlations. The maximum speed that the lane-keeping system can attain (while staying within the ODD) from this research is dependent on the geometric design of the curve. Higher speeds can only be attained at lower lane widths or higher radius of curvature. For a design speed of 120 km/h, the minimum curve radius is 750 m. For a curve radius of 900 m, the maximum attainable speed was 110 km/h provided all the test cases adhered to the 0.3 m offset threshold value used. For sharper curves like 750 m radius, the maximum attainable speed becomes 100 km/h and for curves of radius 1200 m, the maximum attainable speed is 120 km/h. Hence it is found that the automated speed in this research is lower than the design speed for curves sharper than 900 m. As for the disengagements, it was also found in this research that higher speed leads to more deviations beyond the offset threshold value and longer time beyond the threshold (lower exposure values).

The level of impact of weather conditions on the exposure was the lowest compared to the other three ODD attributes tested. This was unexpected given the fact that all five of the OEM manuals that were reviewed reported ODD limitations for weather conditions like fog, rain and snow. In addition, the literature review also points out a strong effect of weather conditions on lane-keeping performance. Moreover, the tested weather conditions are the higher levels of rain and snow offered by Prescan. Further studies are required to capture the effect of weather conditions on the ODD by using other controllers or by testing more ODD attributes to see if the impact of weather becomes prominent in the presence of another ODD attribute that wasn't tested in this study.

7.5. Reflection on the methodology

The main factor of this research is the performance equation based on the 0.3 m lateral offset threshold. The vehicle deviating beyond this threshold value can be indicative of the system performance itself. Therefore, the methodology used in this research can be used to better shape the ODD definition and can also be used to refine the system. More research must be conducted on whether using this 0.3 m offset threshold is a good method for the performance assessment and to see if such a parameter alone can be used to better shape the existing ODD boundaries. Additionally, other factors can determine the ODD boundary of the system. For instance, the 0.3 m offset threshold can hold for two cars following very closely to each other. However, the perceived safety of the driver can become a factor there and hence the performance metric might need to include a headway factor as well when the test vehicle is interacting with a second vehicle.

Using simulation is a good way to test many different driving situations which cannot be replicated in on-road experiments. A certain level of realism has to be achieved in the simulation tool to provide concrete recommendations. There can be many factors within the simulation that can be at play, which if not aware of, can be the reason for the system performing a specific way. In Prescan, the preset weather conditions showed little effect on the lane-keeping performance. It might be a possibility that the preset conditions are not very accurate, or the controller is too good to be realistic. Additionally, the weather conditions didn't have much impact because the lane marking looks very new and clear, where in reality that need not be the case. Therefore, improving the realism on the simulation platform is very crucial for mapping the impact of ODD attributes better in future studies. Prescan do provide functionalities like adding mud patches on the lane marking, modifying tire conditions, fading and dirtiness parametrization of the lane markings. However, this was not the main focus of this study and was not used in the development of the use cases.

7.6. Research limitations

As with any research, there are limitations to this research. They are discussed below.

- The research is limited to the lane-keeping system at a horizontal curve. The system is expected to function in other types of road segments as well. Additionally, the type of curve (left or right) is beyond the scope of this research.

- The use cases are built without including the superelevation at the curve into consideration due to the limitation posed by the simulation software Prescan. If superelevation has to be included in the study, a gradient has to be applied to the start and end of the curve segment and only then an angle of superelevation can be applied to it. Since gradient was not an attribute tested in this study and because it is not realistic to have the vehicle go uphill before the curve and downhill after the curve, the superelevation factor is ignored during the design of experiments. This is a pitfall of the simulation software used. Furthermore, if such a gradient is applied, the camera sensor will be able to see the sky when entering the curve from the initial increasing gradient and at the end of the curve when the road starts sloping down. Including superelevation into Prescan realistically is very important since Prescan is a physics-based simulation platform. Moreover, since the results from this study capture the pattern in the performance observed from the correlation between the ODD attributes, including a superelevation might have the same impact on all the test cases and can result in the same correlation.

- Prescan does not allow the extraction of the infrastructural details from the graphical user interface (GUI) to the Simulink end. This would have been beneficial to better understand the correlation between the performance of the vehicle and the infrastructural ODD attributes tested. If it was possible, then the ODD of the test vehicle during the runtime could have been monitored.

- The performance assessment equation used (Equation 1) is based on the 0.3 m lateral offset threshold which was used to capture the lane-keeping performance changes with varying ODD attributes. If other dynamic attributes are to be tested, the equation has to be modified. Moreover, the 0.3 m lateral offset threshold can be subjective based on the dimensions of the vehicle, i.e. for a wider vehicle the equation might result in more offset threshold exits, especially at a narrow lane width.

- There is an initial peak in the lateral offset visible in all test cases when the vehicle enters the curve segment. This is due to the lack of V2I communication or GPS sensor since in reality the vehicle will have GPS data and can know the vehicle is entering a curve segment beforehand itself.

- The biggest drawback of simulation studies is the combinatorial explosion, which limits this research as well. A total of 540 test cases could be mapped if all the combinations of the ODD attribute values are tested against each other. However, only 130 test cases were possible to test in this research.

- In reality, an ADS will be equipped with so many sensors and not just a camera sensor. The vehicle would then have a sensor fusion model to map the entire surroundings of the vehicle.

- In driver assistance systems like the lane-keeping system, the human driver plays a very crucial role in the performance. However, there is no human driver model included in this research and the interaction between the driver and the system is beyond the scope of this research.

- The interaction with other road users or vehicles is also kept out of scope for this research. Real-life driving situations will include such interactions, but it is not addressed in this research.

- The algorithm for detecting the lane marking was in-built in Prescan and is not very well described in terms of what happens on the back end. It could not be checked or tested if it is similar to a lane-keeping system in use or to check if the correlation found in the study can be attributed to the control algorithm.

- Combinatorial explosion can be resolved by the ‘Prescan360’ framework developed by Siemens. However, that can result in a higher cost in computing infrastructure.

8. Recommendations

The possible next steps are discussed in this chapter to take this research forward. The possibilities are categorized into two steps as described below.

8.1. Scientific recommendations

- The results from the ODD and performance assessment done in this study has to be validated. It can be done by comparing with on-road experiments to check if the trends reported in this study is reported in on-road experiments as well. The impact on the exposure observed in this study by ODD attributes must be explored in detail.

- The degree of correlation between the ODD attributes needs to be mapped out better to compare the impact each ODD attribute has on ODD compliance. Identifying the patterns when ODD attributes interact with each other is a gap that has to be addressed to better understand the ODD.

- Researchers can use the framework proposed in this study to perform the ODD assessment for other ADAS features like ACC or AEBS. To increase the realism of a future ODD assessment of lane marking system, more attributes have to be tested until all the ODD attributes in the ODD definition are covered. These attributes include headway, time of day, condition of lane marking, driving in shadows, wet road surface, the effect of tires in the different weather conditions, type of curve, gradient. Alternatively, OpenStreetMap can be used for defining the use case to increase more realism in the assessment. It was found by Chaudhary (2021) that wet road conditions severely lowered the lane detection performance and that the lane detection performance is significantly less during daytime compared to nighttime. These aspects of ODD were not tested in this thesis and it would be beneficial to study the impact of weather conditions coupled with wet road conditions and nighttime driving situations.

- The ODD assessment can be done for on-road tests and the collected data can be used to conduct a qualitative study to compare the driver's understanding of the ODD presence of a driving situation and the actual ODD of the system. This can provide further insights to check if the driving situation is actually inside ODD or not and if other factors like perceived safety must be taken into account in the ODD definition.

- The application of critical and non-critical ODD attributes can be extended to more ODD studies for lane-keeping systems or other ADAS. Assigning a level of importance to the attributes list relevant to the ODD can save time in testing the ODD boundaries of critical attributes before the non-critical so that higher levels of autonomy reach public roads faster.

8.2. Practical recommendations

- The assessment approach proposed in this study can be used to assess the ODD compliance of thousands of already built use cases on Prescan and that data can be processed to gain a better picture of the ODD of lane-keeping system or any other ADAS.

- The OEMs must provide more information about the system and its ODD. The principle behind defining the ODD by the OEMs is not accessible and providing such information for developers or in testing would be very useful in interpreting the results from lane-keeping behaviour in different test cases. Conveying the underlying principle used by the OEM for the design, testing and validation of their system's ODD would be beneficial for future ODD based use case generation, ODD testing and research.

- Road authorities are advised to develop the ODD of the infrastructure for testing before vehicle launch so that the OEM can test if the system performs well in the built infrastructure before the vehicle is launched into the market. To achieve this, it is recommended to digitalize the road infrastructure so that the ODD assessment can be extended to more realistic testing conditions. This can then be shared with the OEMs so that they can test the system's ODD compliance faster.

- One of the major limitations regarding ODD is the lack of information available to all the stakeholders. A solution would be to bring together the involved stakeholders and conduct a workshop to understand what the objective of each stakeholder is, what are the expectations and how to move forward together. It is recommended to have an open discussion about the ODD of the lane-keeping system or any ADAS between the developer of the system, the policymaker, road authority, data scientist, etc. to have better clarity of the ODD boundaries of the system for all the stakeholders involved.

- Enforcing international regulations for a standard ODD would make it easier for testing the ODD of vehicles and can help avoid the disparity in ODD definitions, ODD boundaries and system names under the same level of autonomy by the different OEMs.

- There should be a specific focus on the performance of the system at narrow lanes at different speeds. Since a higher lane-keeping performance was observed for narrow lanes even at higher speeds, more clarity on it would be useful for lane narrowing and increasing speed limits. This can ultimately result in higher capacity and lower travel times.

- The OEMs can use the results from this study and the assessment method to better define the ODD boundary conditions provided in the vehicle manuals, especially with the lane widths. The results from the study prove that wider lane widths also have an impact on the lane-keeping performance contrary to just narrow lane width as mentioned in the OEM manuals.

- Since road characteristics are seen to have a higher impact on the ODD boundaries, it would be good to revise the design recommendations of geometric design of roadways, which was intended for human drivers in the first place.

- The ODD limitations must be conveyed clearly to the end-users. If the ODD is already tested for a system by the OEM, it would be beneficial to know which attributes were tested by the OEM and what boundary conditions were used for the assessment. Such details can also be compared with this research.

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Appendix A: Prescan

Simcentre Prescan is a physics-based simulation software developed by Siemens for testing ADAS and automated driving. It delivers fully quantified and controlled testing conditions and enables quick and cost-effective testing. Validation of the system performance and its functionality would require billions of testing miles. A bulk of that validation can be done virtually by simulation that can provide a comprehensive physics-based platform that follows a systematic approach. Prescan does exactly this and hence one of the main benefits of using Prescan is that it reduces the amount of work required to bring an ADS to the market. It is equipped with advanced sensor simulation and world modelling. Prescan is also open to third-party interfaces to support industry standards like OpenDRIVE and OpenSCENARIO. The simulation environment consists of mainly three elements, namely the GUI, Simulink and Prescan Viewer. The real-world driving conditions can be replicated by using the elements offers in the Simcentre Prescan database that includes roads, infrastructure components, weather conditions, light sources, actors, etc. The scenario development and equipping the sensor on to the test vehicle is done using the GUI. Simulink acts as the interface for the control systems to design and verify the control algorithms. Running the simulation would then provide much detail into the vehicle performance and its correlation to the driving environment. Furthermore, the parameters for roads, speed, lighting, sensors and many more can be varied to better map the vehicle performance, which would be time consuming and increasingly complex in on-road experiments. Finally, the simulation run can be visualized using the Prescan viewer. This process is illustrated in Figure 56.

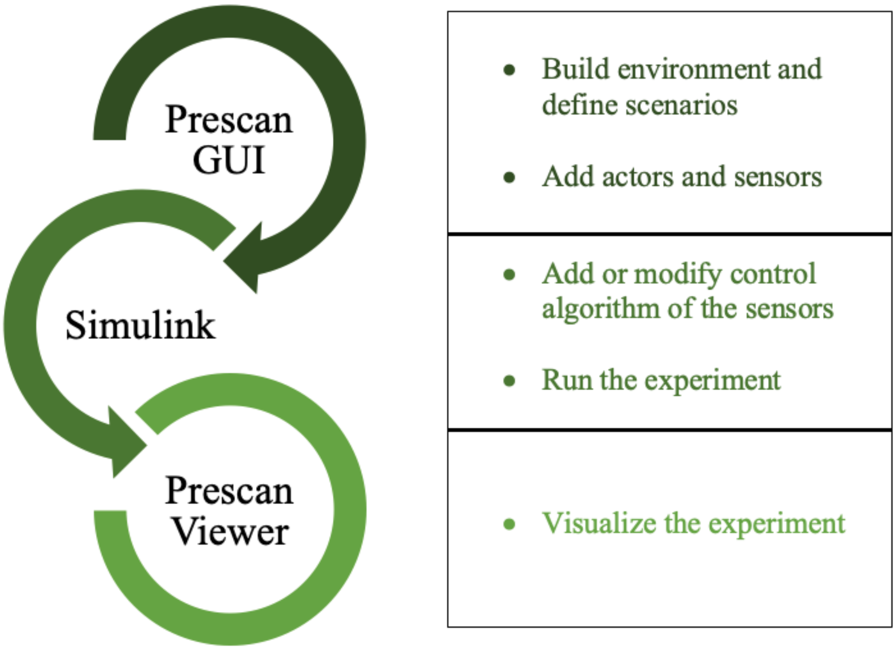

Figure 56: Main components in Prescan

The sample curve segment developed in Prescan GUI is shown in Figure 57. The test vehicle can be seen in the beginning of the road segment and the yellow highlight indicates the range of the sensor equipped. The Simulink environment for the same experiment mainly consists of the Simulink block of the actor that contains the different Simulink blocks of the vehicle within, like the vehicle dynamics, camera sensor, lane-keeping system. The expanded Simulink block of the actor is shown in Figure 58. After running the simulation, the Prescan Viewer visualizes the experiments and shows it in a window while running along with the vehicle parameters and the view from the camera sensor (see Figure 59).

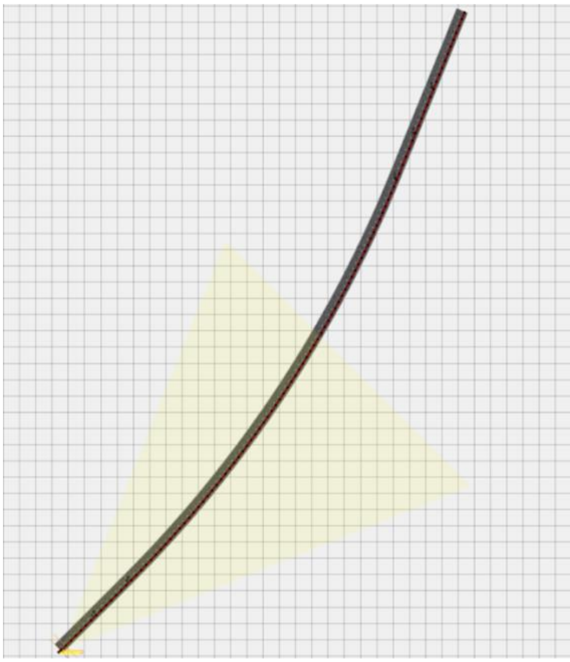

Figure 57: Curve segment in Prescan GUI

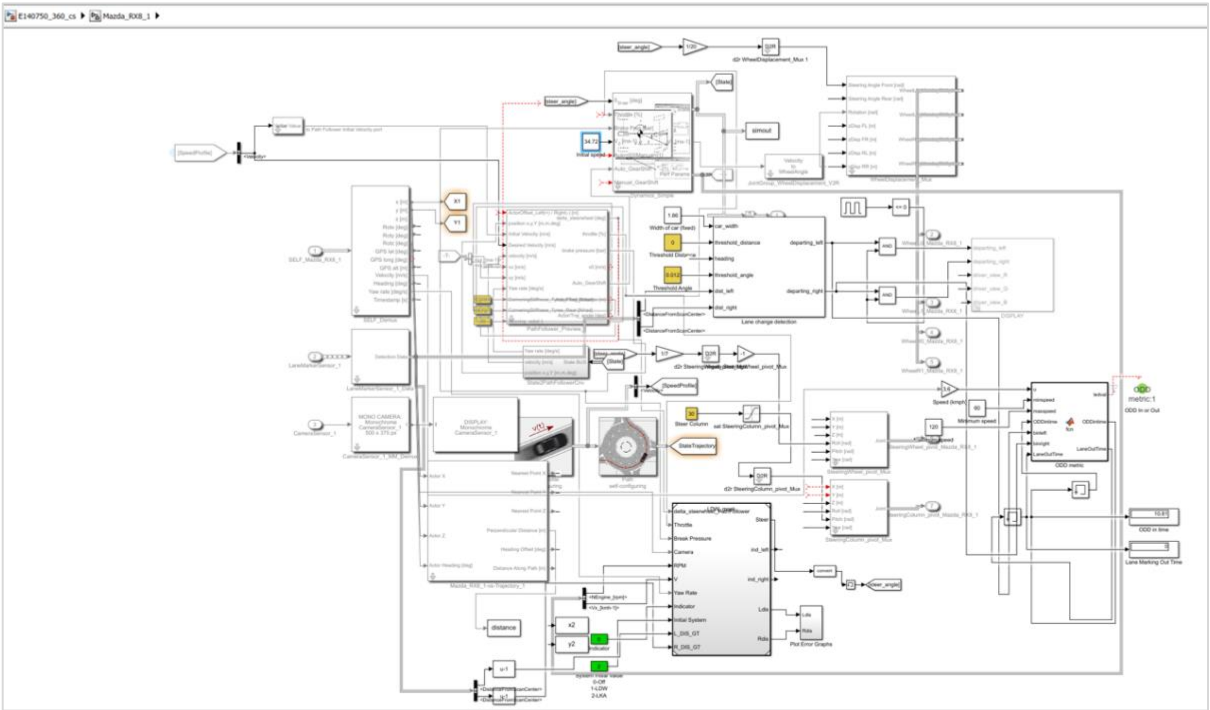

Figure 58: Simulink end of the experiment developed in Prescan GUI

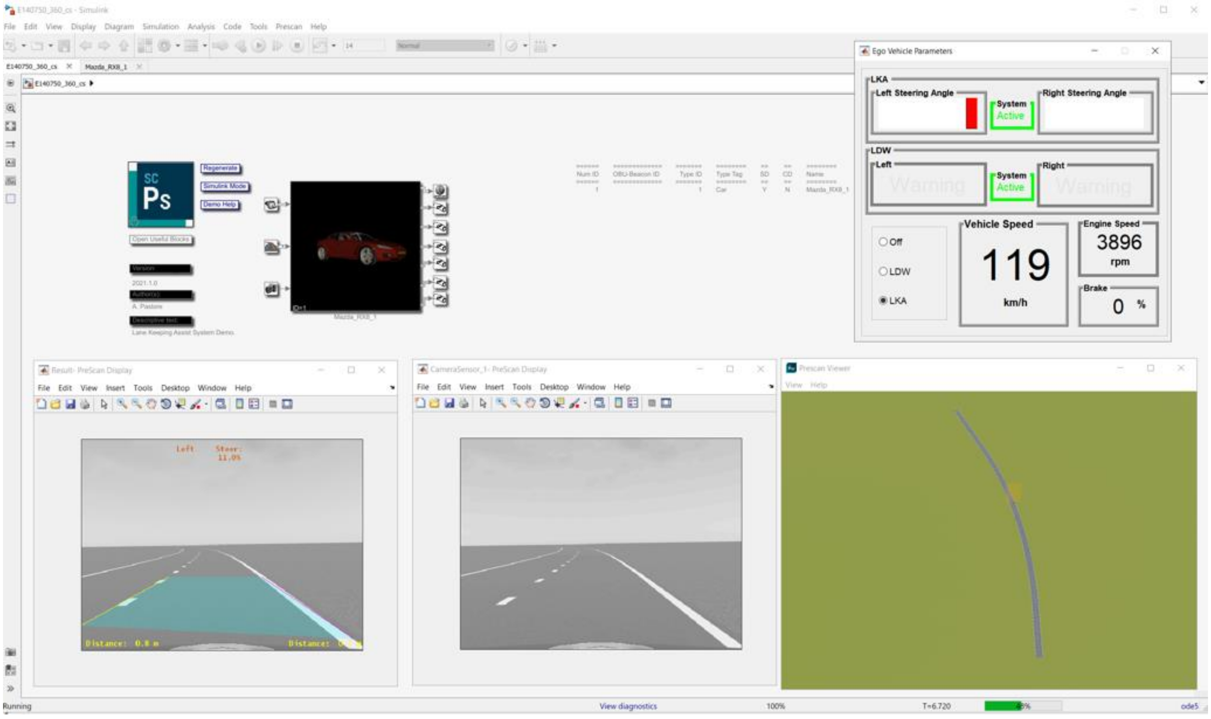

Figure 59: Information provided by Prescan while running the experiment

Appendix B: Simulation Data

B.1. Test cases without precipitation

B.1.1. Mean lateral offset

The mean lateral offset data compiled for 750 m, 900 m and 1200 radii are shown in Table 18, Table 19, and Table 20 respectively.

Table 18: Mean lateral offset data for 750 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.164 m	0.174 m	0.182 m	0.192 m	0.210 m	0.225 m
110 km/h	0.195 m	0.200 m	0.210 m	0.223 m	0.246 m	0.257 m
120 km/h	0.223 m	0.229 m	0.239 m	0.256 m	0.278 m	0.295 m
130 km/h	0.264 m	0.271 m	0.283 m	0.299 m	0.323 m	0.341 m
140 km/h	0.332 m	0.352 m	0.367 m	0.385 m	0.416 m	0.428 m

Table 19: Mean lateral offset data for 900 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.150 m	0.150 m	0.158 m	0.168 m	0.186 m	0.202 m
110 km/h	0.156 m	0.175 m	0.185 m	0.194 m	0.217 m	0.229 m
120 km/h	0.196 m	0.200 m	0.209 m	0.222 m	0.245 m	0.259 m
130 km/h	0.234 m	0.237 m	0.246 m	0.261 m	0.287 m	0.305 m
140 km/h	0.290 m	0.298 m	0.309 m	0.330 m	0.358 m	0.370 m

Table 20: Mean lateral offset data for 1200 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.106 m	0.113 m	0.114 m	0.123 m	0.142 m	0.157 m
110 km/h	0.120 m	0.128 m	0.136 m	0.144 m	0.166 m	0.176 m
120 km/h	0.142 m	0.147 m	0.154 m	0.167 m	0.186 m	0.197 m
130 km/h	0.173 m	0.171 m	0.179 m	0.192 m	0.214 m	0.230 m
140 km/h	0.214 m	0.220 m	0.229 m	0.245 m	0.270 m	0.284 m

B.1.2. Maximum lateral offset

Similarly, the maximum lateral offset data from the simulation runs of 750 m, 900 m, and 1200 m radii are shown in Table 21, Table 22 and Table 23 respectively.

Table 21: Maximum lateral offset data for 750 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.199 m	0.199 m	0.214 m	0.231 m	0.253 m	0.274 m
110 km/h	0.248 m	0.245 m	0.251 m	0.268 m	0.297 m	0.330 m
120 km/h	0.277 m	0.290 m	0.302 m	0.332 m	0.360 m	0.382 m
130 km/h	0.357 m	0.367 m	0.386 m	0.412 m	0.448 m	0.479 m
140 km/h	0.506 m	0.520 m	0.549 m	0.575 m	0.622 m	0.644 m

Table 22: Maximum lateral offset data for 900 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.190 m	0.177 m	0.194 m	0.197 m	0.231 m	0.250 m
110 km/h	0.208 m	0.217 m	0.225 m	0.241 m	0.279 m	0.291 m
120 km/h	0.249 m	0.259 m	0.267 m	0.287 m	0.324 m	0.339 m
130 km/h	0.314 m	0.328 m	0.332 m	0.363 m	0.399 m	0.426 m
140 km/h	0.431 m	0.449 m	0.450 m	0.495 m	0.537 m	0.562 m

Table 23: Maximum lateral offset data for 1200 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
100 km/h	0.137 m	0.134 m	0.136 m	0.153 m	0.183 m	0.206 m
110 km/h	0.167 m	0.163 m	0.176 m	0.190 m	0.220 m	0.225 m
120 km/h	0.186 m	0.196 m	0.199 m	0.221 m	0.248 m	0.264 m
130 km/h	0.237 m	0.238 m	0.254 m	0.267 m	0.308 m	0.332 m
140 km/h	0.326 m	0.331 m	0.348 m	0.376 m	0.419 m	0.438 m

B.1.3. Exposure

The exposure data from the simulation runs of 750 m, 900 m, and 1200 m radii are shown in Table 24, Table 25 and Table 26 respectively. The exposure data is the ratio between the simulation time for which the test vehicle was within the offset threshold value of 0.3 m and the total simulation time of the vehicle at the curve, and hence does not have a unit.

Table 24: Exposure data for 750 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
140 km/h	0.29	0.16	0.12	0.09	0.08	0.08
130 km/h	0.90	0.78	0.61	0.42	0.09	0.08

120 km/h	1.00	1.00	0.98	0.92	0.69	0.41
110 km/h	1.00	1.00	1.00	1.00	1.00	0.92
100 km/h	1.00	1.00	1.00	1.00	1.00	1.00

Table 25: Exposure data for 900 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
140 km/h	0.55	0.53	0.24	0.19	0.14	0.13
130 km/h	0.94	0.93	0.91	0.89	0.73	0.40
120 km/h	1.00	1.00	1.00	1.00	0.93	0.92
110 km/h	1.00	1.00	1.00	1.00	1.00	1.00
100 km/h	1.00	1.00	1.00	1.00	1.00	1.00

Table 26: Exposure data for 1200 m radius curve

Speed	Lane width					
	2.6 m	2.75 m	3.0 m	3.25 m	3.5 m	3.6 m
140 km/h	0.83	0.92	0.91	0.89	0.86	0.66
130 km/h	0.96	1.00	1.00	1.00	1.00	0.93
120 km/h	1.00	1.00	1.00	1.00	1.00	1.00
110 km/h	1.00	1.00	1.00	1.00	1.00	1.00
100 km/h	1.00	1.00	1.00	1.00	1.00	1.00

B.2. Test cases with precipitation

B.2.1. Mean lateral offset

The mean lateral offset data for 2.6 m lane width and 3.6 m lane width at a 900 m radius curve for 100 km/h and 120 km/h and for the different weather conditions is shown in Table 27 and Table 28 respectively.

Table 27: Mean lateral offset data for 2.6 m lane width and 900 m radius curve

Speed	Weather conditions					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.150 m	0.137 m	0.143 m	0.147 m	0.150 m	0.149 m
120 km/h	0.196 m	0.196 m	0.194 m	0.188 m	0.194 m	0.193 m

Table 28: Mean lateral offset data for 3.6 m lane width and 900 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.201 m	0.203 m	0.203 m	0.201 m	0.203 m	0.195 m
120 km/h	0.259 m	0.257 m	0.257 m	0.258 m	0.257 m	0.266 m

Similarly, for 750 m radius of curve, the mean lateral offset data at speeds 100 km/h and 120 km/h for 2.6 m and 3.6 m lane width is shown in Table 29 and Table 30 respectively.

Table 29: Mean lateral offset data for 2.6 m lane width and 750 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.164 m	0.170 m	0.162 m	0.170 m	0.168 m	0.163 m
120 km/h	0.223 m	0.226 m	0.222 m	0.223 m	0.223 m	0.229 m

Table 30: Mean lateral offset data for 3.6 m lane width and 750 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.225 m	0.225 m	0.226 m	0.225 m	0.225 m	0.255 m
120 km/h	0.295 m	0.296 m	0.297 m	0.296 m	0.297 m	0.299 m

B.2.2. Maximum lateral offset

The maximum lateral offset data for 2.6 m lane width and 3.6 m lane width at a 900 m radius curve for 100 km/h and 120 km/h and for the different weather conditions is shown in Table 27 and Table 28 respectively.

Table 31: Maximum lateral offset data for 2.6 m lane width and 900 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.190 m	0.175 m	0.176 m	0.175 m	0.190 m	0.225 m
120 km/h	0.249 m	0.249 m	0.249 m	0.249 m	0.256 m	0.240 m

Table 32: Maximum lateral offset data for 3.6 m lane width and 900 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.250 m	0.250 m	0.250 m	0.250 m	0.250 m	0.277 m
120 km/h	0.339 m	0.339 m	0.334 m	0.339 m	0.340 m	0.387 m

Similarly, for 750 m radius of curve, the maximum lateral offset data at speeds 100 km/h and 120 km/h for 2.6 m and 3.6 m lane width is shown in Table 33 and Table 34 respectively.

Table 33: Maximum lateral offset data for 2.6 m lane width and 750 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.199 m	0.207 m	0.199 m	0.207 m	0.222 m	0.210 m
120 km/h	0.277 m	0.277 m	0.277 m	0.277 m	0.282 m	0.332 m

Table 34: Maximum lateral offset data for 3.6 m lane width and 750 m radius curve

Speed	**Weather conditions**					
	Sun	Fog	Heavy rain	Extreme rain	Heavy snow	Extreme snow
100 km/h	0.274 m	0.274 m	0.274 m	0.274 m	0.274 m	0.284 m
120 km/h	0.382 m	0.382 m	0.382 m	0.382 m	0.383 m	0.390 m

Appendix C: Lateral offset variations

The lateral offset variations are shown in this section. The variation for the weather conditions are already shown in Chapter 6. The figures shown in this section are for the test cases without precipitation and is presented for each radius of the curve.

i. Test cases with 750 m radius

The lateral offset variations for the test cases with 750 m radius, for the speeds 100 km/h, 110 km/h, 120 km/h, 130 km/h and 140 km/h are shown in Figure 60, Figure 61, Figure 62, Figure 63 and Figure 64 respectively.

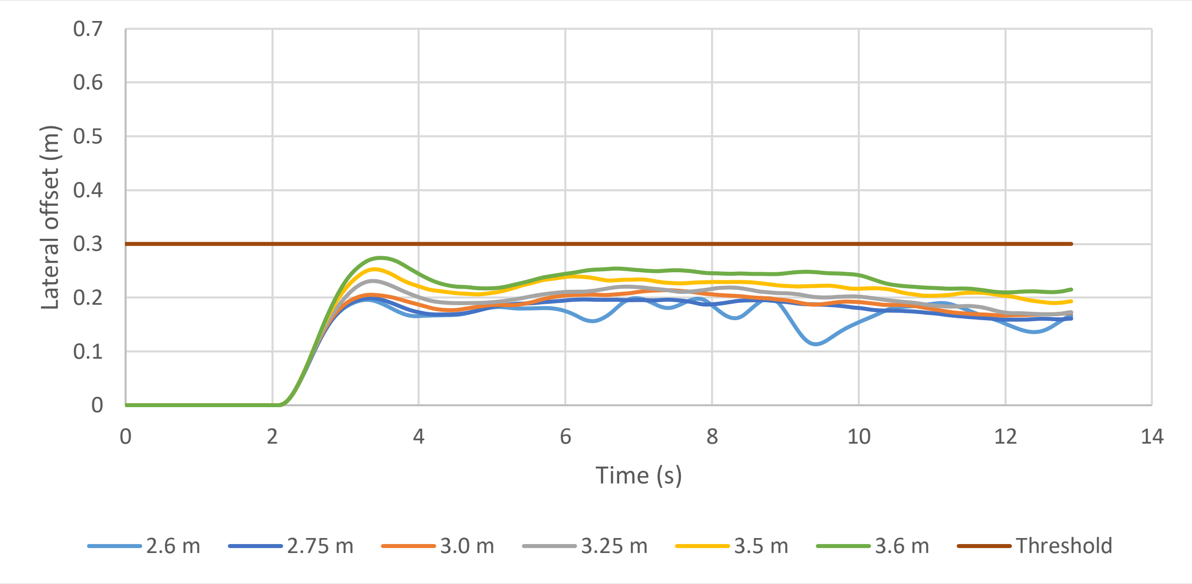

Figure 60: Lateral offset variations for test cases with 750 m radius and speed of 100 km/h

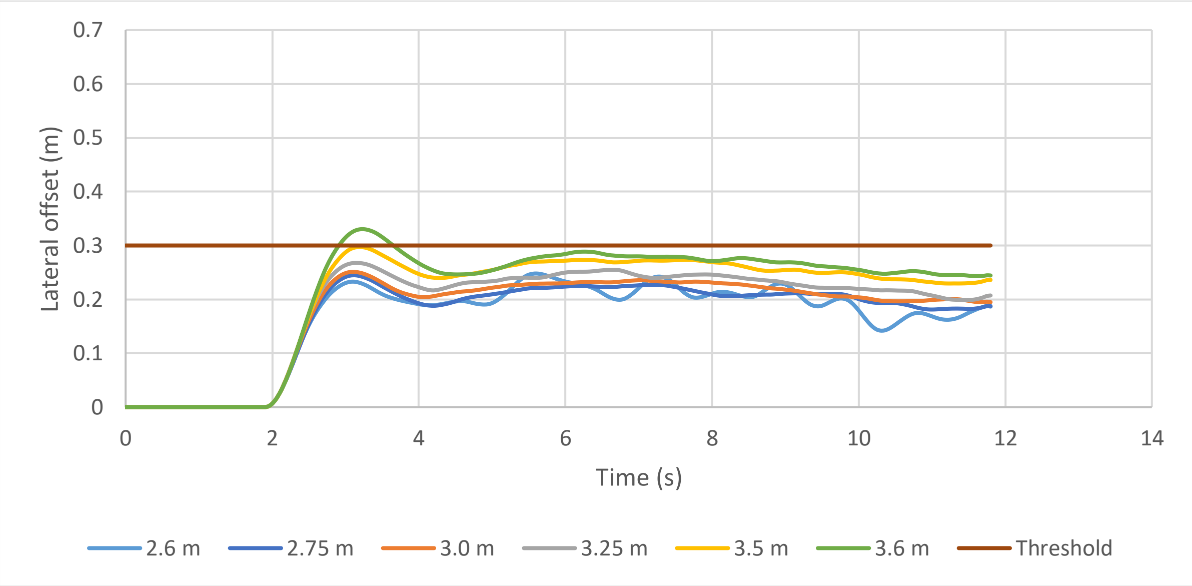

Figure 61: Lateral offset variations for test cases with 750 m radius and speed of 110 km/h

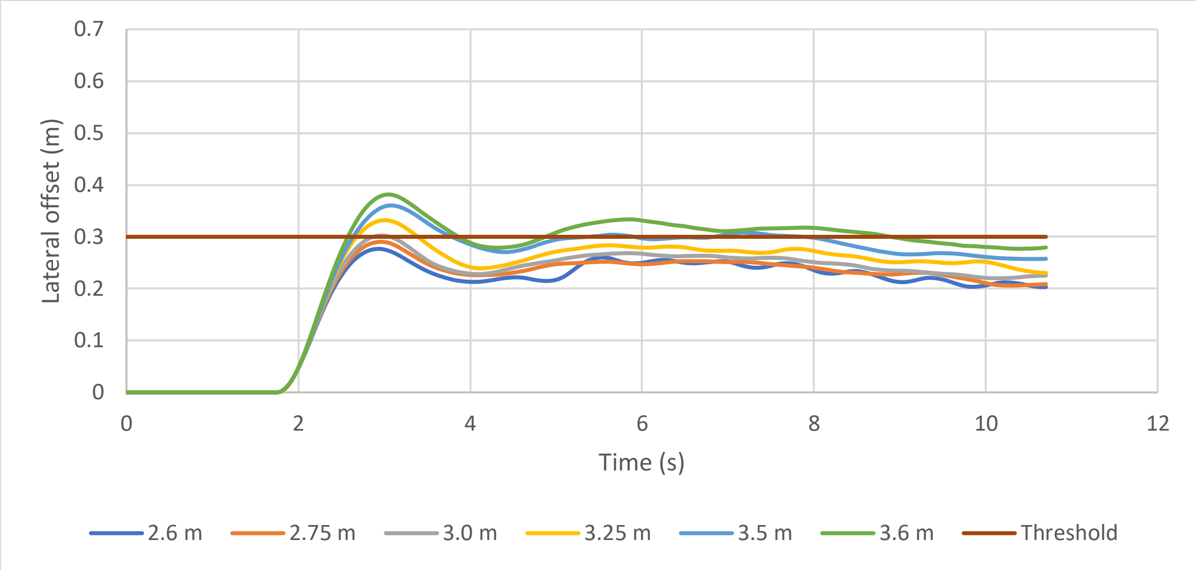

Figure 62: Lateral offset variations for test cases with 750 m radius and speed of 120 km/h

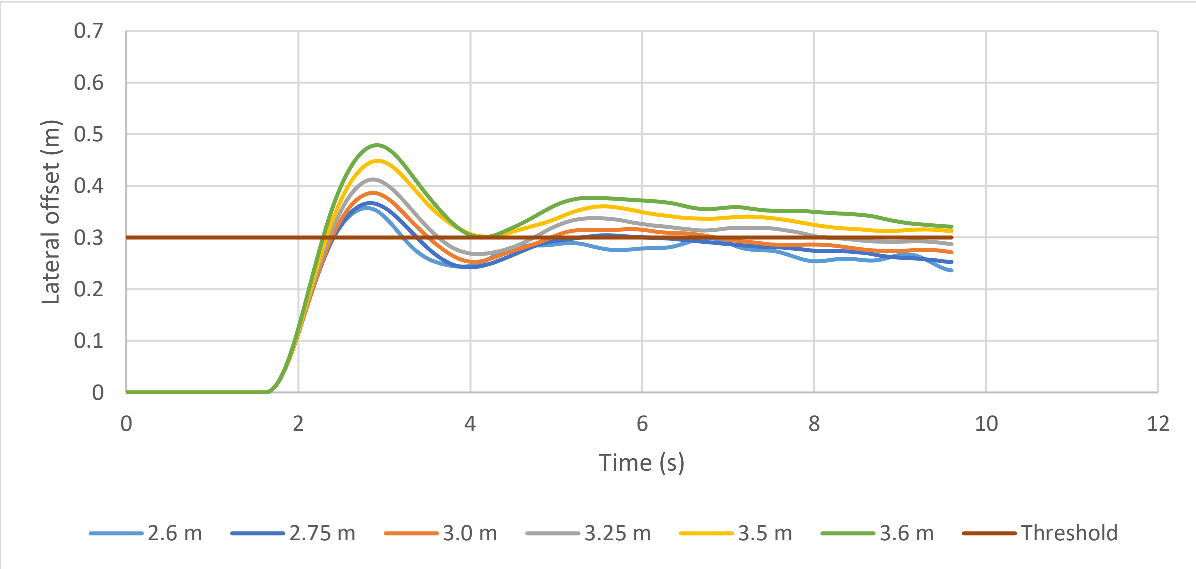

Figure 63: Lateral offset variations for test cases with 750 m radius and speed of 130 km/h

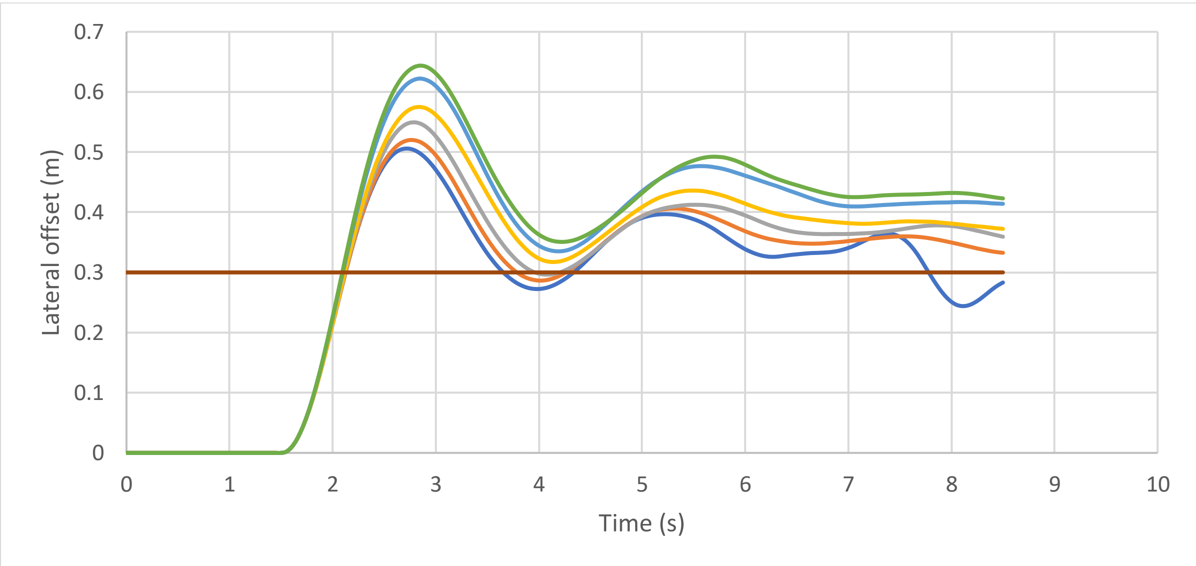

Figure 64: Lateral offset variations for test cases with 750 m radius and speed of 140 km/h

ii. Test cases with 900 m radius

The lateral offset variations for the test cases with 900 m radius, for the speeds 100 km/h, 110 km/h, 120 km/h, 130 km/h and 140 km/h are shown in Figure 65, Figure 66, Figure 67, Figure 68 and Figure 69 respectively.

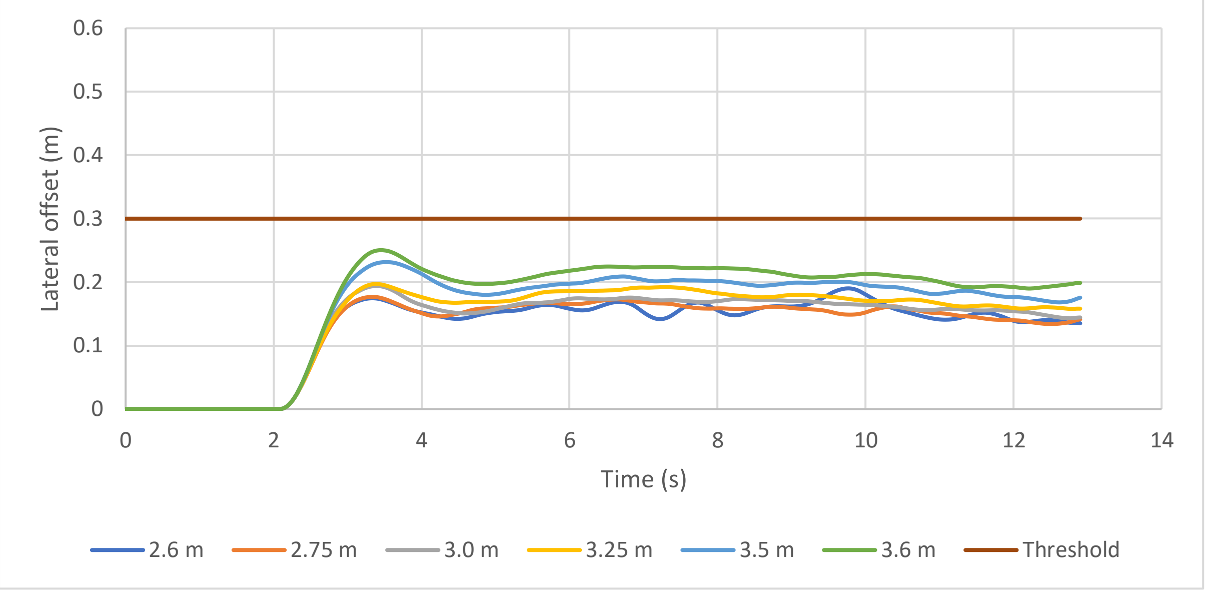

Figure 65: Lateral offset variations for test cases with 900 m radius and speed of 100 km/h

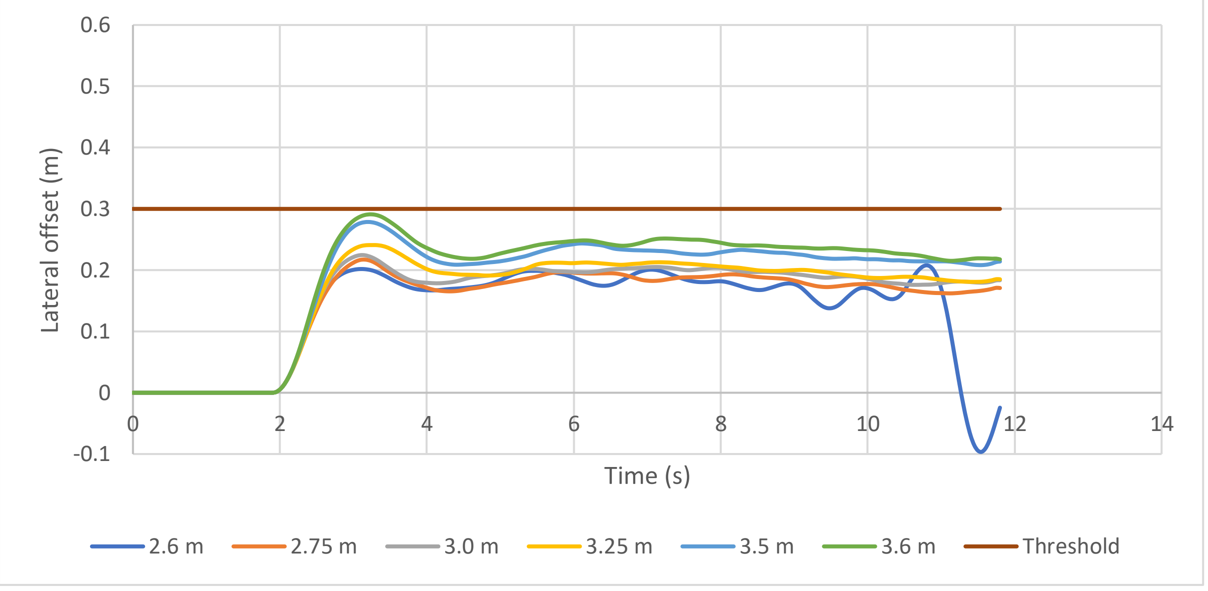

Figure 66: Lateral offset variations for test cases with 900 m radius and speed of 110 km/h

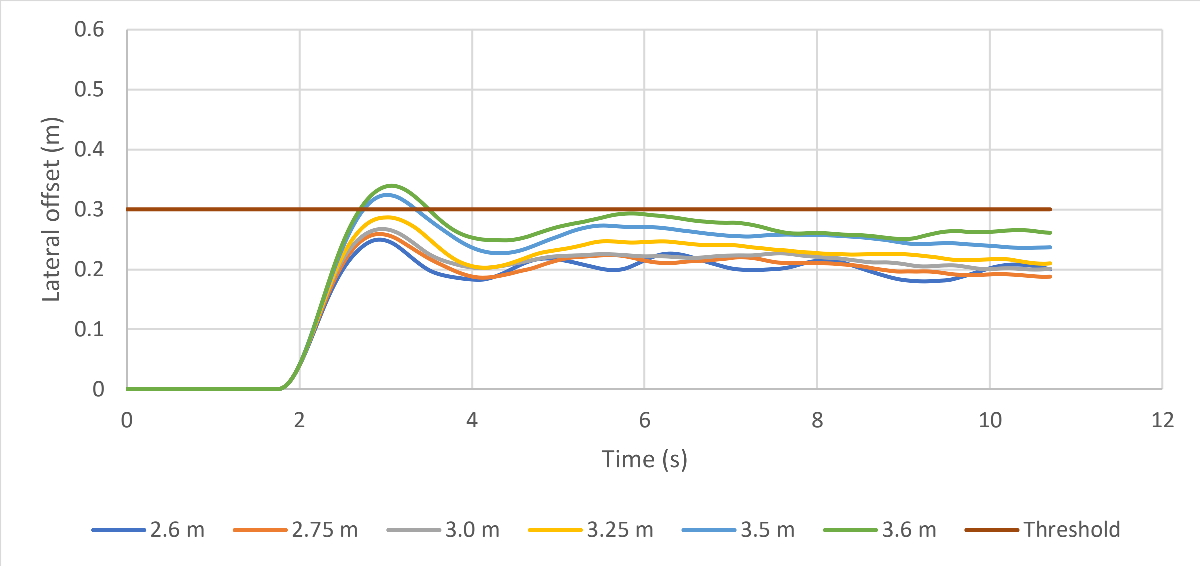

Figure 67: Lateral offset variations for test cases with 900 m radius and speed of 120 km/h

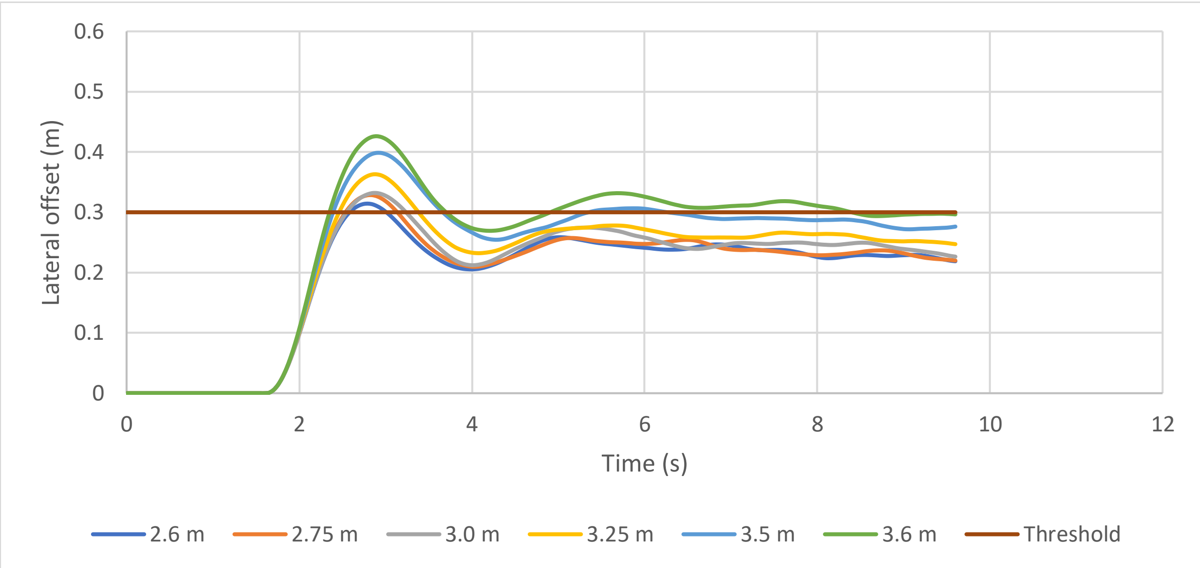

Figure 68: Lateral offset variations for test cases with 900 m radius and speed of 130 km/h

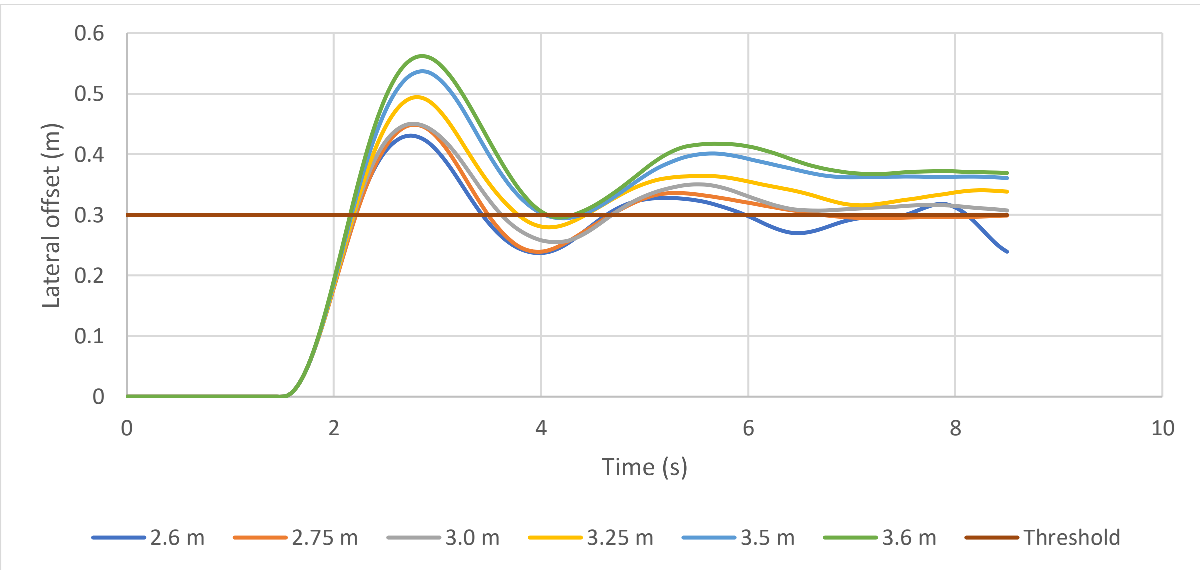

Figure 69: Lateral offset variations for test cases with 900 m radius and speed of 140 km/h

iii. Test cases with 1200 m radius

The lateral offset variations for the test cases with 1200 m radius, for the speeds 100 km/h, 110 km/h, 120 km/h, 130 km/h and 140 km/h are shown in Figure 70, Figure 71, Figure 72, Figure 73 and Figure 74 respectively.

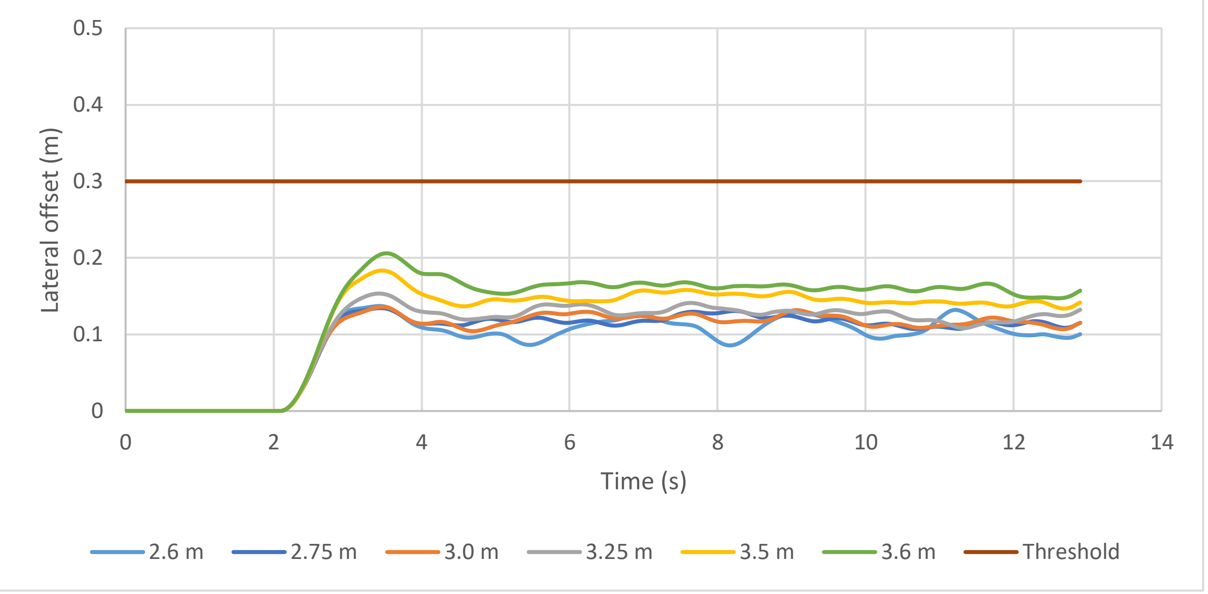

Figure 70: Lateral offset variations for test cases with 1200 m radius and speed of 100 km/h

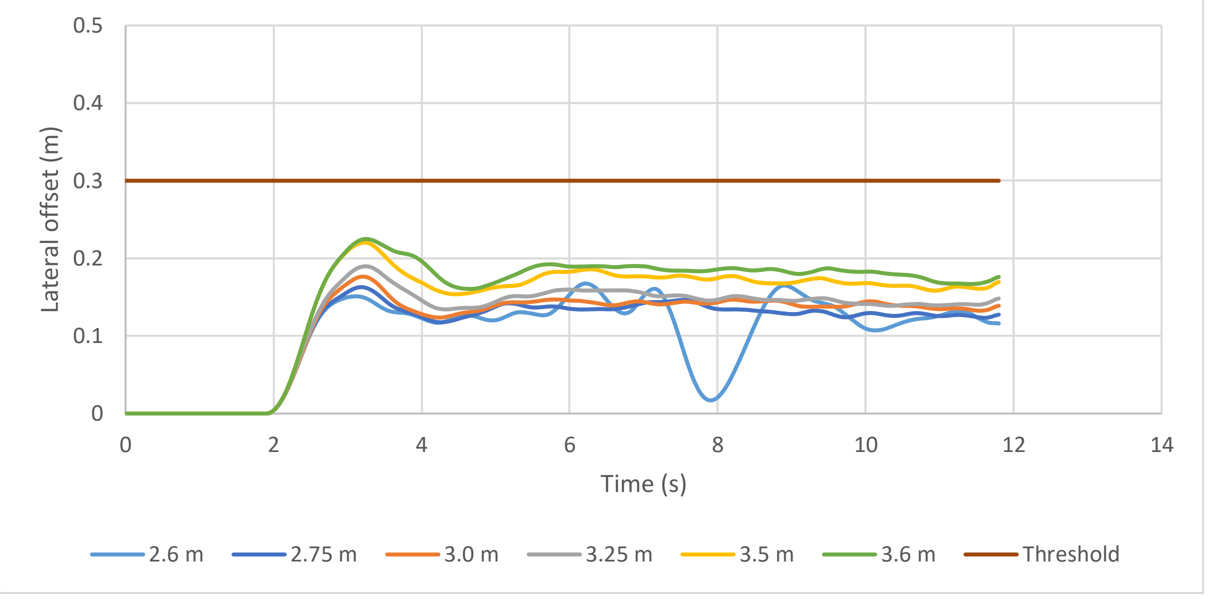

Figure 71: Lateral offset variations for test cases with 1200 m radius and speed of 110 km/h

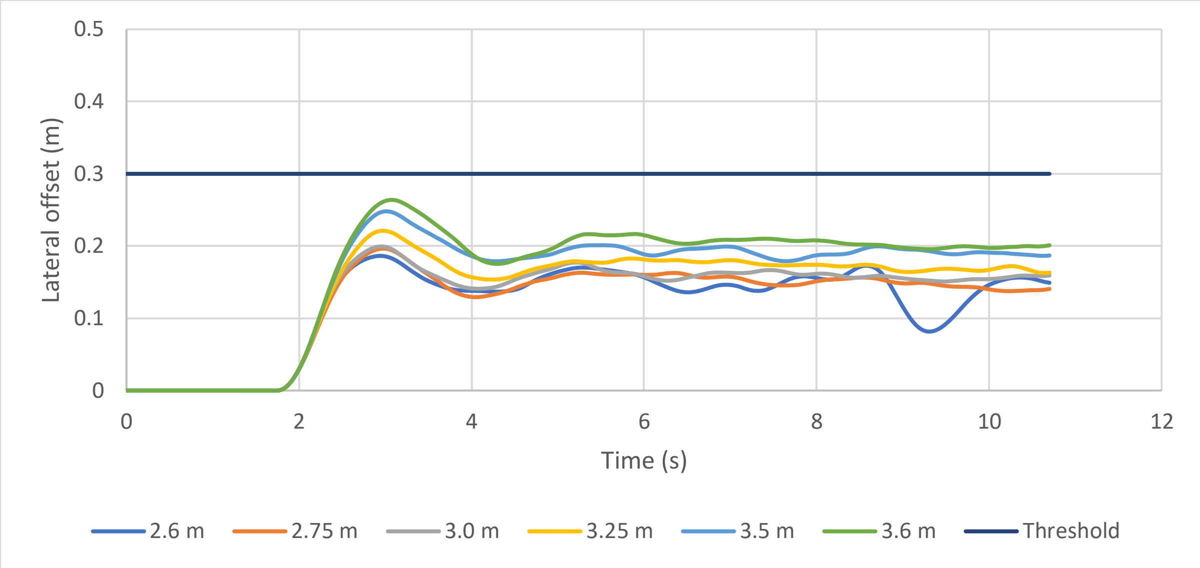

Figure 72: Lateral offset variations for test cases with 1200 m radius and speed of 120 km/h

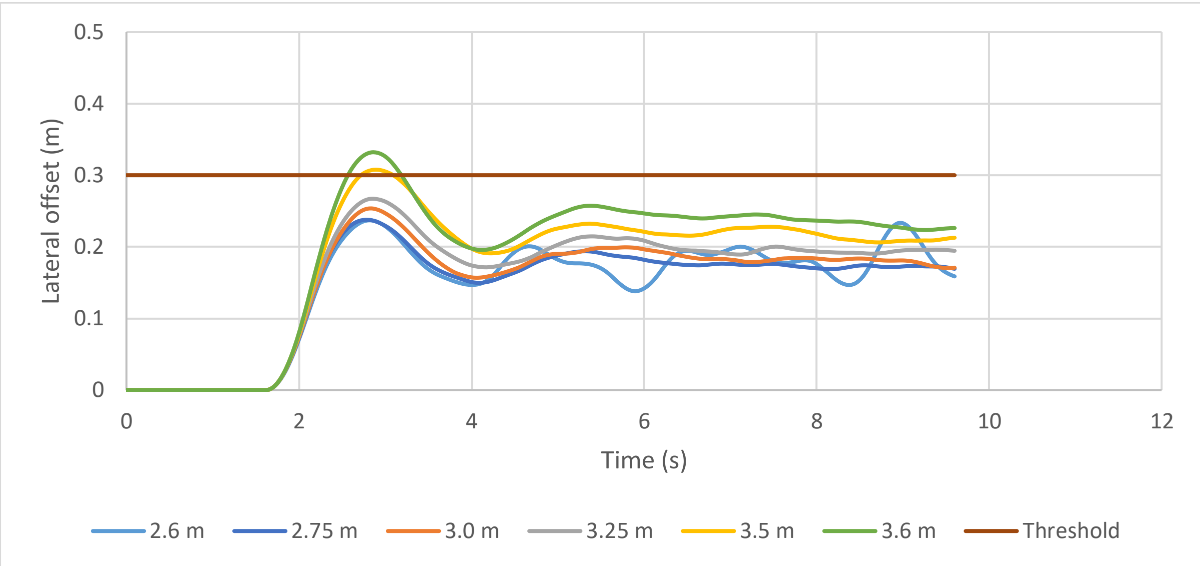

Figure 73: Lateral offset variations for test cases with 1200 m radius and speed of 130 km/h

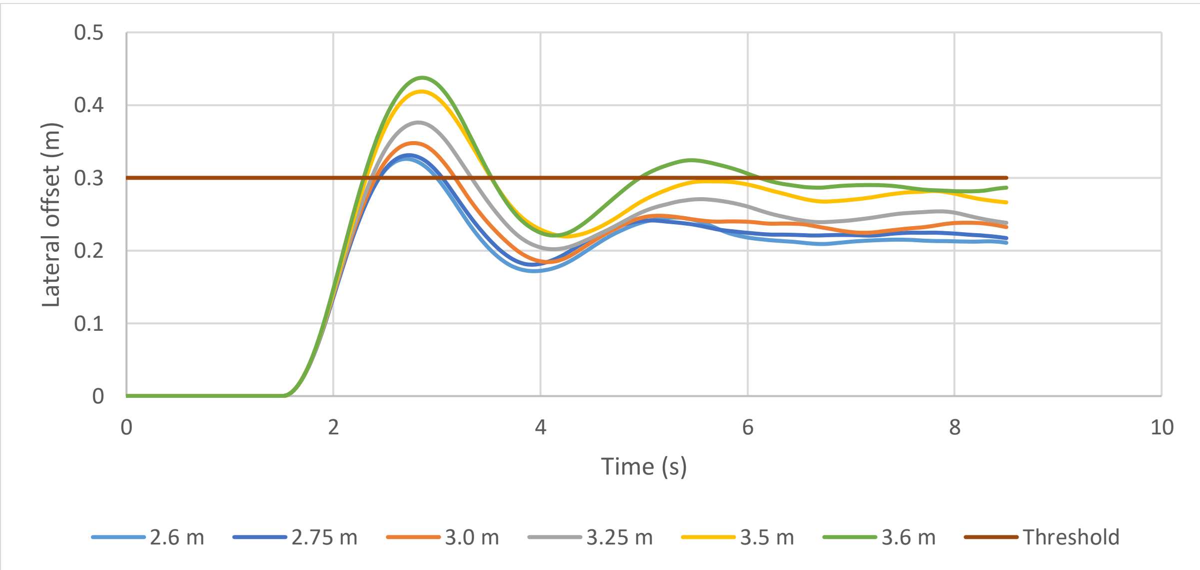

Figure 74: Lateral offset variations for test cases with 1200 m radius and speed of 140 km/h