Predictive Driver Model Development Through DIL Simulation on the OPINA Platform

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ABSTRACT

Autonomous vehicle software needs a driver model to replicate the driver in the vehicle. Driver model determines the driving style and also the safety of the autonomous vehicles. Prediction and anticipation are very important for driving safety. Driving style is also an important factor for passenger comfort. The model should also enable fine tuning for different driving cultures so that road users can estimate the behavior. In this article, a driver model development and validation methodology is demonstrated. Three scenarios have been used to obtain results and compare the real driver behavior with that of the autonomous vehicle. Three drivers have driven in line with the scenarios on the DIL(Driver in the Loop) system and their driving behaviors have been compared with that of the autonomous vehicle software and the methodology to change the parameters to converge with that of the driver and to lead to predictive driver model is demonstrated.

Keywords: Driver model, driver in the loop simulation, predictive driver model

1. INTRODUCTION

In the evolving landscape of intelligent transportation systems, microscopic driver models are essential for accurately simulating vehicle behavior and enhancing the development of Advanced Driver Assistance Systems (ADAS) and Autonomous Vehicles (AVs). These models aim to replicate the dynamics of driving vehicles, both individually and collectively, by capturing the intricate details of human driving behavior. The integration of human driving behavior into automated driving systems not only helps in predicting traffic flow and avoiding collisions but also plays a critical role in the acceptance and reliability of these systems.

Driver models must encapsulate the behavior of both human drivers and autonomous systems, incorporating specific driving styles and preferences. The challenge lies in creating realistic models that account for the myriad of factors influencing a driver's decisions, such as risk assessment, safety, and driving progress. Traditional models like the Intelligent Driver Model (IDM) and its extensions have paved the way for simulating longitudinal driving behaviors and lane-changing decisions. However, these models often fall short in scenarios involving multiple traffic participants and complex driving environments.

To address these limitations, a novel approach to driver model development through Driver-in-the-Loop (DIL) simulation and real data replay is proposed. This method involves using a driver in a simulated environment to perform the same driving tasks as an autonomous vehicle system running in the background. By comparing the driver's actions with those of the automated system, discrepancies can be identified, analyzed, and used to refine the driver model. Data for real world driving can also be digitized through the OPINA[1] HIL system and predictive and anticipative driving can be integrated through rule-based and reinforcement learning.

The integration of DIL simulation provides a dynamic and iterative process for enhancing driver models. It allows for the continuous improvement of models based on real-time feedback from human drivers, thereby capturing a more

[1] www.opinaproject.com

comprehensive range of driving behaviors and responses. This approach not only improves the accuracy of driver models but also ensures that they remain relevant and effective in diverse and evolving traffic scenarios.

This paper introduces a framework for developing driver models using DIL simulation, highlighting its potential to bridge the gap between human and machine driving behaviors. By leveraging the strengths of both human intuition and machine precision, this method aims to create more robust and adaptive driver models that can significantly advance the field of connected and autonomous vehicles.

2. STATE of the ART

The development of driver models for connected and autonomous vehicles (CAVs) is a rapidly evolving field that integrates human factors into vehicle automation. The primary goal is to enhance safety, reliability, and user acceptance by accurately modeling human driving behaviors. This section reviews the state of the art and key contributions in the literature.
Ola Benderius (2012) provides a thorough examination of driver modeling through data collection, model analysis, and optimization. Benderius' work focuses on understanding driver control inputs in various scenarios, such as lane keeping, collision avoidance, and optimal driving. This research emphasizes the importance of real driver data in developing accurate and robust driver models.
Stephanie Lefevre et al. (2014) explored the integration of learning-based driver models with model predictive control for lane-keeping assistance systems. Their research demonstrates how machine learning techniques can enhance the adaptability and accuracy of driver models, providing better support for autonomous driving systems.
Julian Eggert et.al (2015) introduced the Foresighted Driver Model (FDM), which aims to capture the risk-dependent aspects of driving. The FDM considers both the future utility and risks of driving decisions, providing a comprehensive approach to modeling driver behavior in complex traffic environments. This model addresses several limitations of traditional models by considering multiple traffic participants and non-longitudinal risks
Daniel Dauner et al (2023) developed a Predictive Driver Model (PDM) that combines rule-based planning with learned ego-forecasting techniques. This hybrid approach effectively integrates the strengths of both methods, resulting in improved performance in both open-loop and closed-loop scenarios. Ankica Barisic et al. (2023) investigated driver models for Take-Over-Request (TOR) scenarios in autonomous vehicles. Their research focuses on understanding driver responses to TORs and developing models that can accurately predict and facilitate smooth transitions from automated to manual control. Their work represents a significant advancement in the predictive capabilities of driver models.

Jamal Raiyn et.al (2024) highlight the importance of human factors in predicting autonomous driving behavior, particularly in safety-critical events. Their research underscores the need for models that incorporate human reactions to various driving scenarios to improve the predictive capabilities of autonomous systems.

Khazar Dargahi et.al (2024) introduced a multimodal driver monitoring benchmark dataset that captures various aspects of driver behavior in assisted driving automation. This dataset provides a valuable resource for developing and validating driver models, ensuring they account for a wide range of driving conditions and driver states.

The i4Driving project has made significant contributions to the field with several key deliverables:

Modeling Requirements and Framework of Testable Hypotheses (2023): This deliverable outlines the fundamental requirements and hypotheses for modeling driver behavior, emphasizing the need for models that account for the heterogeneity of human drivers.

Experimental Setup for Driving Simulator Experiments (2023): This document describes the experimental setup used to collect data from driving simulator studies. It provides insights into the methodologies for conducting realistic and repeatable driving experiments.

Critical Review of State-of-the-Art Techniques to Model Drivers’ Heterogeneity (i4Driving Deliverable) (2023): This comprehensive review examines various techniques for modeling driver heterogeneity, including probabilistic distributions, machine learning applications, and calibration methods. It highlights the challenges and opportunities in accurately capturing the diversity of driver behaviors.

The literature highlights the multifaceted approach required to develop accurate and robust driver models for autonomous vehicles. By integrating human factors, leveraging data from driving simulators, and employing advanced machine learning techniques, researchers are making significant strides in creating models that can predict and replicate human driving behavior. This article presents a methodology showing how the driving simulator and data replay technique can be used to optimize the driver model.

3. METHODOLOGY

Below a generic methodology and related specific techniques applied in this research are explained emphasizing also the future research work to be performed,

1. Scenario Selection and Design

- **Objective**: Select and design driving scenarios that are representative of typical driving conditions and safety-critical events. For this research NCAP, CVNA Scenario[11] and a rural road driving scenario with a combination of ACC(Adaptive Cruise Control) and overtaking will be used.
- **Approach**:
    - Identify a comprehensive set of scenarios, including urban driving, highway driving, and complex maneuvers (e.g., lane changes, merging, and collision avoidance).
    - Use real-world data and expert input to ensure the scenarios are realistic and challenging.

2. DIL Simulation Setup

- **Objective**: Create a DIL simulation environment that seamlessly integrates a human driver with an autonomous vehicle simulation. The DIL environment to be used is OPINA DIL Platform as explained below with IPG Truckmaker real time simulation system.

3. Data Collection and Synchronization

- **Objective**: Collect comprehensive data on human driving behavior and autonomous vehicle performance in on the DIL system. The same scenario should be driven by at least 10 drivers on DIL. Collect real driving data on the road then replay the data on the HIL dSpace system and digitalize. Compare real driving data with the driver model .
- **Approach**:
    - Instrument the driving simulator to capture detailed driver inputs (e.g., steering, braking, acceleration) and physiological data (e.g., eye movements, heart rate).
    - Simultaneously record the autonomous vehicle's responses, including sensor data (e.g., LiDAR, radar, cameras), control actions, and environmental conditions.
    - Ensure precise time synchronization between human driver inputs and autonomous vehicle actions.
    - Obtain real-world data and digitize the data on the HIL system to fine tune the driving model further

4. Analysis of Discrepancies

- **Objective**: Identify and analyze discrepancies between human driving behavior and autonomous vehicle performance. OPINA DIL system automatically captures the differences.
- **Approach**:
    - Use statistical, rule based and machine learning techniques to compare human driver actions with autonomous vehicle responses across different scenarios.
    - Identify patterns and instances where human drivers deviate from the autonomous system's behavior.
    - Classify discrepancies based on their impact on safety, efficiency, and comfort.

5. Model Refinement and Improvement

- **Objective**: Refine the driver model based on the analysis of discrepancies to better emulate human driving behavior using the above results.
- **Approach**:
    - Develop algorithms that adjust the autonomous vehicle's control strategies to align more closely with human driving patterns.
    - Implement machine learning models that learn from the identified discrepancies to predict and replicate human driver decisions.
    - Continuously iterate the model by integrating new data and feedback from ongoing DIL simulations and real world data.

7. Predictive Driving Model Development

Objective: Enhance the developed model with predictive and anticipative features

Approach:

- Develop a rule based system with use cases to add the driving model predictive features
- Develop a training set using scenarios and real driving examples and generative AI.
- Train the driving model to integrate predictive and anticipative features using trustworthy AI methodology
- Validate with SIL scenarios and real world driving

This methodology leverages the strengths of DIL simulation to create a dynamic and iterative process for developing and refining driver models. By integrating real-world human driver input with autonomous vehicle simulations, this approach aims to produce more accurate, predictive, adaptive, and human-like driver models. The continuous feedback loop between simulation and real-world data ensures that the models remain relevant and effective in enhancing the safety, reliability, and acceptance of autonomous driving technologies.

4. SIMULATION SYSTEM

Driver in the loop system used in this article is a 6 axis realistic system with real vehicle pedals and steering wheel with realistic haptic feedback in line with the road conditions. This system is a part of the OPINA infrastructure and has been developed by SANLAB. The main characteristics of the system is given below.

Simulator Model Sanlab SM1800 DIL(Driver-In-the-Loop)
Motion Platform Model SM1800
Payload(GML=Gross Moving Load) 1800kg
Excursion
Surge: -0.42m/+0.53m
Sway: -0.43m/+0.43m
Heave: -0.40m/+0.35m
Roll: -20.60°/+20.60°
Pitch: -20.20°/+21.10°
Yaw: -24.00°/+24.00°

Velocity
Surge: ±0.80m/s
Sway: ±0.80m/s
Heave: ±0.70m/s
Roll: ±50°/s
Pitch: -±50°/s
Yaw: ±55°/s
Acceleration
Surge: ±7.0m/s²
Sway: ±7.0m/s²
Heave: ±9.0m/s²
Roll: ±300°/s²
Pitch: ±300°/s²
Yaw: ±400°/s²
Peripherals
Visual System: 3x43" Full HD Industrial LCD Panel
Steering Wheels: Professional Series Direct Drive Servo-Force Feedback System
Sound System: Professional Series 5+1 Surround Sound System
Driver Control Panel: 17" Multi-Touch LCD Panel

Trainer Control Panel: 24” Multi-Touch LCD Panel
Access Mechanism: System-Controlled Automatic Access Bridge
Simulation Computer: High-Performance Simulation Computers

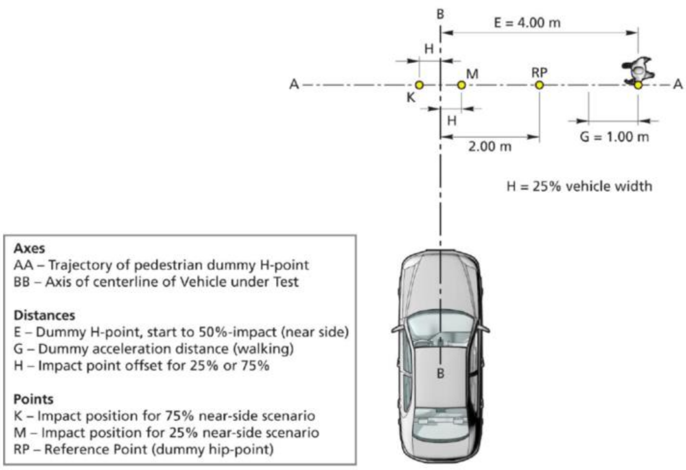
Software

Simulation Software: IPG TruckMaker/CarMaker
Management Software: Sanlab DIL Management Software
Operating System(s): Management Computer-Windows

Simulation Computer-Linux

Simulation SW<->Management SW Integration Mechanism IPG TruckMaker APO Library

5. SCENARIO CREATION



As example scenarios to demonstrate the driver model development methodology, two scenarios have been selected.The first one is a safety scenario which is NCAP CVNA75[11], (Car-to-VRU Nearside Adult). The relevant schema and the related values are shown below in line with NCAP methodology.

Fig 1- NCAP CVNA-75 Scenario

The second scenario is a standard IPGTruckmaker Scenario which combines Adaptive Cruise Control (ACC) and overtaking on rural roads with several bends. This has been selected to show the driver behavior in more extended way. Below the route and some parts of the scenario is depicted using the IPG Movie shots.

Fig 2- The Track

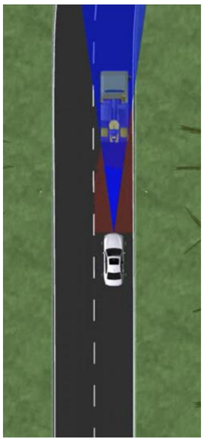


Fig 3- ACC

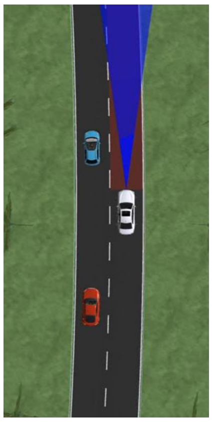


Fig 4- Overtaking

6. DRIVER MODEL and DRIVER Comparisons:

The IPG Truckmaker driver model has 5 different driver types: defensive, normal, aggressive, energy efficient and stressed. Their level can also be adjusted through dynamics, energy efficiency, and nervousness percentages. Driver models can also learn from drivers. One can upload driving data and the model can automatically adjust its parameters to adapt. One can also adjust parameters like speed, acceleration, corner cutting coefficient and change of pedals as shown in the below figure as referenced by IPG. Using these capabilities of IPG Truckmaker driver model can be developed as to adapt to different cultures and driving styles. Below, the driving styles of three different drivers for the NCAP CVNA75 Scenario and rural driving scenario with ACC and overtaking are shown,

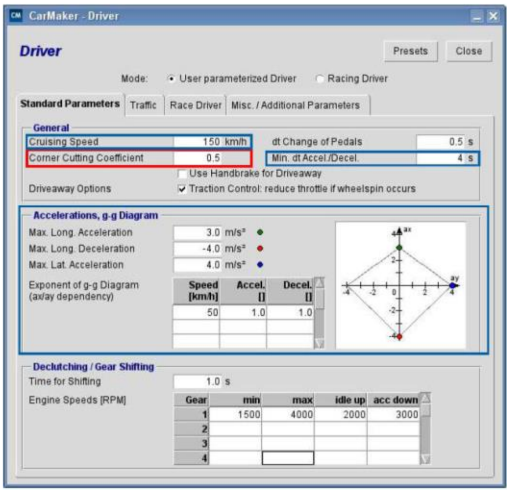
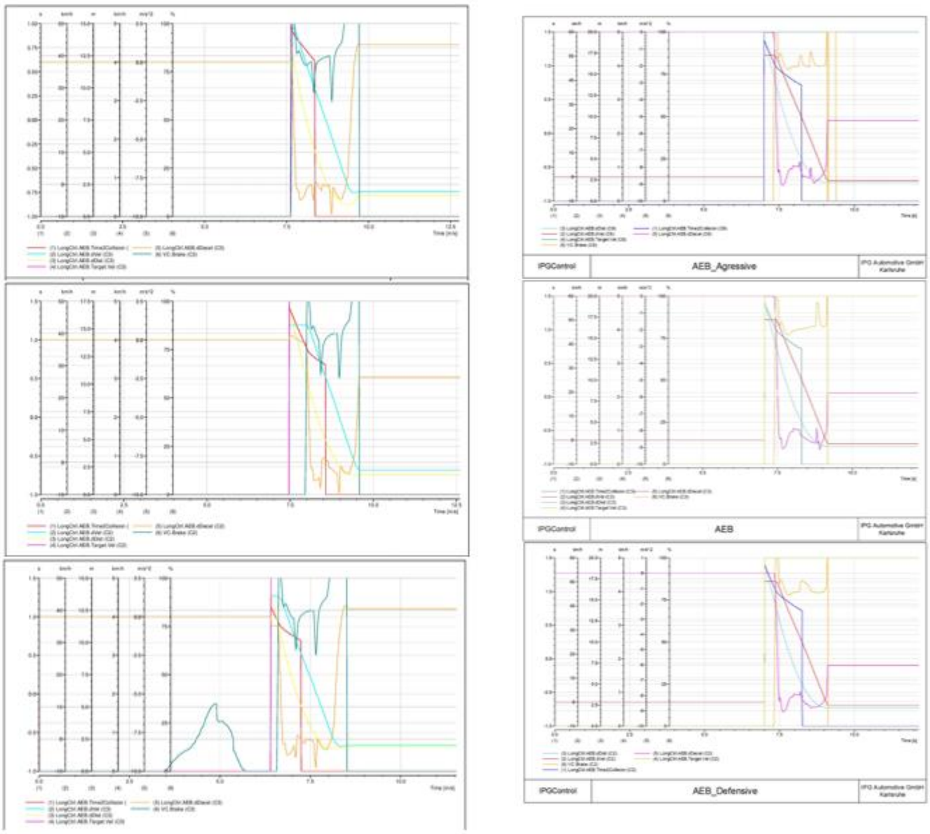


Figure 6 shows the parameters for 3 different drivers for the NCAP scenario, and Fig 7 shows the parameters for three different driving model styles: aggressive, defensive, and normal. As seen from the graphs, deceleration and braking force are the highest for aggressive driving; for normal, the values are in the middle, and for the defensive, they are the lowest, starting the action earlier. We see that the three drivers, driving the scenario on the DIL system are more aggressive than even the aggressive driver. One reason may be that the drivers are not used to driving on DIL and this does not represent their real driving style. To eliminate this possibility, it is important that the drivers are trained properly to drive on the DIL and make it as near as possible to their real driving style. This can be done by measuring the driving style in real-world conditions and comparing the results.

Fig 5- IPG Truckmaker Driving Model additional parameters

Another reason for this discrepancy may be because real drivers style is more realistic. It may be much better to stop as soon as possible as you see the approaching adult from the side. This can be tested by developing the same test in real world environment using OPINA robot mannequin.



The combined rural drive, ACC scenario results are shown in Fig 8. There are different cases in this scenario, but general drving style can be recognised. The agressive driver uses higher speeds and more severe braking. Normal driver lower speeds with less braking. Defensive even lower speeds but with even lower braking force. Third driver’s style is quite near to the normal driving style, but the first two has severe and frequent braking. This shows the importance of the drivers experience onthe DIL system.

Fig. 6- NCAP CVNA 75 Scenario, Drivers’ driving style vs different driving models

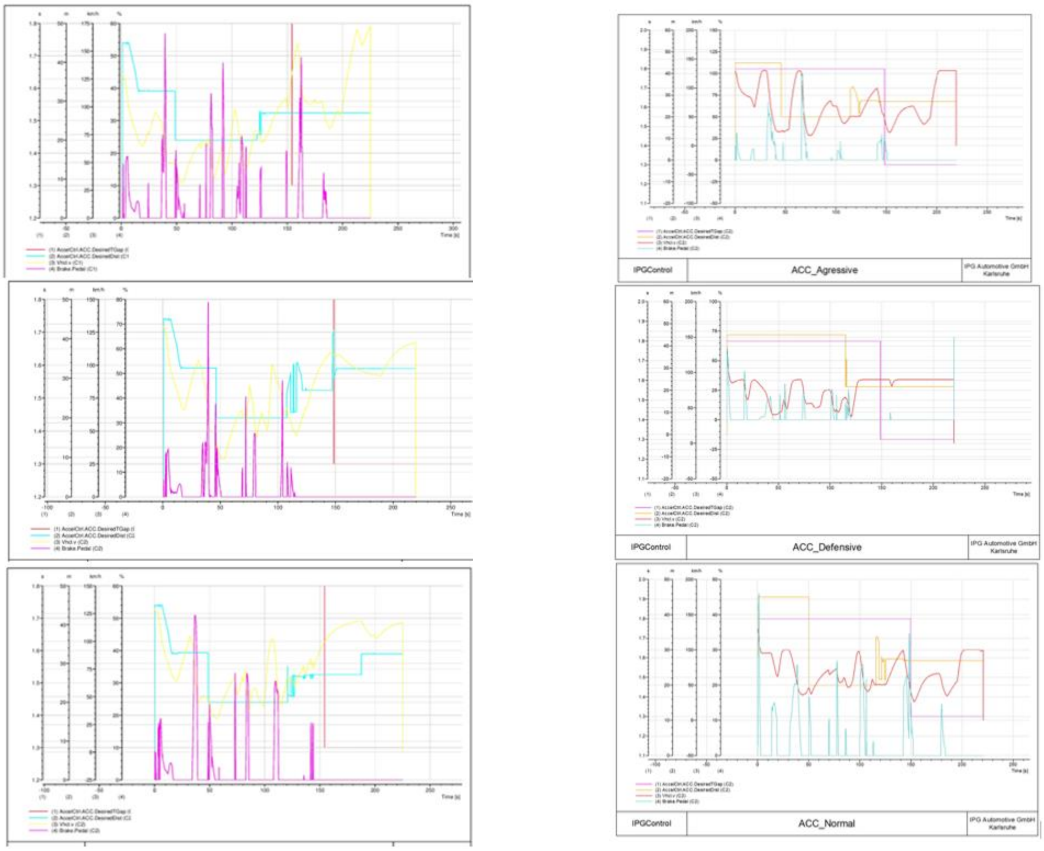


Fig. 7- Rural Driving, ACC and overtake scenario with real drivers' vs Driving models

7. CONCLUSION and FUTURE WORK

The methodology shows that by using the DIL system, a very complex and predictive driver model can be developed and optimized by using real data. However, it is important that the drivers have sufficient driving practice on DIL to allow them to drive as they would on a real vehicle and environmental conditions. Combining different types of scenarios that require prediction will evolve the driver model and enhance the prediction capability through rule-based methodology and trustworthy AI.

As further research, more drivers can be included, and a higher number of parameters for the driver model can be deployed. After DIL, fine-tuning of the driver model can be elaborated through real road data and the data replay function of the OPINA dSpace HIL system. The driver model can be enhanced further to include an emission and energy-optimized velocity profile.

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