A Cognitive Advanced Driver Assistance Systems (ADAS) Architecture for Autonomous-capable Electrified Vehicles

A COGNITIVE ADVANCED DRIVER ASSISTANCE SYSTEMS (ADAS) ARCHITECTURE FOR AUTONOMOUS-CAPABLE ELECTRIFIED VEHICLES

BY

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To my family and loved ones…

Abstract

The automotive industry is seen to be making a monumental paradigm shift from manual to semi-autonomous to fully Autonomous Vehicles. An Advanced Driver Assistance System (ADAS) forms a major building block for realizing these next generation of highly Autonomous-capable Vehicles. Although the general ADAS architecture is widely discussed, limited details are available about the functionality of the modules and their interactions, backed up by scientific justification. This limits the utilization of such an architecture for pragmatic implementation. A Cognitive ADAS Architecture for level 4 Autonomous-capable Electrified Vehicles (EV) is proposed in this thesis. Variations for levels 3 and 3.5 (combination of levels 3 and 4, with the primary fallback through a human driver and the secondary through an Automated Driving System) are also presented.

A validated simulation framework is built for highway driving based on the proposed level 4 architecture for an enhanced Tesla Model S. It was concluded that the autonomous control provided a 28% energy economy increase, on average, compared to human driver control. Through a quantitative sensitivity analysis, the optimal Mission/Motion Planning and energy management are seen in addition to a positive impact on the EV battery, motor, and dynamics, realized from the minimized instantaneous fluctuations. These factors are considered to contribute to this significant increase in the energy economy of an autonomous-controlled EV.

Furthermore, this impact was seen to be relatively higher for autonomous longitudinal vehicle control compared to lateral. This difference in the improved operation of the Autonomous-capable EV components between the Automated Driving System and the human driver control was seen to be the highest for the battery current.

In overall, an increase in vehicle autonomy, resulted in an improvement in the EV performance, dynamics and operation of the battery and motor, compared to a human driver control.

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Notation and Abbreviations

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving System
AEB	Automated Emergency Braking
AI	Artificial Intelligence
ALKA	Active Lane Keep Assist
ASIL	Automotive Safety Integrity Level
AHB	Automatic High Beam
AV	Autonomous Vehicle
BCU	Battery Control Unit
CAN	Controller Area Network
CC	Cruise Control
CACC	Cooperative Adaptive Cruise Control
DDT	Dynamic Driving Task
DVP & R	Design Verification Plan and Report

ECU	Electronic Control Unit
EMS	Energy Management System
EPA	Environmental Protection Agency
EV	Electrified Vehicle
FMEA	Failure Mode and Effect Analysis
FTA	Fault Tree Analysis
FTP	Federal Test Procedure
FTTI	Fault Tolerant Time Interval
GCS	Global Coordinate System
GPS	Global Positioning System
GPU	Graphics Processing Unit
GUI	Graphical User Interface
HAD	Highly Automated Driving
HARA	Hazard Analysis and Risk Assessment
HMI	Human Machine Interface
HWFET	Highway Fuel Economy Test
IDMU	Intelligent Decision-Making Unit

ICE	Internal Combustion Engine
INS	Inertial Navigation System
IoT	Internet of Things
ISO	International Organization for Standardization
ISTEA	Intermodal Surface Transportation Efficiency Act
LIDAR	Light Detection and Ranging
LIN	Local Interconnect Network
MacAUTO	McMaster Institute for Automotive Research and Technology
MARC	McMaster Automotive Resource Centre
MCU	Motor Control Unit
MAN_N	Normal Human Driver
MAN_A	Aggressive Human Driver
MPGe	Miles per Gallon Equivalent
NHOA	No Hands Across America
NHTSA	National Highway Traffic Safety Administration
OCV-R-RC-RC	Open Circuit Voltage – Resistor – Resistor/ Capacitor – Resistor/Capacitor

ODCU	On-board Diagnostics Control Unit
ODD	Operational Design Domain
OEDR	Object and Event Detection and Response
PI	Proportional - Integral
PID	Proportional - Integral - Derivative
PROMETHEUS	Programme for a European Traffic of Highest Efficiency and Unprecedented Safety
QM	Quality Managed
RADAR	Radio Detection and Ranging
SAE	Society of Automotive Engineers
SC03	Speed Correction Driving Schedule
SLAM	Simultaneous Localization and Mapping
SOC	State of Charge
SOTIF	Safety of the Intended Functionality
TCU	Transmission Control Unit
TTP	Time Triggered Protocol
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle

Notations

y_{off}	Offset of the vehicle at the target's position
v	Speed of the vehicle
a_y	Lateral acceleration of the vehicle
ds	Projected distance between the host and the target vehicle an
α	Target vehicle's orientation or angle
t_{tc}	Time required for a collision to occur between the host vehicle and its surrounding target objects
d	Distance between the host and the target vehicles
v_{rel}	Relative velocity between the host and the target vehicles
D_{rel}	Relative deceleration of the target object
t_{tb}	Time threshold brake
τ_B	Brake loss time
D_{max}	Maximum permitted deceleration of the host vehicle without causing a collision with the surrounding target objects
D_{obs}	Target object's actual deceleration

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Chapter 1

Introduction

This section introduces the thesis by describing the motivation, problem statement and an overview of the proposed solution. Furthermore, the thesis contributions, scope of research, research objectives, methodology and the organization of the thesis is summarized in this chapter.

1.1 Motivation

Distracted driving has become one of the major reasons for the increasing number of road accidents worldwide. According to a study by National Highway Traffic Safety Administration (NHTSA), in the U.S. alone, 3,477 people were killed and 391,000 were injured due to distracted driving in 2015 [1]. These alarming statistics on driver distraction demonstrate the significant necessity of evolution in the automotive industry to migrate away from traditional systems which require complete human attention during all times to systems with permissible flexibility for human drivers by minimizing human intervention, if not completely eliminating it, as a starting point.

According to Occupational Safety and Health Administration, on average, a human driver is required to make 200 decisions for every mile traveled [2]. It is practically impossible to ensure such a high driver attention during all scenarios for all drivers. As such, the automotive industry is seeing a major growth of interest in Autonomous Vehicles (AV) mainly due to the relative robust capabilities of a computer or an automated system in Artificial Intelligence (AI), object detection, object tracking, motion planning, intelligent decision making and real-time control in a dynamic environment.

In addition to the above points clearly demonstrating a need for a safer alternative to completely human driver-controlled vehicles, the automotive industry, in general, is hungry for more energy-efficient and optimally designed solutions. This precisely has served as a great motivation for this work which aims to explore some of the widely known yet currently unresolved topics in the field of Autonomous-capable Vehicles.

Specifically, this thesis attempts to address some of the challenges in the field of Autonomous-capable Vehicles especially around the topic of an Advanced Driver Assistance System architecture, especially for higher levels of vehicle automation, which are still in conceptual stages. Furthermore, although safety is regarded as one of the biggest benefits of the AV technology, the relatively less explored advantage in the literature is the contribution of vehicle autonomy in improving the fuel or energy economy of the vehicle. This has also been systematically quantified through the work presented here, supported by vehicle level simulations and a thorough analysis.

1.2 Summary of Problem Statement and Solution

This section provides a summary of the problem statement. The solution proposed through this thesis' research work is also presented.

1.2.1 Problem Statement

The race to having safe and commercially accessible fully autonomous-capable vehicles is evident in the automotive industry. This mega technological transformation is seeing an increased dependency on machines compared to humans, in turn, requiring a more thorough analysis of the research, design and development process of these vehicles in order to have a technology that can primarily match human abilities and ultimately surpass them.

One of the most important questions which comes up for an Advanced Driver Assistance System (ADAS) aimed for the vehicles of Society of Automotive Engineers (SAE) levels 3 to 5 [3], is about the system-level architecture. These Highly Automated Driving (HAD) vehicles are anticipated to have the ability to partially or completely replace human control. Very limited technical publications are available justifying a comprehensive system architecture through a rigorous scientific analysis, even though ADAS serves as a fundamental and a major building block for realizing an Autonomous-capable Vehicle. The limitation is not only quantitative but also qualitative, especially in terms of the details about the various modules, their functionality, and interactions. This is mainly due to the conceptual and proprietary nature of the on-going HAD research. This, in turn, significantly limits the utilization of such an architecture for pragmatic implementation.

In addition, it is critical to combine the understanding from both an autonomy function and a vehicle-level perspective to result in an effective system architecture. Regarding this, the influence of vehicle autonomy on its performance, dynamics as well as the individual vehicle components are also found to be scarcely analyzed in the literature backed up through a rigorous scientific analysis. Important findings from this analysis, are considered to be vital in optimizing the Autonomous-capable Vehicle design. Lastly, although the safety impact of Autonomous-capable Vehicles is widely discussed in the industry, this analysis is also expected to aid in understanding the benefits of migrating to more human-independent vehicle technology from the perspective of improving vehicle performance, optimizing the usage of different vehicle components and so on. These less evaluated topics offer a direct and tangible benefit to the automotive manufacturers and technology or chip providers from the introduction of Highly Automated Driving.

1.2.2 Solution

In order to address the above-described problem regarding the limited availability of literature in terms of the ADAS architectures for enabling the development of Autonomous-capable Vehicles, this thesis proposes a Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles. The architecture represents the systematic functional distribution of the different modules, sub-modules, component examples, their interactions, and interfaces. The primary architecture aims at level 4 Autonomous-capable EVs, however, there are variations offered for levels 3 and 3.5.

Furthermore, this architecture is verified through extensive simulations of an Autonomous-capable EV subjected to varying test cases and external conditions. In addition, through a quantitative analysis of the simulation results, vital conclusions regarding the influence of vehicle autonomy on the Electrified Vehicle performance, dynamics and the operation of components are presented. Also, a comparative analysis between the Automated Driving System, normal human driver and an aggressive driver's partial versus complete lateral and longitudinal vehicle control are offered. The simulation results are also validated based on the standard 5-cycle adjustment method by the Environmental Protection Agency.

1.3 Thesis Contributions

The contributions of this thesis are three-fold. The first contribution is to propose a Cognitive ADAS architecture for a Level 4 Autonomous-capable Electrified Vehicle (EV). The thesis also offers some suggested variations in the architecture to represent a Level 3 and a Level 3.5, which although is not currently part of the SAE J3016 [3], it is considered to be a pragmatic step forward in the Autonomous Vehicle industry. Level 3.5 is offered in this thesis as a combination of 3 and 4 where the primary fall back behavior is routed through the driver followed by the Automated Driving System (ADS) [3], in case of the primary system failure. This will also be explained in more detail in the further sections of the thesis. In order to demonstrate the necessity of the proposed Cognitive ADAS architecture, current literature review and gaps are also pre-discussed.

The second contribution is to verify the proposed architecture by building a pragmatic simulation framework which not only provides the capability of simulating an Autonomous-capable Electrified Vehicle in different operational domains and external conditions but also provides the opportunity to understand the influence of varying levels of vehicle autonomy on the Electrified Vehicle performance, dynamics and its components, in comparison to a normal and an aggressive human driver. Furthermore, an extensive database of vehicle reactions, behavior, dynamics and vehicle component data for a combination of 113 autonomous and semi-autonomous test cases in addition to variations in external conditions was built. This database was not only found to be helpful for conducting the intended analysis but is also considered to be of substantial benefit in carrying out future research for understanding more details (described in the future work section) about the influence of vehicle autonomy on an Electrified Vehicle's battery life, motor power consumption and so on.

The third contribution is to analyze the impact of increased vehicle automation on the Electrified Vehicle's energy economy, dynamics as well as the vehicle components, mainly motor and the battery, through an extensive quantitative sensitivity analysis.

The relevant publications that have resulted from the current research are below:

- K.P. Divakarla, A. Emadi and S.Razavi, "A Cognitive Advanced Driver Assistance Systems (ADAS) Architecture for Autonomous-capable Electrified Vehicles", accepted and to be published in *IEEE Transactions on Transportation Electrification,* DOI: 10.1109/TTE.2018.2870819.
- R. Hamilton, H. Seager, K.P. Divakarla, A. Emadi and S.Razavi, "Modeling and Simulation of an Autonomous-capable Electrified Vehicle: A Review," in *Proc. IEEE Canada Electrical Power and Energy Conference (EPEC 2018),* Toronto, October 2018.
- K. P. Divakarla, A. Emadi, S. Razavi, S. Habibi and F.Yan, "A Review of Autonomous Vehicle Technology Landscape", submitted to *International Journal of Electric and Hybrid Vehicles (IJEHV).*

1.4 Scope of Research

This section will provide a summary of the assumed scope of research. As described in the previous section, one of the major contributions of this thesis is to propose a Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles. The scope for this architecture definition has been restricted to Electrified ground vehicles only. Some examples and general inferences to other types of Autonomous Vehicles have been provided in the thesis for reference, however, the architecture development is focused on EVs. EVs have been chosen as a scope for studying the topics being discussed in this thesis for two reasons. Firstly, majority of the highly Autonomous Vehicles are expected to be electrified for the first generation due to the relative simplicity of the powertrain which is to be combined with complex autonomous control algorithms. This also precisely points towards the second reason for inclining towards the EVs as test Autonomous-capable Vehicles for this study. The relatively simpler EV powertrain enables to focus more extensively on the concerned evaluation of the influence of vehicle autonomy on Electrified Vehicle performance, dynamics, and components. The combination of hybrid or Internal Combustion Engine powertrains and complex autonomous-control mechanisms are anticipated to result in the simultaneous variation of multiple variables making it much more challenging to isolate the impact of Electrified Vehicle autonomy on the aforementioned EV attributes. In addition to the proposed architecture, the test host Autonomous-capable Vehicle modeled in simulations has also been assumed to be an EV for consistency purposes (the long-term aging of the vehicle is not considered in this analysis).

Also, although the proposed architecture is not limited to any particular use case, the highway driving scenarios have been assumed for the simulations. This is mainly to ensure a maximum ADAS feature operation (by avoiding the stop and go nature of the urban traffic) on the road for studying the influence of vehicle autonomy on the energy economy, EV dynamics, and components. As such, a realistic highway driving road was modeled which will be described further in the thesis. The driving environment infrastructure/ objects such as buildings, traffic signal lights, and pedestrians were not included in the current simulation model.

Furthermore, the Cognitive ADAS Architecture is proposed at a system-level. The distribution of higher-level functions and their interfaces at the system level for an Advanced Driver Assistance System are proposed through this architecture. Although the components level breakdown is shown at a high-level for reference, their decomposition to the hardware and software level is considered to be out of scope for this analysis. The architecture is defined to be generic for an easy adaptation of the different functional and sub-functional umbrellas presented to different use cases and target applications. Every sub-block shown in the architecture could be broken down furthermore depending on the intended tier of the automotive application. The proposed architecture is considered to be the building block or the first step forward in defining a systematic functionally distributed modular architecture for an Advanced Driver Assistance System.

The proposed architecture is targeted mainly towards level 4 autonomous-capable EVs. Two different variations of the architecture have also been proposed for levels 3 and 3.5. The various levels of vehicle automation will be described in more detail further in the thesis. The automotive industry is quickly migrating from current levels of 0-2 to 3 and above. The higher levels of vehicle automation have been targeted for the work presented in this thesis mainly to address the limited availability of technical research in this field for understanding the architecture of higher levels of vehicle automation as well as their impact on the different Electrified Vehicle attributes.

Furthermore, although it has been attempted through the proposed architecture to demonstrate the various functions and their interactions within the Advanced Driver Assistance System, certain functions were excluded from the simulations. The fallback response of the system in case of a sensor or an Automated Driving System failure is considered out of the scope for the simulations. This is mainly because the architecture targets a generic audience with system level requirements for a Highly Automated Driving framework; whereas, the intention of the simulations is to demonstrate the impact of vehicle autonomy on the Electrified Vehicle dynamics, components and performance. For this, the simulations are assuming ideal behavior of the Automated Driving System and other components such as the sensor suite. This enables systematic evaluation of the autonomous control's maximum potential at different levels of vehicle automation. Furthermore, due to the limitations in the infrastructure and the too ls, the modeling of Vehicle to Vehicle and Infrastructure as well as Cloud/ Internet of Things (IoT) communication has also been excluded from the scope of the simulations, although presented in the architecture for reference to vehicle external communications.

Lastly, due to the conceptual and proprietary nature of the ongoing industry research along with the commercial unavailability of level 4 Autonomous-capable EVs, experimental analysis is considered out of scope for this study. It has been presented as part of future work based on the expected industry trends which have been described in detail in further sections of this thesis.

1.5 Research Objectives

This section will highlight the main research objectives of the work presented in this thesis. Primarily, the aim is to address the limited technical literature available in terms of the Advanced Driver Assistance System architectures targeting higher levels of vehicle automation by proposing a Cognitive ADAS architecture intended for Autonomous-capable Electrified Vehicles. The objective of this architecture is to provide a system level distribution of the main functions, sub-functions, example components, their interfaces, and interactions.

In addition to proposing the architecture with a detailed description of the various modules and the sub-modules, the aim is also to verify this architecture through simulations of test Autonomous-capable Electrified Vehicle. The model is intended to encompass a wide range of representative use cases coupled with varying external conditions and dynamic driving environments which the Autonomous-capable Vehicle is expected to face on the road in real-life.

The intention of these vehicle-level simulations is not only to provide a framework for verifying the proposed architecture but also to investigate the impact of vehicle autonomy on Electrified Vehicle components, performance, and dynamics. Furthermore, a quantitative analysis of these results in addition to a comparative sensitivity analysis is intended in order to understand how the Electrified Vehicle performance, its components' operation and the overall dynamics differ during the Autonomous Driving System control versus the manual human driver control; and to analyze which control technique offers more beneficial EV results. The objective is also to systematically conclude the reasons behind the improvement in the Electrified Vehicle results during the operation in a particular vehicle control mode.

1.6 Methodology

This section presents the methodology adopted for realizing the thesis contributions described previously. The primary contribution of this thesis is the proposal of a Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles. The architecture aimed at assimilating the various functions within an Advanced Driver Assistance System in addition to visualizing the modular and sub-modular interactions within the vehicle as well as the interfaces external to the vehicle with the dynamic driving environment. For the development of this architecture, an extensive literature review of the available system-level architectures, known ADAS features in highly Autonomous-capable Vehicles, expected functionalities, interactions between the Autonomous and Electrified Vehicle components and so on was performed in addition to conducting a thorough gap analysis for understanding the limitations of the current literature, with the aim of addressing the identified gaps through the proposed Cognitive ADAS Architecture. Furthermore, the proposed Cognitive ADAS Architecture based Autonomous-capable EV simulations guided tremendously in further improving the architecture based on the distribution of the various functions for performing the required semi-autonomous or autonomous operations.

For the development of the simulation model itself, a rigorous tool section process was carried out where multiple simulation software tools were studied. IPG

CarMaker was selected due to the availability of multiple EV demo models, extensive sensor suite and modeling options as well as a variety of ADAS features, autonomous/ semi-autonomous control techniques, external conditions and human driver simulation options. A functional mapping between the proposed Cognitive ADAS Architecture and the developed simulation model is also provided for verifying both the architecture as well as the simulation model. The simulation results acquired clearly demonstrate the fulfillment of the above motivation. An enhanced 2014 Tesla Model S 85 was selected as the test vehicle in order to model a real-life vehicle as much as possible as the work presented in this thesis is expected to serve as a major building block for pragmatic implementation of an Advanced Driver Assistance System with Highly Automated Driving capabilities. The vehicle model was developed from an available demo model in CarMaker as well as by using the publicly available information [4]. An enhancement in the form of an added sensor suite was also made to reflect the difference between the current vehicle technology and the intended level 4 vehicle automation. Furthermore, the simulations also include varying external conditions such as the changes in road, weather, traffic and so on, again to reflect the real-life driving conditions as much as possible. These conditions were selected from an impact on the vehicle performance perspective based on the analysis in [5]. The development of these models will be explained in more details in the further sections of the thesis.

The simulation results have been thoroughly analyzed through systematic quantitative techniques, which will be described in detail further in the thesis. The simulation results analysis focuses on understanding the impact of Electrified Vehicle autonomy on its performance measured in terms of energy economy (Miles per Gallon Equivalent or MPGe), dynamics and components' operation. In addition, a comparison between the Automated Driving System or ADS control, normal human driver and an aggressive human driver is also offered. The results also demonstrate the difference in both human driving test cases as well as within the different levels of vehicle automation.

Lastly, a validation of the above is also offered through a systematic comparison with the Environmental Protection Agency predictions using the 5-cycle adjustment method geared towards the vehicle performance estimation of Electrified Vehicles. The details of this technique will be discussed in the further sections of this thesis.

1.7 Thesis Organization

This thesis is divided into seven chapters. The first chapter introduces the thesis by describing the motivation of the thesis, providing a summary of the problem statement and the solution, and explaining the thesis contributions, scope of research, research objectives and the methodology.

The second chapter provides a background on the Autonomous Vehicles. Firstly, the Autonomous Vehicles are defined. Furthermore, various topics related to the history of Autonomous Vehicles, their benefits and limitations as well as their safety and the Society of Automotive Engineers (SAE) levels of vehicle automation are described. In addition, the different infrastructure and support needed for the deployment of Autonomous Vehicles are also described. Existing features and examples, as well as other types of Autonomous Vehicles besides the ground vehicles and the future industry trends, are also presented in this chapter.

A literature review of the currently discussed Advanced Driver Assistance System architectures in addition to the predictions regarding the increase in Electrified Vehicle performance with the increase in the vehicle autonomy are presented in the third chapter.

The fourth chapter proposes a Cognitive Advanced Driver Assistance System (ADAS) architecture for Autonomous-capable Electrified Vehicles. The assumptions made for this architectural development are also presented. In addition to functionally describing the various modules and sub-modules within the proposed Cognitive ADAS Architecture, a discussion on the components are also provided as examples. Also, the benefits as well as limitations of the proposed architecture are highlighted in this chapter.

Chapter five describes the development of the Autonomous-capable Electrified Vehicle simulation model in addition to the various aspects of the dynamic driving environment and external conditions modeling including the vehicle, traffic, road, weather, and ADAS feature set models. A mapping between the simulation model and the proposed ADAS architecture, in addition to a theoretical walkthrough of the model, is also presented. A validation of the simulation model is also presented.

The simulation setup/test cases in addition to the various vehicle dynamics, vehicle performance, Electrified Vehicle motor, and battery results are presented in chapter six. Furthermore, a thorough quantitative sensitivity analysis is also performed to analyze the impact of vehicle autonomy on Electrified Vehicle performance, dynamics, and components' operation.

Lastly, chapter seven summarizes the thesis conclusions as well as the limitations and future work. In addition, a discussion on the presented work is also shared.

Chapter 2

Background on Autonomous Vehicles

This section describes what an Autonomous Vehicle is (as well as some of the major vocabulary to be used in this thesis), major historical milestones, advantages and limitations, safety, levels of vehicle automation, major aspects related to the deployment of Autonomous Vehicles, existing features and examples, other types of Autonomous Vehicles, and future industry trends.

2.1 What is an Autonomous Vehicle?

A vehicle which is able to perceive its driving environment, make accurate decisions and take control as needed, independent of a human driver, can be termed as an Autonomous Vehicle. A vehicle can also possess partial autonomous capabilities where the Automated Driving System (will be explained further) is able to perform one or a set of functions independent from the human driver. In this thesis, the term "Autonomous Vehicle" will be used when referring to the general field or the technology and the term "Autonomous-capable" Vehicle will be used to refer to a vehicle which is able to operate with a partial or a full autonomy. It should also be noted that a vehicle which is capable of operating at full autonomy, can also be operated at a lower level of autonomy during a degraded mode of operation in case of a failure in the Automated Driving System or its components or if that is intended by the user. One of the other related terms which will be often seen in this thesis as well as in the literature is the Advanced Driver Assistance System or ADAS. ADAS provides a functional system level framework of the technology incorporating the various physical components, functional modules and their interfaces for enabling the autonomous or semi-autonomous control of vehicle driving functions.

In addition, another commonly used term within this thesis is the Automated Driving System or the ADS [3]. As defined in [3], ADS comprises of the entire system including the various components required to autonomously perform all of the major tasks relating to the acceleration, braking, steering and so on within an Autonomous-capable Vehicle. In essence, an ADS can be viewed as existing within an ADAS which is in turn present in an Autonomous-capable Vehicle.

2.2 History

Historical advancements through time have had a major impact on the currently available Autonomous Vehicle technologies. This section will focus on some of those major landmarks [6]. One of the very first autonomous cars was built in 1926 and was called the Linriccan Wonder [6]. The operating principle was very simple. It consisted of a transmitting antenna which captured radio signals from another car that would be following it. The car’s motion was then controlled by small electric motors which were in turn connected to circuit breakers receiving signals from an antenna. In December 1926, Achen Motors showcased a modified version of the Linriccan Wonder, in Milwaukee, which was known as the Phantom Auto.

The year 1939 could be marked as another major stepping stone in the development of Autonomous Vehicles. Electrified cars which were powered using embedded circuits were presented at the world fair by Normal Bel Gedde [6]. 1940s marked one of the first successful Cruise Control (CC) systems [7]. General Motors had sponsored their Futurama exhibit. Following this, in 1953, RCA labs had built a small autonomous car which would be controlled based on a pattern of wires. General Motors in collaboration with Leland Hancock and L.N. Ress were able to develop this idea further and take it to the actual road. As a result, Firebird, which consisted of a series of experimental semi-autonomous vehicles, was launched in the General Motors Auto show called Motorama in the 1960s [8] - [10]. This period had already marked successful simulations of primary vehicle controls such as automatic braking, accelerating and steering. These vehicles mainly worked with the help of devices which were installed within the roadway in order to guide the vehicles.

Inspired by the Firebird, in 1966, a similar driver-less car was developed by the Communication and Control Systems Laboratory team at the Ohio State University. This technology of embedded devices within the roadway guiding the vehicle had become very popular in the 1960s. Following a similar concept, vehicles were also controlled by embedded magnetic cables. Citroen DS is one such example of an autonomous car developed by the Transport and Road Research Laboratory in the United Kingdom [11] - [13].

The concept of vehicle automation was well supported by the Bureau of Public Roads in the United States of America with their experimental initiative of an electronically controlled highway, within the states such as California, Massachusetts, New York, and Ohio [14]. Following this, Bundeswehr University, Munich, also developed an autonomous van sponsored by Mercedes. In addition, the Prometheus project conducted by EUREKA during the period of 1987 to 1995 also gained a lot of importance in the field of Autonomous Vehicles [15] - [16]. One of the first Adaptive Cruise Control (ACC) implementations was seen in 1991 [17]. Some of the other Autonomous Vehicle projects during this time period included the ones by the United States Department of Defense's Defense Advanced Research Projects Agency, Carnegie Mellon University, the Environmental Research Institute of Michigan, University of Maryland, Martin Marietta and the SRI International [8]. The combined project with the various universities was known as the Autonomous Land Vehicle Project [18] – [21].

Furthermore, various political changes mainly in terms of the ISTEA Transportation Authorization Bill of 1991, in addition to the establishment of the National Highway System Consortium in the United States became major stepping stones in the development of driver-less vehicles. Daimler - Benz' VaMP, Bundeswehr University Munich's Vita-2, Dickmanns' driver-less S-Class Mercedes, Carnegie Mellon University's Navlab, more popularly called as No Hands Across America or NHOA and Alberto Broggi's ARGO were some of the major exciting successful Autonomous-capable Vehicle projects during the period of 1990s [21] - [26].

Finally, more sophisticated and efficient designs of Autonomous Vehicles were explored in the 2000s [6]. Various off-road, military as well as public transportation options were evaluated for the implementation of autonomous capabilities. One prominent example is a public ground transportation system called ParkShuttle, which was implemented in the Netherlands [27] - [29]. Also, the United States' efficient military demo vehicles became exemplars in demonstrating the application of Autonomous Vehicles [30].

2.3 Benefits and Limitations

The inclusion of Autonomous Vehicles within the mainstream would be highly advantageous mainly for reducing the number of road accidents that may result due to driver distraction. In addition, it can be useful for medical or emergency, military and space applications where minimal human intervention might be permitted. Furthermore, it can assist disabled people in increasing their mobility. Traffic management based on safe vehicle arrangement is another major advantage of

Autonomous Vehicles. Also, optimization of parking space can be facilitated with the use of Autonomous Vehicles. The Autonomous Vehicle can drop off the passenger and park itself at a distant location and pick up the passenger when required.

In addition to the above-discussed advantages, Autonomous Vehicles also offer a significant benefit from an automotive manufacturer perspective. Increasing the level of vehicle automation within a vehicle will be beneficial in reducing human involvement which in turn can be helpful in eliminating certain redundant components [31] from the vehicle's powertrain design. In other words, certain modifications could be done to the powertrain in terms of the various components that need to be connected for an optimal performance in order to offer lighter, cheaper and easier to manufacture vehicle designs. However, it is to be noted that the elimination of current vehicle components such as the steering wheel cannot be realized until the evolution of the Autonomous Vehicle technology up to level 5. Policies and regulations can also be expected to play a significant role here in shaping the human driver responsibility at the higher vehicle automation levels which might further impose restrictions on the complete elimination of some currently existing vehicle components.

Furthermore, as described in [32], the Autonomous Vehicles could result in fuel economy improvement offering an immediate tangible commercial benefit to the automotive industry and environmental benefits, at large. However, the exact impact of vehicle autonomy can only be assessed through a quantitative analysis backed up by reasonable simulations. This is also precisely the topic which has been explored, at length, in this study.

In contrast to the advantages discussed above, there are also some challenges associated with the Autonomous Vehicles. Since majority of the vehicle control is based on an internal computer, its malfunction can be problematic. Having redundant loops within the control system that can serve as a back-up, in case of a failure of the main system, is essential. In addition, it might result in a loss of jobs due to the replacement of drivers, depending on the level of vehicle automation. Liability or insurance in case of an accident is also raised as a big question. Neither the driver nor the computer can be held solely responsible for any deviation in the desired vehicle control. Also, the benefits of Autonomous Vehicles are more evident when both the surrounding vehicles as well as the infrastructure is in coordination with it. As such, a change of the infrastructure is needed in order to incorporate Autonomous Vehicles in the mainstream. Furthermore, due to the comprehensive knowledge of the internal computer about the passengers' daily usage and activity, concerns can arise due to the loss of passenger privacy. Lastly, cyber security becomes a major concern due to the possibility of external malicious attacks into the host vehicle's system.

2.4 Safety of Autonomous Vehicles

As the automotive industry is making the transition from conventional vehicles to more automated vehicles, the level of complexity within the vehicle systems and dependency on the computer-oriented decision making has increased considerably, thus, resulting in a need for more robust, safe, and dependable vehicles. The overall safety within an Autonomous-capable Vehicle can be categorized into three broad umbrellas - functional safety, Safety of the Intended Functionality (SOTIF) and cybersecurity. This section summarizes the main concepts associated with the three categories and discusses the current establishments or work in progress for each.

1) Functional Safety

International Organization for Standardization (ISO) 26262 is an automotive functional safety standard followed widely across the automotive industry [33]-[35]. The scope of ISO 26262 is restricted to avoiding malfunctioning behavior caused by electrical and electronic systems as well as their interactions [33]. Parts 1 to 4 are the most applicable for carrying out the system level functional safety analyses of Advanced Driver Assistance Systems.

It is important to realize that risk cannot be reduced to zero even in the best-predicted systems. The intention is, instead, to bring down the risk to an acceptable reasonable level. This acceptance criteria is defined based on the application space of the system under study. Furthermore, the ideology is to prevent the violation of top-level safety goals of a system which could be caused due to failures affecting safety critical functionalities.

Automotive Safety Integrity Level (ASIL) is a key classifier used in the functional safety analyses in order to segregate one system from another in terms of its safety criticality. ASIL is in turn dependent on three major factors – severity, exposure and controllability [34]-[35]. Severity represents the extent of harm which could occur in case a hazardous failure was to happen. It ranges from 0 to 3, where 0 represents the lowest severity and 3 represents the highest. Exposure estimates the probability of a particular event occurring. It is not to be confused with the probability of a failure occurring in that particular event. It ranges from 0 to 4; 0 representing the lowest probability and 4 representing the highest probability to be present in a situation which could become hazardous if it were to coexist with a failure in that situation. Controllability identifies the ability of either the driver or any other passenger involved to be able to avoid the hazardous situation at hand. It ranges from 0 to 3 where 0 represents the highest controllability and 3 represents the lowest. ASIL is then determined based on the selections for severity, exposure, and controllability as described in [35]. The ASIL classifications range from A to D, where A represents a system with the lowest safety criticality and D represents a system with the highest safety criticality. Besides ASIL A-D, systems can also be classified as Quality Managed or QM. Such a system does not need any additional special functional safety treatment as per ISO 26262, instead, it is accepted to be sufficiently designed as per the quality management processes within the company.

Ensuring safety during engineering design is challenging. It includes both the prediction of failures or hazards well before time, in addition to designing redundancies within the system to address those failures, if they were to occur in the future. Risk is anticipated beforehand using various standardized functional safety analyses such as Hazard Analysis and Risk Assessment (HARA), Failure Mode and Effect Analysis (FMEA), Fault Tree Analysis (FTA), Design Verification Plan and Report (DVP & R) and so on [33]. The main goal of these work products is to make sure that various failures, effect of the failures on the system, measure of risk due to the failures and the various risk mitigation strategies, to avoid the hazards is evaluated methodically. Then, based on the analysis, extra redundant features are added to the system as a precaution. Majority of the failure prediction and mitigation planning can be based on knowledge from the past systems, conceptual brainstorming, experimental analysis, or thorough simulations.

2) Safety of the Intended Functionality (SOTIF)

Violation of a top-level safety goal need not only result from a system failure. A system could be functioning exactly as intended, free of malfunctions, yet, could result in a hazardous behavior if it has limitations in terms of its usage in an application space. This is the exact concern which SOTIF tries to address. ISO (SOTIF) PAS 21448 is currently under development which attempts to describe the various SOTIF analyses systematically [36]. Limitations in the used technology (e.g. sensors) and human driver related topics (e.g. interaction between the driver and ADS) are well-known applications of where SOTIF might be applicable [36]. For example, even if a sensor on an Autonomous-capable Vehicle is functioning without any failures, there is a possibility of a severe hazard, if an object detection outside the sensor's range capabilities is intended. Similarly, an Autonomous-capable Vehicle could result in an inevitable crash if the Human Machine Interface (HMI) is unsuccessful in capturing the driver attention within the Fault Tolerant Time Interval (FTTI), in a case, when a driver is the Automated Driving System's fallback option to take the vehicle control. Both examples would be SOTIF classified.

From a solution perspective for technological limitations, sensor fusion has gained credibility for ensuring adequacy of the perception domain [37]-[38]. Building redundancy within a system is a classic approach for avoiding availability issues. In addition, a safety case should be built on the basis of thorough brainstorming of critical use cases.

As identified in [39], human factors is also a very important aspect in designing safe Autonomous Vehicle systems. It is practically impossible to predict before-hand how every human driver might react in every situation. Attentiveness of the driver becomes even more vital if they are part of a vehicle's safe stop maneuver or degradation [39]. There might be multiple factors including age, gender, driving experience, cognitive loading, personality, driving knowledge, trust on the vehicle systems, drowsiness level, external driving conditions and so on that could have an effect on a driver's distraction level. Designing an efficient HMI that would not only understand the driver's needs but also be able to communicate with them effectively to make sure they are attentive, could be the first step in addressing this issue [36]. Vehicles equipped with sophisticated physiological measurement devices and video cameras could also help in capturing the driver attention metrics [40].

3) Cyber Security

The last category described in this section for ensuring an overall safety is cybersecurity [41]. This realm of safety deals with malicious attacks or intrusion into the vehicles' systems by an external agent, resulting in a compromise in the vehicle's safe control and a catastrophic privacy loss. Through such intervention, it could be possible to take complete control of the vehicle's primary DDT, depending on the level of dependency on the ADS. The risk of having cyber-security attacks is increasing with the higher amounts of connectivity seen for highly Autonomous-capable vehicles through V2X, cloud and IoT. There are multiple access points which could give external sources a provision for reaching to the safety critical islands of the vehicle. The sensors, actuators, communication, data processing and application layers have been identified as the vulnerable layers for such attacks in [42]. As prescribed in [41], having enough resiliency and encryption within safety critical elements is essential in order to prevent such attacks from happening. Even if they were to occur in unlikely scenarios, a timely fault reaction should be designed in order to make sure that a safe transition to a fallback system takes place within the FTTI.

2.5 Levels of Vehicle Automation

When it comes to AVs, there is a common misconception that an Autonomous Vehicle can only refer to a completely driver-less vehicle. However, that is not the complete story. There are various levels of autonomy that can categorize these vehicles. According to the Society of Automotive Engineers (SAE) J3016 standard, there are six distinct levels of vehicle automation [3]. These levels are categorized based on four parameters – control of lateral and longitudinal vehicle motion, Object and Event Detection and Response (OEDR), Dynamic Driving Task (DDT) and Operational Design Domain (ODD). OEDR mainly consists of the perception, response formulation and reaction with an AV. DDT includes all of the vehicular activities performed that contribute to a particular motion of the vehicle [3]. ODD refers to a scope of conditions in which the vehicle has been designed to operate in. Depending on how the responsibility for these 4 categories is allocated between a human driver versus the Automated Driving System (ADS), a level of vehicle autonomy is assigned.

1) Level 0

Level 0 (No Driving Automation) is the first level where the driver is mainly responsible for all the major control of the vehicle consisting of steering, braking and throttle. In this level, although the driver is taking the responsibility for the entire DDT, other active safety systems may be present on the vehicle. Blind spot monitoring, collision warning, and lane departure warning systems are some examples of level 0 automation.

2) Level 1

Level 1 (Driver Assistance) is the second level of vehicle automation. In this level, the driver is still mainly responsible for the overall vehicle control. However, level 1 automation allows for the use of an automated system that may support the driver in only one of the lateral or longitudinal vehicle motion control. The responsibility for the OEDR and DDT fallback is still on the driver. Some examples of level 1 automation include Adaptive Cruise Control, electronic stability control, automatic braking and lane keeping.

3) Level 2

The next level of autonomy is the Level 2 (Partial Driving Automation). In this level, the ADS is permitted to take control of both the lateral and the longitudinal vehicle motion. However, the driver is still expected to supervise the ADS and take responsibility for the OEDR and DDT fall back. Tesla Autopilot can be classified as a level 2.

4) Level 3

The fourth level of autonomy is referred to as the Level 3 (Conditional Driving Automation). At this level, the autonomous system is able to take primary control of the vehicle, including the lateral and longitudinal control and the OEDR, ensuring a safe operation. However, it is advisable for the driver to be present in case a switch of the operation mode is intended by the ADS from autonomous to driver controlled. As such, the DDT fallback still remains as the human driver, adding additional layers of complexity, unlike the other levels lower and higher than this.

5) Level 4

The fifth level of vehicle automation is termed as Level 4 (High Driving Automation). In this level of vehicle automation, the automated system is expected to take full control of the vehicle with no intervention expected from the driver. In other words, the system is responsible for the OEDR, vehicle's full control and the DDT fallback. However, the ODD is still expected to be limited, unlike Level 5, which is the final level.

6) Level 5

In Level 5 (Full Driving Automation), the ADS is again expected to take full responsibility of the entire vehicle control, OEDR and the DDT fallback, however, the ODD is no more limited to only a few use cases.

2.6 Support Needed for Autonomous Vehicle Deployment

Although some lower levels of Autonomous Vehicles are already commercially available, when it comes to deploying higher levels of Autonomous Vehicles, especially 3 to 5, there is a significant support needed for ensuring their intended operation on the road as well as for gaining the maximum benefit out of this evolution [43] - [44].

Primarily, the infrastructure including roads, buildings, traffic signals/signs, other vehicles, communication networks (enabling V2X), cloud framework, computation methodologies, and so on needs major modification and revamping to meet the demands of a higher-level Autonomous Vehicle [43] - [44]. The current transportation policies would also need to be updated in order to better delegate the responsibilities as well as liabilities between the ADS and the human driver. This could, in turn, result in a modification of insurance policies, legal procedures as well as other standards currently governing the transportation regulations in various states [43] - [44]. According to [45], for safety and security reasons, a remote driver or authority can be expected to keep track of the highly Autonomous-capable Vehicles at all times. With the upcoming trends such as vehicle platooning, the maturity of safe and secure communication networks become a priority. Traffic management can also be considered crucial to avoid any unintended disturbance or immobility of the surrounding traffic due to a large set of vehicles participating in a platoon. The vehicles' transition in and out of platoon in addition to any support activities also need to be managed through advanced ADAS infrastructure [46].

Furthermore, a significant amount of driver training and education is needed for the autonomous functionalities within the vehicle, in order to increase their credibility, confidence, and desirability. In addition, with a mix of autonomous, semi-autonomous and manual vehicles on the road, a disciplined driving environment with minimized possibility of misuse, is ideal for the deployment of higher levels of Autonomous Vehicles.

Lastly, it is needless to talk about the progress required on the sensor fusion, computation capabilities, intelligent learning, Internet of Things, and so on in order to ensure adequate and efficient transition to higher levels of Autonomous Vehicles [43] - [44].

2.7 Existing Autonomous Features in Ground Vehicles and Examples

This section provides a summary of the major autonomous features currently existing in the market. Many higher-level features are a combination of several lower-level ones. Also, the utility of a feature completely depends on the intended level of autonomy for the vehicle using that particular feature.

1) Cruise Control (CC)

Cruise Control is one of the most primitive semi-autonomous capabilities that has been deployed in the automotive industry. It enables the driver to set a maximum speed for the car to cruise on. It does not automatically brake in case of a nearing obstacle, which could result in a front-end collision (if the driver does not brake). It also does not take into account any surrounding vehicles that might want to come into the host vehicle's lane. Cruise Control is generally most effective for highway driving. Majority of the cars today already come with an option of a traditional cruise control.

2) Adaptive Cruise Control (ACC)

Adaptive Cruise Control is an enhancement of the CC technology. It allows the drivers to set a minimum distance between the host and the vehicle in the front in addition to the maximum speed. The ACC controller then uses the most conservative approach to maintain a safe distance from the vehicle in the front with the aim of avoiding front-end collisions. However, the vehicle is still not capable, just based on ACC, of modifying its planned actions, in case another vehicle signals to enter into the host vehicle's lane. Some examples of cars already having ACC include Toyota Corolla, Honda Civic, Subaru Impreza, Nissan Sentra, Honda Accord, Toyota Prius, Hyundai Ioniq, Volkswagen Jetta, Subaru Crosstrek, Subaru Legacy, Mazda CX-3, Mazda 3, Honda CR-V, Hyundai Elantra, Kia Niro, and so on [47].

3) Automatic Emergency Braking (AEB)

AEB is one of the sub-features supported by some of the other comprehensive features described in this section. Under activation, AEB supports in automated braking, as required. For example, during the operation of the Rear Cross Assist feature (will be described below), if there is a static or a dynamic obstacle noticed in the rear path of the host vehicle, the reverse maneuver will be stalled with the help of AEB. Acura, Alfa Romeo, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Fiat, Ford, Genesis, GMC, Honda, Hyundai, Infiniti, Jeep, Kia, Lexus, Lincoln, Mazda, Mercedes, Porsche, Subaru, Toyota, Volkswagen, Volvo, and so on are some examples of cars with the AEB feature available [48].

4) Active Brake Assist

The Brake Assist [49] feature enables the identification of sudden braking while driving. It then assists the driver by providing additional pressure while braking. The Navigation-Brake Assist technology [50] helps in detecting the stop signs ahead of time and thus aids in braking as applicable. Some examples of cars supporting the Active Brake Assist feature include Toyota [49]-[50], Volvo [51], Mercedes [52], and so on.

5) Active Lane Keep Assist

The Active Lane Keep Assist system helps in providing timely Lane Departure Warning to the driver in case the vehicle gets diverted from the current lane unintentionally [53]. In such situations, it can also support the driver by activating the AEB and automatically steering the vehicle back into the lane with the help of Radar Cruise Control. This technology mainly works by recognizing the lines on the road and steering the vehicle according to the changes in the road curvature, while keeping Lane Centering active for the duration of the drive cycle. Some examples of cars already supporting this feature include Toyota [53], Acura, Audi, BMW, Buick, Cadillac, Chevy, Ford, Genesis, GMC, Hyundai, Infiniti, Lexus, Lincoln, Mazda, Mercedes, Subaru, Volvo, et cetera [54].

6) Active Lane Change Assist

When a lane change request is initiated by the driver, the Active Lane Change Assist feature can aid in automatic maneuver or steering in the intended lane after following Blind Spot Monitoring (will be described below). This lane change operation may also be activated by the ADS instead of the human driver, depending on the level of vehicle autonomy. Hyundai Sonata, Porsche Macan, Subaru Legacy, Mazda 3, Lexus ES, Volvo S60, Toyota Tacoma, Range Rover Evoque, Chevrolet Volt, Dodge Charger, et cetera are some examples of the cars that have an option of supporting the Active Lane Change Assist functionality [55].

7) Active Blind Spot Assist

The Blind Spot Monitoring technology [56] can help in the accurate detection of another vehicle existing in the host Autonomous-capable Vehicle's blind spot. Since the blind spot of another vehicle is one of the riskiest areas to be present on the road, this functionality can be very helpful to address the road safety issue arising due to driver distraction. If another static or dynamic obstacle is detected in the blind spot of the host vehicle, during a lane change operation, AEB activation will prevent the driver from making this lane change. The range of alerts or warnings (visual, audio and haptic) provided to the driver and the Automatic Steering operation in order to prevent the lane change, depends on the level of vehicle autonomy. Mercedes-Benz [57] and Nissan Infiniti [58] are classic examples of the implementation of this feature.

8) Automated Parking

Automated Parking is another useful feature, especially in cosmopolitan cities, for optimization of parking spaces and increasing the driver convenience. This feature can firstly aid in the parking space detection and then in carrying out the required maneuver into the detected parking space. Furthermore, Automated Parking can also be enhanced for Parallel Parking, which can be quite challenging in areas with heavy traffic flow, in order to provide the Self Parallel Parking feature. Some examples of cars which support the Automated Parking feature include Volvo S90, Toyota Prius, Chrysler Pacifica, Chevrolet Malibu, BMW 5 Series, Ford F-150, Mercedes Benz S-Class, Tesla Model S, and so on [59].

9) Rear Cross Traffic

The Rear Cross Traffic feature enables the drivers to carry out the reversing maneuver (e.g. out of a parking lot, driveway, and so on) with the help of a rear-view camera. In case of a dynamic or a static obstacle detected in the vehicle's reverse path, depending on the level of vehicle autonomy, the Autonomous-capable Vehicle could decide to alert the driver (Rear Cross Traffic Warning) to stop the vehicle's reverse maneuver or the vehicle could assist the driver by enabling the

AEB (Rear Cross Traffic Assist). Audi Q2 and Lexus RX are a couple of examples that have implemented the Rear Cross Traffic Assist feature [60] - [61].

10) Autopilot

The Autopilot feature offers one of the most advanced autonomous functionalities [4]. It is able to result in automatic steering of the vehicle, when commanded, by making sure that the vehicle is well centered within the lane. Using the autopilot feature, it is also possible to change lanes according to the lane change signal used. In addition, it is able to adapt well to the driving environment and adjust the vehicle control accordingly. This functionality comprises of a combination of various other autonomous features such as lane centering, Adaptive Cruise Control (ACC) based on the traffic awareness and park assist. Tesla was one of the first contenders of the Autopilot [4].

11) Automatic High Beam (AHB)

AHB assists the drivers by switching between low beam and high beam lighting depending on the surrounding lighting conditions in the Autonomous Vehicle's driving environment. This helps in automatically optimizing the driving visibility for the driver. This technology has already been in the market for a few years. Multiple cars including Mazda, Subaru, Toyota, and so on are some examples that support this feature [62].

12) Adaptive Front Lighting System

Intelligent Adaptive Front-lighting system [13] enables better visibility on the road by automatically adjusting the direction of the headlights based on the road curvature. Similar to AHB, the Adaptive Front Lighting system has also been absorbed in the market for a few years. Some examples of cars offering this feature include Volkswagen Jetta, Mazda, Hyundai Elantra, Infiniti Q50, Subaru Outback, Volvo S60, and so on [63].

2.8 Other Types of Autonomous Vehicles

The use of autonomous capabilities is not only restricted to ground vehicles but very largely applied to other areas as well [64]. Unmanned aircraft systems have many wide applications. These can be very useful in the agriculture industry by helping the farmers in irrigation, monitoring, application of fertilizers, planting and pollination [65] – [67]. These aircraft systems can also be helpful for military applications such as rescue during natural calamities, emergencies, and situations permitting minimal human intervention [64]. Aerial Surveillance for data capturing or media purposes is another application [68]. Delivery of various goods can also become more efficient with the use of autonomous aircraft systems [69] – [74].

Marine is another area where the use of unmanned systems is of a significant advantage. Observation of ocean beings [43], oil and gas surveys and autonomous cargo shipments [73] are some of the applications of underwater autonomous systems. Underwater security systems could also be installed with the help of autonomous submarines [74].

Autonomous spacecraft have been in existence for a very long time. In majority of the space explorations, since human involvement is very difficult due to the surroundings, unmanned equipment can be very beneficial [75].

The driver-less train is another major example of an Autonomous Vehicle [76]. Since the observation of surroundings in terms of Object Detection and Tracking might be carried out in the same environment for every trip, the incorporation of autonomous capabilities to eliminate redundant driver-based activities is credible.

In overall, the existence of autonomous capabilities in vehicles helps in reducing the scope of driver errors. However, the autonomous functionality incorporated into the vehicles depends on the required level of autonomy as per the application domain.

2.9 Predicted Future Trends

This section highlights some of the major anticipated ADAS technologies which are being researched or tested currently. Furthermore, timeline predictions as publicly expressed by some of the major car manufacturers for various levels of Autonomous Vehicles, planned for commercial release in the near future, are also presented. The autonomous or semi-autonomous features which are currently available today have already been described previously.

1) Cooperative Adaptive Cruise Control (CACC)

CACC is one of the most sophisticated forms of Adaptive Cruise Control (ACC). It enables more informed decision making by extracting information from the smart driving environment through Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication [77]. For example, if the surrounding vehicles or infrastructure could communicate the traffic conditions to the host Autonomous Vehicle before-hand, it could then plan its execution path accordingly.

2) Autonomous Flying Car

Since a few years, the concept of autonomous ground cars is being explored further to discover the possibilities of a major technological transformation in the form of an autonomous flying car. There is incredible potential to such a technology if realized, mainly in optimizing the traffic flow. Such an autonomous flying car concept has been described in [78]. It has also been identified in [78] that the complex combination of automotive and aerospace parts for ensuring an efficient design could be one of the major roadblocks currently.

3) Autonomous Fuel Cell Car

While the biggest Autonomous Vehicle industry buzz has been around the Autonomous Electrified and Hybrid Vehicles, the realm of fuel cell vehicles in the space of autonomy is also being explored. One such concept SAE level 4 autonomous fuel cell car is currently undergoing testing as described in [79].

The dynamic timeline predictions offered by major car manufacturers in the realm of autonomous driving provide insights into the Autonomous Vehicle deployment roadmap [80] - [96]. As such, in Fig. 2.1, an attempt has been made to capture a snapshot of these current publicized predictions [80] - [96] in no specific order. A classification according to the various levels of Autonomous Vehicles predicted to be deployed, at a given time, by some of the major car manufacturers has been presented here. Acronym "L" has been used to represent "Level" of vehicle automation. For example, L3 would refer to a Level 3 Autonomous Vehicle. In order to avoid double counting, the technology or Autonomous Vehicle platform providers and chip manufacturers have been excluded from this figure. It is not the intent of this figure to provide any comparison on the commercial availability of these Autonomous-capable Vehicles from different manufacturers as the solutions are expected to have variations in the SAE levels of automation, geo-fencing requirements, application space, and technology. Instead, the intention of Fig.2.1.

is to provide a visual representation of the clustering of varying levels of Autonomous-capable Vehicles for a respective timeline.

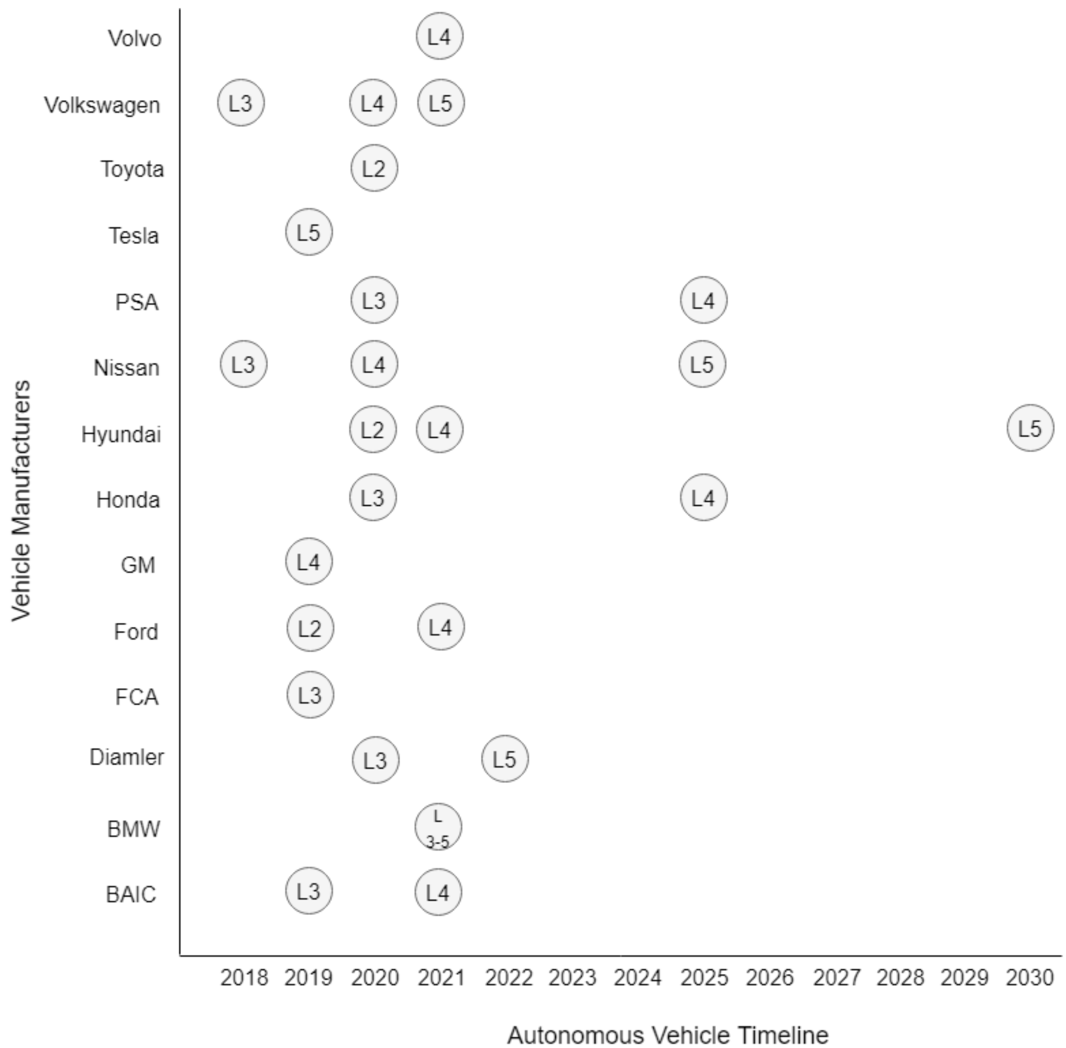

Fig.2.1. Mapping of Autonomous Vehicles Timeline to the SAE Levels of Automation as Predicted by Some of the Major Car Manufacturers.

Chapter 3

Fundamentals of the Autonomous Vehicle Technology

This chapter provides a review of the current ADAS architectures and literature exploring the impact of Electrified Vehicle autonomy on its performance. This will become very critical in demonstrating the gap analysis between the available literature and the requirements of the industry.

3.1 Review of Current Advanced Driver Assistance System Architectures

This section will provide a summary of the existing literature in terms of the different ADAS architectures and provide a gap analysis. As previously mentioned, the current technical publications describing an ADAS architecture for vehicles with higher levels of autonomy, are limited both in number as well as in terms of the encompassing functions that are able to comprehensively represent such a system.

A possible hierarchical illustration of the various perception functions within an ADAS architecture is shown in [97]. The autonomous features are described as an output of the situational analysis. Although, the architecture well represents the high-level breakdown of the various perception functions, the other functions of the system including the actuation and decision-making are not included. While [98] presents a good high-level representation of the actuation and perception systems, decision making is not explained as part of the ADAS control. Furthermore, the driver is shown as part of an HMI feedback, although no control is routed through the driver to the actuation systems. Similarly, [99] provides a detailed breakdown of both the perception and the actuation systems, however, the decision making or planning within an autonomous-capable vehicle is not shown in similar details. The ADAS architecture is also well described in [100]. The perception is broken down in terms of sensing domain and environmental characterization and the decision making is represented in terms of the threat assessment and the counter-measure decision algorithms. However, the actuation interface to various vehicle systems is not clearly identified. Furthermore, [101] provides a very detailed representation of the ADAS architecture with unique terminology. The architecture is described with the aid of multiple diagrams. Accurate perception, localization, mapping, and navigation are explained in this architecture in details. The interaction with the external infrastructure with the help of a Cloud environment is also described. However, the challenge is due to the limited representation of the decision making and actuation within the ADAS architecture. The ADAS architecture in [102] well represents the sensing, processing, actuation and the resulting autonomous or semi-autonomous features on a high level. However, the interfaces between them are not represented. This prevents understanding the flow of information from one module to the other. In addition, [103] also provides a systematic modular representation of the ADAS architecture. It dives deep into the perception, localization and mapping aspects. A reasoning and decision-making layer in addition to the path planning layer is also shown, although the details of the various functions are not demonstrated. Furthermore, the ADAS control layer showing the transmission of various signals including steering, braking and throttle is also presented, however, its interface to other higher-level actuation systems such as energy management, powertrain, and so on are not evident.

Similarly, there have been several attempts for representing the system level ADAS architecture [104]-[107]. However, the challenge is to comprehensively present the details of the various functions, components as well as the interfaces between them at different abstraction levels. Furthermore, it is also critical to identify the role of the important actors – ADS and the human driver. A summary of the above described literature is also visually represented in Fig.3.1 [97]-[107]. This thesis attempts to address some such gaps and offer a Cognitive ADAS Architecture for an Autonomous-capable Electrified Vehicle. In addition, the proposed ADAS architecture targets the higher levels of vehicle automation, which still seem to be in the conceptual stage in the automotive industry, making its availability with accurate details backed up by scientific justifications scarce in the literature.

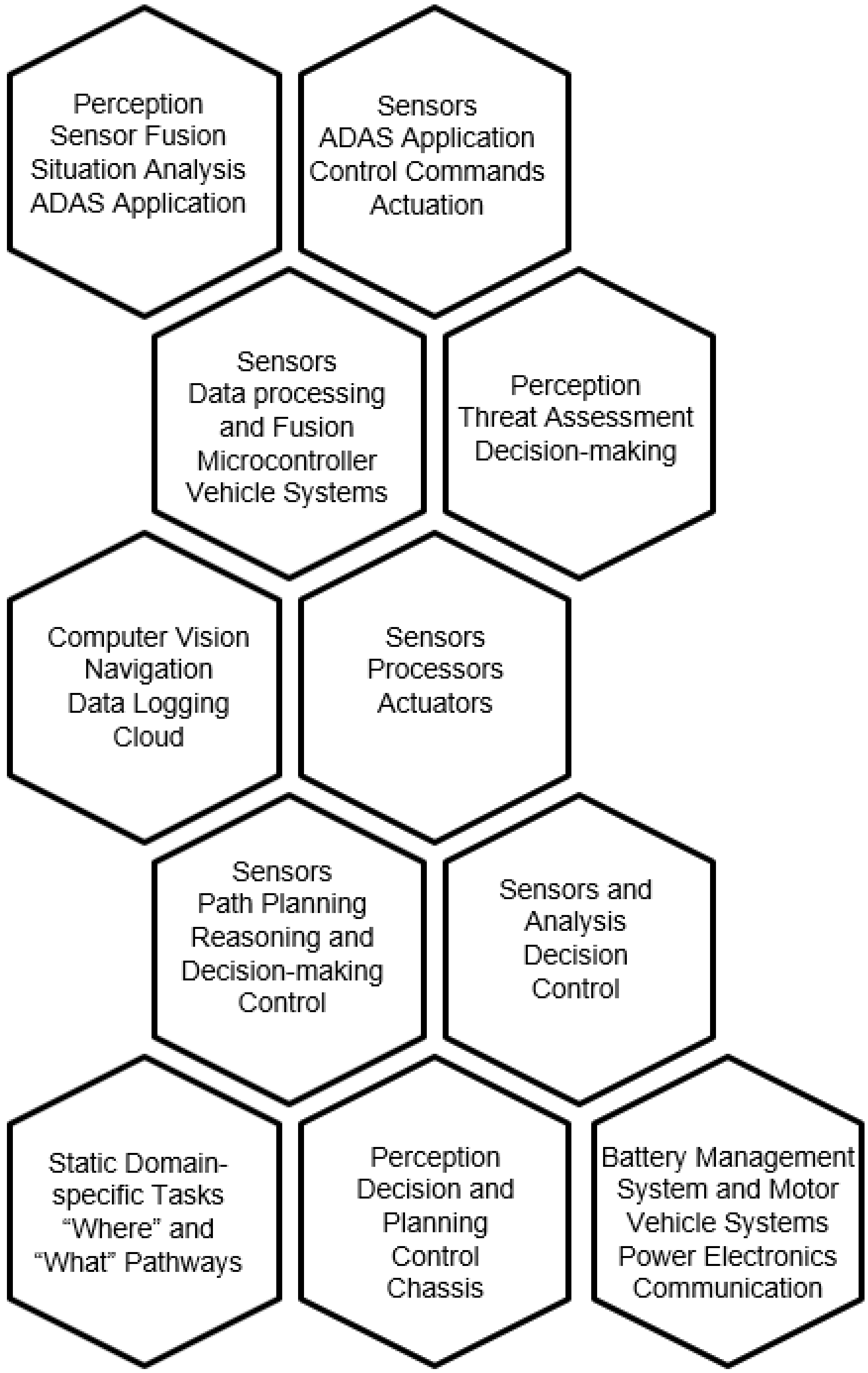

Fig.3.1. Summary of the Major ADAS Architecture Topics Discussed in the Current Literature.

3.2 Review of Existing Literature on the Impact of Vehicle Autonomy on Vehicle Performance

In addition to the ADAS architectures, this thesis also attempts to address the topic of the impact of vehicle autonomy on its performance. This section will review some of the existing literature on this topic and provide a gap analysis.

Regarding the topic of the impact of vehicle autonomy on vehicle dynamics and fuel economy, there are multiple intuitions about smooth acceleration and deceleration profiles, optimal control strategies and energy management as well as elimination of human factors and driver inefficiencies which could have a positive impact on both the dynamics and the fuel consumption of the vehicle [108]-[113], [114]-[118]. While [108] predicts an overall decrease of 2 to 4 percent in fuel consumption based on a report by the Intelligent Transportation Society of America, [109] estimates a 10% increase in the fuel economy due to the efficiency improvements from autonomous control algorithms. Similarly, a 10 to 15 percent fuel economy benefit is also highlighted by [110], due to the possibility of vehicle platooning (cutting down the aerodynamic drag by moving vehicles with a specific distance gap), components re-design and so on. Furthermore, according to [111], the better driving efficiency, lower congestion, improved acceleration/deceleration patterns in addition to the benefit due to platooning can also result in very high reductions in fuel consumption. Also, [112] claims that the vehicle interconnectivity through V2V and V2I communication can play a major role in improving the fuel economy by as much as 10 %. An overview of the fuel economies for different vehicles through years has been shown in [113]. The autonomous-capable vehicles are predicted to exhibit more eco-friendly driving through their impact on the engine, accessory loads, rolling resistance and so on [113]. In [114], Model Predictive Control is used to anticipate future trajectories of the vehicle, which in turn is expected to aid in fuel economy improvements. Furthermore, a 40% improvement in fuel economy is predicted in [115] based on a simulation study of Toyota Prius' engine, battery state of charge and the fuel economy itself. The main reason for this significant improvement is accounted to better control strategies arising from the autonomous control of hybrid powertrain resulting in a more fuel-efficient driving [115]. Optimal Energy Management, connectivity, and intelligent driving styles are also seen as major contributors to fuel economy improvement in [116], [117] and [118] respectively.

Furthermore, the variations in the vehicle performance (for urban and highway driving) based on the different operation modes of the hybrid and plug-in hybrid vehicles, including the blended mode, is also discussed in the literature [119], [120].

Despite many different predictions on the percentage of fuel economy improvement and the reasons behind it, the challenge is to systematically demonstrate the relationship, backed up by a thorough scientific analysis, between different levels of autonomous control and the Electrified Vehicle components specifically, which can, in turn, result in significant energy savings. As such, this thesis provides this analysis through a simulation-based framework, established on the proposed Cognitive ADAS Architecture. The intention of this work is to not only support this analysis for existing vehicle automation levels but also for the future autonomous levels 3 and above which are only seen to be conceptual at this stage in the automotive industry.

Chapter 4

A Cognitive Advanced Driver Assistance Systems (ADAS) Architecture for Autonomous-capable Electrified Vehicles

This section proposes a Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles [121]. The different modules and sub-modules, as well as their interactions, are described in detail. Assumptions made for this architectural development are also provided. A discussion on the various component examples that are used within this ADAS architecture is also provided. Lastly, the benefits and applications, as well as the limitations of the proposed Cognitive ADAS Architecture, are presented.

4.1 Assumptions

This section describes some of the major assumptions that were made for the development of the proposed Cognitive ADAS Architecture. Primarily the architecture is targeted towards Autonomous-capable Electrified Vehicles. Furthermore, the intended level of vehicle automation is 4 for the primary architecture presented. Variations of the architecture for levels 3 and 3.5 have also been offered, which will be described in detail further in the thesis. The next assumption made for the architecture definition is about the level of abstraction. As described in the Scope of Research section, since it is practically impossible to define an architecture which can address all the functions at all the levels including the Autonomous-capable Vehicle, platform, chips and the technology levels with a comprehensive mapping of all the functions and their interactions; the architecture was assumed to be at a system-level addressing the various functions, example components, the interactions between them and the vehicle internal and external interfaces in a modular and systematic approach. As such, it is also assumed that for an efficient and optimal design of an Autonomous-capable EV, such an extensive functional breakdown is further studied at lower abstraction levels (presented as future research), similar to the one presented in this thesis at the system-level. This can be performed by further decomposing the functions presented in a modular and sub-modular manner from the proposed Cognitive ADAS Architecture. Lastly, it is also assumed that the vehicle manufacturer will include optimal redundancy for providing a safe implementation of this architecture for addressing any irreversible failures within any of the modules or the sub-modules presented in the Cognitive ADAS Architecture. The required communication between the redundant systems can be carried out through the central ADAS Management System which contains the Onboard Diagnostics Collection Unit encompassing the sanity information of all the modules and the sub-modules within the architecture. More details about the architecture will be presented in the next section on Proposed Cognitive ADAS Architecture.

4.2 Proposed Cognitive ADAS Architecture

This section primarily proposes the Cognitive ADAS Architecture for a Level 4 Autonomous-capable Electrified Vehicle [121]. Before presenting the details of the proposed Cognitive ADAS Architecture, the major steps for the functionality of an Autonomous-capable Vehicle from a simplistic and a high-level perspective is depicted through Fig.4.1 [122]. As it can be seen from the below block diagram, the Autonomous-capable Vehicle actions can be classified into three broad categories – Perceive, Decide and Execute [123].

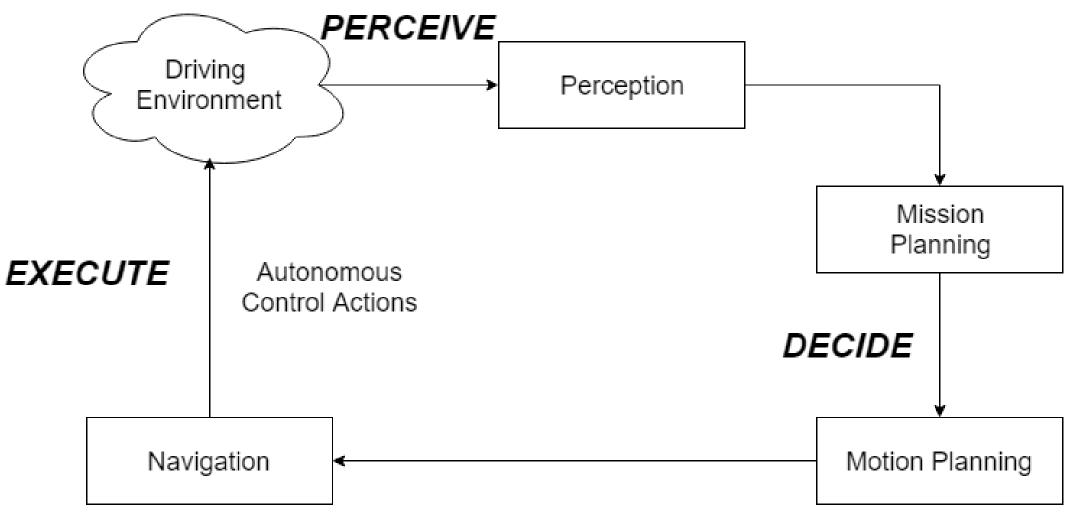

Fig.4.1. High-level ADAS Architecture.

The detailed Cognitive ADAS Architecture itself is presented in Fig.4.2. It is termed as "Cognitive", being inspired by the series of functions within a human brain [121], [124]-[125]. The motivation of this architecture is to present the various aspects of an Autonomous-capable Electrified Vehicle at a system level, including the different functions, sub-functions, component examples, their interfaces and interactions [3], [97]-[107], [121], [126]-[133]. The intention is also to assimilate the known information about Electrified Vehicles with the Perception and Cognition topics, which are currently being explored in the literature, to understand their system level interaction, along with the human driver responsibility, for Highly Automated Driving framework. The architecture presented here can be applied to various use cases such as highway, urban, off-road, and so on. However, urban applications could be expected to have much higher performance requirements mainly in terms of the Perception and Cognition functions due to the extremely dynamic driving environment. Variations of this architecture are also shown for levels 3 and 3.5 in Fig. 4.3. and 4.4 respectively. Level 3.5 is not currently part of the SAE levels of vehicle automation, however, it has been proposed in this thesis, as an insight into the future industry trends, to incorporate other combinations of the ADS and human driver's control distribution, which are not part of the current literature. A level 3.5 is a combination of 3 and 4 with the primary fallback routed through the human driver, followed by the ADS, in case of an inattentive driver. The main changes in these architectures are seen for the fallback configuration which are also highlighted in red within the architectures. In addition, the in-vehicle communication networks are shown with a solid line, whereas the vehicle external communication networks (with at least one end-point existing external to the vehicle) with a dashed line.

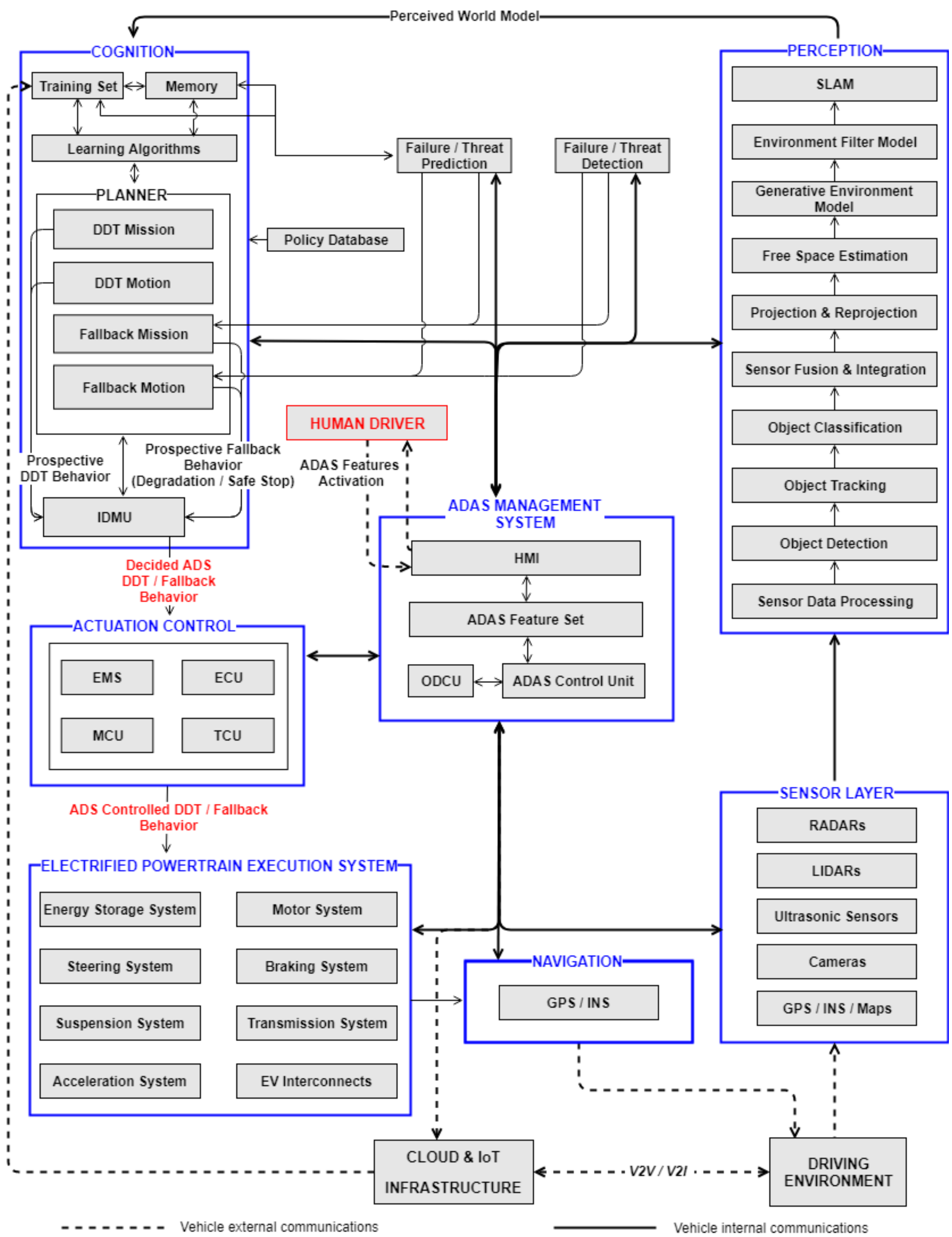

Fig.4.2. Proposed Cognitive ADAS Architecture for Level 4 Autonomous-capable Electrified Vehicle.

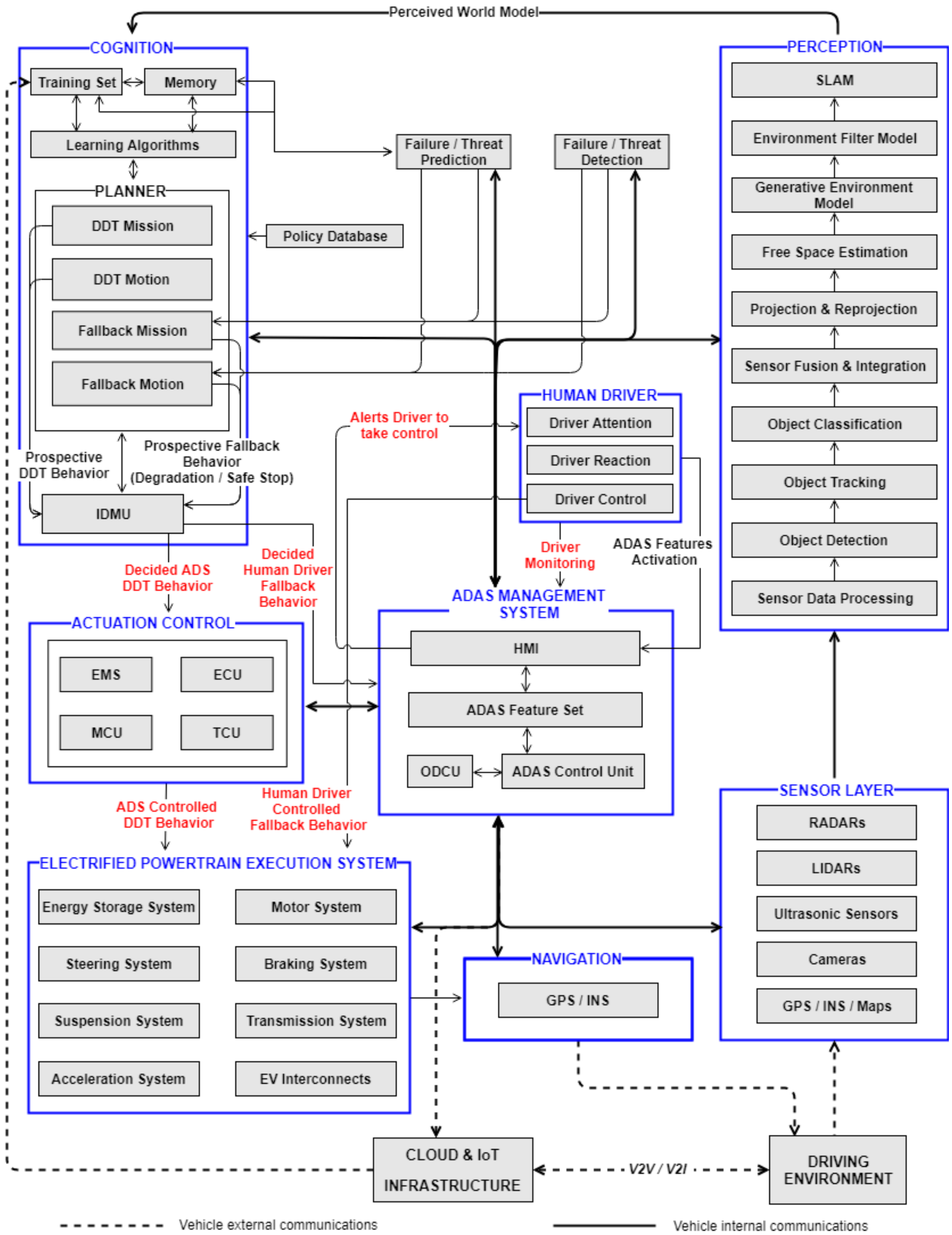

Fig.4.3. Proposed Cognitive ADAS Architecture for Level 3 Autonomous-capable Electrified Vehicle.

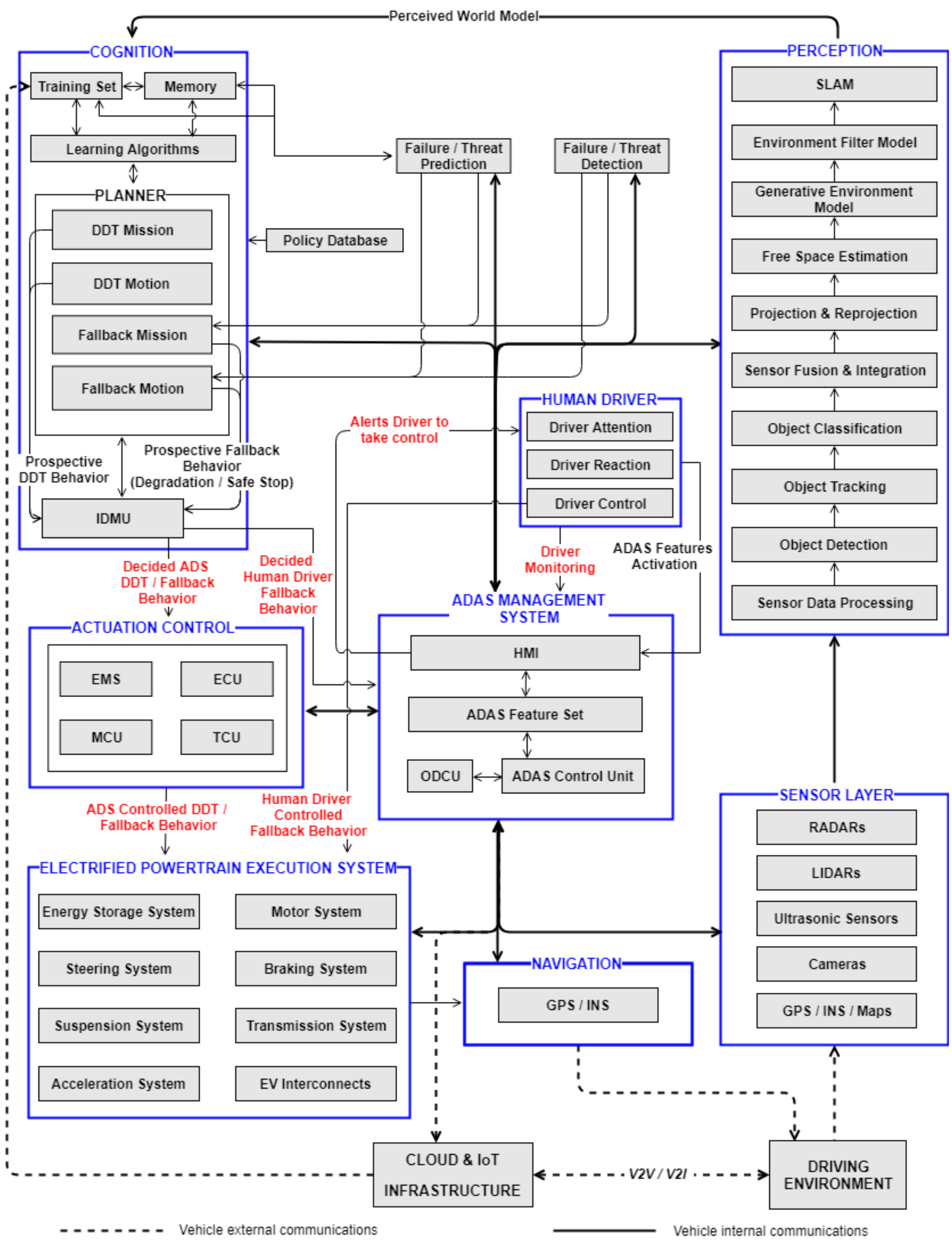

Fig.4.4. Proposed Cognitive ADAS Architecture for Level 3.5 Autonomous-capable Electrified Vehicle.

4.2.1 Sensor Layer

The proposed Cognitive ADAS Architecture cycles in a closed-loop. The primary interface, however, between an Autonomous-capable EV and its driving environment, which can consist of other vehicles, infrastructure, static and dynamic obstacles, and pedestrians, and so on is the Sensor Layer. This layer represents the raw data collected through the physical sensors mounted on the Autonomous-capable EV including RADARs, LIDARs, Ultrasonic sensors, Cameras, Global Positioning System (GPS), Inertial Navigation System (INS) and the High Definition Map data. It is expected that the sensor suite selected would include a diversity in the technology as well as redundancy to ensure an accurate 360-degree surround vision for the Autonomous-Capable EV at all times.

4.2.2 Perception

The raw sensor data from the Sensor Layer is received by the Perception block. The perception module primarily aids in the accurate interpretation of the Autonomous Vehicle's driving environment. The raw image data is pre-processed before performing any other Perception functions. This greatly helps in filtering out any unnecessary noise which can be computationally expensive to process.

Following the sensor data processing, the Object Detection stage needs to be taken care of. The Autonomous-capable Vehicle needs to detect all kinds of objects including moving vehicles and pedestrians, motorcycles, bicycles, animals, stationary vehicles and pedestrians, traffic signals, stop signs and the other dynamic and static objects present in the driving environment. As specified in [122], the Deformable Part Models Algorithm can be used for accurate Object Detection [134]. In [135], to increase computational efficiency, parallel algorithms implemented on Graphics Processing Unit (GPU) are designed to accelerate the information processing.

The next step is called Object Tracking [122]. In addition to detecting where a particular object is in the concerned scope of space on the road, it is also vital to track the changes in their position. In other words, the motion of the objects needs to be detected and updated in real time. This will provide the Autonomous Vehicle with a better understanding of its dynamic environment, which in turn will be helpful in updating its intelligent control as part of a closed loop control system. Detected and tracked objects can then be classified based on the interpretation of their attributes in order to analyze whether and what type of a control action needs to be taken to satisfy the real-time requirements of the dynamic driving environment.

The next step in the Perception layer is the Sensor Fusion and Integration. Sensor Fusion includes the use of redundant and diverse technology or sensor suite to look upon the same region of interest in order to increase the confidence level of the sensing output. The Sensor integration includes aggregation of the multiple sensor data in order to produce the 360-degree surround view Perception required for Highly Automated Driving.

Projection and Re-projection are the next steps in the process of accurate perception [33]. Following Sensor Fusion and Integration, the information needs to be summarized and combined in order to get a better three-dimensional depth estimate of the interested space on the road. These steps aid in an accurate estimation of the free space between the host vehicle and the surrounding objects in its immediate field of view. Free Space Estimation will be very crucial in establishing an accurate trajectory plan for the Autonomous-capable EV, which will be explained further in the Cognition sub-section.

Following this, a generative model of the driving environment is established. This generative model goes through an extensive filtration process to establish Simultaneous Localization and Mapping (SLAM) which only focuses on the area of interest of the Autonomous-capable EV [122]. During SLAM, the Autonomous-capable Vehicle is first sensed and accepted into its driving environment. Then an accurate real-time 3D map is generated and updated frequently as the vehicle goes through its drive cycle. As described in [122], a three-dimensional Normal Distributions Transform algorithm [136] can be utilized in order to perform accurate matching and mapping operation with the 3D cloud data.

4.2.3 Cognition

The perceived world model, once established, is transmitted to the Cognition block. This block can be interpreted as the “brain” of the Autonomous-capable EV, which understands the information seen and plans for prospective vehicle behavior. The Cognition block develops its intelligence based on the various Learning Algorithms, training received as well as past events-based Memory [125] and Cloud-based feedback from other vehicles (Vehicle to Vehicle or V2V) and infrastructure (Vehicle to Infrastructure or V2I). The training set, which is the current training repository, is expected to receive this feedback. The current learning, training, and planning become a part of the Memory for future events. A Policy database which dictates the rules and regulations of the driving environment, traffic and road serves as an important input to the Planner. Both the Mission or the destination and the Motion or the maneuvers to reach to the destination are calculated by the Planner. A Dynamic Driving Task (DDT) and Fallback Mission and Motion are planned. The use of conformal spatio-temporal lattices [137] for planning the motion according to the changes in the environment has been demonstrated in [122].

The DDT behavior (including the normal functions of the vehicle such as acceleration, braking, and steering) is intended to be executed as part of the normal Autonomous-capable EV behavior, whereas, the Fallback behavior is executed in case there is a failure, or a threat/ malicious attack predicted or detected within the

ADS. The Failure/ Threat Prediction is normally based on the comparison of current events with the past events knowledge. Failure/ Threat Detection is enabled through a central ADAS Management System (to be described further below). The Intelligent Decision-Making Unit (IDMU) analyzes the output from the Cognition block and decides whether the DDT behavior or the Fallback behavior should be executed. For the level 4 architecture, both the DDT and Fallback behavior are controlled by the ADS; whereas for level 3, the human driver is responsible for the Fallback behavior and in 3.5 [3], the primary Fallback is routed through the driver and the secondary through the ADS, in case the driver is not alert enough to take back vehicle control when requested. At this point, certain ADS functionality may be at a degraded level than normal. It is important to note that between a DDT and a Fallback behavior, only one of them is executed at a time, depending on the decision made by the IDMU, based on the Perceived World Model and the requirements of the dynamic driving environment. Similarly, for a level 3.5, the Fallback control is routed either through the ADS or the Human Driver, one at a time. This decision is made by the ADAS Management System based on the sub-systems' sanity information collected by the On-board Diagnostics Control Unit (ODCU), which will be described further in the ADAS Management System. When the Human Driver is in the control loop for levels 3 and 3.5, there are multiple internal feedback loops to primarily alert the driver to take back vehicle control through an HMI and then to constantly monitor driver's attention, reaction, and control, as shown in Fig.4.3. and 4.4 respectively. Current literature describing the human driver attention capturing techniques has been previously summarized in section 2.4. This Fallback response is extremely critical in ensuring that the vehicle is able to respond to unexpected events or foreseen failures and threats. The time required by the system to respond to these emergencies will mainly depend on two factors – the type of Fallback response being executed, and the performance/ computation capabilities of the sensor suite being considered. The expectation is to have a redundant sensor suite to enable timely detection, classification, planning, reaction and thus a timely and safe Fallback system response, within the Fault Tolerant Time Interval (FTTI) [33]. It is also expected for the Autonomous-capable EV to be able to communicate back to the driver any important vehicle relevant information as needed (for all levels of vehicle automation); for example, the perceived driving environment, executed actuation controls and so on through the HMI.

4.2.4 Actuation Control

The decided Autonomous-capable EV behavior, either DDT or Fallback is communicated by the Intelligent Decision-Making Unit to the Actuation Control block, which in turn consists of an Energy Management System (EMS), Electronic Control Unit (ECU), Motor Control Unit (MCU) and Battery Control Unit (BCU). The Actuation Control block not only makes decisions about the control actions for various sub-units but also communicates the specific expected behavior to the respective Execution sub-units within the Electrified Powertrain Execution System. In case of a level 3.5 and 4, both the DDT and Fallback behavior is expected to be routed through the Actuation Control. In a level 3 architecture, since, the human driver is responsible for the fallback behavior, the human controlled actions are directly routed through the Electrified Powertrain Execution System, as can be seen in Fig.4.3. This is to ensure that in case of an ADS failure, the human driver is able to override ADS decided execution commands in order to perform a safe stop maneuver.

4.2.5 Electrified Powertrain Execution System

This block consists of various sub-units that execute the expected steering, braking and throttle behavior of an Autonomous-capable EV. The various systems such as Energy Storage, Motor, Steering, Braking, Acceleration, Suspension, Transmission, and the various EV Interconnects between them are considered to be part of the Electrified Powertrain Execution System. This block receives execution commands either from the Actuation Control or the Human Driver, depending on the level of intended autonomy, as previously described.

4.2.6 Navigation

The actions performed by the Electrified Powertrain Execution System are routed through the Navigation system in order to make sure that the Autonomous-capable

EV's real-time behavior matches the intended behavior based on the dynamic requirements of its driving environment. As previously mentioned, since the presented architecture is part of a closed loop system, the actions performed by the autonomous-capable EV are expected to contribute back to its driving environment. Furthermore, the ADAS Control Unit in conjunction with the Onboard Diagnostics Collection Unit (ODCU) which will be described further, helps in understanding whether the vehicle is on the desired trajectory at every milestone. In the case of a significant deviation, the control and tracking input would be updated accordingly in order to cover the difference. A smaller duration in between the milestone checks would result in a more accurate vehicle control. As suggested in [122], the Pure Pursuit Algorithm can be used for this path following step [138].

4.2.7 ADAS Management System

The proposed Cognitive ADAS Architecture also includes a central ADAS Management System which comprises of the Human Machine Interface (HMI), a database of ADAS features and their associated functionality algorithms as well as an ADAS Control Unit and the Onboard Diagnostics Collection Unit or ODCU. Unlike at levels 3 and 3.5 that demand increased driver responsibility for ensuring Fallback behavior, at a level 4 autonomous capability, although a human driver is not expected to directly perform any DDTs, it is expected that the various autonomous/ semi-autonomous features will only be activated based on a user request, possibly through an HMI interface. Based on the user request, the intended ADAS features are activated and according to their required functionality, the ADAS Control Unit decides on the arbitration of the rest of the blocks which are part of the proposed Cognitive ADAS Architecture. It also takes in input from the ODCU which receives all the diagnostics information from the rest of the modules within the architecture. This link is very helpful to know if there has been any failure in the ADS or an external threat has been perceived based on Cloud and IoT infrastructure. The current literature discusses the use of both in-vehicle and Cloud-based vehicle diagnostics [139]. Multiple sensors for monitoring the voltage, temperature, fuel consumption and even the driver behavior are currently available internal to the vehicle. However, Autonomous-capable vehicles might see a growth in the amount of complex computations that need to be performed in real time, especially for trajectory planning, impacting the computational cost. Cloud-based solutions are seen to be especially beneficial here to leverage the complex computation capabilities external to the vehicle. [139] presents an approach for Cloud-based driver monitoring and vehicle diagnostics estimation. Ensuring secure communication between the host vehicle and the Cloud infrastructure is crucial to avoid compromising with vehicle’s privacy. Furthermore, it is also important to ensure that certain safety critical functions of the vehicle are performed internally to avoid any latency issues arising from Cloud communication.

As such, the ADAS Management System looks upon the Sensor Layer, Perception, Cognition, Failure/Threat Detection, and Prediction, Actuation Control, Electrified Powertrain Execution System, Navigation, Human Driver and the Cloud and IoT infrastructure layer. In addition to the previously mentioned utility of the Cloud and IoT Infrastructure layer for communication of vital driving environment insights established through V2V and V2I communication to the Cognition and the ADAS Management System, it is also expected that the host Autonomous-capable EV will be able to communicate back its relevant information (position, any accident information on the road and so on) from the ADAS Management System to the rest of the driving environment. In other words, a bi-directional information exchange is expected between the host AV and the rest of the driving environment as part of the V2V/ V2I based Cloud and IoT layer.

4.3 Discussion on Autonomous-capable Electrified Vehicle Components

The Cognitive ADAS Architecture was proposed in the last section while describing the different modules, sub-modules, interfaces, and interactions between them. Some examples of the components which could be seen as part of this architecture were also presented. This section offers a discussion on some of those major components seen within an Advanced Driver Assistance System. It is beyond the scope of this analysis to present the ideal selection of the Hardware or Software as they would depend upon the intended application and would surface out at the lowest abstraction level. Since, the Cognitive ADAS Architecture is presented at the system level, some of the major components such as the sensors, communication networks and so on that would be seen at the vehicle level of a highly Autonomous-capable EV (levels 3 and above) are shared here [122], [140]-[143].

One of the most important components of Autonomous-capable Vehicles is the sensor suite equipped within them. This is mainly because environment detection is a critical function for the intelligent decision making within such vehicles. However, the type of sensors or equipment used within the Autonomous Vehicles depends on the functionality required. Light Detection and Ranging (LIDAR) sensors are generally used in order to provide a three-dimensional map of the vehicle's environment, including an accurate measure of the distance between the Autonomous Vehicle and the surrounding objects within both a short as well as a long-range [122].

These sensors work by measuring the time taken by objects to reflect a beam of laser light indicating their distance from the measuring point [140]. These sensors are not only helpful for collision avoidance but also for Path Planning. In addition to LIDAR sensors, RADAR sensors are also very useful for the Perception as well as the Motion Planning stage [140]. They work mainly by using radio waves once again to detect the objects in the surroundings in order for the Autonomous-capable Vehicle to form a perception of its environment. Furthermore, Ultrasonic sensors work on a similar principle. The distance between a car and a near-by obstacle can be gauged by the echo produced at the collision of the ultrasonic sound waves and the neighboring object [141]. In addition, as described in [144], infrared cameras, which work on the concept of heat emission, might be seen especially useful for night vision.

Specialized cameras, including video cameras [140], stereo cameras providing a three-dimensional vision [141] and 360-degree cameras [142] can also be used for detecting important road information such as traffic signal light, stop signs as well as dynamic objects on the road.

No one sensor can be expected to provide enough accuracy to match or exceed human vision. A combination of sensors must be used redundantly and with diversity through Sensor Fusion and Integration. Furthermore, it is critical to process the information collected by the sensors, through an Image Processing Unit, to extract the most meaningful information, which can then be used by the Intelligent Decision-Making Unit within the Autonomous-capable Electrified Vehicle.

Also, the Autonomous Vehicle's driving environment, namely other vehicles and infrastructure such as smart buildings, traffic signs and so on are also capable of holding useful information for the AV's accurate Perception. As such, Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communications are recently promoted concepts [145] in this area. In addition to the V2V/ V2I vehicle external communication networks, which are routed through Cloud and IoT infrastructure, the vehicle internal communications are expected to be equally critical (categorized by SAE as Class A, B, and C for low, medium and high communication speeds respectively) [146]-[148]. The Controller Area Network or CAN [146]-[148] is one of the majorly used Class C communication networks for in-vehicle communication between the different modules and sub-modules (through a CAN bus) presented as part of the Cognitive ADAS Architecture. Besides CAN, there are multiple other protocols that have been traditionally developed for in-vehicle communication including Local Interconnect Network (LIN) as a low cost – low speed alternative to CAN, SAE J1850, covering Class A and B networks, ISO 9141 as an alternative to SAE J1850 enabling communication with diagnostic ports, the deterministic Time-Triggered Protocol (TTP) intended for SAE Class C applications, FlexRay for safety-critical systems and so on [146]-[148]. The selection of these protocols depends entirely on the cost, intended level of safety, targeted application and so on.

In addition to the various sensors and communication networks, one of the other important components of an Autonomous-capable Electrified Vehicle is its central computer [140] that serves as a major decision-making unit. A Microcontroller Unit or a Microprocessor Unit could be coupled as an input to the Decision-making System. The major role of the components in the Cognition layer is to collect the processed sensor information and take real-time decisions for the Autonomous-capable EV. The motivation at this stage is to imitate a human brain which understands its perceived driving environment and makes an informed decision based on the traffic rules (which in the case of the Autonomous-capable EV, is dictated by a Policy database, as per the proposed Cognitive ADAS Architecture). Again, similar to the human brain, which is trained to learn from the past, an Algorithm Database, fed by reinforcement learning, can feed into the Decision-making System as a closed loop in order to constantly update the decisions, as needed.

The set of real-time decisions made in the Cognition layer are then transferred accordingly to the various control units inside the Autonomous Vehicle such as the Motor Control Unit (MCU), Transmission Control Unit (TCU), Electronic Control Unit (ECU), Energy Management System (EMS), Advanced Driver Assistance System Control Unit and so on so that the decisions made can be efficiently transformed into the type of real-time actions or behavior that the Autonomous Vehicle needs to exhibit in order to fulfill the dynamic requirements on the road. It is to be noted that these components completely depend on the vehicle powertrain (e.g. Hybrid Autonomous, Electrified Autonomous, Internal Combustion Engine Autonomous and so on). Similarly, the vehicle powertrain also dictates the type of components actually responsible for executing the decided actions on the road. Some examples could include the Steering System, Braking System, Acceleration

System and so on as already described in the Cognitive ADAS Architecture.

Furthermore, the overall vehicle Navigation System encompassing the Global Positioning System (GPS), coupled with the Inertial Navigation System (INS), Tachometer, Altimeter, Gyroscope, Odometer and so on form an important element within the Cognitive ADAS Architecture [140], [143]. The vehicle Navigation System can not only aid in Simultaneous Localization and Mapping but also in guiding the executed actions to be in the planned navigation path, hence represented in both the Senor and Navigation layers. The Human Machine Interface (HMI) is also a key element in this sphere. The HMI can not only display the perceived driving environment but also dictate actions for human control depending on the level of vehicle automation.

Lastly, the Cloud platform and the Internet of Things (IoT) infrastructure are essential for communication between the three functions – Perceive, Decide and Execute [141]. This is a virtual layer of communication which exists between the Autonomous-capable EV and the rest of the driving environment and is present external to the vehicle. The other utilities of this layer for Failure / Threat prediction have already been described in the Proposed Cognitive ADAS Architecture section.

4.4 Benefits and Applications

This section describes the advantages and applications of the proposed Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles. The most significant benefit of this architecture is the systematic distribution of the different functions, components, their interfaces and interactions at a system level. The modular approach provides an advantage of remodeling the architecture to represent different levels of automation, powertrains such as Electrified, Hybrid or Internal Combustion Engine and varied hierarchies of abstraction, in addition to serving as a primary building block in realizing a highly Autonomous-capable EV.

Furthermore, the pragmatic representation of the information flow through the architecture enables the development of a simulation model or a testbed in order to verify and validate the various Autonomous Vehicle systems before investing in real scale testing. In addition, the proposed architecture is helpful for targeting higher levels of Electrified Vehicle automation (levels 3 and above) applications. This is of a great value to the automotive industry especially due to the limited literature in the field of Highly Automated Driving.

In addition, the proposed architecture can aid in further decomposition of the system-level functional requirements which are key in the implementation of the Cognitive ADAS Architecture. An integrated development process across the various tiers of the automotive industry with the technology meeting the system demands would be essential for realizing the highly Autonomous-capable vehicles.

4.5 Challenges

This section addresses some of the challenges or limitations with the proposed Cognitive ADAS architecture. One of the challenges faced during the architecture development was to systematically represent the enormous number of functions carried out at different abstraction levels for the operation of an Autonomous-capable EV within a Highly Automated Driving Framework. It is practically impossible to demonstrate the complex functionalities to the last abstraction layer. This end-to end integration of intricate functions could also be one of the key challenges in implementing the architecture. As such, the scope of the architecture definition was restricted only to be at the system level. The architecture, however, provides the benefit of adopting a modular approach, which can aid in simply expanding each of the last hierarchies of sub-modules to decompose the next level of details.

In addition, as previously described in the Scope of Research section, this architecture is mainly focused on Electrified Vehicles to prevent the complex mapping between the autonomous and hybrid/ ICE powertrain controls which would be needed for other types of vehicles such as Hybrids and ICE. However, the architectural representation provides the benefit of scalability to target other ground vehicles (including light weight, heavy duty, off-road and so on) with simple modifications in the Actuation Control and the Execution System, which will be described in detail further in the thesis.

Chapter 5

Development of the Autonomous-capable Electrified Vehicle Simulation Model

This section will describe the development of the Autonomous-capable Electrified Vehicle simulation model and its dynamic driving environment [121], [149]. The IPG CarMaker simulation software was utilized for carrying out the vehicle-level simulations described in this thesis. These simulations have proved to be extremely crucial for verifying the hypothesis around the positive impact of increased vehicle autonomy in increasing an Electrified Vehicle performance. The simulation platform also enables in the virtual implementation of the proposed Cognitive ADAS Architecture targeting up to level 4 vehicle autonomy. The conceptual nature of the present higher levels of automated driving architectures (level 3 and above) make the verification through commercial experimentation far from reality. This is also where the simulations play an essential role in enabling more systematic and corroborated development of optimal ADAS architectures and AV designs. In addition to serving as a virtual verification platform for the proposed Cognitive ADAS Architecture and enabling in concluding the impact of Electrified Vehicle autonomy on vehicle performance, these simulations also enable in understanding the impact of vehicle autonomy on the Electrified Vehicle dynamics and various components such as the motor and battery. Furthermore, validation of the simulation model is also presented.

5.1 Autonomous-capable Electrified Vehicle Model

This sub-section will cover the major aspects associated with the Autonomous-capable Electrified Vehicle modeling. An enhanced 2014 Tesla Model S 85 [4] has been used as a test vehicle for performing the simulations described in this study. To model this test vehicle, a demo Tesla Model S [150] provided by IPG CarMaker was utilized. This demo model was then modified by including an additional sensor suite, which will be described further, in order to represent a level 4 Autonomous-capable Electrified Vehicle. The sensor suite was adequately selected and modeled to represent geo-fenced level 4 highway driving scenarios for this study.

It is not the intention of this thesis to claim an optimal sensor suite selection for commercial deployment in a level 4 Autonomous-capable EV. This is considered as out of scope for this study. The selection of sensor technology will be widely dependent on the intended level of vehicle autonomation, required redundancy to fulfill safety considerations and the assumed driving scenarios that a vehicle will encounter in its lifetime.

There are 12 sensors that have been modeled for the simulations. These include 1 Slip Angle sensor, 1 Inertial sensor, 4 Object sensors, 1 Free Space sensor, 1 Traffic Sign sensor, 1 Line sensor, 1 Road sensor, 1 Collision sensor and 1 Global Navigation sensor. The sensor parameterization for the test vehicle has been scaled based on their addition on other demo vehicle models available in IPG CarMaker. The parameters for the various sensors can be seen in Tables 1 to 8. The reference for the position has been taken as the rear bottom right corner of the test vehicle in CarMaker.

All the sensors are assumed to be ideal; as such, fallback behavior of the vehicle in case of a sensor failure is considered out of scope for this analysis. This is mainly to enable maximum ADAS features activation period to study the impact of vehicle autonomy on Electrified Vehicle performance and dynamics.

The test vehicle is modeled with a Slip Angle sensor. This sensor is helpful in identifying the side slip angle at the location mounted [151]. An inertial sensor is also included in the vehicle model. This sensor is helpful in measuring the position, velocity, and acceleration of the vehicle where mounted. This sensor can be especially helpful in the Object Tracking function described in the proposed Cognitive ADAS Architecture by tracking the vital vehicle data from both the host and the target vehicles in order to plan the immediate vehicle path accordingly. The parameters for Slip Angle and Inertial sensors are shown in Table 5.1 and 5.2 respectively.

Table 5.1. Slip Angle Sensor Parameters

Slip Angle Sensor	
Position x/ y/ z [m]	2.51 / 0 / 0.578

Table 5.2. Inertial Sensor Parameters

Inertial Sensor	
Position x/ y/ z [m]	3.1 / 0.3 / 0.77
Orientation x/ y/ z [deg]	0.0 / 0.0 / 0.0

The Object sensors are also crucial in ensuring accurate detection and tracking of the dynamic obstacles. Four Object sensors including RADARs (left, right and front) and a front camera were used. For a level 4 autonomous function, a 360-degree surround vision is expected for the vehicle to have complete knowledge of its surroundings at all times. The Object Detection, Tracking, Classification and Sensor Fusion and Integration happen in the background of the CarMaker software [151] in order to provide an accurate monitoring of the dynamic driving environment surrounding the host vehicle. The parameters for the Object sensors can be found in Table 5.3. As it can be seen from below, the target is detected by these sensors based on Nearest in Path mode calculation. This means that the Object sensors will only detect the objects in the host vehicle's estimated trajectory, which are closest to the host vehicle within a particular range. Furthermore, a calculation class of Nearest Point is selected for the Object sensors. This ensures a conservative Object Detection approach by always having the nearest point of an object, even if on the surface, to be used for free space estimation. The rest of the sensor parameters below are based on the available demo models in CarMaker. They are scaled to fit the exteriors of the test vehicle. The sensor data is refreshed or updated based on the specified update frequency and cycles offset.

Table 5.3. Object Sensors Parameters

Object Sensors	Left Radar	Right Radar	Front Radar	Camera
Observation radius [m]	700	700	700	700
Position x/ y/ z [m]	4.3 / 0 / 0.63	4.3 / 0 / 0.63	4.6 / 0 / 0.43	2.86 / 0 / 1.25
Orientation x/ y/ z [deg]	0/ 0 / 0	0 / 0 / 0	0 / 0 / 0	0 / 1 / 0
Field of view h / v [deg] (max 180)	16 / 4	16 / 4	16 / 10	45 / 45
Range min / max [m]	150	10	200	100
Update [Hz] - Cycles offset	1000 - 1	1000 - 0	60 - 0	60 - 1
Target detection	Nearest in path	Nearest in path	Nearest in path	Nearest in path
Calculation class	Nearest Point	Nearest Point	Nearest Point	Nearest Point
Traffic object quantities	Yes	Yes	Yes	Yes

Following Object Detection, it is critical for the Autonomous-capable EV to be able to assess the free space that is available between itself or the host vehicle and the immediate targets detected. A front Free Space sensor is modeled with the parameters provided in Table 5.4 below. This sensor aids in understanding the host vehicle's free or available action space by dividing the field of view into horizontal (h) and vertical (v) segments as specified below.

Table 5.4. Free Space Sensor Parameters

Front Free Space Sensor	
Position x/ y/ z [m]	2.86 / 0.0 / 1.26
Orientation x/ y/ z [deg]	0.0 / 0.0 / 0.0
Field of view h / v [deg]	179 / 10
Range min / max [m]	0.1 / 150
Update [Hz] - Cycles offset [-]	25 - 0
Segments h / v [-]	200 / 1

Furthermore, a level 4 Autonomous-capable EV is anticipated to interact with other vehicles and infrastructure through V2V and V2I communication respectively, as depicted in the proposed Cognitive ADAS Architecture. Although, due to the infrastructural limitations, these are considered out of scope for the simulations in this study, a traffic sign sensor has been added with the parameters provided in Table 5.5 below for scalability of the simulation framework.

Table 5.5. Traffic Sign Sensor Parameters

Traffic Sign Sensor	Front Camera
Position x/ y/ z [m]	2.86 / 0.0 / 1.26
Orientation x/ y/ z [deg]	0.0 / 0.0 / 0.0
Field of view h / v [deg] (max 90)	80 / 45
Range min / max [m]	50

Update [Hz] - Cycles offset [-]	30 - 0
Detection of all signs	Yes

A line sensor is an ideal camera [151] which is capable of detecting the line markings, traffic barriers and so on. This sensor is essential for keeping the vehicle's lateral deviations from the center of the lane minimal, especially during autonomous lateral control. The parameters for the line sensor used in the simulations of this study can be found in Table 5.6 below.

Table 5.6. Line Sensor Parameters

Line Sensor	
Position x/ y/ z [m]	2.86 / 0.0 / 1.26
Orientation x/ y/ z [deg]	0.0 / 0.0 / 0.0
Field of view h / v [deg] (max 90)	50 / 50
Range min / max [m]	100
Update [Hz] - Cycles offset [-]	30 - 0

In addition to the lane markings, it is also important to detect other road properties such as curvature, slope and other lane relevant information such as width, vehicle lateral deviations [151] and so on in order to perform the required autonomous or semi-autonomous functions for the current simulations. The road sensor with the parameters described in Table 5.7 below is helpful in ensuring the above-described detections.

Table 5.7. Road Sensor Parameters

Road Sensor	
Preview distance [m]	10
Consider bumps	Yes

Lastly, the Global Navigation sensor is crucial in performing the navigation functions described in the proposed Cognitive ADAS Architecture. The parameters for the Global Navigation sensor can be found in Table 5.8 below. A default elevation mask has also been applied, as can be seen below, in order to avoid capturing any signals below a certain elevation. This improves the atmospheric propagation time by filtering out the signals with lower elevations [151].

Table 5.8. Global Navigation Sensor Parameters

Global Navigation Sensor	
Position x/ y/ z [m]	0.0 / 0.0 / 0.0
Update [Hz] - Cycles offset [-]	10 - 0
Elevation Mask [deg]	10.0

5.2 Traffic Model

An Autonomous-capable Vehicle is anticipated to encounter dynamic traffic during its drive cycle. It is expected to be able to accurately detect, track and classify the dynamic traffic objects in addition to planning a safe trajectory around the traffic conditions by making sure that the Autonomous-capable Vehicle does not create a threat for itself or the rest of the traffic objects in the immediate region of interest.

This section will describe modeling of the traffic conditions for the various simulation test cases. As it can be seen from the test cases setup described in the next section of the thesis, there are three different possibilities for the traffic conditions – no traffic, lead vehicle only or multi-object traffic set.

The cases where only a lead vehicle is used as a traffic object, a Volkswagen Beetle 2012 has been assumed as the lead vehicle. This object has been kept constant throughout all the test cases with only a lead vehicle in order to carry out the analysis in an unbiased manner. This particular traffic object has been selected randomly for the purposes of the simulations of this study. An Autonomous-capable Host Vehicle is expected to accurately function on the road in any type of traffic conditions. In order to model reaction of the host vehicle, when following a lead traffic vehicle, the parameters described in Table 5.9 have been assumed. A minimum safe distance of 10 m between the host and the lead vehicle has been selected. This has been selected keeping compact as well as larger vehicles such as trucks, buses and so on in mind. Furthermore, since it is essential to keep consistent test conditions for an unbiased analysis, these parameters have been selected to support safe autonomous-capable driving in ideal as well as adverse driving environment conditions. The rest of the parameters have been kept as the default values provided by IPG CarMaker for a lead vehicle follow mode. The energy efficient driving coefficient ranges from 0 to 1, where 0 represents the least energy efficient driving and 1 represents the highest energy efficient driving. The default value of 0.75 has been assumed for the current simulations. The general and motion model parameters for the lead vehicle are shown in Tables 5.10 and 5.11 respectively. The lead vehicle maneuvers are shown in Table 5.12.

Table 5.9. Host Vehicle Parameters for Reacting to Lead Traffic Vehicle

Host Vehicle Traffic Parameters	
Mode	Following Lead Vehicle
Min. Time Gap (sec)	1.8
Max. Time Gap (sec)	5.0
Min. Distance (m)	10
Max. Distance (m)	250
Energy efficient driving (0 -1)	0.75

Table 5.10. General Parameters for the Lead Traffic Vehicle

General Parameters	
Description	Volkswagen Beetle 2012
Detectable by	Sensors, Autonomous traffic
Dimension l / w / h [m]	4.28 / 1.82 / 1.28
Orientation x / y / z [deg]	0 / 0 / 0
Basic offset x / z [m]	0.0 / 0.19
Center of mass x [m]	2.15
Start position s / t [m]	100 / 0.0

Table 5.11. Motion Model Parameters for the Lead Traffic Vehicle

Motion Model	
Overall mass [kg]	1530
Moment of inertia lxx / lyy / lzz [kgm^2]	470 / 2080 / 2160
Overhang front / rear [m]	0.7 / 0.75
Front cornering stiffness [N/rad]	1.4e5
Rear cornering stiffness [N/rad]	1.2e5
Roll stiffness rate [Nm/rad]	1.6e5
Roll damping rate [Nms/rad]	1.6e4
Pitch stiffness rate [Nm/rad]	2.3e5
Pitch damping rate [Nms/rad]	2.3e4
Maximum steer angle [deg]	40.0

Table 5.12. Lead Traffic Vehicle Maneuvers

Maneuver – Update rate 200 Hz	
Start time (sec)	Longitudinal Maneuver (km/h)
t = 200	v = 70
t = 400	v = 100
t = 600	v = 80
t = 700	v = 100

In addition, as described in the test cases setup in the next section of this thesis, the Autonomous-capable Electrified vehicle is also simulated against multi-object dynamic traffic. This multi-object traffic set is generated stochastically within

CarMaker to have a random selection of varying traffic objects. A car ratio of 90% has been assumed for generating the traffic [152]. The make and model of all the realistic traffic objects including their vehicle data (powertrain, body and so on) was stochastically generated. Their maneuvers and velocity profiles were manually adjusted for the traffic to have an impact on the host vehicle. The generated traffic set has been consistently used for all the ADS and manual human driver control test cases with multi-object traffic set. Traffic density is adjusted to have up to 4 traffic objects impacting the host vehicle throughout the drive cycle. Since, the objective of the current study is not to simulate conditions such as traffic jams but to analyze the potential impact of vehicle autonomy on Electrified Vehicle dynamics, a near to fully operational highway driving scenario is needed to be considered.

The following highway driving maneuvers were incorporated for the test cases with multi-object traffic set. These maneuvers were selected based on the commonly discussed ones in the literature [153]-[154].

- Sudden braking of lead vehicle
- Acceleration of lead vehicle
- Lane change of lead vehicle causing the host vehicle to react to a different lead vehicle.
- The new lead vehicle has sudden speed drop compared to the original cruise speed.

The above described maneuvers are illustrated in Fig. 5.1 (a)-(d).

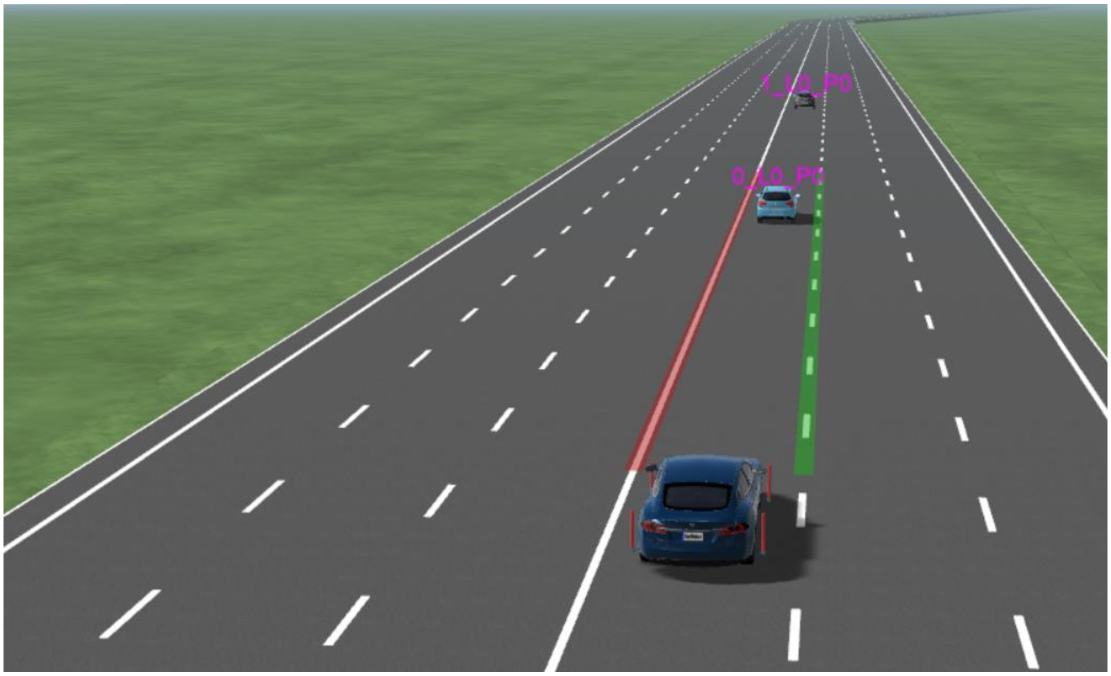

Fig.5.1 (a). Sudden braking of lead vehicle.

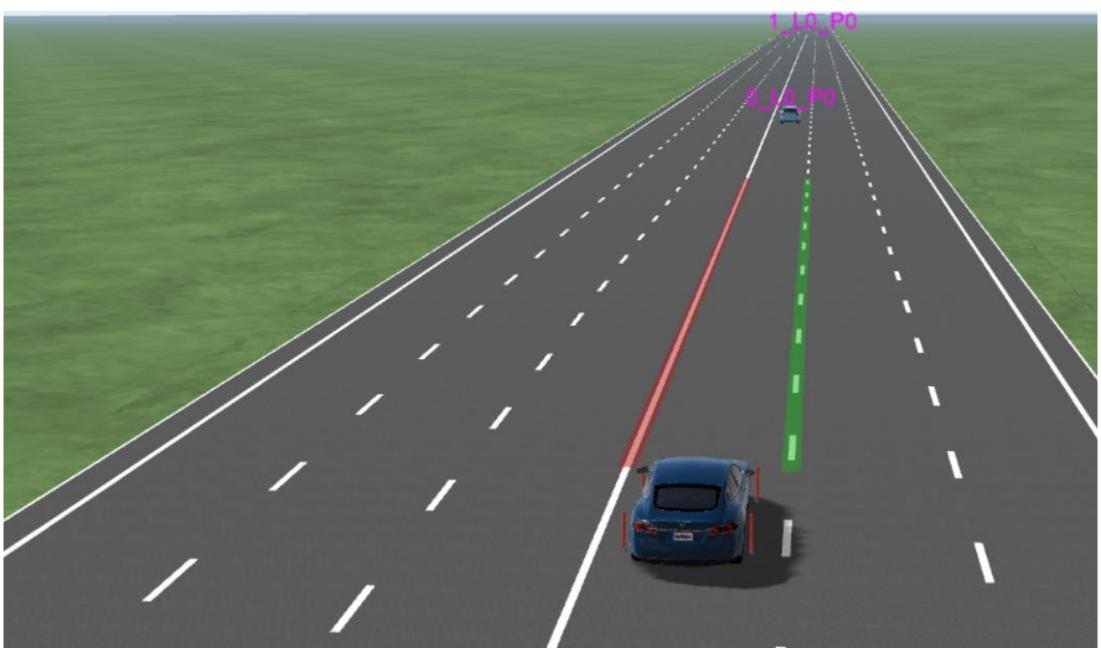

Fig.5.1 (b). Acceleration of lead vehicle.

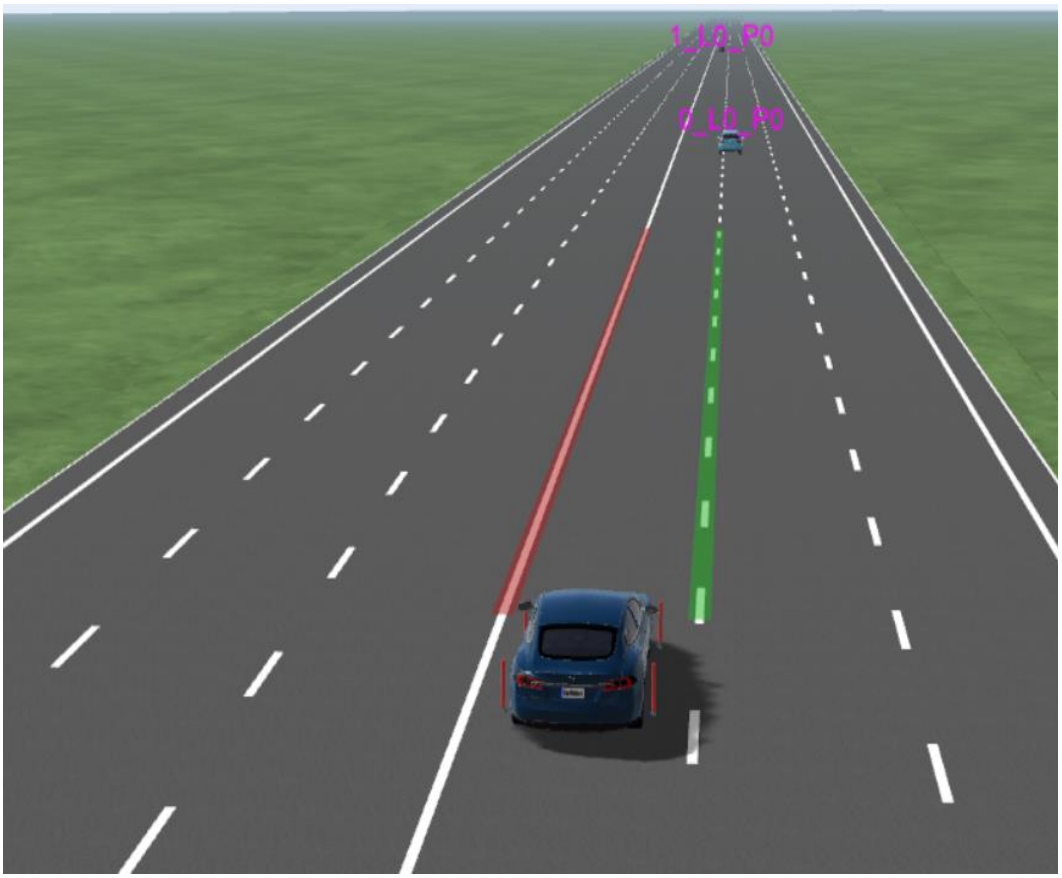

Fig.5.1 (c). Lane change of lead vehicle.

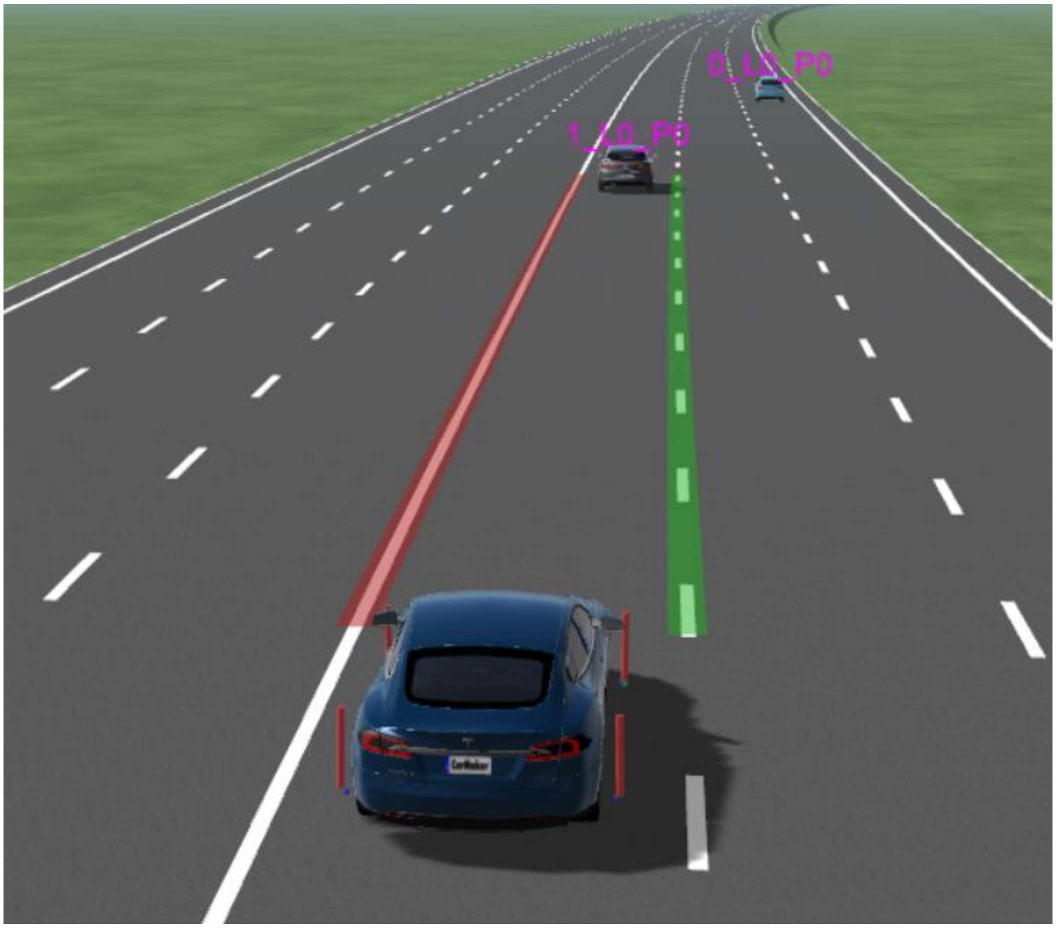

Fig.5.1 (d). New lead vehicle with a sudden speed drop.

The first traffic object is a 2015 Citroen C3. The general parameters and the motion model parameters for the first traffic object are shown in Tables 5.13 and 5.14 respectively. The dynamic maneuvers of the traffic object are shown in Table 5.15. A positive lane change indicates a change to the left lane by the number of lanes specified. Similarly, a negative lane change indicates a change to the right lane.

Table 5.13. General Parameters for the First Traffic Object

General Parameters	
Name	Traffic 0
Description	2015 Citroen C3
Detectable by	Sensors, Autonomous traffic
Dimension l / w / h [m]	3.83 / 1.64 / 1.31
Orientation x / y / z [deg]	0 / 0 / 0
Basic offset x / z [m]	0.0 / 0.00001
Center of mass x [m]	2.16
Start position s / t [m]	500 / 0.036

Table 5.14. Motion Model Parameters for the First Traffic Object

Motion Model	
Overall mass [kg]	1230
Moment of inertia lxx / lyy / lzz [kgm^2]	460 / 1370 / 1480
Overhang front / rear [m]	0.74 / 0.66
Front cornering stiffness [N/rad]	8.1e4
Rear cornering stiffness [N/rad]	6.6e4
Roll stiffness rate [Nm/rad]	1.04e5
Roll damping rate [Nms/rad]	1.04e4
Pitch stiffness rate [Nm/rad]	2.5e5
Pitch damping rate [Nms/rad]	2.5e4
Maximum steer angle [deg]	40.0

Table 5.15. First Traffic Object Maneuvers

Maneuver – Update rate 200 Hz		
Start time (sec)	Longitudinal Maneuver (km/h)	Lateral Maneuver
t = 150	auto = 80	
t = 170	v = 60	
t = 175	v = 100	
t = 176	v = 100	LaneChange = -2
t = 182	v = 100	

The second traffic object is a 2016 Renault Megane. The general parameters for this traffic object are provided in Table 5.16. The motion model parameters and the traffic object's dynamic maneuvers are shown in Table 5.17 and 5.18 respectively.

Table 5.16. General Parameters for the Second Traffic Object

General Parameters	
Name	Traffic 1
Description	2016 Renault Megane
Detectable by	Sensors, Autonomous traffic
Dimension l / w / h [m]	4.36 / 1.81 / 1.21
Orientation x / y / z [deg]	0 / 0 / 0
Basic offset x / z [m]	0.0 / 0.0011
Center of mass x [m]	2.4
Start position s / t [m]	510 / -0.053

Table 5.17. Motion Model Parameters for the Second Traffic Object

Motion Model	
Overall mass [kg]	1320
Moment of inertia lxx / lyy / lzz [kgm^2]	550 / 1740 / 1950
Overhang front / rear [m]	0.92 / 0.77
Front cornering stiffness [N/rad]	1.6e5
Rear cornering stiffness [N/rad]	1.1e5
Roll stiffness rate [Nm/rad]	1.45e5
Roll damping rate [Nms/rad]	1.45e4
Pitch stiffness rate [Nm/rad]	3.0e5
Pitch damping rate [Nms/rad]	3.0e4
Maximum steer angle [deg]	40.0

Table 5.18. Second Traffic Object Maneuvers

Maneuver – Update rate 200 Hz	
Start time (sec)	Longitudinal Maneuver (km/h)
t = 400	auto = 80
t = 500	v = 100
t = 550	v = 30

The third traffic object is a 2005 MB Citaro O345. The general and the motion model parameters for this traffic object are provided in Tables 5.19 and 5.20 respectively. The dynamic traffic maneuvers are provided in Table 5.21.

Table 5.19. General Parameters for the Third Traffic Object

General Parameters	
Name	Traffic 2
Description	2005 MB Citaro O345
Detectable by	Sensors, Autonomous traffic
Dimension l / w / h [m]	11.89 / 2.55 / 2.65
Orientation x / y / z [deg]	0 / 0 / 0
Basic offset x / z [m]	0.0 / 0.185
Center of mass x [m]	6.0
Start position s / t [m]	600 / 0.064

Table 5.20. Motion Model Parameters for the Third Traffic Object

Motion Model	
Overall mass [kg]	13700
Moment of inertia lxx / lyy / lzz [kgm^2]	11040 / 26700 / 26850
Overhang front / rear [m]	2.77 / 3.39
Front cornering stiffness [N/rad]	4.9e5
Rear cornering stiffness [N/rad]	6.4e5
Roll stiffness rate [Nm/rad]	1.7e6
Roll damping rate [Nms/rad]	1.7e5
Pitch stiffness rate [Nm/rad]	8.3e6
Pitch damping rate [Nms/rad]	8.3e5
Maximum steer angle [deg]	40.0

Table 5.21. Third Traffic Object Maneuvers

Maneuver – Update rate 200 Hz		
Start time (sec)	Longitudinal Maneuver (km/h)	Lateral Maneuver
t = 10	auto = 120	y_abs = -2

The last traffic object stochastically generated is a 2016 Honda Ridgeline. The general parameters, motion model parameters, and the dynamic traffic maneuvers are shown in Tables 5.22, 5.23 and 5.24 respectively.

Table 5.22. General Parameters for the Fourth Traffic Object

General Parameters	
Name	Traffic 3
Description	2016 Honda Ridgeline
Detectable by	Sensors, Autonomous traffic
Dimension l / w / h [m]	5.32 / 1.94 / 1.49
Orientation x / y / z [deg]	0 / 0 / 0
Basic offset x / z [m]	0.0 / 0.09
Center of mass x [m]	2.77
Start position s / t [m]	610 / 0.060

Table 5.23. Motion Model Parameters for the Fourth Traffic Object

Motion Model	
Overall mass [kg]	2016
Moment of inertia lxx / lyy / lzz [kgm^2]	1080 / 4080 / 4380
Overhang front / rear [m]	0.91 / 1.18
Front cornering stiffness [N/rad]	1.4e5
Rear cornering stiffness [N/rad]	1.5e5
Roll stiffness rate [Nm/rad]	2.4e5
Roll damping rate [Nms/rad]	2.4e4
Pitch stiffness rate [Nm/rad]	3.4e5
Pitch damping rate [Nms/rad]	3.4e4
Maximum steer angle [deg]	40.0

Table 5.24. Fourth Traffic Object Maneuvers

Maneuver – Update rate 200 Hz	
Start time (sec)	Longitudinal Maneuver (km/h)
t = 10	v = 130

5.3 Road Model

The test road that has been used in the simulations for this study will be described in this subsection. A motorway or highway with three driving lanes in one direction with a shoulder lane on the right has been constructed using the Scenario/ Road builder in CarMaker. A similar road structure has been replicated for the oncoming traffic with a divider lane separating the two. The road images can be seen in Fig. 5.2.

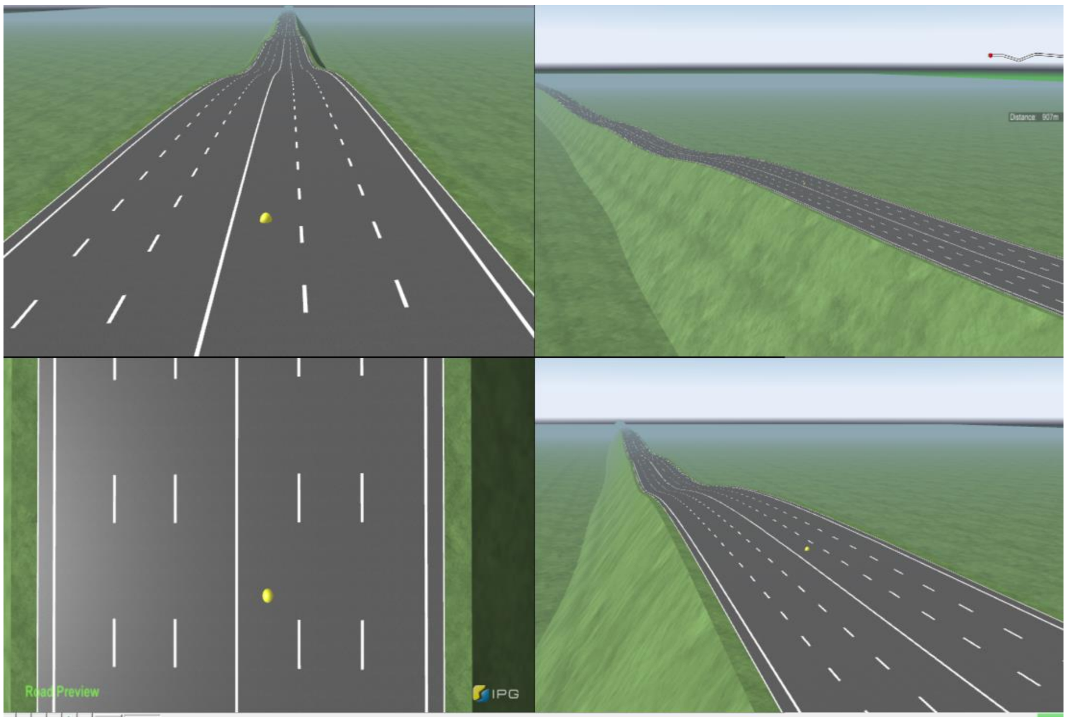

Fig.5.2. Test Road in CarMaker.

The overall length of the road is 25 km, requiring anywhere about 800 to over 1000 seconds to complete the trip depending on the autonomous function or vehicle control mode initiated. The US traffic and road rules, with right-hand traffic, have been assumed for building the Policy database described in the proposed Cognitive ADAS Architecture. The parameters for different speed selections can be found in Table 5.25 below. Furthermore, a CarMaker default lane width of 3.5 m was assumed for the lanes. In addition, a Global Coordinate System (GCS) with a projection mode of Flat Earth, which is also a default selection in CarMaker was used for all road relevant GCS calculations.

Table 5.25. Speed Limit Definitions for Different Types of Roads

Type of Road	Speed Limit (km/h)
Urban	50
Country	100
Motorway	100
Roundabout	30
Ramp	70
Dirt-track	30

As it can be seen from the test cases setup in the next section, two different types of roads were assumed for evaluating different autonomous or semi-autonomous driving functions. The first one (Road 1) is a flat road, with no gradient variations. The second one (Road 2) includes gradient variations, which were built into the current road definition, based on the Pikes Peak in Colorado, US, which was available in CarMaker demo roads from the measurements provided by 3D Mapping Solutions GmbH [155]. This was helpful in constructing a realistic road slope profile for the simulations. This demo road slope profile was scaled to fit the test road's length as well as the autonomous/ semi-autonomous use cases studied in the simulations of this thesis. The slope and elevation profile can be seen below in Fig.5.3 and 5.4 respectively.

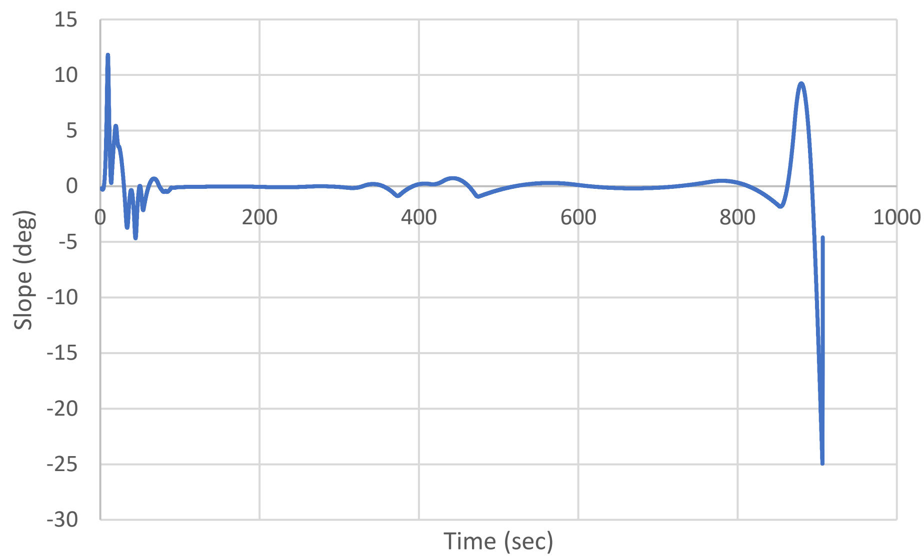

Fig.5.3. Road 2 Slope profile.

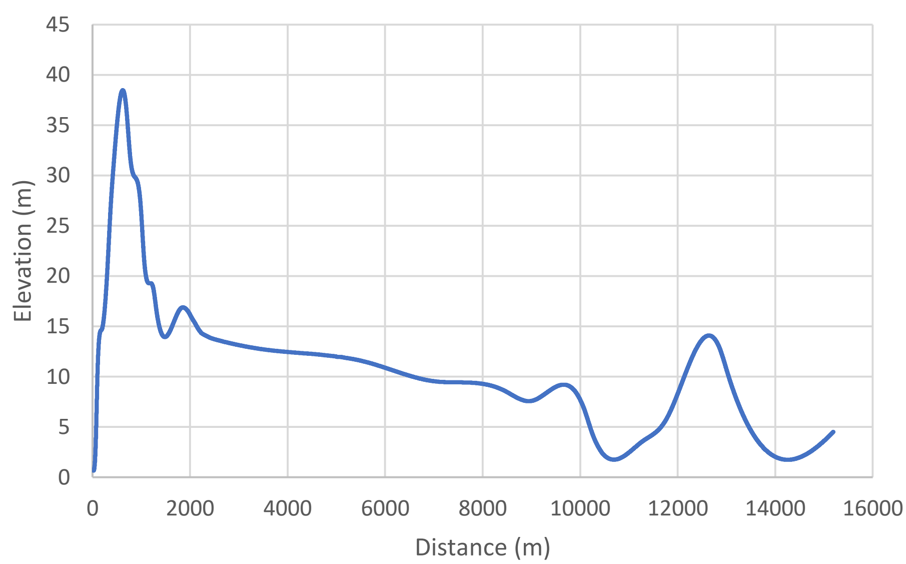

Fig.5.4. Road 2 Elevation profile.

5.4 Weather model

Two different weather models have been considered for the simulations in this study including ideal and adverse weather conditions. The ideal weather condition parameters are mostly based on the default values provided by IPG CarMaker. Some parameters such as the reference temperature have been adjusted based on the EPA city and highway averages [156]. Likewise, the air density is also adjusted accordingly [157]. Since air humidity can vary depending on the location, time of the year or even day, and so on, a default value provided by the CarMaker tool was assumed. Also, a default solar radiation provided by CarMaker was assumed for all simulations.

For modeling adverse weather conditions, the EPA cold temperature test procedure's reference temperature was assumed [156] and the air density was calculated accordingly [157]. Furthermore, about 50% reduction in the visibility due to fog is also considered. Since, according to [158], above 40 mm/h precipitation is assumed as heavy rainfall, a value of 45 mm/h is assumed for modeling adverse weather conditions.

According to the Beaufort Wind Scale [159], a wind speed of 20 km/h categorized as Moderate Breeze, is also used for modeling the adverse weather conditions. Extreme wind speeds categorized as hurricane have not been included in the adverse weather conditions model as the intention is to enable modeling of realistic adverse environment conditions, with a reasonable probability of occurrence, permitting the operation of the vehicle simulation. The edge case scenarios such as a storm or hurricane are out of the scope of this analysis as they could even prevent the AV from starting during such extreme conditions when simulated in a virtual environment. Towards the upper bound of the friction coefficients presented in [160] for wet road conditions were also considered for adverse weather conditions model. As such, a road friction coefficient of 0.7 was assumed to depict a wet driving condition. A temperature offset depending on the time of the day is also accounted for based on the below available default CarMaker profile shown in Fig.5.5.

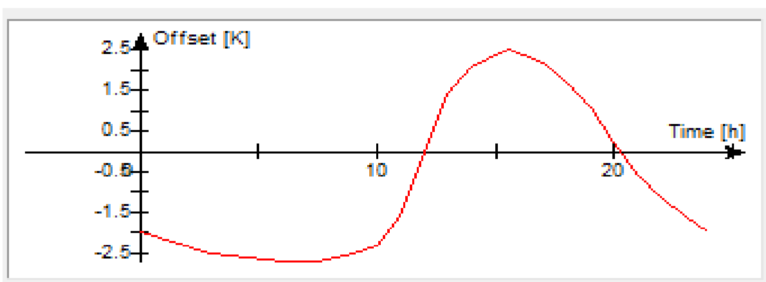

Fig.5.5. Temperature Offset Profile Depending on the Time of the Day.

The parameters used within the environment model of the IPG CarMaker simulation can be found summarized in the Table 5.26 below.

Table 5.26. Weather Model Parameters

Properties	Ideal Weather	Adverse Weather
Reference Temperature [°C]	25	-7
Air Density [kg/m^3]	1.18	1.33
Air Pressure [bar]	1.013	1.013
Air Humidity [60%]	60	60
Solar Radiation [W/m^2]	400	400
Rain Rate [mm/h]	0	45
Visual Range in Fog [m]	200	100
Wind Velocity [km/h]	N/A	20
Wind Angle [deg]	N/A	2 (coming from front left)
Road Friction Coefficient	1	0.7

5.5 ADAS Feature Set Model

This sub-section will describe the development of the different autonomous/ semi-autonomous functions including the traditional Cruise Control, Adaptive Cruise Control, Active Lane Keep Assist and a combination of the above including Traction Control to depict a level 4 autonomous functionality. Depending on the level of vehicle automation, the engagement of ADS versus a human driver will differ. This has been described through Table 5.27 below. As it can be seen from the test cases setup in the next section, the ADS control is compared to normal as well as aggressive driver's manual control.

Table 5.27. ADS and Human Driver Responsibility for Longitudinal and Lateral Vehicle Control

ADAS Feature Set	Longitudinal Control – ADS Responsibility	Longitudinal Control – Human Driver Responsibility	Lateral Control – ADS Responsibility	Lateral Control – Human Driver Responsibility
Traditional Cruise Control	Partial	Partial	N/A	Complete
Adaptive Cruise Control	Complete	N/A	N/A	Complete
Active Lane Keep Assist	N/A	Complete	Complete	N/A
L4 (ACC + ALKA + Traction Control)	Complete	N/A	Complete	N/A

In order to model these various combinations of autonomous, semi-autonomous and manual human driver control, parameters, as shown in Tables 5.28 to 5.53, have been used. The different parameters that were used to model the normal driver, aggressive driver and ADS control include the delta change of pedals, corner cutting coefficient, minimum delta acceleration and deceleration, maximum longitudinal and lateral acceleration and maximum lateral acceleration. The delta change of pedals is the time required by the driver to switch from the accelerator to the brake [150]. The corner cutting coefficient depicts the lateral deviations of the driver or the ADS from the lane center while remaining within the lane [150]. It ranges from 0 to 1, where 0 depicts no deviation and 1 depicts maximum deviation within the lane to use up the entire lane width. The minimum delta acceleration and deceleration is the time taken by the driver to switch between the acceleration and deceleration maneuvers [150]. In addition, the vehicle longitudinal and lateral control (ADS and human driver) were implemented using a default PI and PID controller respectively in CarMaker (will be described further).

Furthermore, a g-g diagram is also constructed based on the specified speed, acceleration and deceleration exponents which is shown in Fig. 5.6 to 5.11. This diagram is helpful in depicting the maximum boundary limits of the dependency between the lateral and longitudinal acceleration and deceleration [150]. Also, different declutching or gear shifting parameters (which dictate the maximum and minimum engine speeds based on the pre-determined driver models), maximum steering wheel angle, velocity, and acceleration are also specified. All of the above-described parameters are selected based on the recommended values in CarMaker for normal or an aggressive driver. In order to model the ADS control, defense driving parameters have been assumed. In addition to the above-described parameters, tolerated longitudinal and lateral deviations, as well as reaction times based on the frequently used values in the literature, have been assumed. For a normal driver, a longitudinal deviation of 10 km/h [161]-[162] and a lateral deviation of 0.25 m [162] is assumed. Similarly, a longitudinal deviation of 20 km/h

[163] was assumed for an aggressive driver. The speed deviations described in [163] were scaled according to the operational domains of the simulation in order to simulate longitudinal velocity deviations modeling aggressive driving behavior. Likewise, the more adverse case of lateral deviations, resulting in 0.52 m, due to aggressive driving behavior as described in [164] was assumed. An average human driver reaction time of 1.5 seconds was also used for all cases [165]-[168].

Table 5.28. General Parameters for ADS under Traditional Cruise Control

Cruising Speed (km/h)	**dt Change of Pedals (s)**	**Corner Cutting Coefficient**	**Min. dt Accel./Decel. (s)**	**Traction Control**
100	0.5	0.5	8	No

Table 5.29. Acceleration Parameters for ADS under Traditional Cruise Control

Max. Long. Acceleration (m/s^2)	**Max. Long. Deceleration (m/s^2)**	**Max. Lat Acceleration (m/s^2)**	**Exponent of g-g Diagram**		
			Speed (km/h)	Accel.	Decel.
2.0	-2.0	4.0	50	0.5	0.5

Table 5.30. Declutching / Gear Shifting Parameters for ADS under Traditional Cruise Control

Time for Shifting (s)	**Engine Speeds (RPM)**			
1.0	min	max	idle up	acc down
	1000	3000	1500	2000

Table 5.31. Lateral and Longitudinal Deviation Parameters for ADS under Traditional Cruise Control

Tolerated Deviation		**Reaction Time**		**Max. Steering Wheel Angle (deg)**	**Max. Steering Wheel Velocity (deg/s)**	**Max. Steering Wheel Accel. (deg/s^2)**
Long Km/h	Lateral m	Long (s)	Lateral (s)	630	500	3000
0.0	0.25	0.0	1.5			

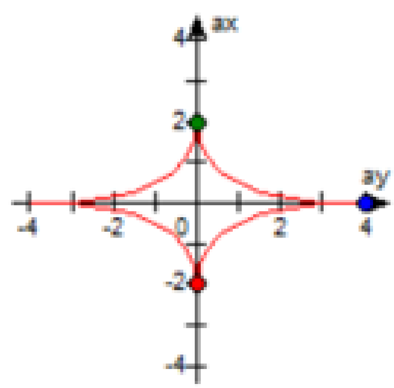

Fig. 5.6. g-g Diagram for ADS Traditional Cruise Control.

Table 5.32. General Parameters for ADS under Adaptive Cruise Control

Cruising Speed (km/h)	**dt Change of Pedals (s)**	**Corner Cutting Coefficient**	**Min. dt Accel./Decel. (s)**	**Traction Control**
100	0.75	0.5	8	No

Table 5.33. Acceleration Parameters for ADS under Adaptive Cruise Control

Max. Long. Acceleration (m/s^2)	**Max. Long. Deceleration (m/s^2)**	**Max. Lat Acceleration (m/s^2)**	**Exponent of g-g Diagram**		
			Speed (km/h)	Accel.	Decel.
2.0	-2.0	3.0	50	0.5	0.5

Table 5.34. Declutching / Gear Shifting Parameters for ADS under Adaptive Cruise Control

Time for Shifting (s)	Engine Speeds (RPM)			
1.5	min	max	idle up	acc down
	1000	3000	1500	2000

Table 5.35. Lateral and Longitudinal Deviation Parameters for ADS under Adaptive Cruise Control

Tolerated Deviation		Reaction Time		Max. Steering Wheel Angle (deg)	Max. Steering Wheel Velocity (deg/s)	Max. Steering Wheel Accel. (deg/s^2)
Long Km/h	Lateral m	Long (s)	Lateral (s)	630	250	1500
0.0	0.25	0.0	1.5			

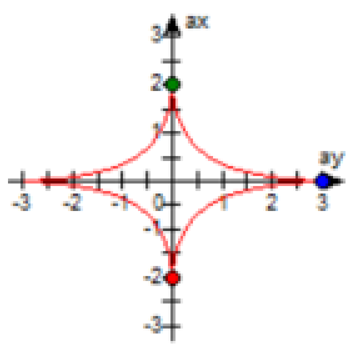

Fig. 5.7. g-g Diagram for ADS Adaptive Cruise Control.

Table 5.36. General Parameters for ADS under Active Lane Keep Assist

Cruising Speed (km/h)	dt Change of Pedals (s)	Corner Cutting Coefficient	Min. dt Accel./Decel. (s)	Traction Control
100	0.5	0.25	4	No

Table 5.37. Acceleration Parameters for ADS under Active Lane Keep Assist

Max. Long. Acceleration (m/s^2)	**Max. Long. Deceleration (m/s^2)**	**Max. Lat Acceleration (m/s^2)**	**Exponent of g-g Diagram**		
			Speed (km/h)	Accel.	Decel.
3.0	-4.0	4.0	50	1.0	1.0

Table 5.38. Declutching / Gear Shifting Parameters for ADS under Active Lane Keep Assist Control

Time for Shifting (s)	**Engine Speeds (RPM)**			
	min	max	idle up	acc down
1.0	1500	4000	2000	3000

Table 5.39. Lateral and Longitudinal Deviation Parameters for ADS under Active Lane Keep Assist Control

Tolerated Deviation		**Reaction Time**		**Max. Steering Wheel Angle (deg)**	**Max. Steering Wheel Velocity (deg/s)**	**Max. Steering Wheel Accel. (deg/s^2)**
Long Km/h	Lateral m	Long (s)	Lateral (s)	630	250	1500
10.0	0	1.5	0.0			

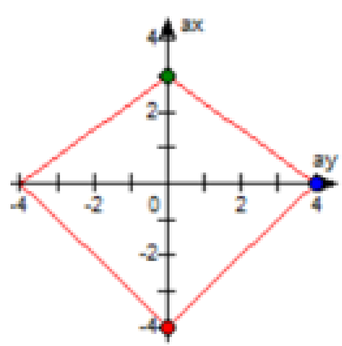

Fig. 5.8. g-g Diagram for ADS Active Lane Keep Assist Control.

Table 5.40. General Parameters for ADS under Level 4 Autonomous Function

Cruising Speed (km/h)	dt Change of Pedals (s)	Corner Cutting Coefficient	Min. dt Accel./Decel. (s)	Traction Control
100	0.75	0.25	8	Yes

Table 5.41. Acceleration Parameters for ADS under Level 4 Autonomous Function

Max. Long. Acceleration (m/s^2)	Max. Long. Deceleration (m/s^2)	Max. Lat Acceleration (m/s^2)	Exponent of g-g Diagram		
			Speed (km/h)	Accel.	Decel.
2.0	-2.0	3.0	50	0.5	0.5

Table 5.42. Declutching / Gear Shifting Parameters for ADS under Level 4 Autonomous Function

Time for Shifting (s)	Engine Speeds (RPM)			
	min	max	idle up	acc down
1.5	1000	3000	1500	2000

Table 5.43. Lateral and Longitudinal Deviation Parameters for ADS under Level 4 Autonomous Function

Tolerated Deviation		Reaction Time		Max. Steering Wheel Angle (deg)	Max. Steering Wheel Velocity (deg/s)	Max. Steering Wheel Accel. (deg/s^2)
Long Km/h	Lateral m	Long (s)	Lateral (s)			
0.0	0	0.0	0	630	250	1500

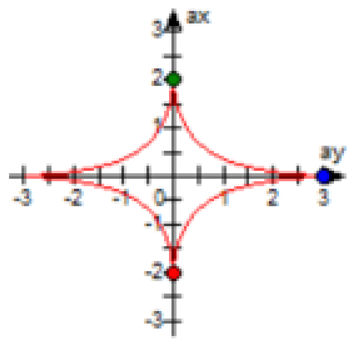

Fig. 5.9. g-g Diagram for ADS Level 4 Autonomous Function.

Table 5.44. General Parameters for Normal and Aggressive Human Driver Control

Driving Behavior	Cruising Speed (km/h)	dt Change of Pedals (s)	Corner Cutting Coefficient	Min. dt Accel./Decel. (s)	Traction Control
Normal	100	0.5	0.5	4	No
Aggressive	100	0.25	0.8	0.5	No

Table 5.45. Acceleration Parameters for Normal and Aggressive Human Driver Control

Driving Behavior	Max. Long. Acceleration (m/s^2)	Max. Long. Deceleration (m/s^2)	Max. Lat Acceleration (m/s^2)	Exponent of g-g Diagram		
				Speed (km/h)	Accel.	Decel.
Normal	3.0	-4.0	4.0	50	1.0	1.0
Aggressive	4.0	-6.0	5.0	50	1.5	1.5

Table 5.46. Declutching / Gear Shifting Parameters for Normal and Aggressive Human Driver Control

Driving Behavior	**Time for Shifting (s)**	**Engine Speeds (RPM)**			
		min	max	idle up	acc down
Normal	1.0	1500	4000	2000	3000
Aggressive	1.0	2500	5000	3000	4500

Table 5.47. Lateral and Longitudinal Deviation Parameters for Normal and Aggressive Human Driver Control

Driving Behavior	**Tolerated Deviation**		**Reaction Time**		**Max. Steering Wheel Angle (deg)**	**Max. Steering Wheel Velocity (deg/s)**	**Max. Steering Wheel Accel. (deg/s^2)**
	Long (Km/h)	Lateral (m)	Long (s)	Lateral (s)			
Normal	10.0	0.25	1.5	1.5	630	500	3000
Aggressive	20.0	0.52	1.5	1.5	630	500	20000

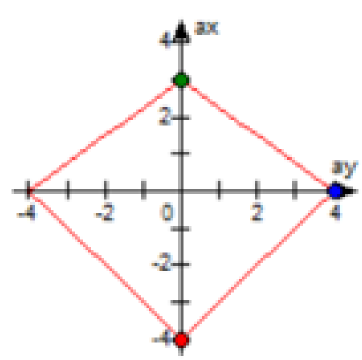

Fig. 5.10. g-g Diagram for normal human driver control.

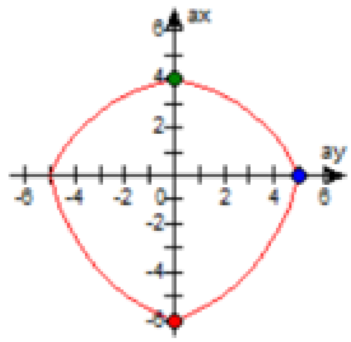

Fig. 5.11. g-g Diagram for aggressive human driver control.

Table 5.48. ACC Control Parameters for ADS (incl. L4 longitudinal control)

Control Model	Acceleration Control + ACC
Acceleration function	ACC
Acceleration controller factor P [-]	0.001
Acceleration controller factor I [-]	0.001
Referenced object sensor	RadarL
Brake threshold [-]	0.2
Initial time distance [s]	1.8
Minimal distance [m]	10
Minimal acceleration [m/s^2]	-2.5
Minimal acceleration [m/s^2]	1.0
Distance controller factor kd [-]	36.0
Distance controller factor kv [-]	2.0
Velocity controller factor kv [-]	13.0

Table 5.49. Generic lateral control parameters for ADS (incl. L4 lateral control)

Control Model	Generic Lateral Control
Initial line detection mode	Line Sensor
Referenced road sensor	AlongR
Lane keeping assist system	Yes
Minimal velocity [km/h]	55.0
Maximal assist torque [Nm]	2.0
Time constant PT1 filter [s]	0.003
Maximal lane width [m]	7.0
Minimal lane width [m]	1.8
Curvature controller factor P [-]	2.0
Curvature controller factor I [-]	0.2
Curvature controller factor D [-]	0.0
Maximal deviation distance [m]	0
Assist torque coefficient [Ns^2]	2.05
Lane departure warning	Yes
Minimal velocity [km/h]	55.0
Distance departure warning [m]	0.2

5.6 Mapping of the Simulation Model to the Proposed ADAS Architecture

This section presents a functional mapping between the proposed Cognitive ADAS Architecture and the simulation model developed in CarMaker. Although this simulation model presents one specific adaptation of the architecture, the various concepts discussed regarding the sensors, vehicle control techniques (ADS and human driver) weather, road and traffic modeling can be generalized for the overall highly automated driving framework.

The sensor parameters are defined through the Vehicle Data Set in the Parameters section. Different parameters are used to define the sensors, depending on their type. Some of these parameters include the mounting position, orientation of the sensor, range, field of view, update frequency and so on. As previously described, a combination of slip angle, inertial, object (RADAR and Camera), free space, traffic sign, line, road, collision, and global navigation are the different types of sensors used for the simulation model. The sensor suite is a physical layer existing on the Autonomous-capable EV. The Perception layer functions itself happen in the background through semiconductor technologies. Similarly, the Perception functions including the Sensor Data Processing, Object Detection, Tracking, Classification, Sensor Fusion and Integration, Free Space Estimation, driving environment model generation/ filtration and the SLAM happen in the background of the simulation model. The successful operation of these functions can be assessed from the IPGMovie Animation of the simulation which highlights the various attributes of the driving environment perceived. The detection of driving environment in a level 4 test case, including the traffic objects, lane markings and the Region of Interest can be seen in Fig. 5.12, 5.13 and 5.14 respectively.

Furthermore, the sensor outputs can also be generated using the IPGControl to assess any gap between the expected output and the simulation result.

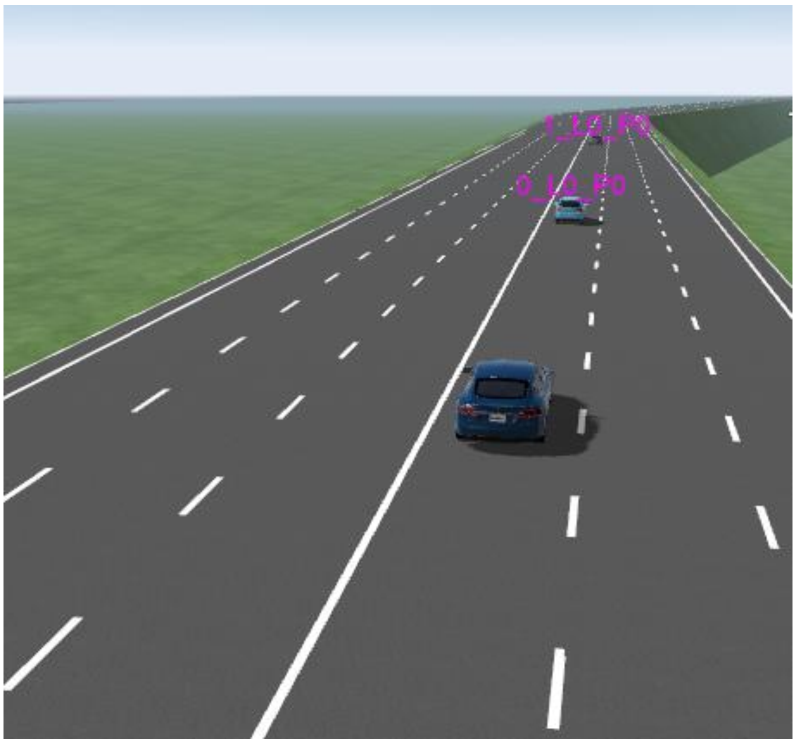

Fig.5.12. Detection of Traffic Objects by Host Autonomous-capable EV.

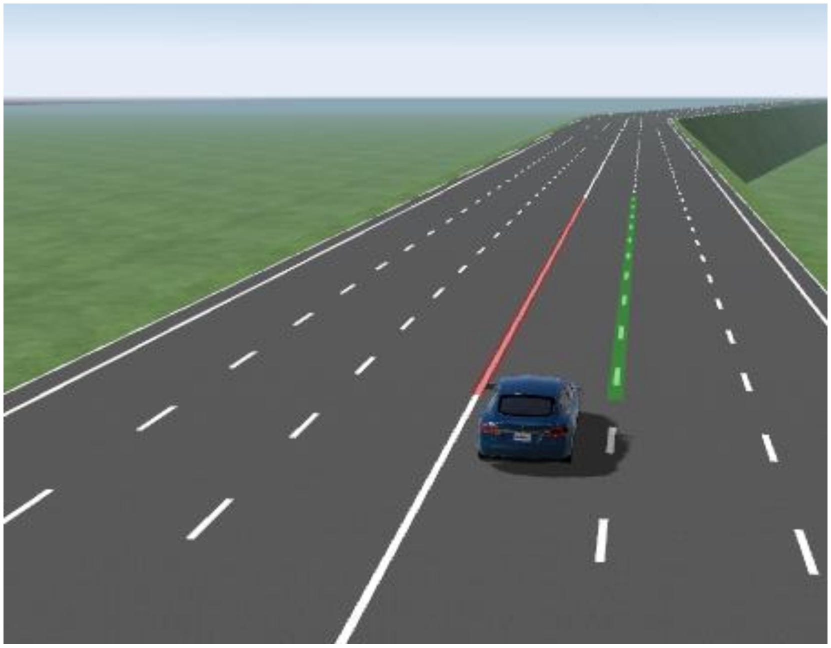

Fig.5.13. Detection of Lane Markings by Host Autonomous-capable EV.

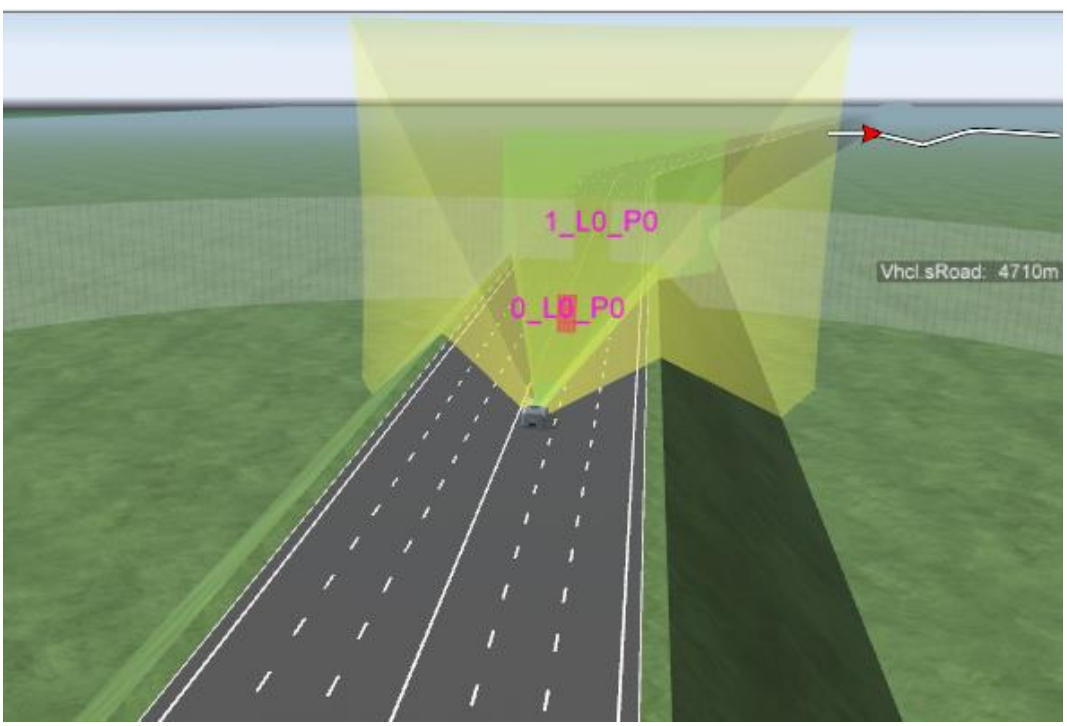

Fig.5.14. Host Autonomous-capable EV's Sensors Field of View.

Following Perception, the Cognition layer makes critical decisions about the host vehicle's immediate and long-term maneuver. The Policy database which serves as an important input to Cognition is defined using the Scenario Settings within the Scenario/ Road Parameters. The different localized speed limit settings for different types of roads such as urban, country, motorway, roundabout, ramp and dirt track are defined. The current country of operation, driving side, and so on are also specified here. The Policy database only specifies the general rules of the road which should not be disobeyed in any circumstance. However, this should not be confused with maximum speed or minimum safe distance specifications, for example, which are defined as part of an autonomous or semi-autonomous control. The Mission and Motion Plan are defined using Longitudinal and Lateral Dynamics within the Maneuver Parameters. Furthermore, the long-term mission plan is also based on the road definition modeled within the Scenario/ Road Parameters. The maneuvers can also be modified depending on the actor – normal driver, aggressive driver or the ADS within the Driver Parameters under Maneuvers. The ADAS Control Unit parameters are also specified as part of the Driver Parameters within the Longitudinal and Lateral Dynamics in Maneuver Parameters. The control technique, as well as initialization of an ADAS feature, is performed through the Vehicle Control GUI within the Car Parameters. The types of control (generic lateral, ACC, general longitudinal, AEB, Lane Departure Warning, Lane Keep Assist and so on), their associated control parameters and referenced sensors for carrying out the required control techniques are specified here.

Furthermore, the Actuation Control functions are parameterized through the Powertrain Control Unit within the Vehicle Data Set (Car Parameters). The type of powertrain and the associated control models are selected here based on a library of control techniques available. The Electrified Powertrain Execution System modeling is performed through the General, Drive Source, Driveline, and the Power Supply Parameters within the Vehicle Data Set. The CarMaker default options for the demo Tesla Model S were used, for both the Actuation Control and the Electrified Powertrain Execution System modeling, for the purposes of the simulations presented in this study. The battery is parameterized using the default Chen model with an OCV-R-RC-RC circuit [151]. This enables the use of CarMaker's default curve for the voltage factor based on the SOC %. The initial SOC is assumed to be 70% for all test cases as seen previously. The motor torque versus rotational speed profile (Characteristic Value model) has been selected to be the default for Tesla Model S demo model. Furthermore, the motor efficiency profile is based on the rotational speed gathering the data from an available 2D look-up table.

The Navigation system modeling is performed through the Global Navigation and Inertial sensors definition within the Vehicle Data Set. Lastly, the driving environment itself can be defined through the Scenario/ Road, Environment and Traffic Parameters. Although, a stochastic generation of the traffic data based on fixed Traffic Density and Car Ratio is possible through the Traffic parameterization within the Scenario/ Road editor, and is recommended for development of unbiased random traffic, it is necessary to make sure that the stochastically generated data is within the host vehicle's immediate Region of Interest to be able to study the impact of the external traffic on the host Autonomous-capable EV. As such, it is recommended to manually adjust the stochastically generated traffic using the Traffic Parameters in order to make sure that the above-described constraints are met.

5.7 Theoretical Analysis and Walkthrough of the Model

Some of the major theoretical concepts relating to the current simulation model, which is based on the proposed Cognitive ADAS Architecture, will be described in this section. Firstly, it is critical to understand how the Object Detection is taking place within the simulation model [151]. As it was described in the Sensor Model section previously, the target detection is being performed by using the Nearest in Path and Nearest Point calculation technique. Through these techniques, the host Autonomous-capable EV is not only able to assess the traffic object's position or location on the road but is able to perform an accurate free space estimation based on the projected trajectories of both the host and the immediate traffic objects. The sensors' field of view is analyzed for any of the traffic objects within the immediate Region of Interest by following the below [151].

$$y_{off} = \left(\frac{v^2}{Abs(a_y)} - \sqrt{\left(\frac{v^2}{Abs(a_y)} \right)^2 - (ds * \cos(\alpha))^2} \right) * sign(a_y)$$

Where, y_{off} is the offset of the vehicle at the target's position, v is the speed of the vehicle, a_y is the lateral acceleration of the vehicle ($sign(a_y)$ is helpful in understanding the direction of the vehicle offset), ds is the projected distance between the host and the target vehicle and α is the target vehicle's orientation or angle [151]. The projected distance is illustrated through Fig. 5.15 below [151]. This projected path is calculated by CarMaker in the background.

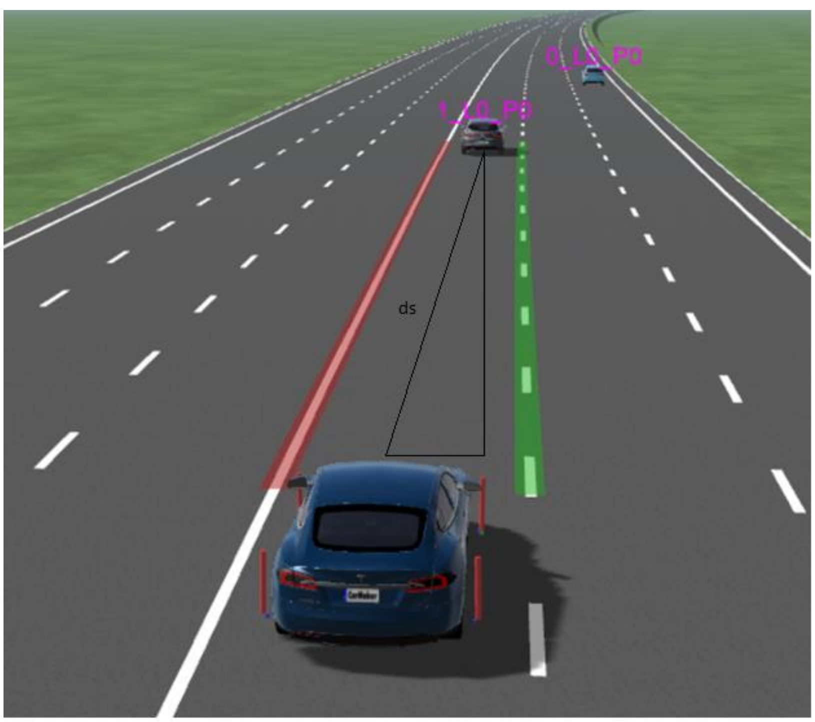

Fig.5.15. Illustration of the Projected Distance Between Host and Lead Vehicle.

Following this, it is analyzed whether the traffic objects fall within the projected host vehicle's trajectories which is the intersection of the below trajectory limits [151].

$$\left(y_{off} - \frac{lane\ width}{2}\right) < \ (ds * \sin(\alpha)) \ < \left(y_{off} + \frac{lane\ width}{2}\right)$$

It is important to make sure that the Planner, described within the Cognitive ADAS Architecture, correctly plans the long- and short-term Mission and Motion with an intention to avoid collisions with the surrounding objects in the host vehicle's driving environment, at all times.

Furthermore, the simulations in this thesis demonstrate a vehicle automation of up to level 4. The Level 4 autonomous control includes a combination of both the lateral and the longitudinal control performed by the ADS. Some of the theoretical background behind these control strategies are described below. The Adaptive Cruise Controller or ACC provides the required longitudinal control for the Autonomous-capable host EV. CarMaker implements two different closed-loop control strategies depending on the situation of the dynamic driving environment to simulate real-life ACC conditions [151]. The host vehicle velocity is controlled to be the set desired maximum speed by the user if no target object is detected within the immediate Region of Interest. The distance between the host vehicle and the lead vehicle is controlled to be the minimum safe distance specified by the user if there is a target object detected within the immediate Region of Interest. This manipulation of the longitudinal acceleration is performed by changing the positions of the brake and the throttle pedals using a PI controller in CarMaker.

In addition to ACC, Automated Emergency Braking or AEB also forms a vital functionality of the level 4 autonomous control. As described previously in the thesis, AEB is a safety critical function which helps in controlling the vehicle velocity as needed per the requirements of the dynamic driving environment. CarMaker performs the AEB control by following the below calculations for time to collision and time threshold brake to identify if a braking intervention is required by the ADS for the host Autonomous-capable EV [151].

For a stationary or a very slow-moving target object, the time to collision is calculated as follows in CarMaker [151]:

$$t_{tc} = \frac{d}{v_{rel}}$$

Where t_{tc} is the time required for a collision to occur between the host vehicle and its surrounding target objects, d is the distance between the host and the target vehicles and v_{rel} is the relative velocity between the host and the target vehicles [151].

In addition, if the target object's acceleration is reducing, the time to collision is calculated as follows [151]:

$$t_{tc} = \frac{\sqrt{v_{rel}^2 - 2dD_{rel}} - v_{rel}}{D_{rel}}$$

Where, D_{rel} is the relative deceleration of the target object [151].

Furthermore, the time threshold brake is also calculated depending on whether the target object is moving or not. This further signifies the importance of Object Tracking for accurate Object Classification and Free Space Estimation. The time threshold brake is calculated as follows for the static traffic objects [151]:

$$t_{tb} = \tau_B + \frac{v_{rel}}{2D_{max}}$$

Where, t_{tb} is the time threshold brake, τ_B is the brake loss time and D_{max} is the maximum permitted deceleration of the host vehicle without causing a collision with the surrounding target objects [151].

Also, the time threshold brake for dynamic target objects is calculated as follows [151]:

$$t_{tb} = \tau_B + \frac{v_{rel} + D_{rel}\,\tau_B}{2(D_{max} - D_{obs})}$$

Where, D_{obs} is the target object's actual deceleration [151].

Lastly, the Active Lane Keep Assist System provides lateral vehicle control by the ADS. As previously discussed in the thesis, lateral control of the vehicle is critical from a safety perspective. Unintended lane departures, especially in the evaluated highway scenarios could also be fatal depending on the conditions of the dynamic driving environment. This is implemented in CarMaker using a PID controller to make sure that vehicle is always kept at the center of the lane unless a lane change is intended by the user [151]. The lateral deviation angle and distance in addition to the perceived path curvature is taken as inputs into the PID controller for tuning against the target path curvature, in turn to produce the steering assist torque required to bring the host Autonomous-capable EV back to the center of the lane, in case any unintended deviation has occurred [151].

5.8 Validation

Validation is an essential step for a model or a simulations-based analysis in identifying the accuracy of the assumptions made, simulations performed, and analysis conducted. This section will describe the above validation for the simulations being studied in this thesis. The model will be validated using the

Environmental Protection Agency or EPA standard driving test procedures or driving cycles. There are different driving cycles available for city and highway driving [156], [169]-[171], [119]. Due to the commercial unavailability of a level 4 Autonomous-capable Electrified Vehicle, experimental validation was considered out of scope for this research. However, it is presented as a part of future research, anticipating the market availability of such vehicles in the future. The Cognitive ADAS Architecture proposed in this thesis is expected to form a fundamental building block in realizing Highly Automated Driving commercially in the upcoming years. The positive validation results to be described further also forms as a basis for the validation of the proposed Cognitive ADAS Architecture to which the simulation model has been mapped, as previously described in the thesis.

EPA has been one of the central organizations in establishing standard test procedures for testing the different vehicles for their performance on a dynamometer by incorporating driving conditions which a vehicle might encounter on the road. EPA proposes a 5-cycle test method including the various standard driving cycles such as the Federal Test Procedure (FTP), Highway Fuel Economy Test (HWFET), US06 or the Supplemental Federal Test Procedure, Speed Correction Driving Schedule (SC03) and FTP under cold temperatures [156]. FTP represents city driving with regularly stopping traffic [156]. The HWFET represents the free-flow highway traffic [156]. The US06 represents city and highway driving with aggressive driving behavior [156]. The SC03 driving cycle represents the use of air conditioning within the vehicle during adverse warm weather outside [156]. Lastly, the FTP drive cycle is repeated under extreme cold weather conditions outside [156]. These standard drive cycles were run using the current simulation model by also incorporating the test conditions specified as per [156]. The velocity over time profiles established using the current simulation model for the above standard driving cycles are shown in Fig. 5.16 to 5.20 below. These profiles generated through the simulation model can be seen to be the same as [156].

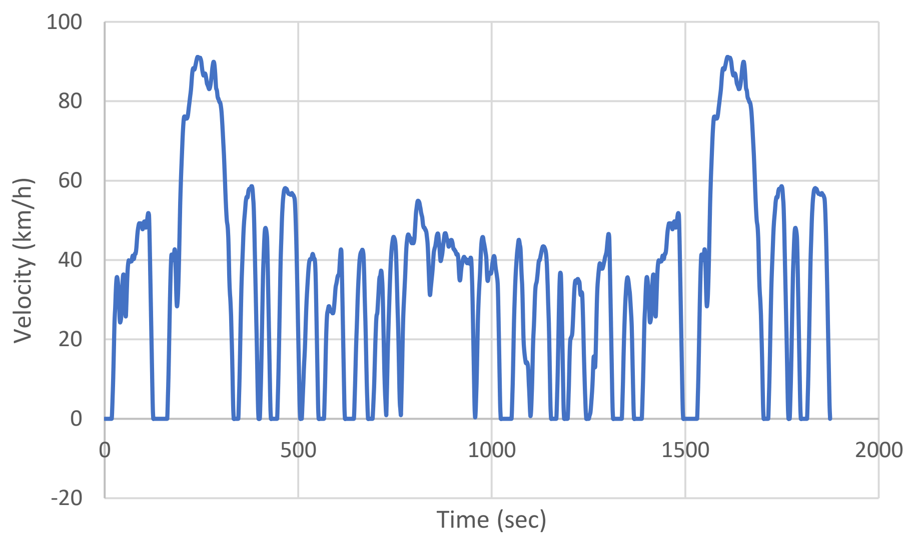

Fig.5.16. FTP-75 Standard Driving Cycle Generated Through the Simulation Model.

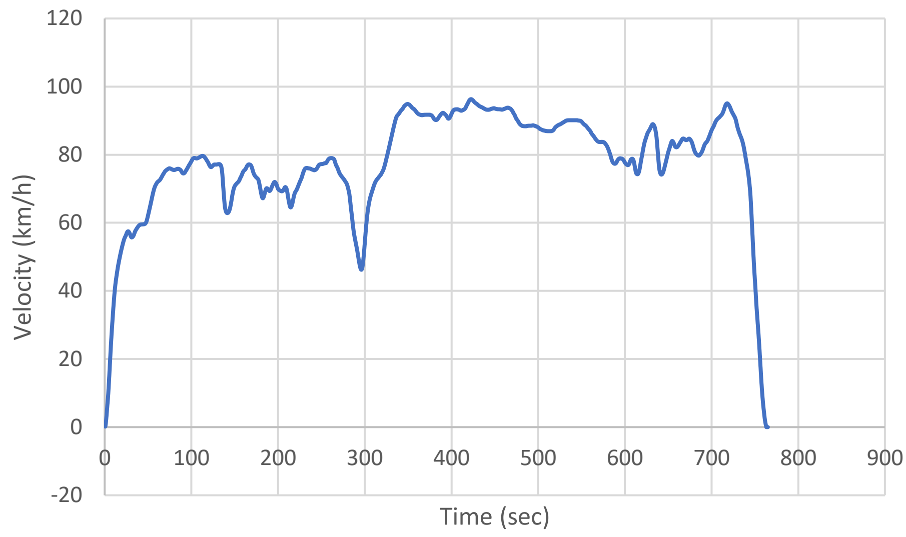

Fig.5.17. HWFET Standard Driving Cycle Generated Through the Simulation Model.

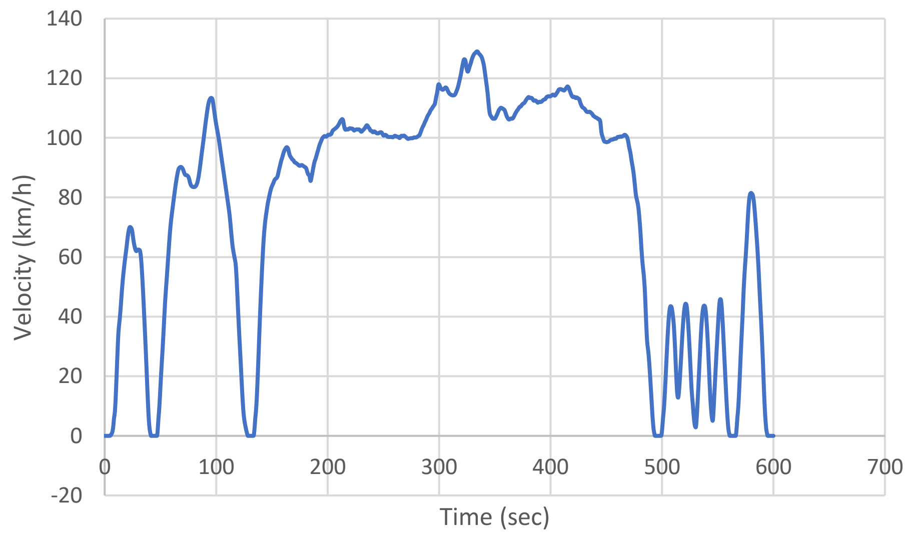

Fig.5.18. US06 Standard Driving Cycle Generated Through the Simulation Model.

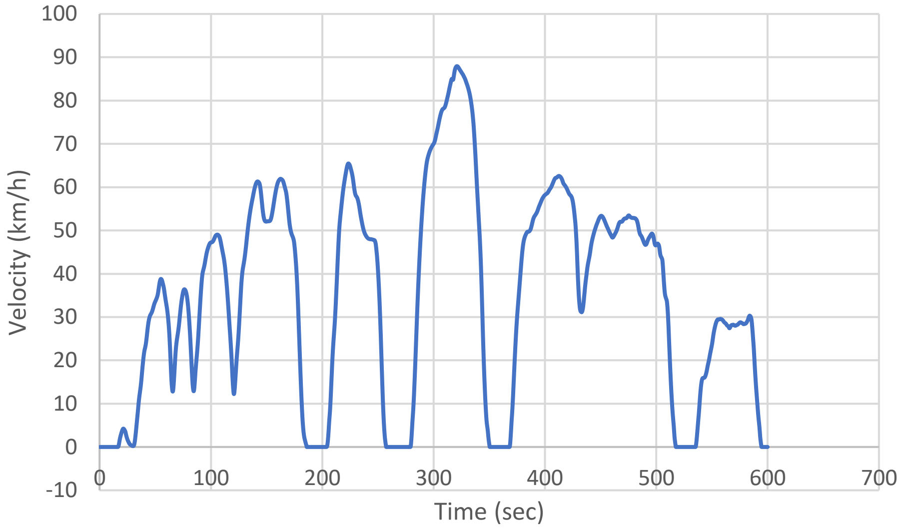

Fig.5.19. SC03 Standard Driving Cycle Generated Through the Simulation Model.

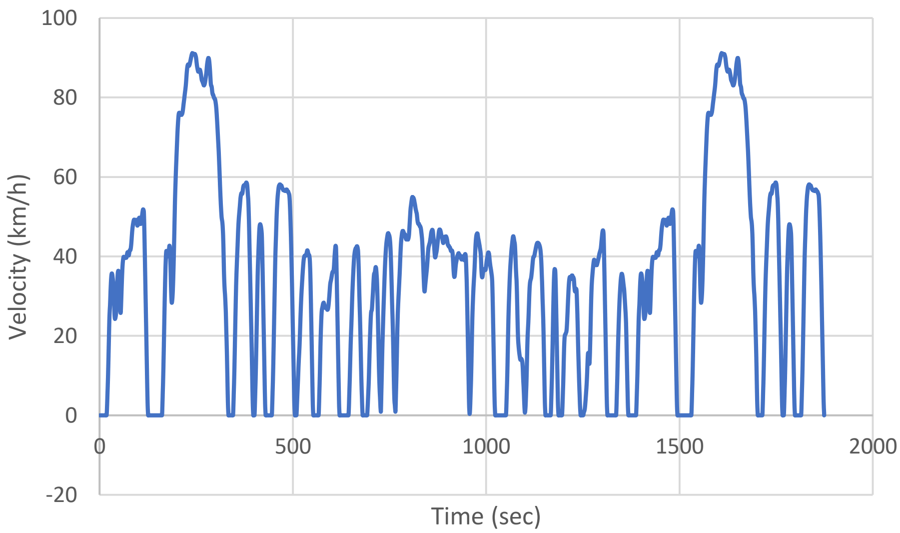

Fig.5.20. FTP-75 with a Cold Start Standard Driving Cycle Generated Through the Simulation Model.

In order to further validate the simulations and analysis presented in this thesis, the test Electrified Vehicle performance results are compared with the EPA predictions. The EPA predictions for MPGe are based on the 5-cycle adjustment method established for the EVs [172]. This method enables scaling the acquired results from the 5-cycle test with a factor of up to 0.7 in order to reflect the numbers for EVs. This scaling factor has been established by EPA in order to incorporate any difference between the Internal Combustion Engine (ICE) vehicles and the EVs as the original test procedures have been established for the ICE vehicles. The published EPA values for the 2014 Tesla Model S's MPGe are 88 for city driving and 90 for highway driving giving a combined MPGe of 89 following a weighted average of 55% and 45 % for the city and highway respectively [173]. The scaled MPGe values acquired from the 5-cycle adjustment method performed using the current simulation model for 2014 Tesla Model are shown in Table 5.50 below.

Table 5.50. MPGe Values Acquired from the Standard Driving Cycles Simulation

Standard Driving Cycle	**MPGe**
FTP-75	84
HWFET	84
US06	61
SC03	81
FTP-75 with cold start	83

From the above MPGe values, it can be seen that the Electrified Vehicle performance results acquired from the current simulation model are comparable to the EPA predictions, which further emphasize the robustness of the simulation model. The minor discrepancy noticed could be due to an adjustment factor applied by EPA to decrease the dynamometer based MPGe results to reflect the real-life conditions based on the proprietary past vehicle data collected. Furthermore, the adaptability and scalability of standard driving cycles for Autonomous-capable Vehicles are still being studied in the industry, limiting the knowledge of any scaling needed to incorporate Autonomous Vehicle control and maneuvers.

Chapter 6

Verification through Vehicle-level Simulations

This chapter describes the simulation setup as well as the various test cases. In overall, there are 113 test cases – 108 functional and 5 validation test cases (which have been presented in the previous chapter) with about 60 unique combinations of the ADS, human driver and 7 external conditions variations. In addition, the simulation results, as well as analysis including a quantitative sensitivity analysis, is also presented to understand the impact of vehicle autonomy on Electrified Vehicle performance, dynamics and the operation of the various components.

6.1 Simulation Setup and Test Cases

This section describes the formulation of 108 functional test cases which will be utilized to understand the impact of Electrified Vehicle autonomy on energy economy as well as various Electrified Vehicle components and dynamics. The 108 functional test cases depict six different autonomous features with varying levels of automation. They include traditional Cruise Control (CC), Adaptive Cruise Control (ACC), Automated Emergency Braking (AEB), Active Lane Keep Assist (ALKA) and a combination of multiple longitudinal and lateral autonomous control functions in addition to Traction Control to depict a Level 4 or L4 autonomous function [174]-[177]. These functions have been selected mainly due to their enormous impact on the vehicle dynamics and performance during highway driving. The autonomous functions of varying levels are compared with two types of manual driving – normal and aggressive driving behavior. Furthermore, variations in external conditions – specifically in road (flat versus with gradient profile), weather (ideal versus adverse) and traffic (no traffic, lead vehicle only or dynamic traffic maneuvers). This results in about 60 unique combinations of ADS and manual driving use cases with varying external conditions. These are summarized in Table 6.1 and 6.2. The split between the ADS control and the normal (MAN_N) or the aggressive driver (MAN_A) is also shown in these tables. Out of the 108 functional test cases, primary vehicle control by the ADS, normal human driver and aggressive human driver accounts for 36 test cases each. Although some of the human driving test cases could be reused for the comparative analysis, due to the identical longitudinal and lateral control responsibility distribution, every human driver test case is compared with a different ADS test case each time, resulting in the data set of 108 functional test cases in overall.

Tests 1 to 36 model primary highway driving maneuvers for traditional Cruise Control, Adaptive Cruise Control, Active Lane Keep Assist and a combination of ACC, ALKA and Traction Control, simulating SAE level 4 autonomous highway driving. The ADS has a primary vehicle control responsibility for either longitudinal control or lateral control or both in the above test cases. On the other hand, tests 37 to 60 attempt to imitate the above-described maneuvers when completely controlled (longitudinal and lateral) by the human driver (normal or aggressive driving behavior) instead of the ADS. As described above, all the test cases also incorporate changes in the external conditions. In all of the ADS specific cases with partial human driver responsibility, a normal driver behavior is assumed. For example, in the test cases with ACC, the longitudinal control is being performed by the ADS, whereas, the human driver is responsible for the vehicle's lateral control. In such a case with partial vehicle control responsibility lying with the ADS and partially with the human driver, a normal driving behavior is assumed. The assumptions and parameterization of the external condition models have already been described in Chapter 5 of this thesis.

Table 6.1. ADS Complete or Partial Control Test Cases

Test ID	ADAS Feature	Primary Longitudinal Control	Primary Lateral Control	Road	Weather	Traffic Density
1	CC	ADS	MAN_N	Road 1	Ideal	No Traffic
2	CC	ADS	MAN_N	Road 2	Ideal	No Traffic
3	CC	ADS	MAN_N	Road 1	Adverse	No Traffic
4	CC	ADS	MAN_N	Road 2	Adverse	No Traffic
5	CC	ADS	MAN_N	Road 1	Ideal	Multi-object Traffic Set
6	CC	ADS	MAN_N	Road 2	Ideal	Multi-object Traffic Set
7	CC	ADS	MAN_N	Road 1	Adverse	Multi-object Traffic Set
8	CC	ADS	MAN_N	Road 2	Adverse	Multi-object

						Traffic Set
9	CC	ADS	MAN_N	Road 1	Ideal	Lead Vehicle Only
10	CC	ADS	MAN_N	Road 2	Ideal	Lead Vehicle Only
11	CC	ADS	MAN_N	Road 1	Adverse	Lead Vehicle Only
12	CC	ADS	MAN_N	Road 2	Adverse	Lead Vehicle Only
13	ACC + AEB	ADS	MAN_N	Road 1	Ideal	Lead vehicle only
14	ACC + AEB	ADS	MAN_N	Road 2	Ideal	Lead vehicle only
15	ACC + AEB	ADS	MAN_N	Road 1	Adverse	Lead vehicle only
16	ACC + AEB	ADS	MAN_N	Road 2	Adverse	Lead vehicle only
17	ACC + AEB	ADS	MAN_N	Road 1	Ideal	Multi-object Traffic Set
18	ACC + AEB	ADS	MAN_N	Road 2	Ideal	Multi-object Traffic Set
19	ACC + AEB	ADS	MAN_N	Road 1	Adverse	Multi-object Traffic Set
20	ACC + AEB	ADS	MAN_N	Road 2	Adverse	Multi-object Traffic Set
21	ALKA	MAN_N	ADS	Road 1	Ideal	No Traffic
22	ALKA	MAN_N	ADS	Road 2	Ideal	No Traffic
23	ALKA	MAN_N	ADS	Road 1	Adverse	No Traffic
24	ALKA	MAN_N	ADS	Road 2	Adverse	No Traffic
25	ALKA	MAN_N	ADS	Road 1	Ideal	Multi-object

						Traffic Set
26	ALKA	MAN_N	ADS	Road 2	Ideal	Multi-object Traffic Set
27	ALKA	MAN_N	ADS	Road 1	Adverse	Multi-object Traffic Set
28	ALKA	MAN_N	ADS	Road 2	Adverse	Multi-object Traffic Set
29	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 1	Ideal	Lead vehicle only
30	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 2	Ideal	Lead vehicle only
31	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 1	Adverse	Lead vehicle only
32	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 2	Adverse	Lead vehicle only
33	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 1	Ideal	Multi-object Traffic Set
34	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 2	Ideal	Multi-object Traffic Set
35	L4 (ACC + AEB+ ALKA + Traction Control)	ADS	ADS	Road 1	Adverse	Multi-object Traffic Set
36	L4 (ACC + AEB+ ALKA +	ADS	ADS	Road 2	Adverse	Multi-object

	Traction Control)					Traffic Set

Table 6.2. Manual Human Driver Complete Control Test Cases

Test ID	Description	Longitu-dinal Control	Lateral Control	Road	Weather	Traffic Density	Driver Behavior
37	Manual comparison for Test # 1 and 21	MAN_N	MAN_N	Road 1	Ideal	No Traffic	Normal
38	Manual comparison for Test # 1 and 21	MAN_A	MAN_A	Road 1	Ideal	No Traffic	Aggressive
39	Manual comparison for Test # 2 and 22	MAN_N	MAN_N	Road 2	Ideal	No Traffic	Normal
40	Manual comparison for Test # 2 and 22	MAN_A	MAN_A	Road 2	Ideal	No Traffic	Aggressive
41	Manual comparison for Test # 3 and 23	MAN_N	MAN_N	Road 1	Adverse	No Traffic	Normal
42	Manual comparison for Test # 3 and 23	MAN_A	MAN_A	Road 1	Adverse	No Traffic	Aggressive
43	Manual comparison for Test # 4 and 24	MAN_N	MAN_N	Road 2	Adverse	No Traffic	Normal
44	Manual comparison for Test # 4 and 24	MAN_A	MAN_A	Road 2	Adverse	No Traffic	Aggressive
45	Manual comparison for Test # 5, 17, 25 and 33	MAN_N	MAN_N	Road 1	Ideal	Multi-object Traffic Set	Normal
46	Manual comparison for Test # 5,	MAN_A	MAN_A	Road 1	Ideal	Multi-object Traffic Set	Aggressive

	17, 25 and 33						
47	Manual comparison for Test # 6, 18, 26 and 34	MAN_N	MAN_N	Road 2	Ideal	Multi-object Traffic Set	Normal
48	Manual comparison for Test # 6, 18, 26 and 34	MAN_A	MAN_A	Road 2	Ideal	Multi-object Traffic Set	Aggressive
49	Manual comparison for Test # 7, 19, 27 and 35	MAN_N	MAN_N	Road 1	Adverse	Multi-object Traffic Set	Normal
50	Manual comparison for Test # 7, 19, 27 and 35	MAN_A	MAN_A	Road 1	Adverse	Multi-object Traffic Set	Aggressive
51	Manual comparison for Test # 8, 20, 28 and 36	MAN_N	MAN_N	Road 2	Adverse	Multi-object Traffic Set	Normal
52	Manual comparison for Test # 8, 20, 28 and 36	MAN_A	MAN_A	Road 2	Adverse	Multi-object Traffic Set	Aggressive
53	Manual comparison for Test #9, 13 and 29	MAN_N	MAN_N	Road 1	Ideal	Lead vehicle only	Normal
54	Manual comparison for Test #9, 13 and 29	MAN_A	MAN_A	Road 1	Ideal	Lead vehicle only	Aggressive
55	Manual comparison for Test #10, 14 and 30	MAN_N	MAN_N	Road 2	Ideal	Lead vehicle only	Normal
56	Manual comparison for Test #10, 14 and 30	MAN_A	MAN_A	Road 2	Ideal	Lead vehicle only	Aggressive
57	Manual comparison for Test #11, 15 and 31	MAN_N	MAN_N	Road 1	Adverse	Lead vehicle only	Normal

58	Manual comparison for Test #11, 15 and 31	MAN_A	MAN_A	Road 1	Adverse	Lead vehicle only	Aggressive
59	Manual comparison for Test #12, 16 and 32	MAN_N	MAN_N	Road 2	Adverse	Lead vehicle only	Normal
60	Manual comparison for Test #12, 16 and 32	MAN_A	MAN_A	Road 2	Adverse	Lead vehicle only	Aggressive

For the six different ADAS feature sets being evaluated in this study, the responsibility lying on the ADS versus the human driver, once the ADAS feature is activated, could differ depending on the feature set. The Table 5.27 in Chapter 5 has already demonstrated this distribution of host vehicle longitudinal and lateral control. The configuration or the initiation of the various autonomous/ semi-autonomous features are not counted in for this distribution. For example, for an ACC feature, it is assumed (hence, not considered a "responsibility" explicitly) that the human driver has to set a minimum safe distance and maximum desired speed.

Traditional Cruise Control:

Test 1 simulates traditional Cruise Control, where a constant set point or speed is specified by the user for the host vehicle. Realistically, the ADS maintains this set speed until the functionality is deactivated by the user. The correlation with the surrounding traffic, for example, in case of a suddenly slowed down target vehicle in front of the host vehicle, is not detected or controlled by the ADS, instead, this responsibility of slowing down the host vehicle by braking accordingly lies on the human driver. As such, based on the above description, partial longitudinal control is performed by ADS; whereas, the lateral control is solely human driver's responsibility. This particular test case assumes a 0% traffic density, ideal weather conditions on Road 1. Furthermore, the host vehicle is expected to start from rest and accelerate to reach the set speed, which is 100 km/h, in this case. Tests 2 to 12 model traditional Cruise Control with variations in external conditions such as the road (gradient), weather and traffic density as can be seen in Table 6.1 above. Tests 37 to 60 provide a manual human driver comparison to these ADS test cases as seen in Table 6.2.

For the human driver-controlled test cases, both the 'normal' and 'aggressive' driving behaviors are simulated, distinguished by suffixes 'N' and 'A' respectively in the vehicle control descriptions and results analysis shown further in the thesis.

Adaptive Cruise Control:

Adaptive Cruise Control or ACC is an advancement of the traditional Cruise Control discussed previously. ACC offers complete longitudinal control by the ADS. The user is expected to define a minimum safe distance between the host and the lead vehicle as well as a desired maximum speed of the host vehicle. The ACC controller uses the most conservative technique in order to avoid a front-end collision. Tests 13 to 20 simulate ACC with variations in the external conditions as shown in Table 6.1. A Volkswagen Beetle 2012 is simulated as a lead vehicle for all the test cases (with only a lead vehicle in the traffic set) in order to maintain consistency for vehicle dynamics comparison. This was randomly selected as an example target in order to fulfill the requirements of the maneuver follow model, especially for ACC and level 4 test cases. The exact make or model of this lead vehicle is insignificant to the functionality of the ACC controller and is only mentioned here for informational purposes. The Perception system itself is expected to be robust enough to offer a 360-degree surround field of view in order to accurately detect and classify all types of objects including cars, trucks, pedestrians, and other dynamic or static obstacles. For tests 13 to 16, only the lead vehicle is assumed to be present in the immediate driving environment of the host vehicle. The lead vehicle maneuver is configured such that its speed profiles vary throughout the simulation cycle. The maneuvers described in the Traffic section above are assumed for this lead vehicle. A significant operational presence of the ADS is ensured for the sensitivity analysis on the impact of Electrified Vehicle autonomy on the vehicle dynamics and performance which will be described in the next sections. The expectation for the host vehicle is to adapt to these variations in the lead vehicle's speed profiles such that an optimal plan is developed by the host vehicle in order to reach its intended destination. This not only includes arbitration between the minimum safe distance and the maximum desired speed but also manipulation according to the rules defined by the Policy database at all times.

In addition, tests 17 to 20 also simulate the ACC functionality in the presence of multiple traffic objects with dynamic behavior. The setup and configuration of these traffic objects and their maneuvers have been described in detail previously in the thesis within the Traffic Model section. Every traffic object is seen to have a different type of an impact on the host vehicle. The host vehicle is expected to react optimally in every dynamic situation on the road, relative to a human driver, resulting in an overall optimal eco-driving and vehicle control. Tests 45 to 60 simulate the replication of the above ACC based ADS maneuvers completely by a human driver both for longitudinal and lateral vehicle control.

Automated Emergency Braking:

Automated Emergency Braking or AEB is an extremely useful feature on the road especially in highway scenarios, with both the host and the traffic vehicles operating at high speeds where any adverse collision could be fatal. The primary role of AEB is to prevent a collision from occurring by braking the vehicle, as needed. In addition to preventing from an anticipated threat, AEB can also aid in optimal braking of the vehicle by avoiding sudden jerks which cannot only impact the vehicle components and the overall vehicle performance but can also pose a severe threat to traffic vehicles behind the host vehicle due to inadequate time for driver or a system (ADS) reaction.

For the simulations presented in this thesis, AEB has been combined with ACC test cases. Hence, tests 13 to 20 cover the AEB functionality. These tests also incorporate ADS control under varying external conditions. In addition, the tests 45 to 60 simulate normal and aggressive driving behavior under similar driving conditions. The comparative analysis between the ADS control versus the human driver will be described in the next section on Simulation Results and Analysis.

Active Lane Keep Assist:

Active Lane Keep Assist or ALKA assists the driver in maintaining the lateral control of the vehicle by minimizing if not completely eliminating any unintended deviations of the host vehicle from the center of the lane. ALKA can contribute significantly for ensuring safety of the host vehicle as well as the surrounding vehicles in the immediate field of view by preventing any accidental lane departures. This can be especially helpful with pre-occupied traffic vehicles in the host vehicle's adjacent lanes, especially in the blind spot position. In case of any driver misuse or oversteer out of the intended lane, the ALKA is also expected to steer the vehicle back into the lane, especially under the threat of a side collision. Depending on the system developer, it is also possible to ensure that the host vehicle assists the user by steering the vehicle back into the center of the lane as soon as the wheels are detected to touch the lane boundaries.

In order to understand the impact of maintaining the lateral control of the vehicle on the Electrified Vehicle performance, dynamics and components, multiple ALKA based simulations are carried out as part of this study. Tests 21 to 28 simulate the ADS control for the ALKA function. Similar to the tests described above, the ALKA function is also simulated under varying external conditions including the road, weather, and traffic. In addition, a comparative analysis is also performed with normal and aggressive driving behavior as described in further sections of the thesis. The tests 37 to 52 simulate manual driving behavior under the same external conditions. The parameters used, and assumptions made for normal and aggressive driver's lateral deviations, on average, have been described in the ADAS Feature Set Model section.

Traction Control:

Similar to the other autonomous-capable functions described above such as CC, ACC, AEB and ALKA, the Traction Control can offer an incredible safety support to the host vehicle, especially, during adverse weather conditions. Traction Control is helpful for reducing the acceleration when wheel spins occur [150]. In addition to having safety benefits, Traction Control is also expected to provide stability and have a positive influence on the performance of the Electrified Vehicle dynamics. The simulations for Traction Control have been combined with the L4 Autonomous Control simulations, which will be described further in the thesis.

Tests 29 to 36 simulate the ADS responsibility for Traction Control, including the influence of external conditions. On the other hand, tests 45 to 60 provide a manual human driving comparison for these tests, including the normal and the aggressive driving behavior.

L4 Autonomous Control:

L4 is the highest level of vehicle automation function that will be incorporated in this thesis. L4 autonomous control requires both the longitudinal and the lateral vehicle control to be completely performed by the ADS. The human driver is neither needed nor expected to be attentive or take back complete or partial control of the vehicle. In order to perform a level 4 autonomous control, the ADS needs to be able to detect, track and classify objects, estimate free space accurately, perform Mission and Motion Planning and finally, execute as planned. Such a high level of vehicle automation can be extremely beneficial not only for ensuring safety of the host and the traffic vehicles but also for improving the vehicle performance. The next section will walk through the analysis for understanding the impact of Electrified Vehicle autonomy on the vehicle's dynamics, components as well as the energy economy.

Some of the above described semi-autonomous functions such as ACC, ALKA, AEB and Traction Control have been combined to simulate an L4 Autonomous Control in this study. The tests 29 to 36 simulate the ADS responsibility for an L4

Autonomous Control. These test cases also perform this analysis under the influence of varying external conditions. The main motive of modeling these external conditions is to prove the ability of autonomous vehicle control to outperform human control, in terms of improving the vehicle performance and having a positive impact on the Electrified Vehicle dynamics and components. Furthermore, a comparison of the ADS test cases for L4 Autonomous Control and completely human driver-controlled test cases has also been provided. The normal and aggressive driving behaviors exhibited while completely controlling the longitudinal and lateral behavior of the vehicle, under similar driving conditions, is simulated through tests 45 to 60.

6.2 Simulation Results and Analysis

This section describes the simulation results as well as the analysis accompanied with it. The simulation results are divided into four major categories – energy economy and consumption, vehicle dynamics, Electrified Vehicle motor, and battery results.

6.2.1 Energy Economy and Consumption Results

The energy economy (MPGe) and consumption results for all the ADS control test cases as well as their comparisons with the normal and aggressive human driver are presented in this section. The MPGe for each test case is calculated by following the below:

MPGe = (33.7 kWh/ 1 Gallon) / (Total energy consumption for the trip in kWh/ total miles driven)

Fig. 6.1 (a) and (b) show the MPGe values for all the 108 functional test cases as well as their average and standard deviation error bars respectively. It can be clearly seen how the ADS control cluster is located much higher on the plot, on average, followed by the normal human driver control and lastly, the aggressive human driver control. This shows that the vehicle performance measured in terms of the energy economy (MPGe) is significantly higher for ADS control or under semi-autonomous/ autonomous vehicle control. On average, a 28 percent increase is noticed through semi-autonomous/ autonomous control of the test Electrified Vehicle. This percent increase breaks down to a 22 percent and a 35 percent increase of energy economy for ADS control compared to the normal and aggressive human driver control respectively. This increase in energy economy with an increase in vehicle automation is one of the most significant findings of this thesis.

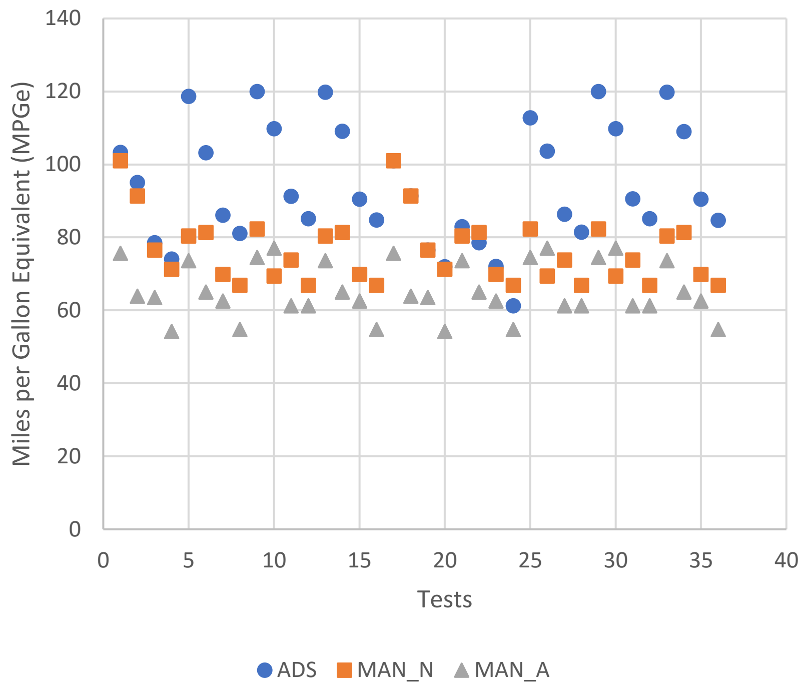

Fig.6.1 (a). MPGe Values for the 108 Functional Test Cases.

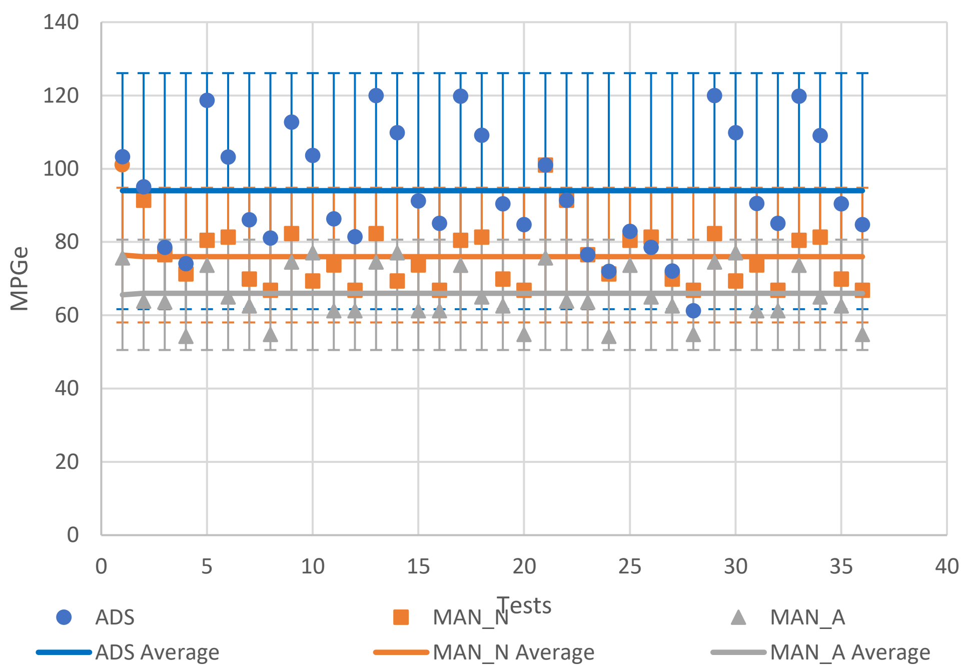

Fig.6.1 (b). MPGe Values for the 108 Functional Test Cases with Mean and Standard Deviation Error Bars.

Many different theoretical predictions regarding the increase in vehicle performance with the increase of autonomy were presented in section 3.4. Table 6.3 summarizes the Electrified Vehicle performance results, in terms of MPGe, for ADS versus manual human control (including an average of normal and aggressive driving behavior), collected through the simulations presented in this thesis. These results, once again strongly demonstrate that the vehicle performance during ADS control has surpassed the average performance under manual human control in every single test case.

Table 6.3. Comparative Analysis of the MPGe Values for ADS and Manual Human Driver Control Test Cases

Test	ADS	MAN
Test 1	103	88
Test 2	95	78
Test 3	79	70
Test 4	74	63
Test 5	119	77
Test 6	103	73
Test 7	86	66
Test 8	81	61
Test 9	113	78
Test 10	104	73
Test 11	86	68
Test 12	81	64
Test 13	120	78
Test 14	110	73
Test 15	91	68
Test 16	85	64
Test 17	120	77
Test 18	109	73
Test 19	90	66

Test 20	85	61
Test 21	101	88
Test 22	91	78
Test 23	77	70
Test 24	72	63
Test 25	83	77
Test 26	79	73
Test 27	72	66
Test 28	61	61
Test 29	120	78
Test 30	110	73
Test 31	91	68
Test 32	85	64
Test 33	120	77
Test 34	109	73
Test 35	90	66
Test 36	85	61

Similar to Fig. 6.1 (a) and (b) which breaks down the impact of human driver control into a normal and an aggressive driver, Fig. 6.2 (a) and (b) which show the comparison between ADS control and an average human driver control in addition to the mean and standard deviation error bars respectively, the ADS control cluster of the MPGe values is seen to be significantly higher than the average human driver test cases. The p-value is calculated to be $4.6 * 10^{-6}$ showing the statistical significance of the analysis. Furthermore, the energy economies are also broken down per the different ADAS features simulated in addition to the mean and the standard deviation error bars as shown in Fig. 6.3 (a) and (b) respectively. The respective manual comparisons for them are also offered. For every ADAS feature, the MPGe was seen to be higher with ADS control compared to human driver, except the ALKA where the ADS and the normal driver MPGe values were seen to be almost the same. The aggressive driver control MPGe was however still lower than the ADS as well as the normal human driver. This is mainly because it was noticed that the impact of lateral vehicle control on the Electrified Vehicle energy economy is relatively lower than the impact of the longitudinal control which is evident through the Fig. 6.3 (a) and (b). It is also seen that the values for ACC and level 4 were almost the same mainly because of ACC serving as the primary longitudinal control even for level 4. Furthermore, this similarity is explicitly demonstrated also due to a lower impact of the vehicle lateral control. In addition to the ADS control dominating the energy economy results, in overall, the higher energy economy with ACC compared to CC further signifies the increase in energy economy with the increase in vehicle automation level.

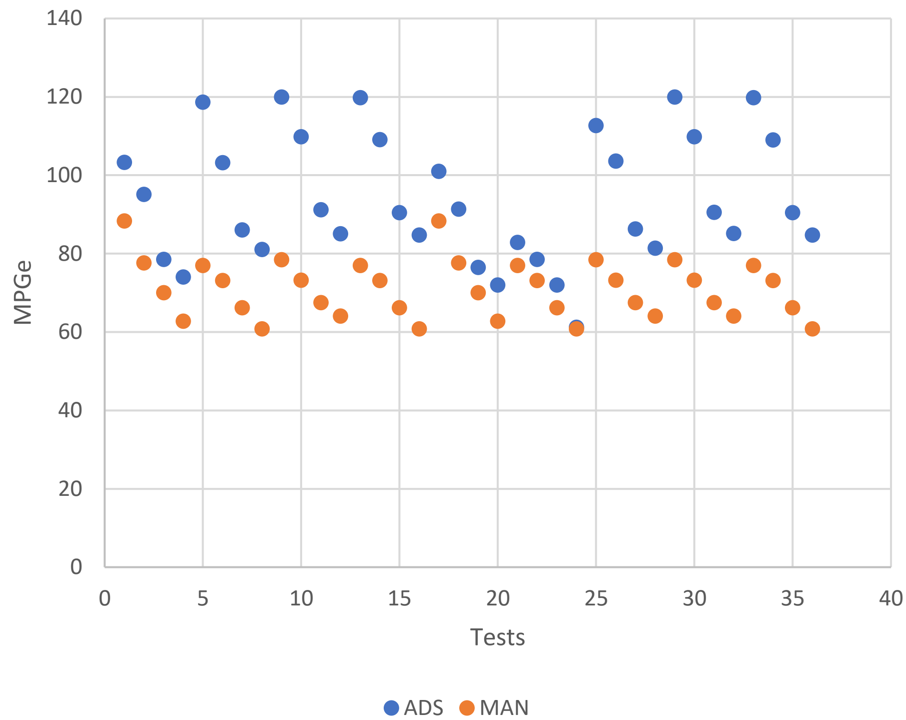

Fig. 6.2 (a). MPGe Values Comparison for the ADS and Human Driver Control Test Cases.

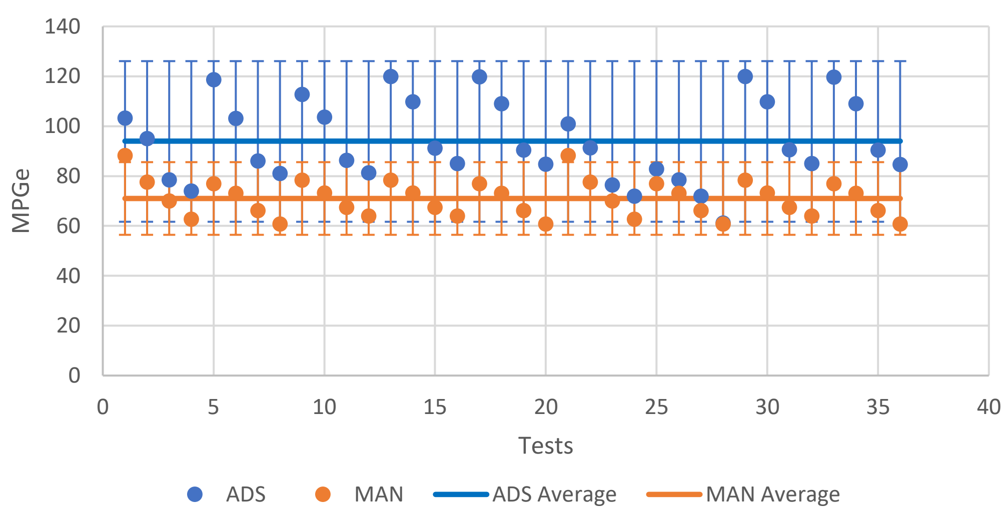

Fig. 6.2 (b). MPGe Values Comparison for the ADS and Human Driver Control Test Cases with Mean and Standard Deviation Error Bars.

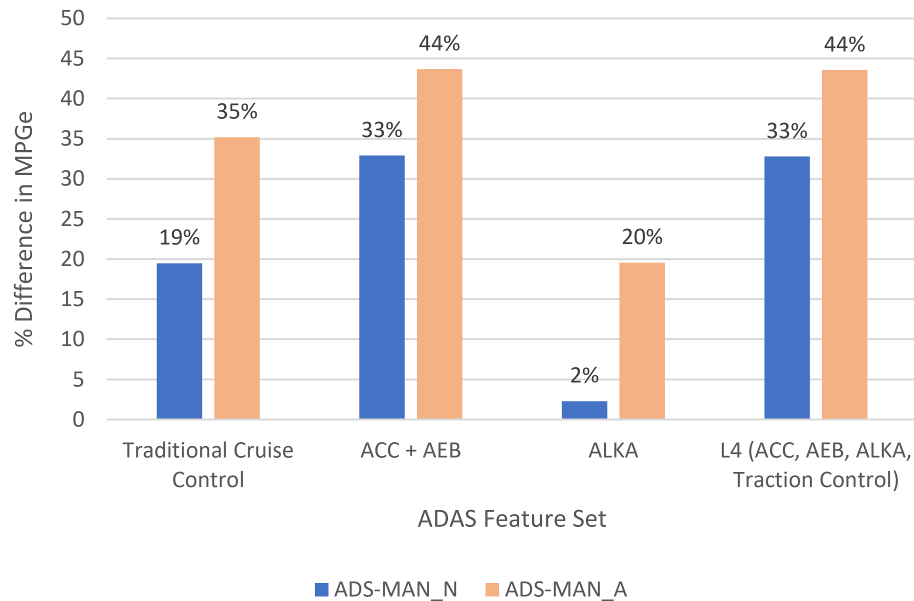

Fig. 6.3 (a). Percent Difference in MPGe per ADAS Feature.

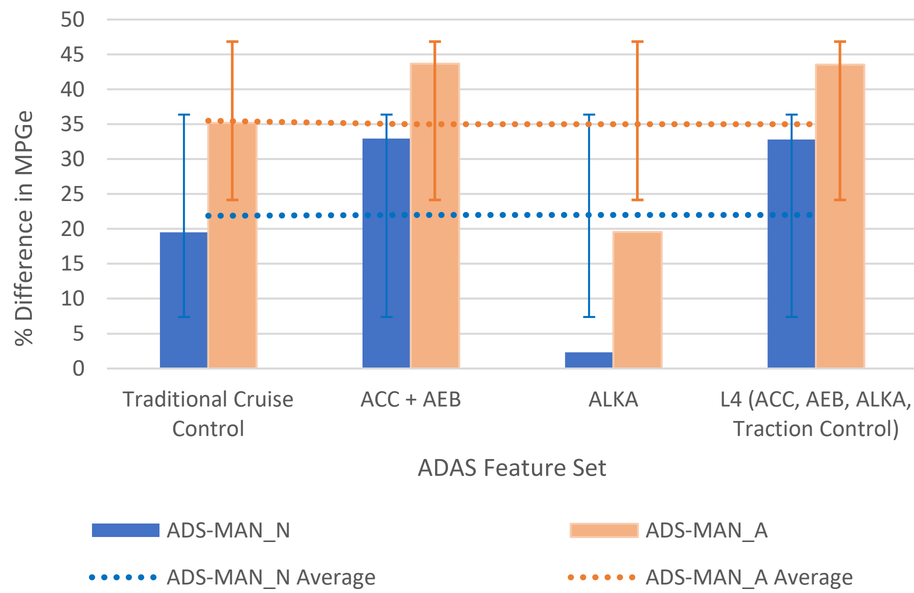

Fig. 6.3 (b). Percent Difference in MPGe per ADAS Feature with Mean and Standard Deviation Error Bars.

The rest of this section and the next ones will explore the reasons behind this significant improvement in Electrified Vehicle performance with an increase in the vehicle automation. The ADS control is expected to exhibit optimal operation of the different Electrified Vehicle components as well as energy management by reducing the instantaneous sudden fluctuations in their profiles. This, in turn, is expected to improve the energy economy through an optimal eco-driving while simultaneously reacting to the real-time requirements of the dynamic driving environment. The energy consumption for the test cases with traditional Cruise Control incorporating the variations in the different external conditions can be seen in Fig. 6.4 to 6.15. Its respective manual comparisons for normal and aggressive driving behavior can also be seen in these figures. In overall, it can be seen that the energy consumption from ADS control is significantly lower than the respective manual human driver comparisons, thus resulting in an improvement in the energy economy during autonomous/ semi-autonomous vehicle control.

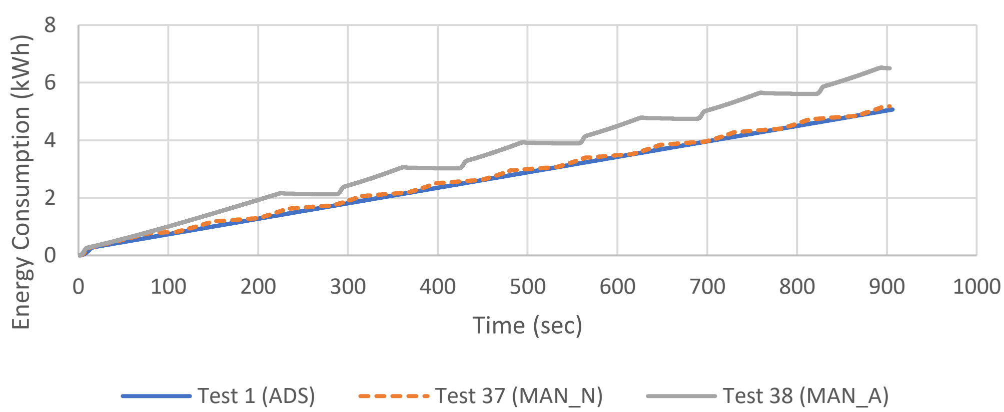

Fig. 6.4. Energy Consumption for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

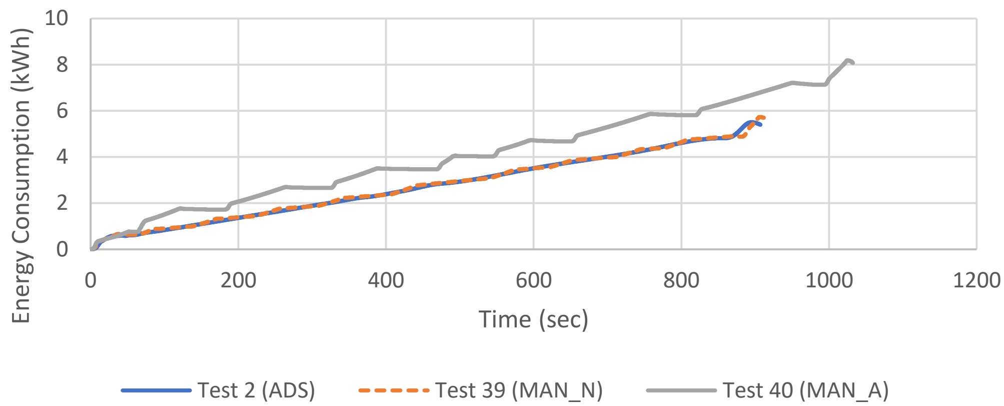

Fig. 6.5. Energy Consumption for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

In addition to the relatively lower energy consumption seen during ADS control compared to its respective manual human driver test cases, it is also evident through these figures that the instantaneous fluctuations in the energy economy profiles are the highest for the aggressive human driver, followed by the normal driver and lastly the ADS control. In other words, the ADS control profiles are seen to be much more streamlined with lower instantaneous fluctuations (sudden fall or rise).

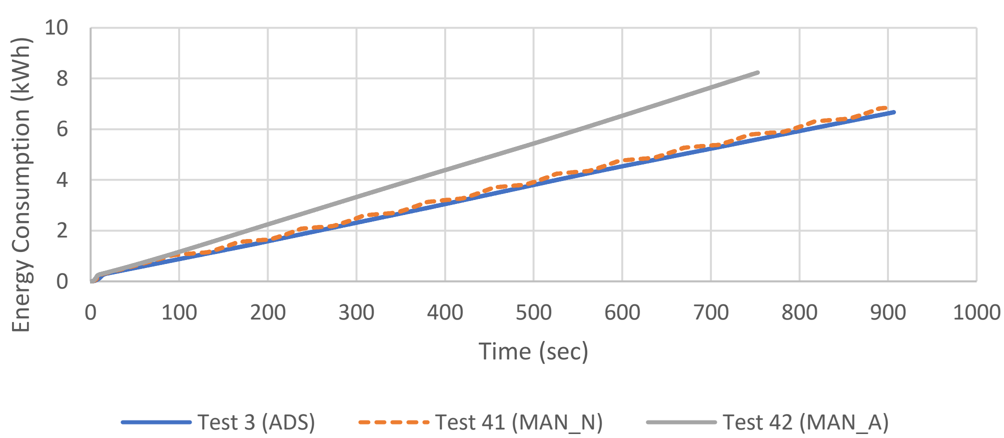

Fig. 6.6. Energy Consumption for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

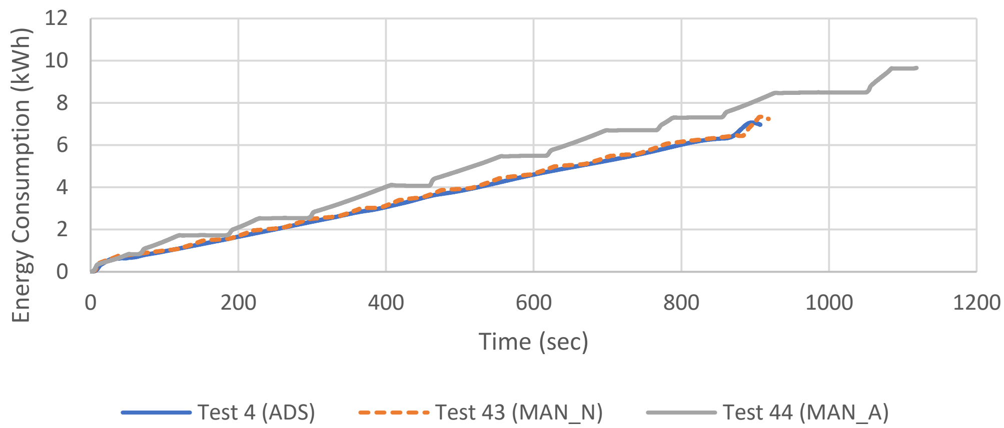

Fig. 6.7. Energy Consumption for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

Higher fluctuations, as seen in the case of human driver control test cases, is expected to cause inefficient operation of the Electrified Vehicle components to meet these instantaneous demands. It is also anticipated to result in their long-term wear. The quantification of these fluctuations and further analyses are offered in the next section of this thesis.

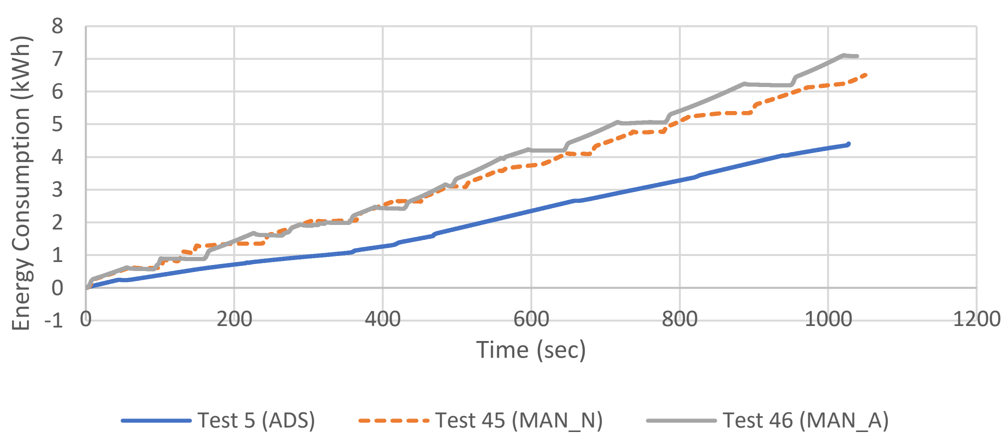

Fig. 6.8. Energy Consumption for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

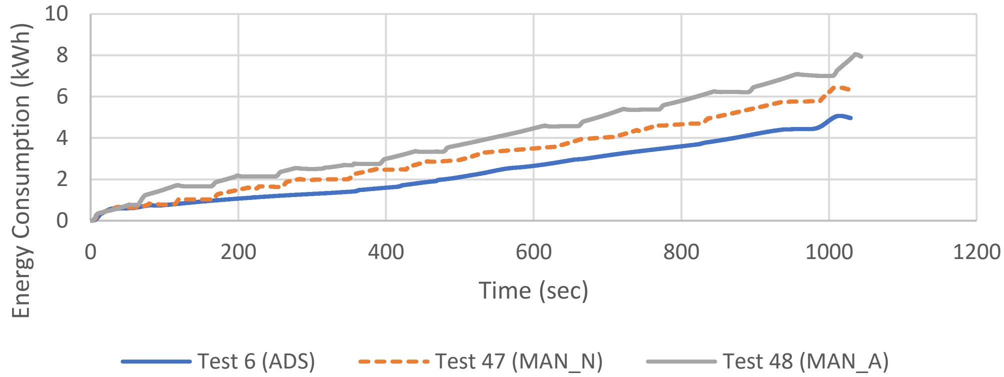

Fig. 6.9. Energy Consumption for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

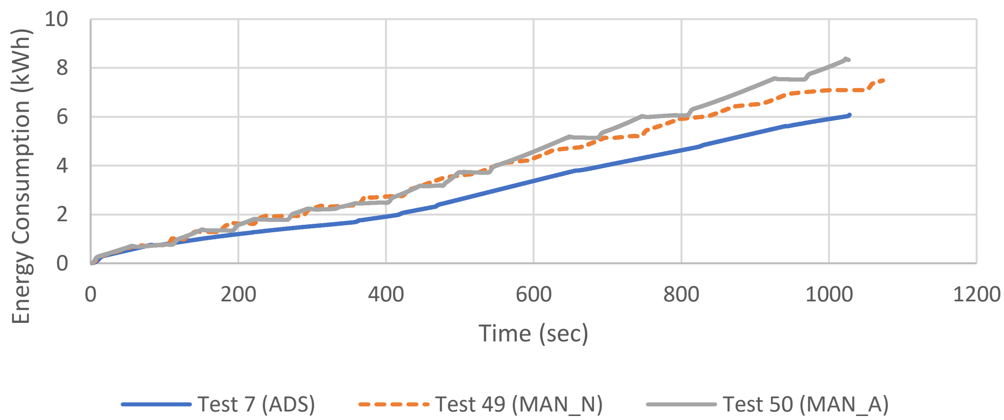

Fig. 6.10. Energy Consumption for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

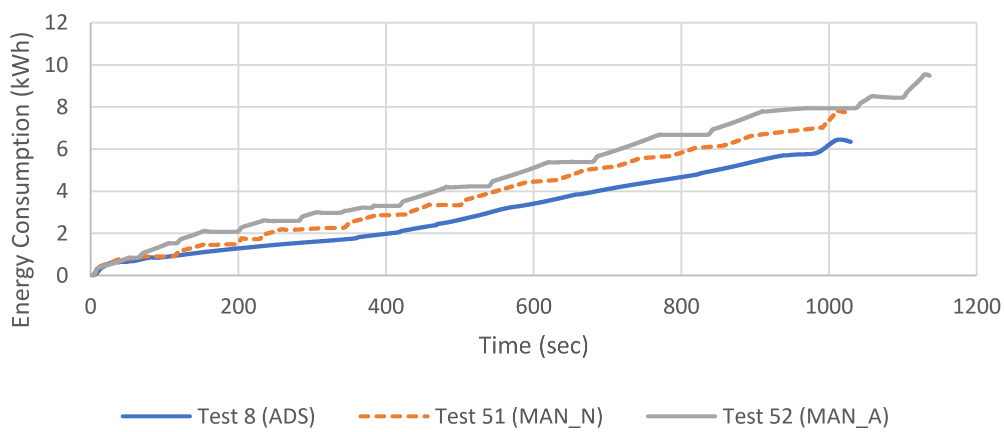

Fig. 6.11. Energy Consumption for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

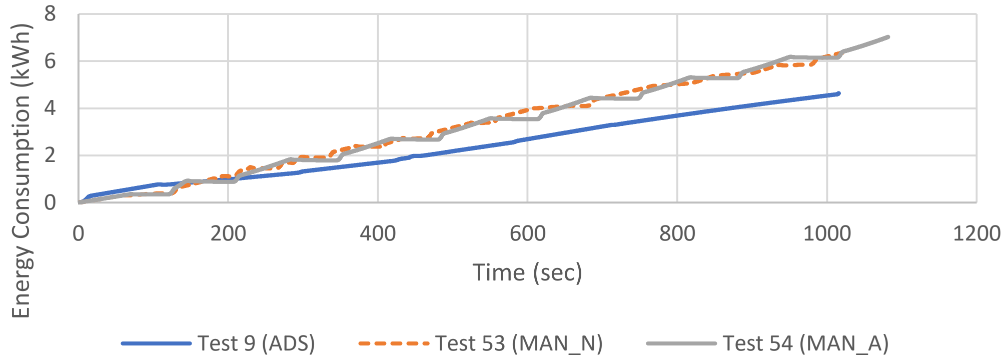

Fig. 6.12. Energy Consumption for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

The plots for ACC (including AEB) test cases compared with normal human driving and aggressive driving test cases are shown in Fig. 6.16 to 6.23. The energy consumption for ideal conditions is provided in Fig. 6.16. Fig. 6.17 to 6.23 show variations in the different external conditions including traffic, road, and weather.

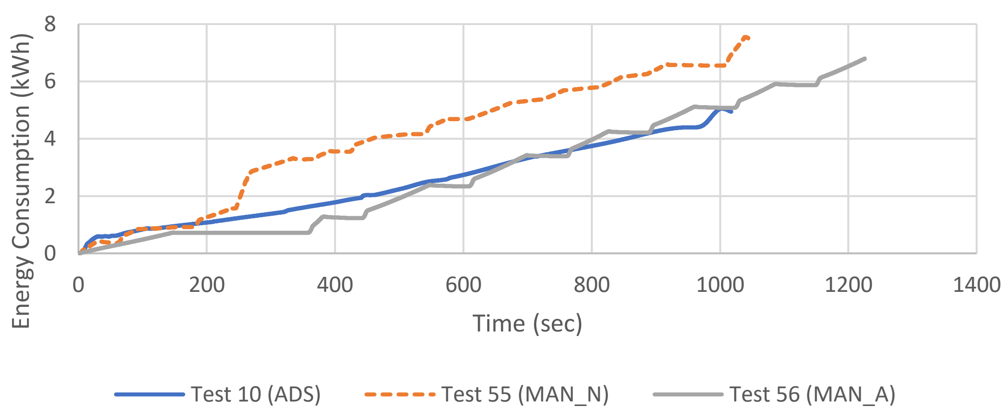

Fig. 6.13. Energy Consumption for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

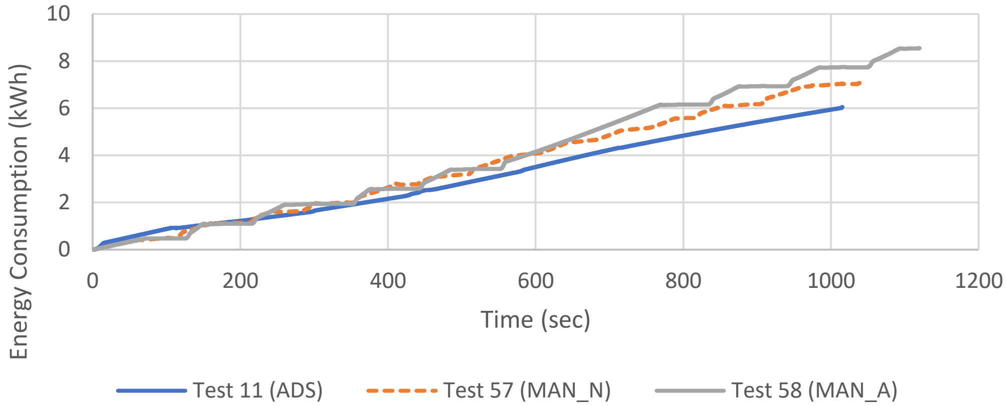

Fig. 6.14. Energy Consumption for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

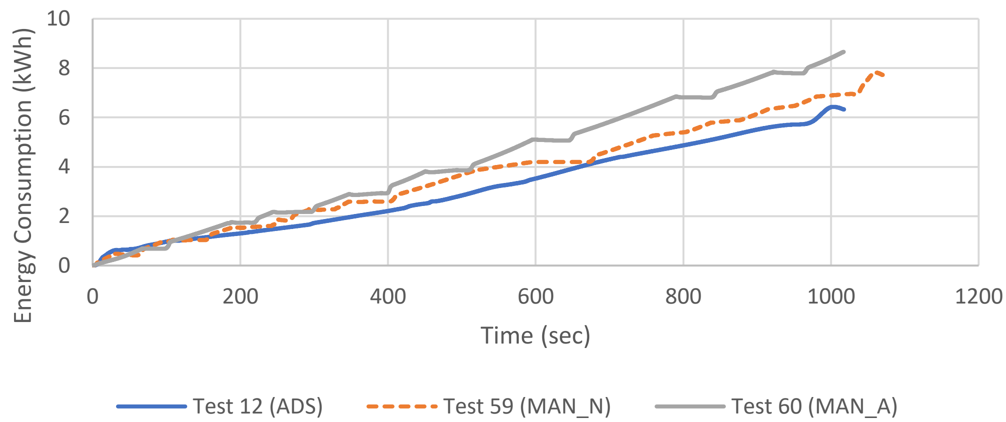

Fig. 6.15. Energy Consumption for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

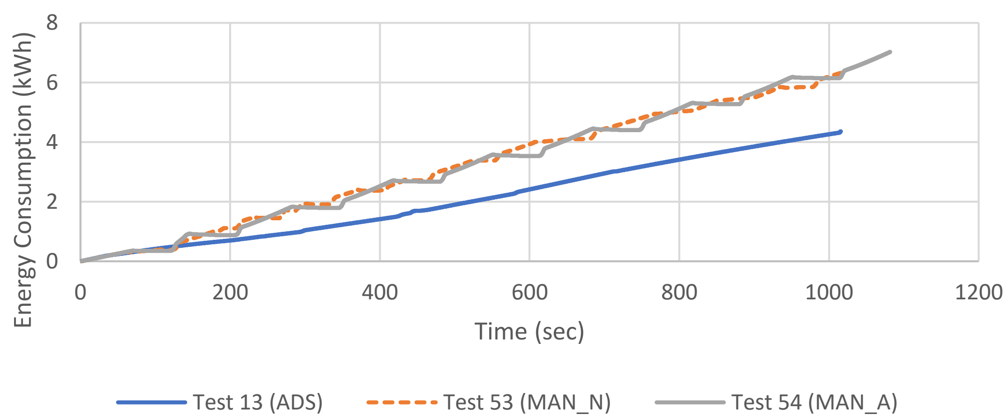

Fig. 6.16. Energy Consumption for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

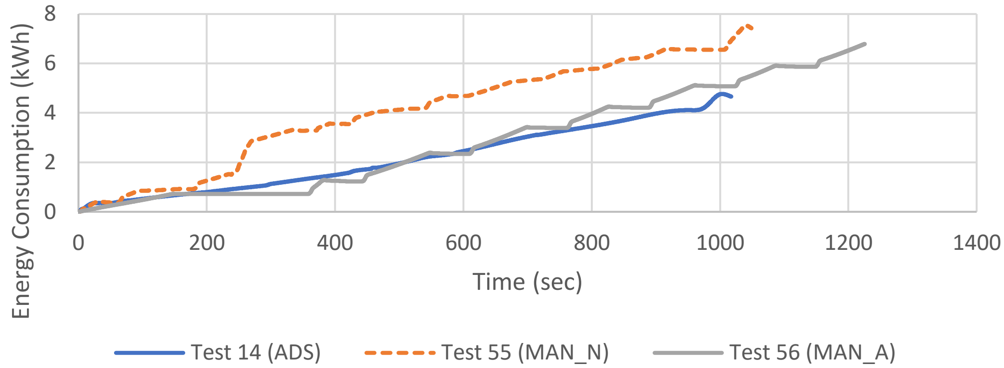

Fig. 6.17. Energy Consumption for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

The test cases with a combination of multiple adverse conditions such as gradient-based hilly road with adverse weather, dynamic traffic with adverse weather, dynamic traffic with gradient-based hilly road and a combination of the hilly road, adverse weather and dynamic traffic, were the most challenging in terms of the impact on the Electrified Vehicle components to meet these requirements.

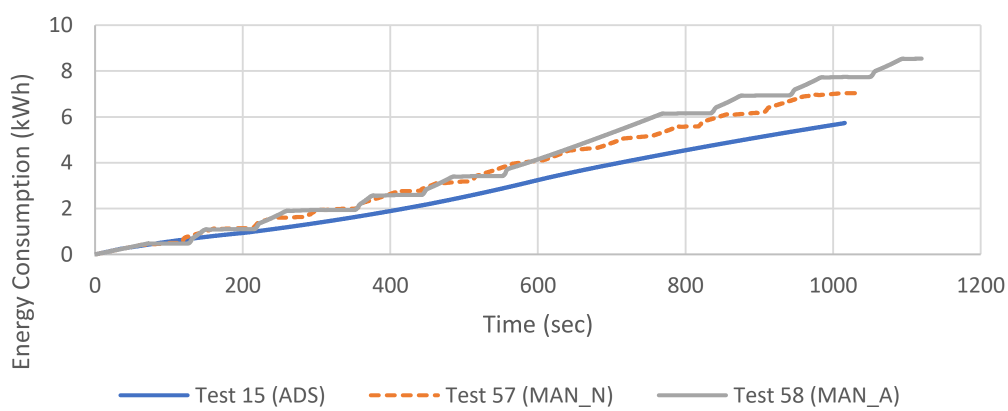

Fig. 6.18. Energy Consumption for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

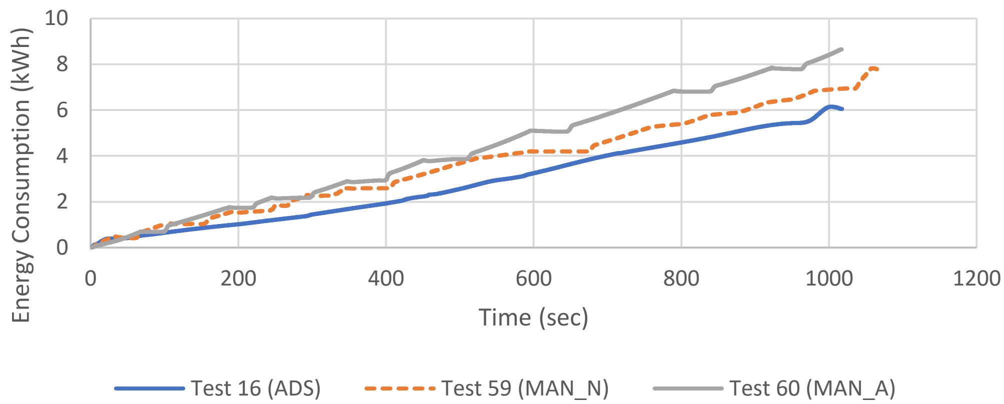

Fig. 6.19. Energy Consumption for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

However, even in the presence of one or multiple varying external conditions, ADS has surpassed the energy consumption results compared to the normal and aggressive driver control, on average. In all of these cases, the energy consumption, in addition to the instantaneous fluctuations in energy consumption are seen to be significantly lower for the ADS control compared to the human driving test cases, on average.

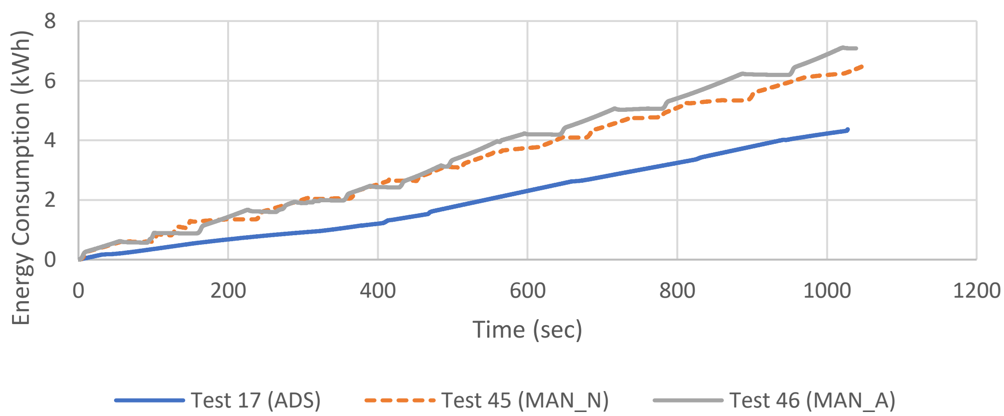

Fig. 6.20. Energy Consumption for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

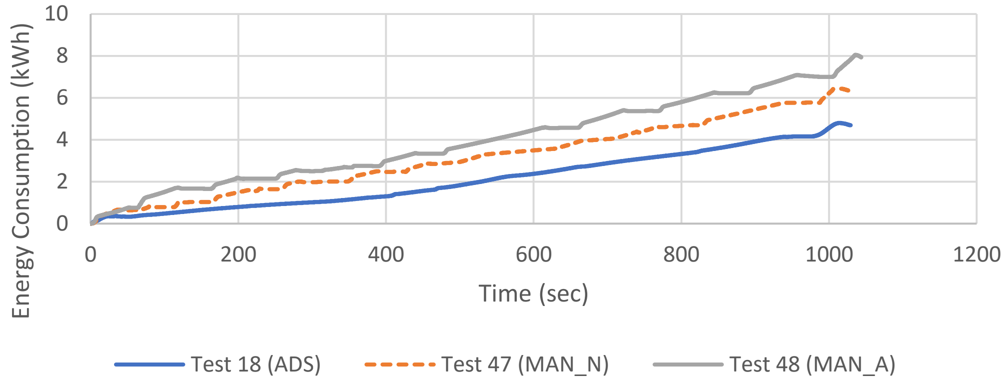

Fig. 6.21. Energy Consumption for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

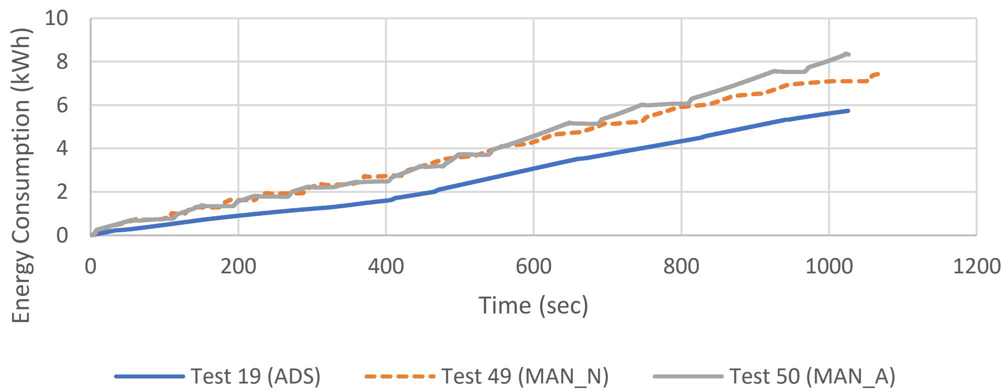

Fig. 6.22. Energy Consumption for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

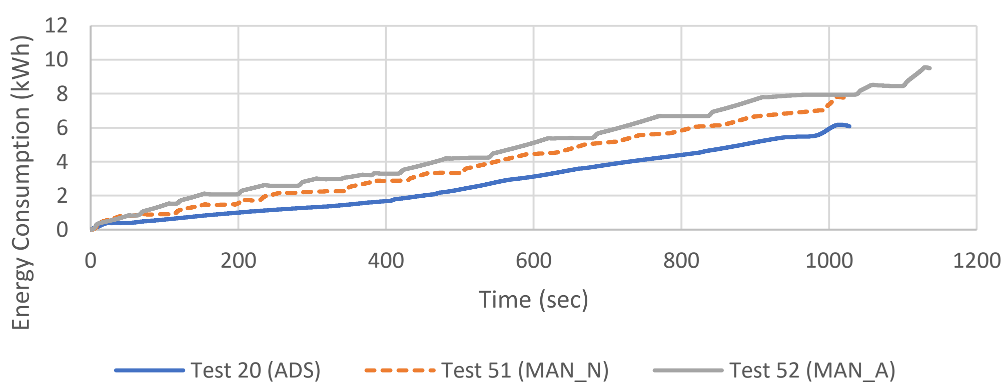

Fig. 6.23. Energy Consumption for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

The energy consumption results for Active Lane Keep Assist are shown in Fig. 6.24 to 6.31. Similar to the results described above, the ALKA results are also plotted for both the ideal external conditions as well as the non-ideal ones varying in different combinations. The variations in these external conditions are mainly simulated to represent real-life driving conditions which the Autonomous-capable Electrified Vehicle might encounter on the road. The intention is thus to test the performance of ADS control in all the different conditions to verify the hypothesis of the ADS control offering a better Electrified Vehicle performance, dynamics and components' operation, especially for the motor and battery which will be discussed in the further sections of this chapter.

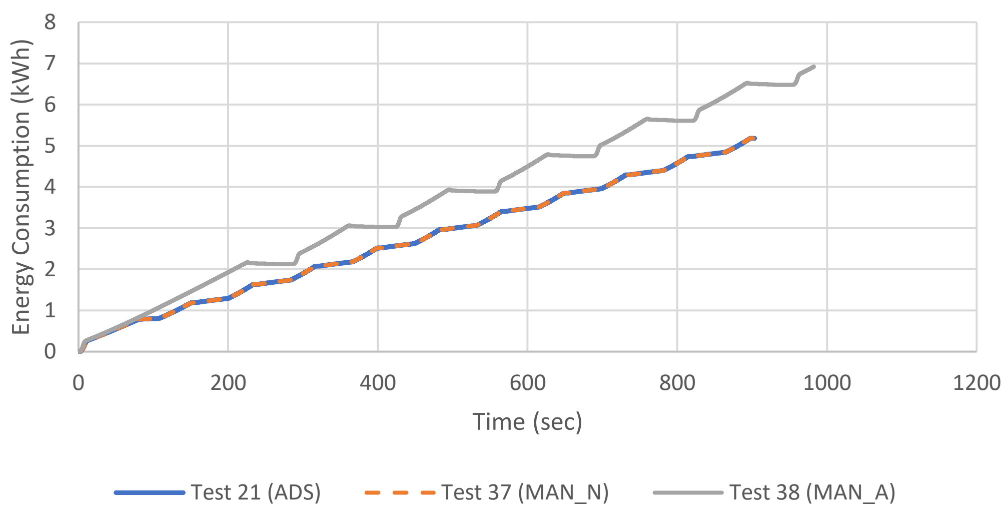

Fig. 6.24. Energy Consumption for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

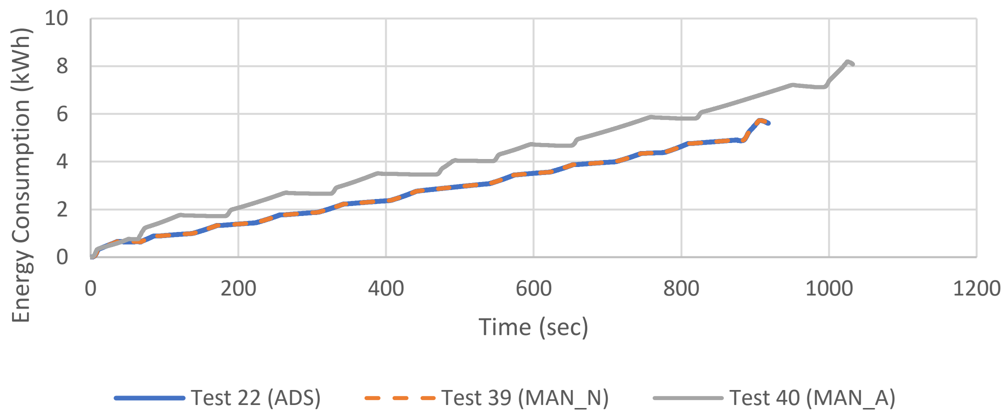

Fig. 6.25. Energy Consumption for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

The Active Lane Keep Assist feature offers a lateral control for the host Autonomous-capable EV. This feature is extremely important for ensuring safety of the host as well as the surrounding vehicles by preventing any unintended lane departures. Furthermore, ALKA offers vehicle stability by minimizing the lateral deviations from the lane center as much as possible. This is also helpful for ensuring passenger comfort.

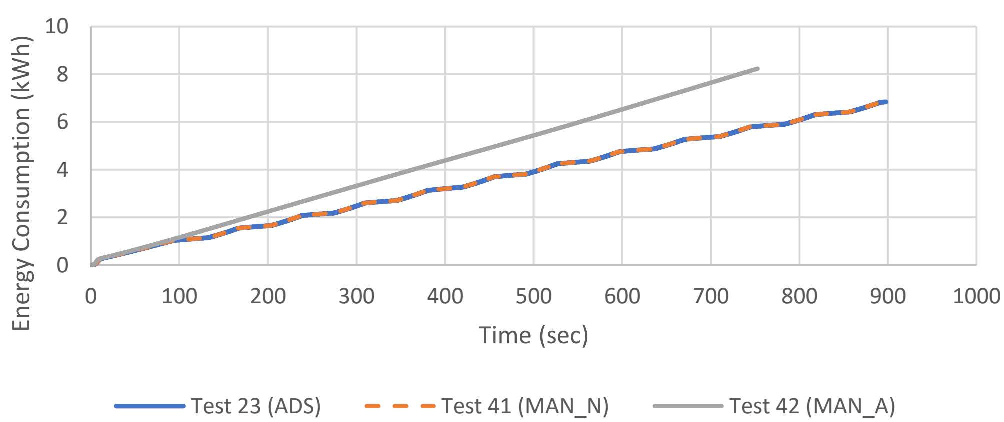

Fig. 6.26. Energy Consumption for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

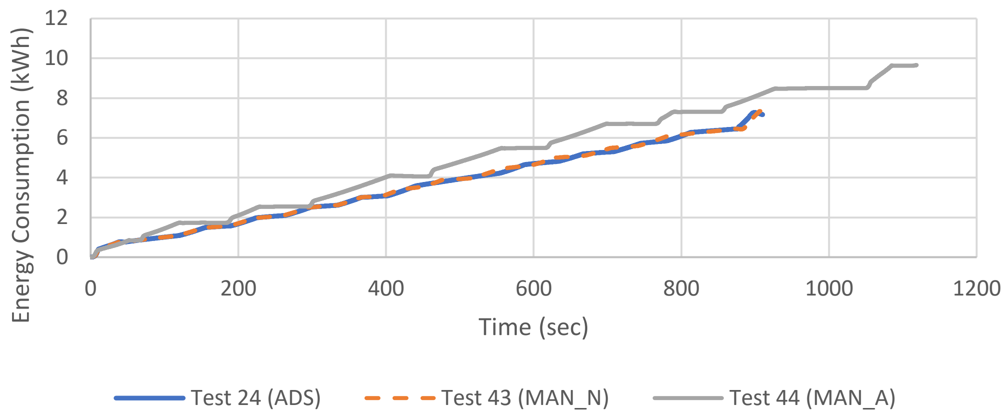

Fig. 6.27. Energy Consumption for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

Although ALKA offers immense safety, vehicle stability and passenger comfort on the road through lateral control of the vehicle by ADS, its impact on the energy consumption and hence the energy economy of the Electrified Vehicle is slightly different from the results expressed for CC and ACC which offer longitudinal vehicle control by the ADS.

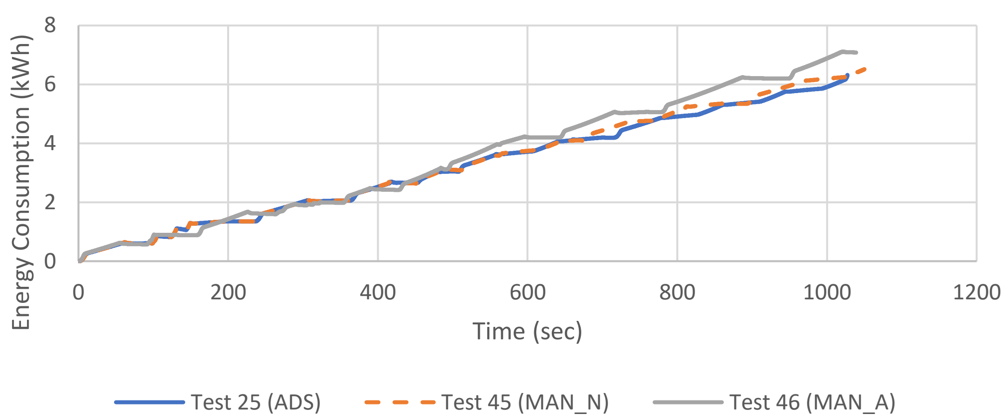

Fig. 6.28. Energy Consumption for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

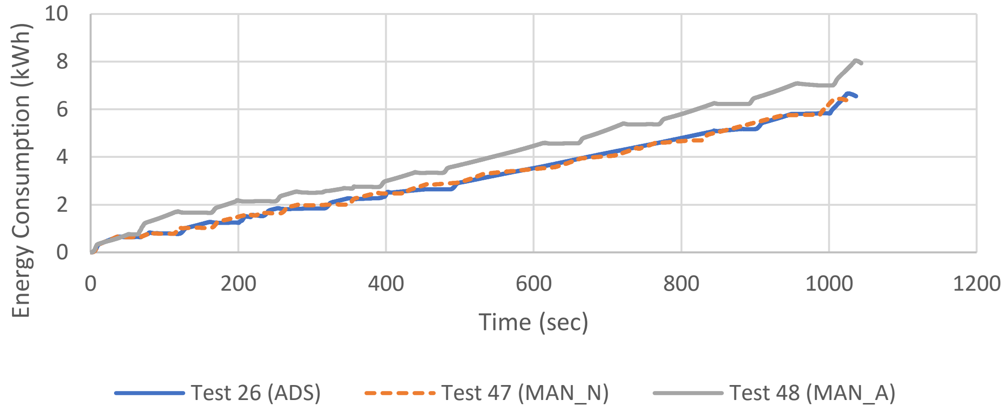

Fig. 6.29. Energy Consumption for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

The ALKA results show that the relative impact of autonomous lateral control on energy consumption compared to manual human driver, on average, is lower than the relative impact of autonomous longitudinal control, which is seen to be significantly higher. Although the profiles for ADS control are very comparable to the normal human driver, a higher energy consumption is still noticed for aggressive driver control compared with ADS. This is also because of the range of lateral deviations modeled for a normal driver versus an aggressive driver. The impact of autonomous lateral vehicle control is expected to be higher if higher deviations are encountered on the road. The lateral deviations modeled for the normal driving conditions reflected in this thesis are based on the existing literature as explained in Chapter 5 of this thesis.

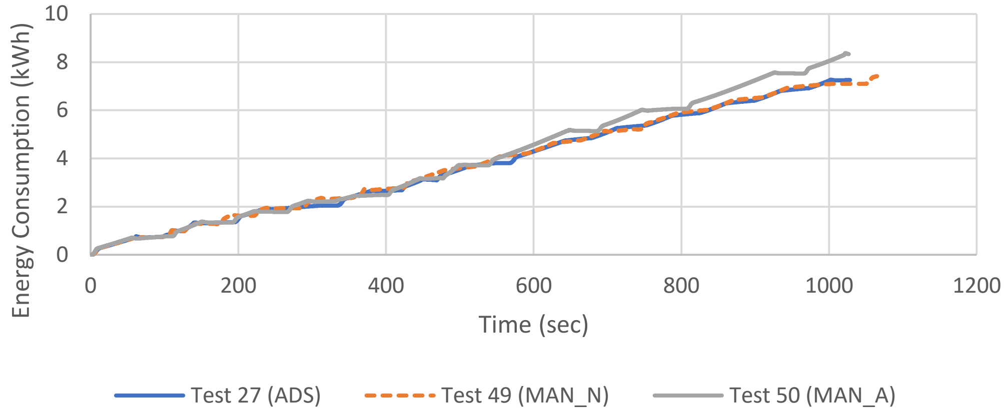

Fig. 6.30. Energy Consumption for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

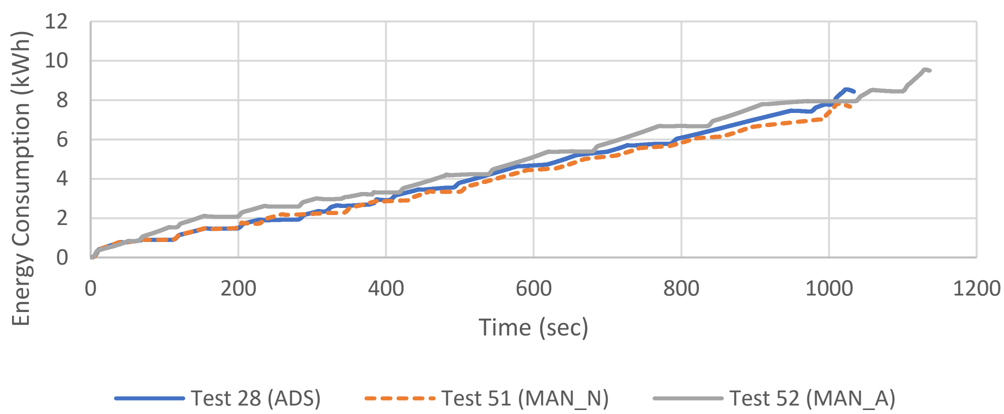

Fig. 6.31. Energy Consumption for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

Lastly, the energy consumption results for the level 4 autonomous control which is a combination of vehicle longitudinal control with ACC and AEB as well as the vehicle lateral control with ALKA in addition to the traction control for adverse weather and road conditions are shown in Fig. 6.32 to 6.39. As it can be seen from below, energy consumption was higher for human driver control, in some cases, compared to the ADS control. This is mainly due to the higher time needed under human driver control for the test Autonomous-capable EV to complete the trip duration on the road for the same driving environment conditions.

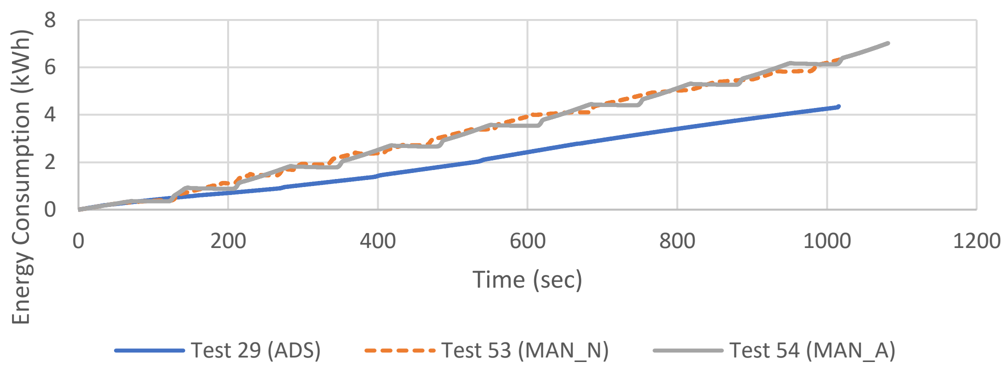

Fig. 6.32. Energy Consumption for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

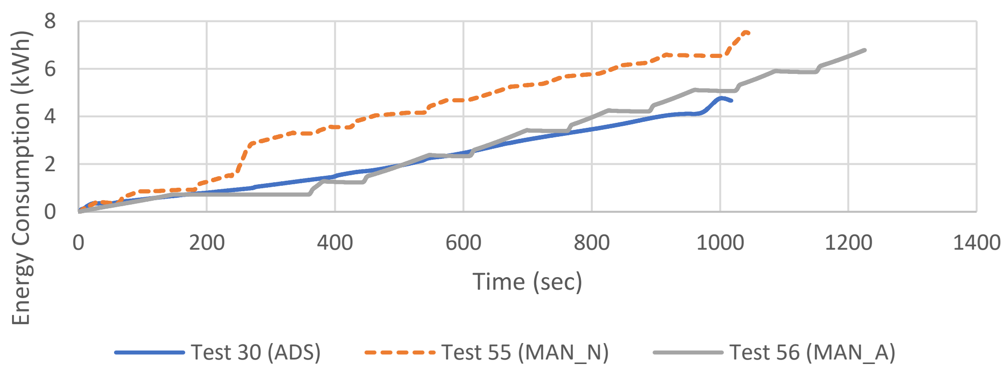

Fig. 6.33. Energy Consumption for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

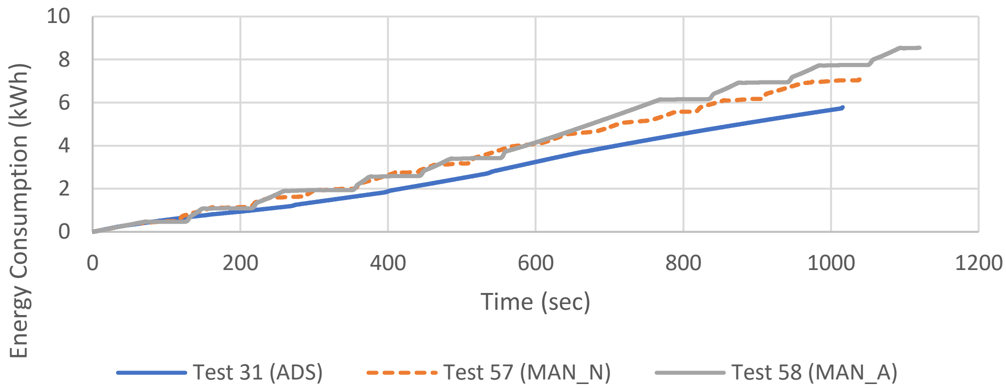

Fig. 6.34. Energy Consumption for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

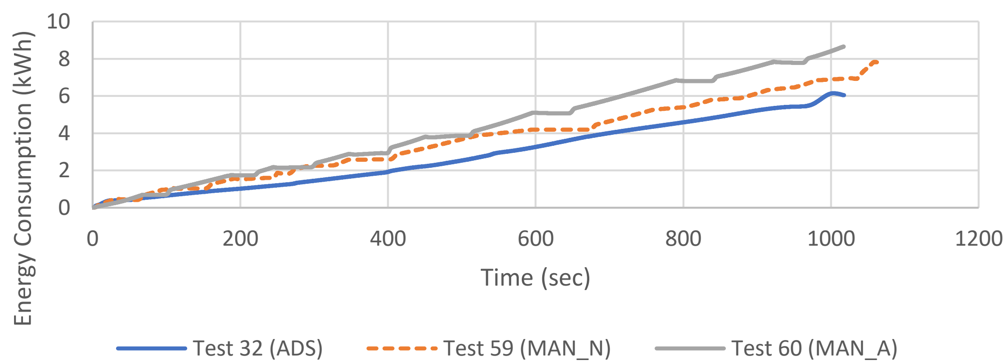

Fig. 6.35. Energy Consumption for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

These results also include an influence of the varying external conditions such as the traffic, road, and weather. Level 4 is the highest level of vehicle automation implemented in the simulations presented in this thesis. These results also demonstrate a superior vehicle performance that can be acquired through an increase of vehicle autonomy due to the decrease in overall energy consumption as well as the instantaneous fluctuations.

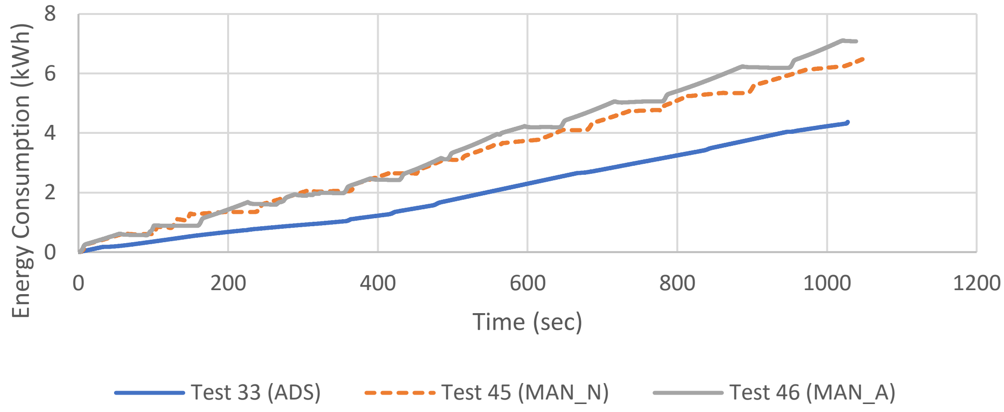

Fig. 6.36. Energy Consumption for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

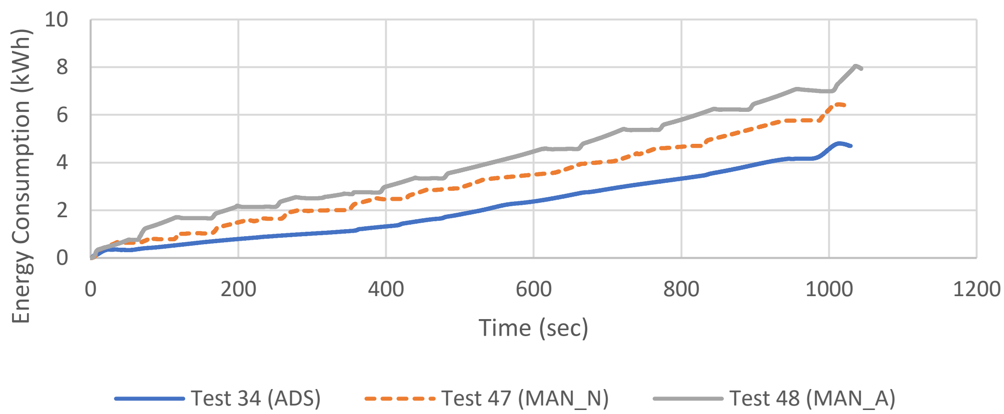

Fig. 6.37. Energy Consumption for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

Due to the relatively lower influence of Autonomous Vehicle lateral control and the dominating impact of the Autonomous Vehicle longitudinal control on the energy consumption and hence the EV energy economy, the results seen for level 4 autonomous control are comparable to the ACC results.

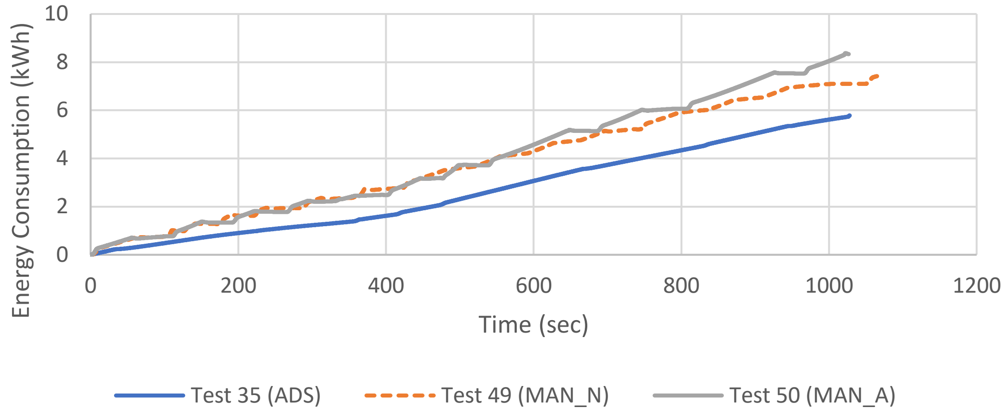

Fig. 6.38. Energy Consumption for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

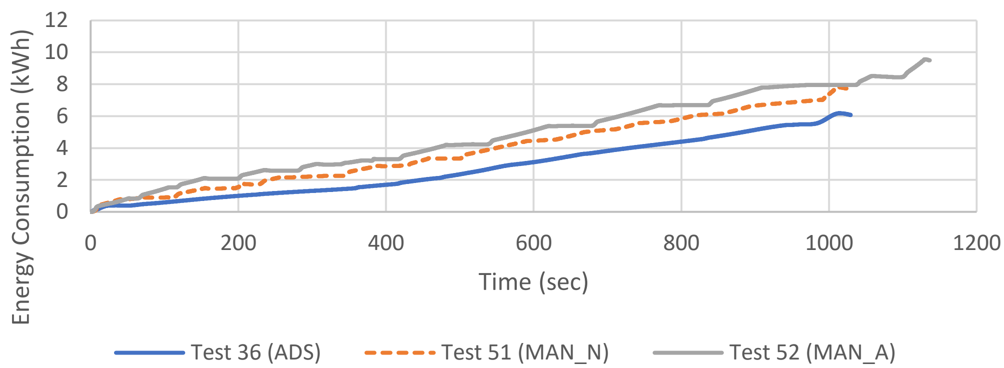

Fig. 6.39. Energy Consumption for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

In overall, the energy consumption results and analysis presented in this sub-section shows the improved vehicle performance with the increase in vehicle automation or the increased ADS responsibility.

6.2.2 Vehicle Dynamics Results

This section presents the velocity profiles acquired for the various ADS, normal human driver and the aggressive driver test cases. The velocity profiles for CC and its manual comparisons with varying external conditions can be seen in Fig. 6.40 to 6.52.

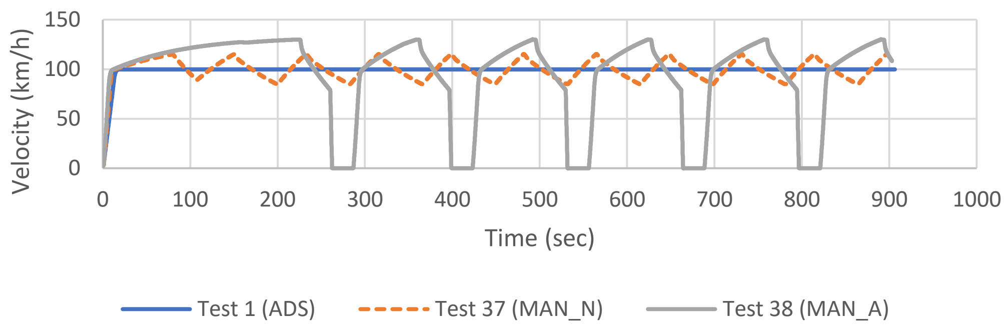

Fig. 6.40. Velocity Profiles for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

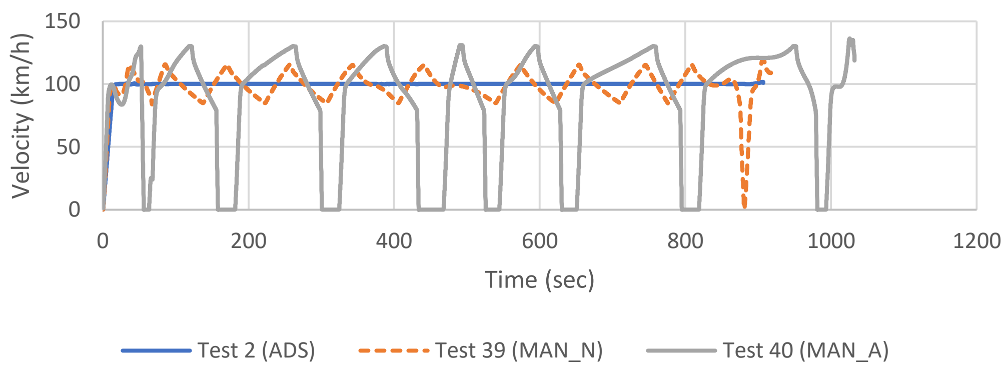

Fig. 6.41. Velocity Profiles for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

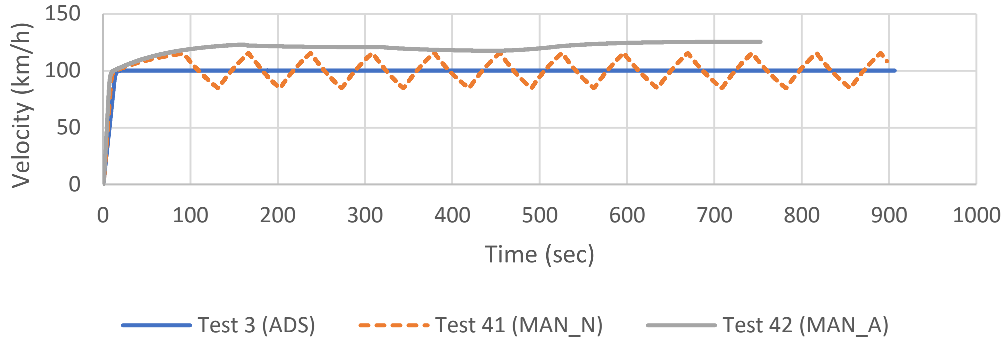

Fig. 6.42. Velocity Profiles for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

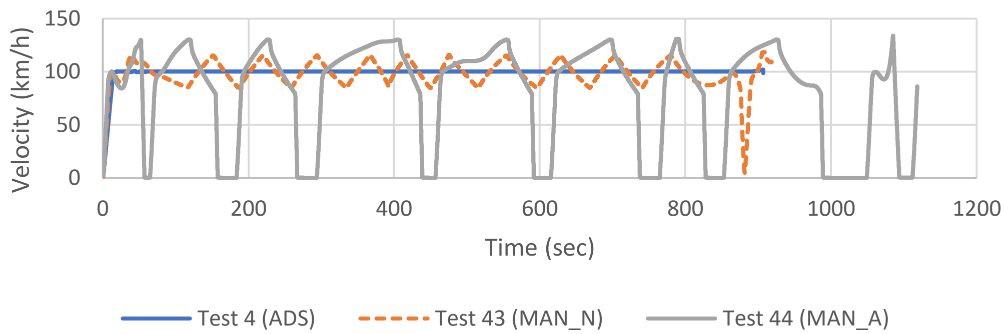

Fig. 6.43. Velocity Profiles for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

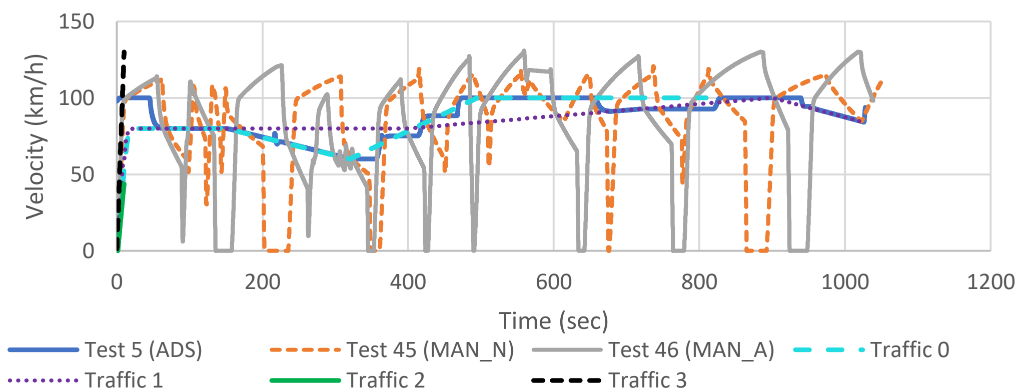

Fig. 6.44. Velocity Profiles for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

As it can be seen from these figures, the Cruise Controller is able to maintain the desired speed with minimum deviations, unlike the manual driving test cases. This efficiency of a Cruise Control to improve the Electrified Vehicle energy economy is better seen in highway driving scenarios with a streamlined traffic flow.

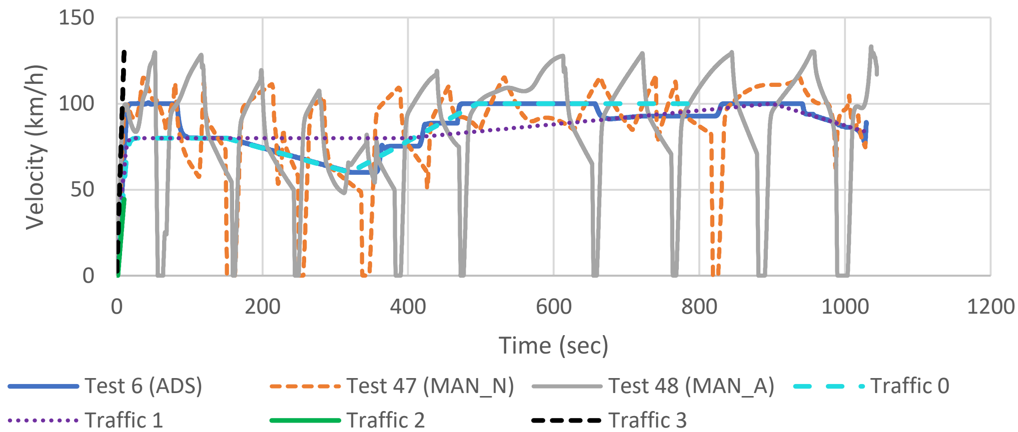

Fig. 6.45. Velocity Profiles for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

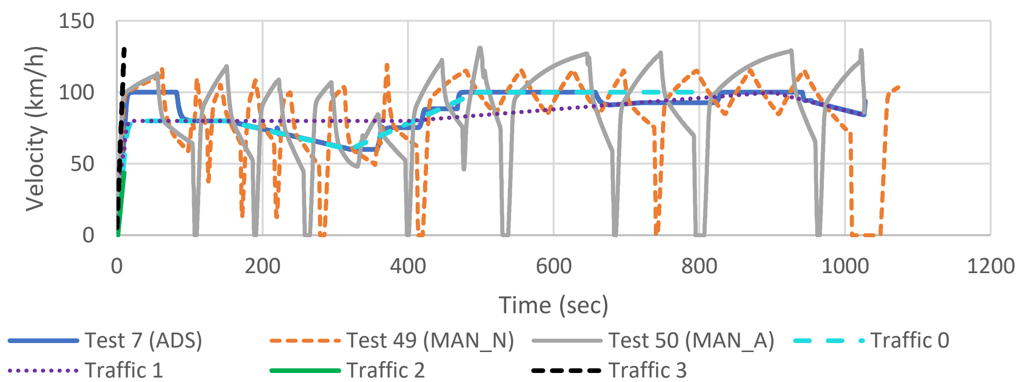

Fig. 6.46. Velocity Profiles for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

Since the sudden changes in the driving environment have to be assessed by the driver in order to brake the vehicle, during CC, it is not seen to be as efficient compared to ACC which will be discussed further. However, the benefit from CC in terms of reducing the instantaneous fluctuations compared to normal and aggressive human driver control is still evident, even in the presence of dynamic traffic.

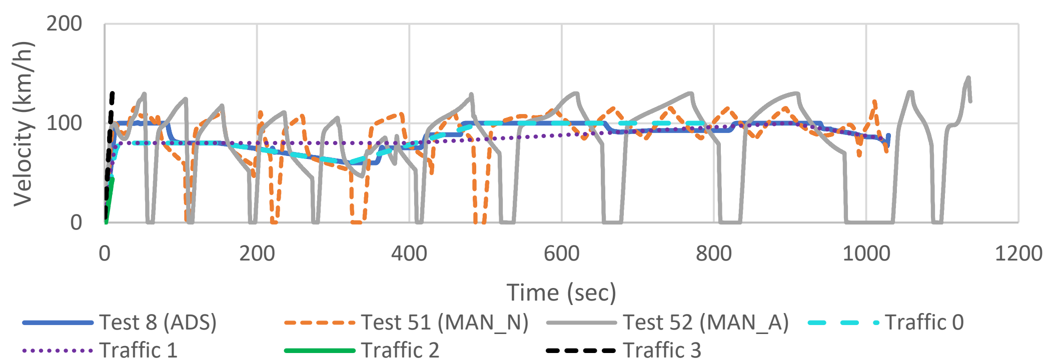

Fig. 6.47. Velocity Profiles for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

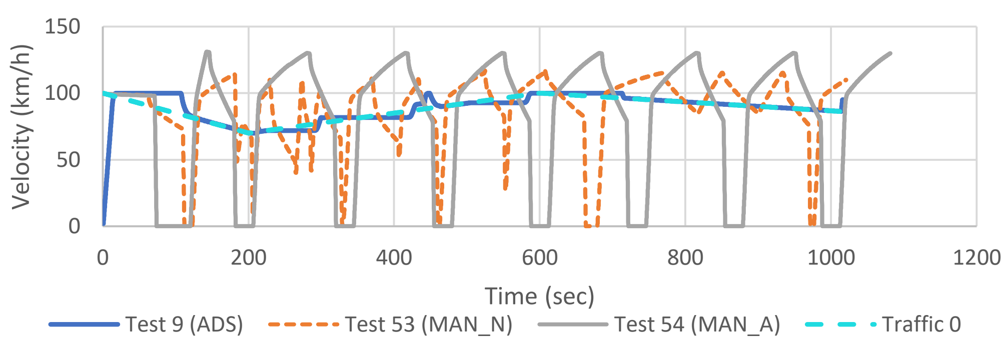

Fig. 6.48. Velocity Profiles for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

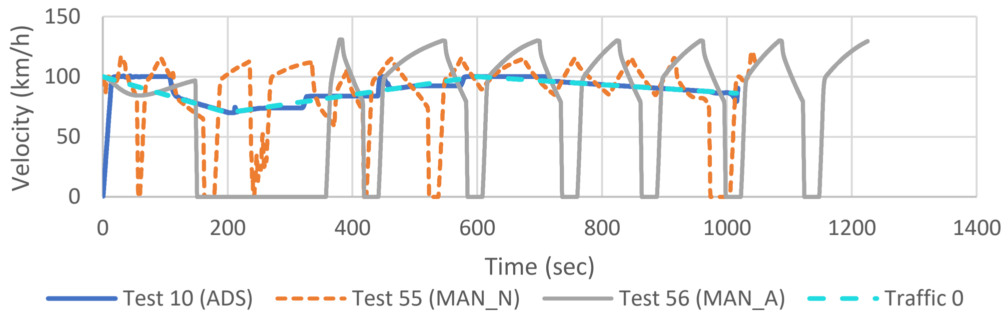

Fig. 6.49. Velocity Profiles for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

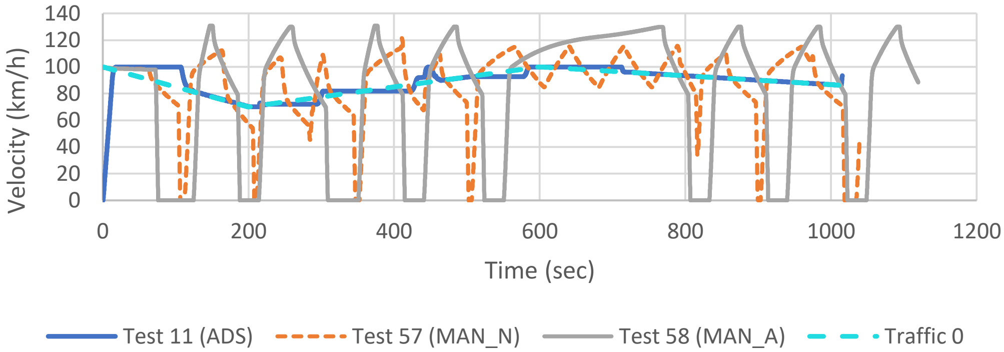

Fig. 6.50. Velocity Profiles for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

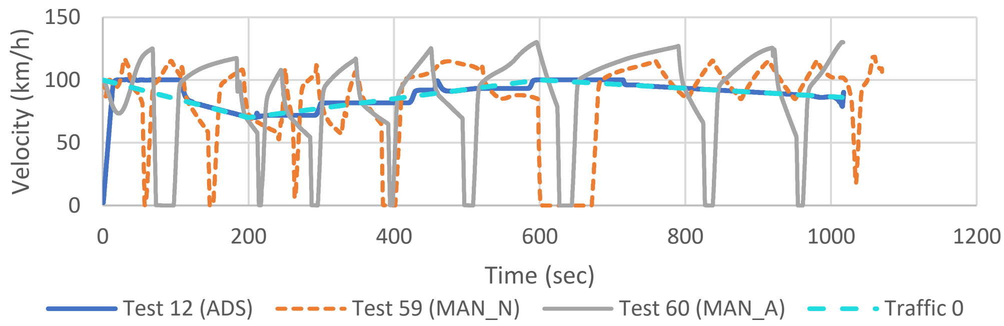

Fig. 6.51. Velocity Profiles for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

The results for the Adaptive Cruise Control in combination with the Automated Emergency Braking is shown in Fig. 6.52 to 6.59. These test cases present the ACC controller with varying combinations of dynamic traffic as described previously in Chapter 5 of this thesis.

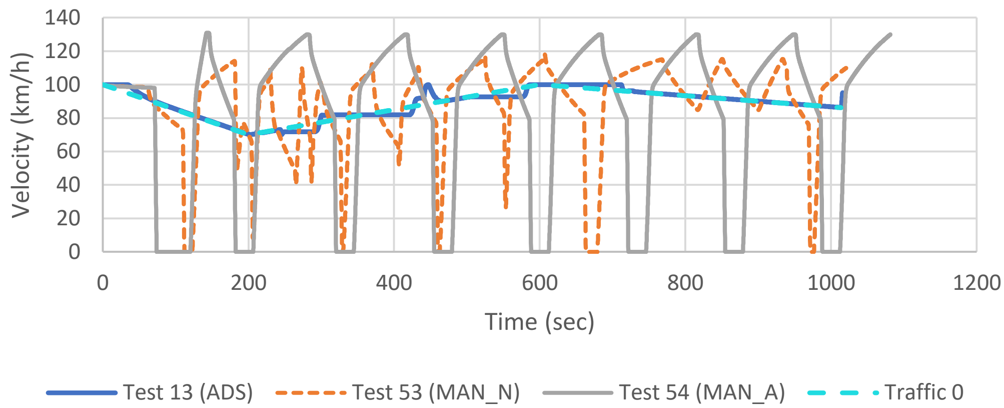

Fig. 6.52. Velocity Profiles for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

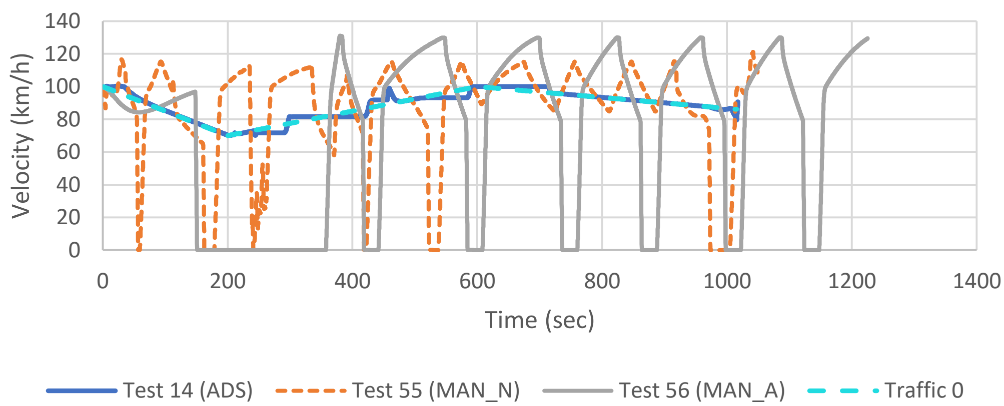

Fig. 6.53. Velocity Profiles for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

Furthermore, the different road and weather conditions are also tested to verify the hypothesis. In all the cases, the autonomous longitudinal control offered through ACC has been able to better meet the requirements of the dynamic driving environment compared to both the normal and the aggressive driver control.

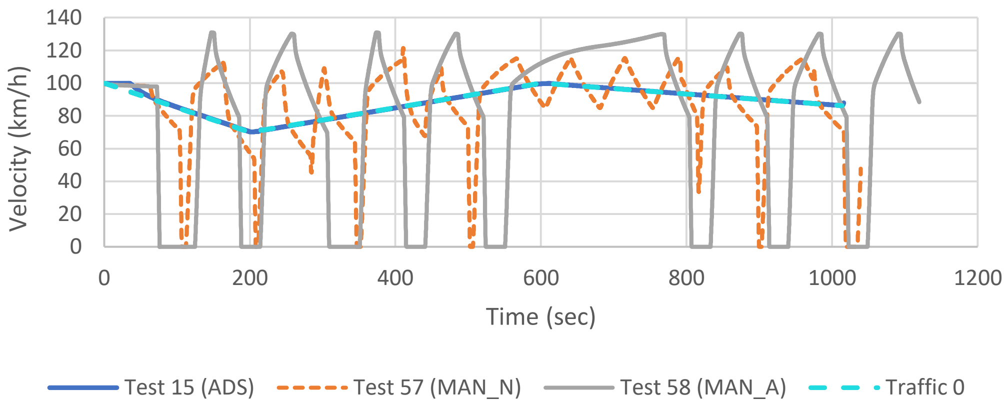

Fig. 6.54. Velocity Profiles for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

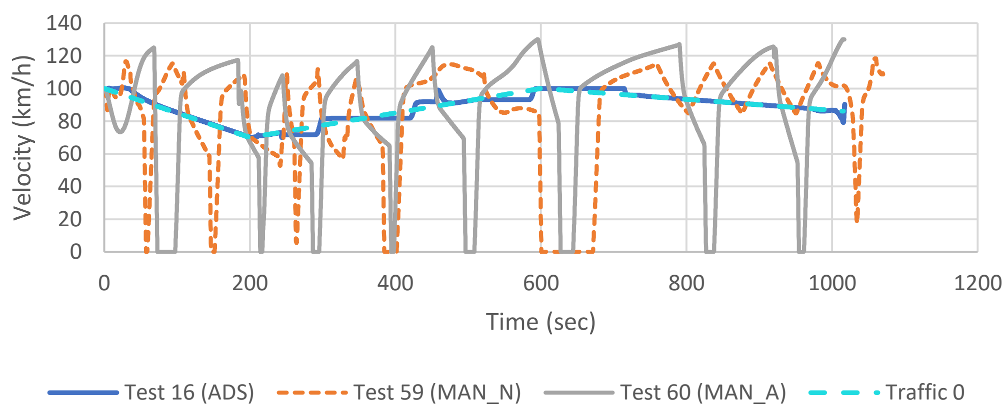

Fig. 6.55. Velocity Profiles for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

In addition, the instantaneous fluctuations are also seen to be relatively lower for the ADS control resulting in a smoother or more streamlined profile. Also, when the ACC test cases are compared with the CC test cases, the former has been seen to outperform the latter in terms of the vehicle dynamics results as well.

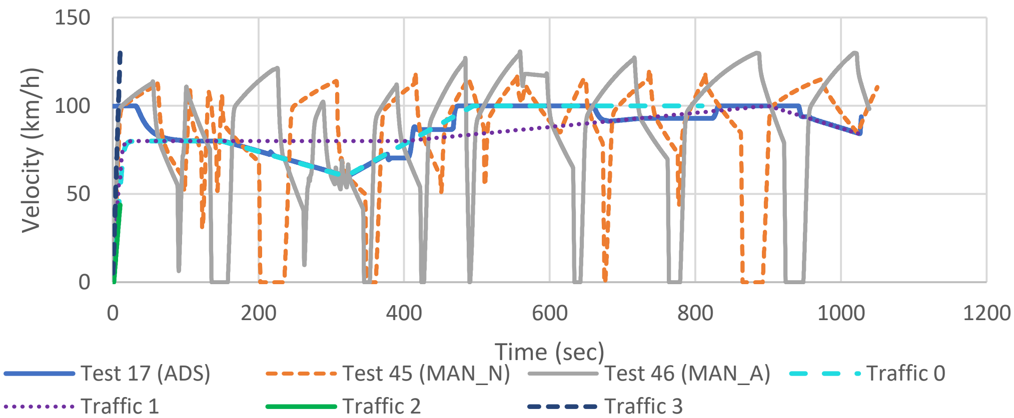

Fig. 6.56. Velocity Profiles for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

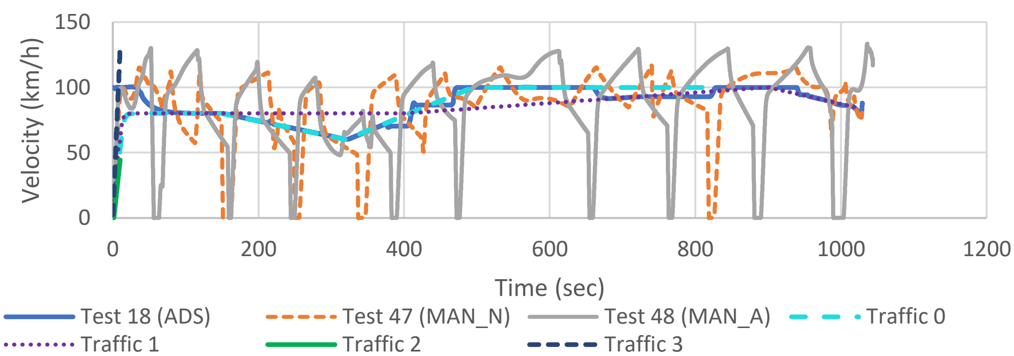

Fig. 6.57. Velocity Profiles for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

This demonstrates the reasoning behind a better energy economy with an increased vehicle automation for longitudinal vehicle control. Since, both the dynamic driving environment recognition as well as reaction in terms of the throttle and braking behavior are performed by the ADS, the EV performance is seen to be better with ACC test cases compared to the CC where the dynamic environment detection and reaction are partially performed by the human driver.

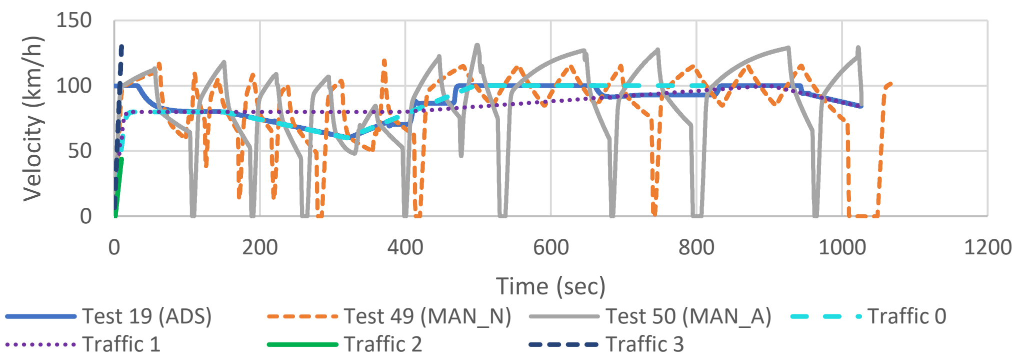

Fig. 6.58. Velocity Profiles for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

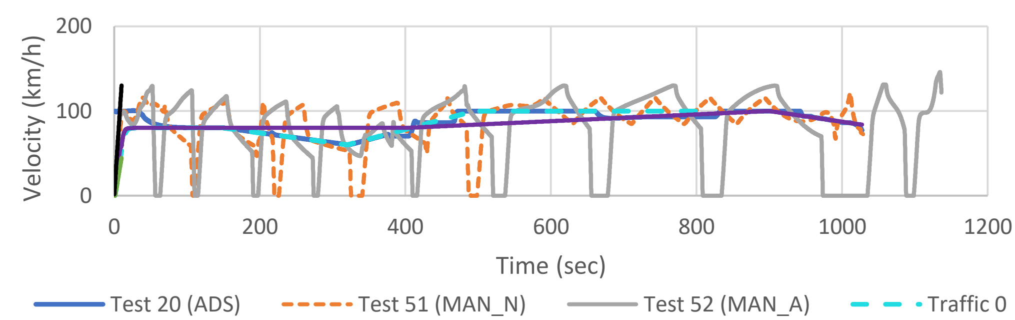

Fig. 6.59. Velocity Profiles for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

The results acquired for the ALKA test cases and their manual human driver comparisons can be seen in Fig. 6.60 to 6.67. In the ADS based test cases for ALKA, the longitudinal vehicle control is still assumed to be performed by a normal human driver as described in Chapter 5. This is shown through the comparable graphs for the ADS and normal human driver velocity profiles. The difference, however, compared to the aggressive driving results is also evident.

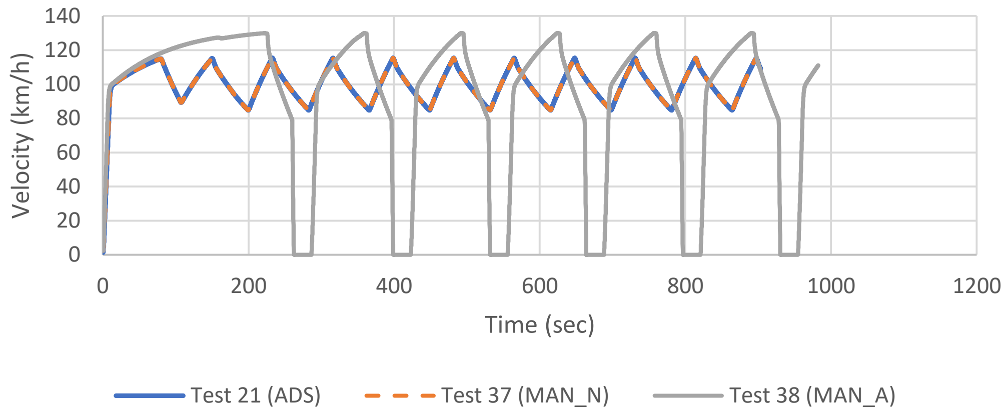

Fig. 6.60. Velocity Profiles for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

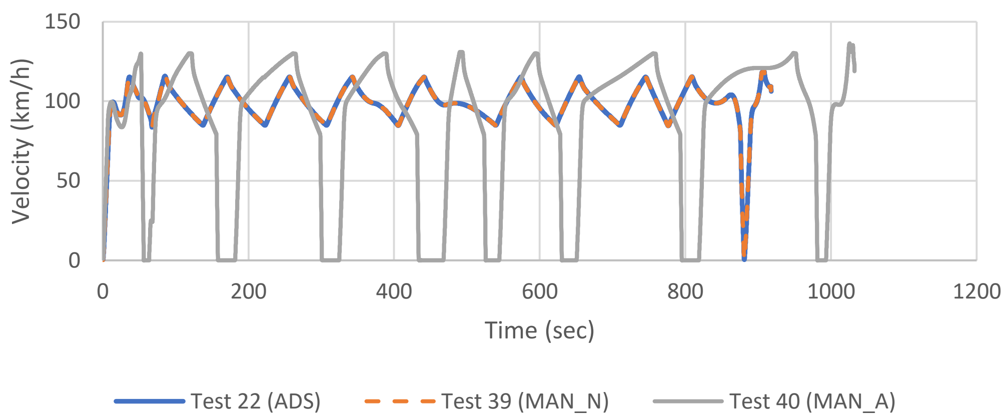

Fig. 6.61. Velocity Profiles for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

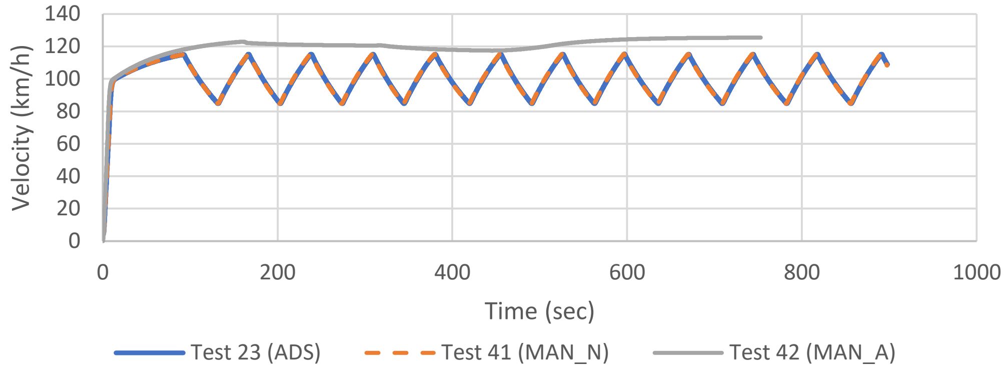

Fig. 6.62. Velocity Profiles for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

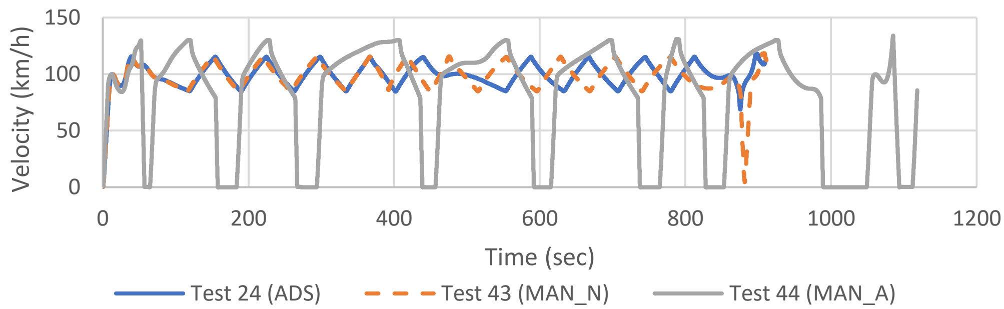

Fig. 6.63. Velocity Profiles for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

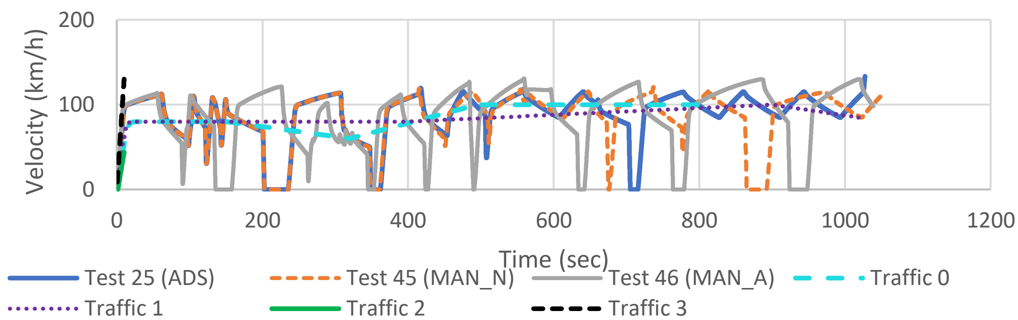

Fig. 6.64. Velocity Profiles for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

Furthermore, despite of normal driver controlling the longitudinal maneuvers of the Autonomous-capable EV during autonomous lateral vehicle control, there are some deviations noticed in the results for ADS versus normal human driver. This is mainly seen when one or multiple external conditions are modeled to be non-ideal. The discrepancy arises from the different controls offered through the three combinations - lateral control with ADS and longitudinal control with the normal human driver, lateral and longitudinal control with a normal human driver and lateral and longitudinal control with an aggressive driver.

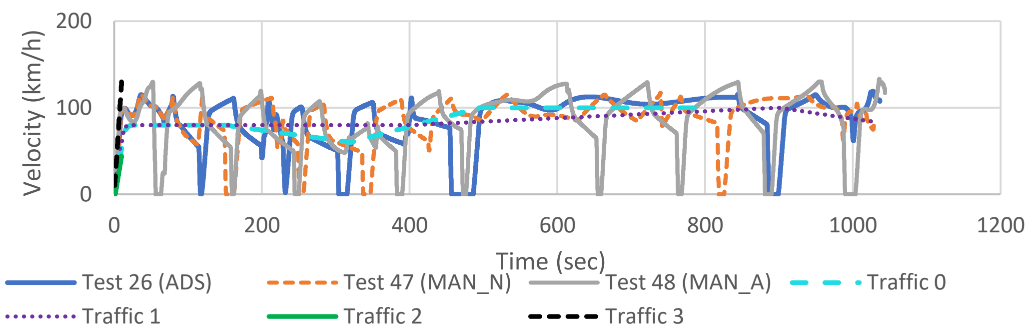

Fig. 6.65. Velocity Profiles for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

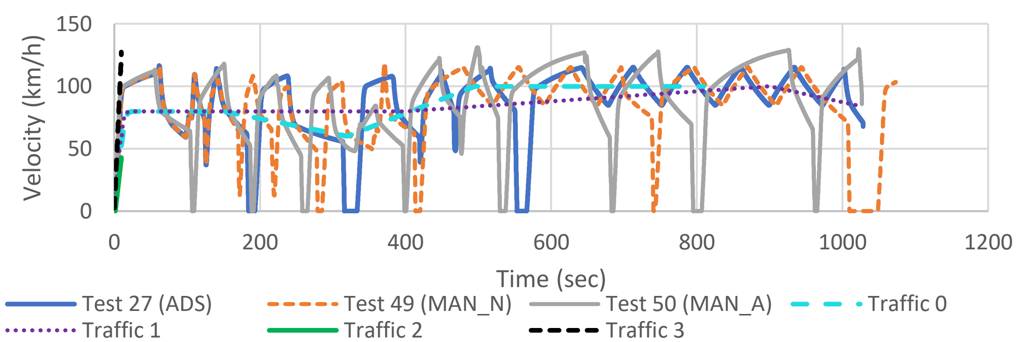

Fig. 6.66. Velocity Profiles for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

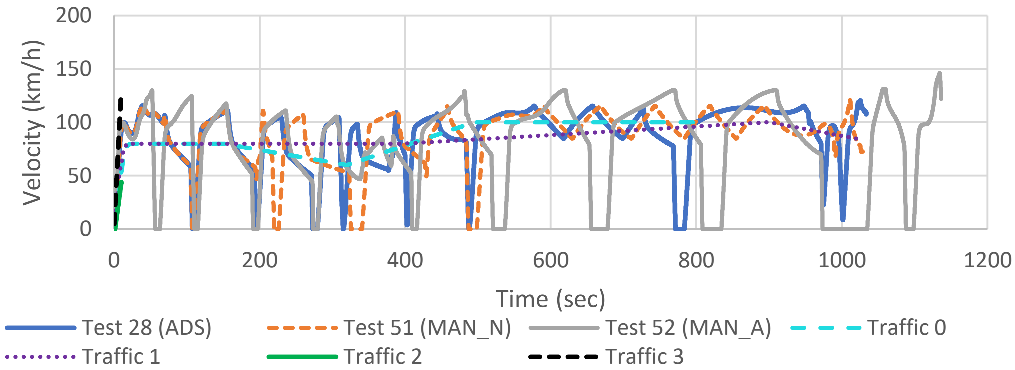

Fig. 6.67. Velocity Profiles for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

Lastly, the vehicle dynamics results for the level 4 autonomous control can be seen in Fig. 6.68 to 6.75. These results also include the variation in the external conditions such as traffic, weather, and road. These results show the tracking of the traffic objects performed with minimal deviations between the expected and the current velocity profiles.

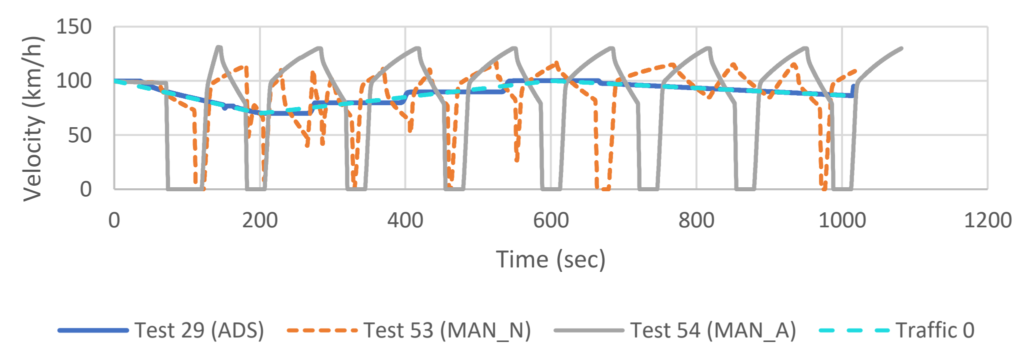

Fig. 6.68. Velocity Profiles for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

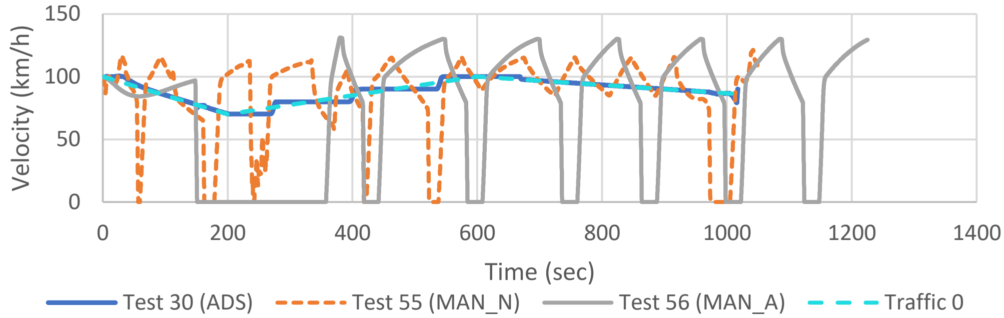

Fig. 6.69. Velocity Profiles for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

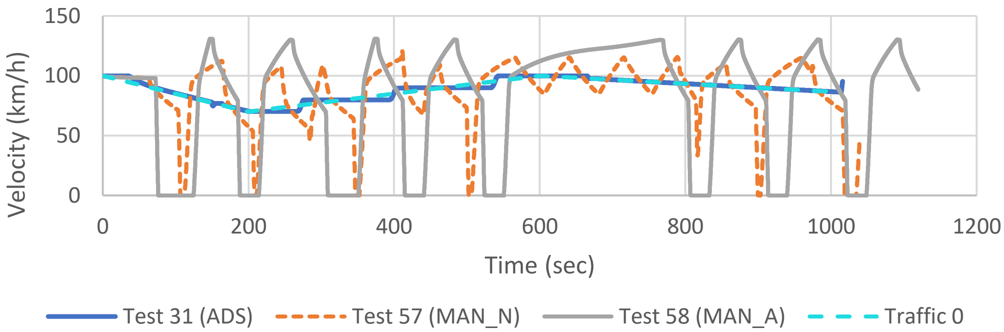

Fig. 6.70. Velocity Profiles for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

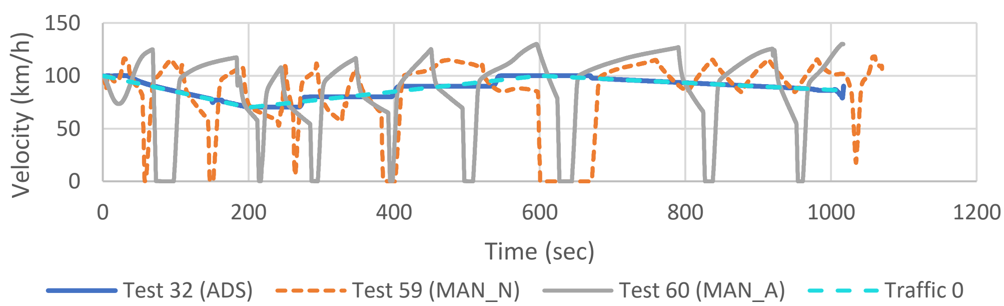

Fig. 6.71. Velocity Profiles for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons (including traffic).

In addition, it can also be seen that the traction control ADAS feature provides an extra support especially during the test cases with adverse road and weather conditions by preventing the slipping of the vehicle due to wheel spins which can affect both the lateral stability and the longitudinal control of the vehicle.

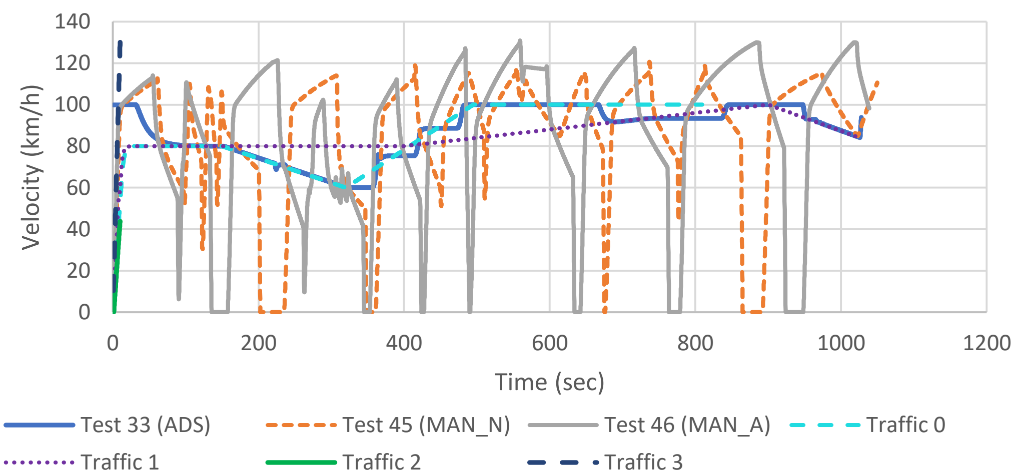

Fig. 6.72. Velocity Profiles for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

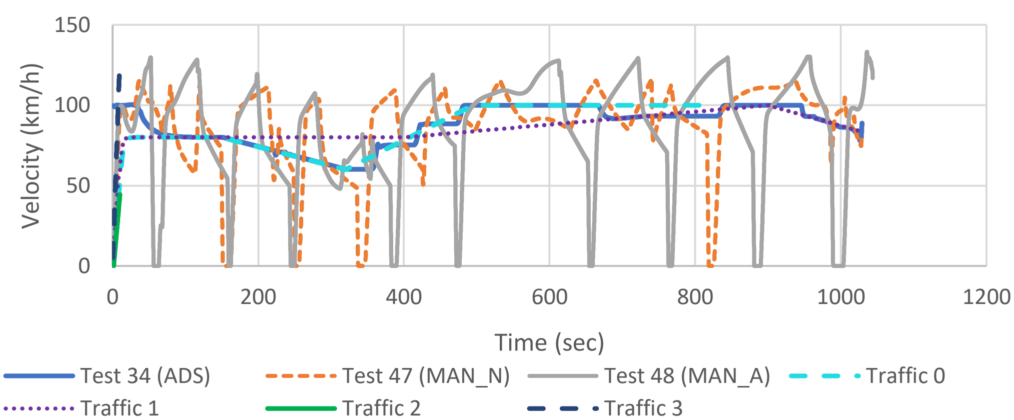

Fig. 6.73. Velocity Profiles for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

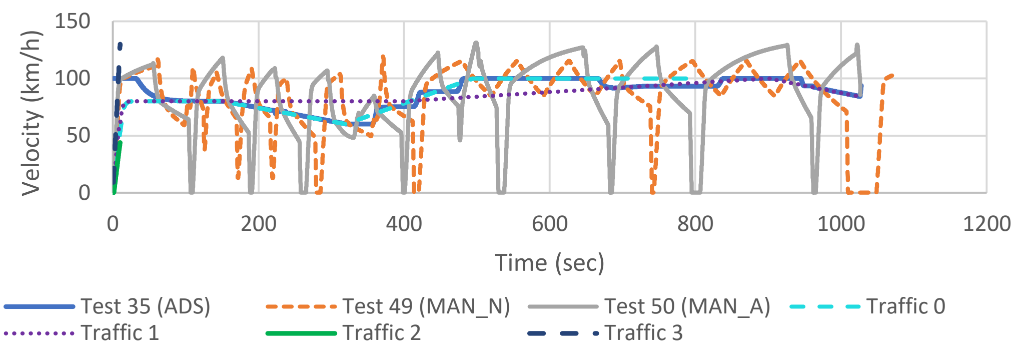

Fig. 6.74. Velocity Profiles for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

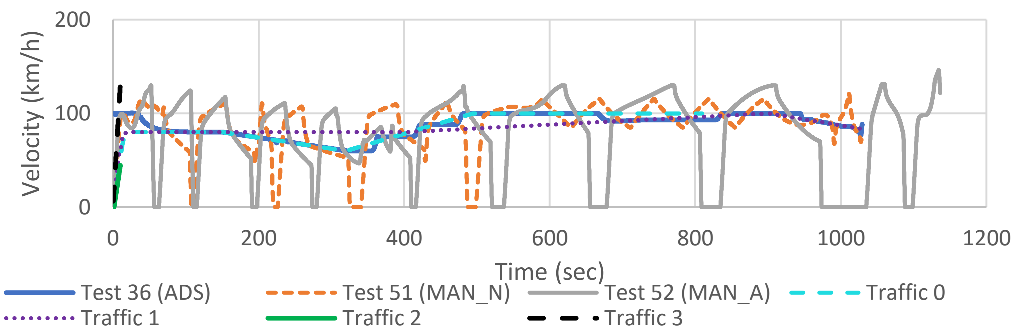

Fig. 6.75. Velocity Profiles for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons (including traffic).

In overall, the vehicle dynamic results also demonstrated the optimal eco-driving and planning during ADS control compared to both the normal human driver and the aggressive driver control.

6.2.3 Electrified Vehicle Motor Results

This section presents the results for the Electrified Vehicle motor in terms of motor speed and torque. The results for test cases with Cruise Control and their corresponding manual comparisons have been shown in Fig. 6.76 to 6.99. The Electrified Vehicle motor results are studied mainly to understand the impact of Electrified Vehicle autonomy on the motor, compared to human driver control. Although, the motor speed profiles depict the same trend as the vehicle speed, the magnitude variations are important to note.

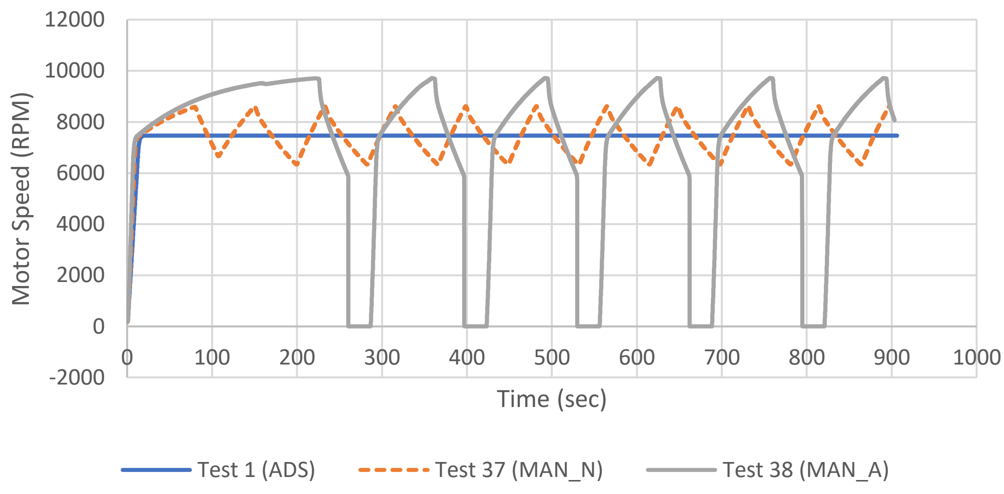

Fig. 6.76. Motor Speed for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

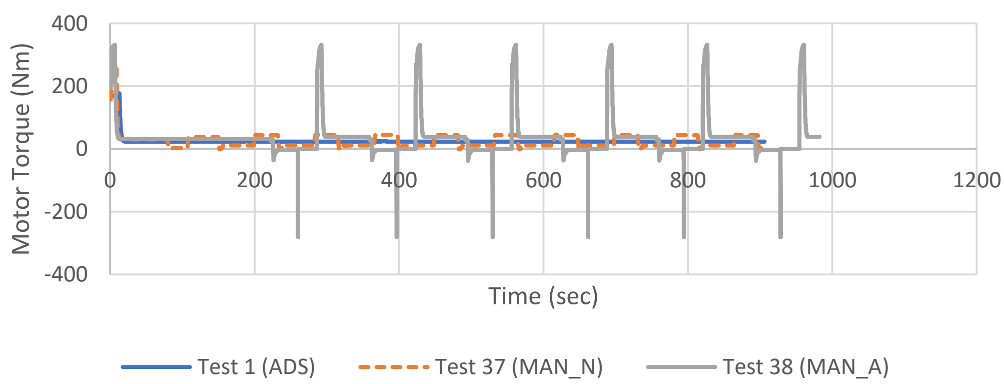

Fig. 6.77. Motor Torque for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

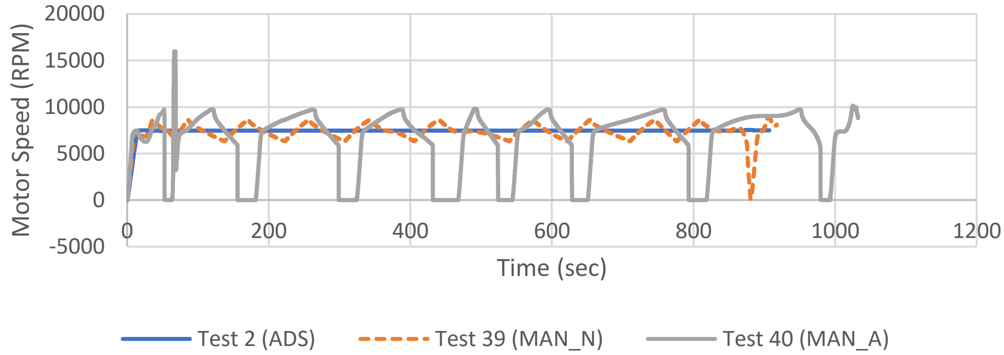

Fig. 6.78. Motor Speed for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

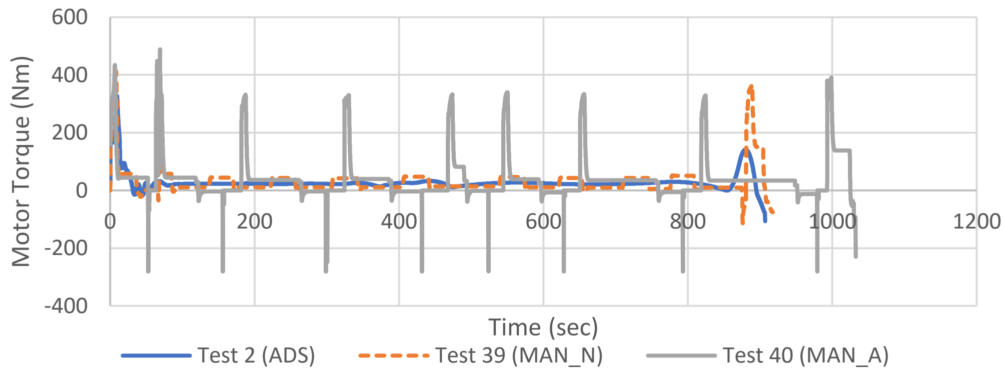

Fig. 6.79. Motor Torque for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

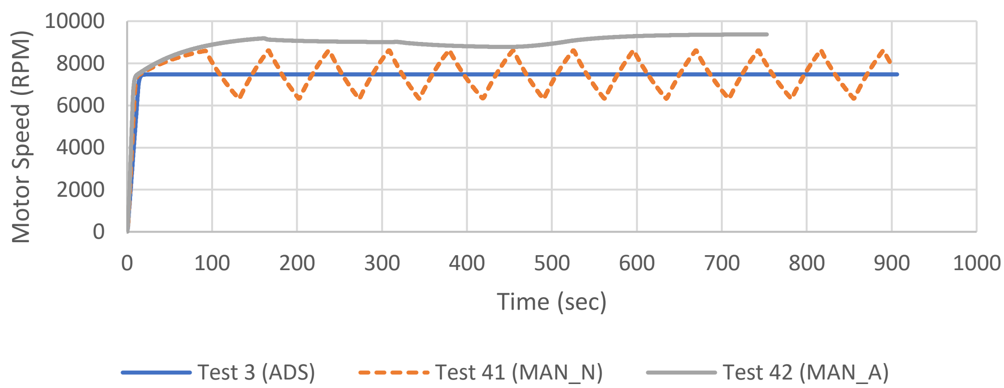

Fig. 6.80. Motor Speed for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

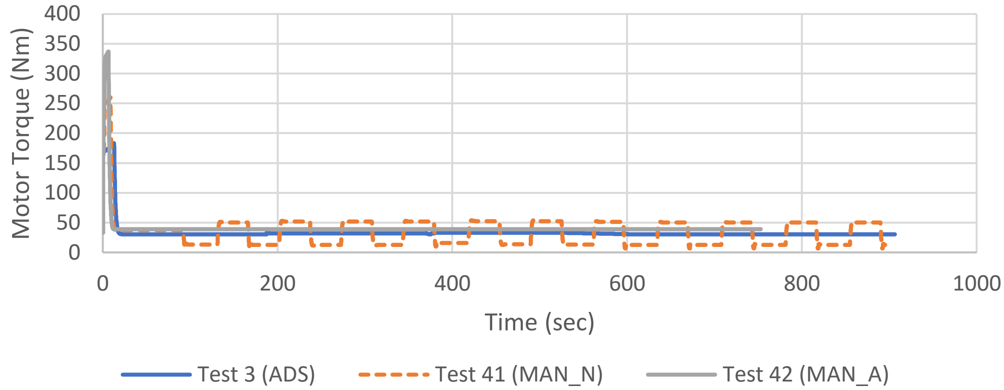

Fig. 6.81. Motor Torque for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

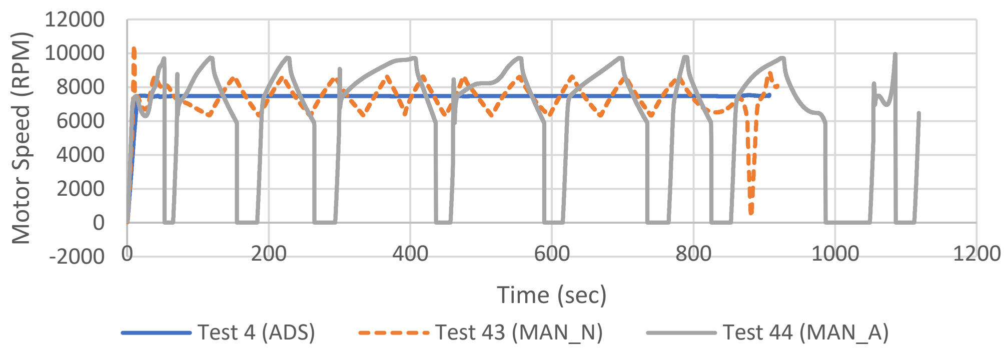

Fig. 6.82. Motor Speed for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

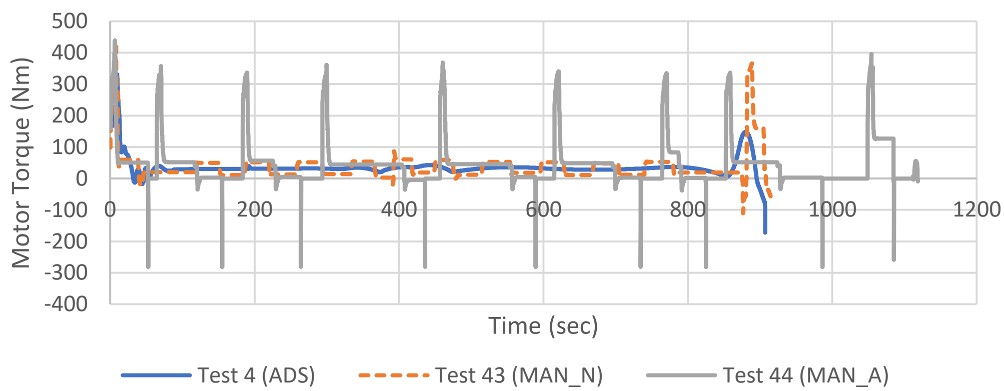

Fig. 6.83. Motor Torque for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

In overall, the instantaneous fluctuations were seen to be higher for the human driver-based test cases compared with the ADS control. Also, the magnitudes itself for motor speed and torque were seen to be higher, on average, for the aggressive driver followed by the normal human driver and lastly the ADS control.

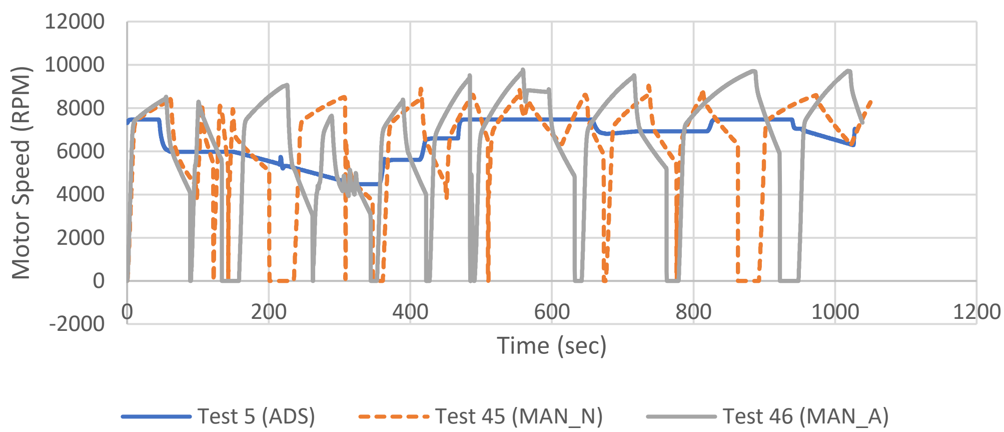

Fig. 6.84. Motor Speed for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

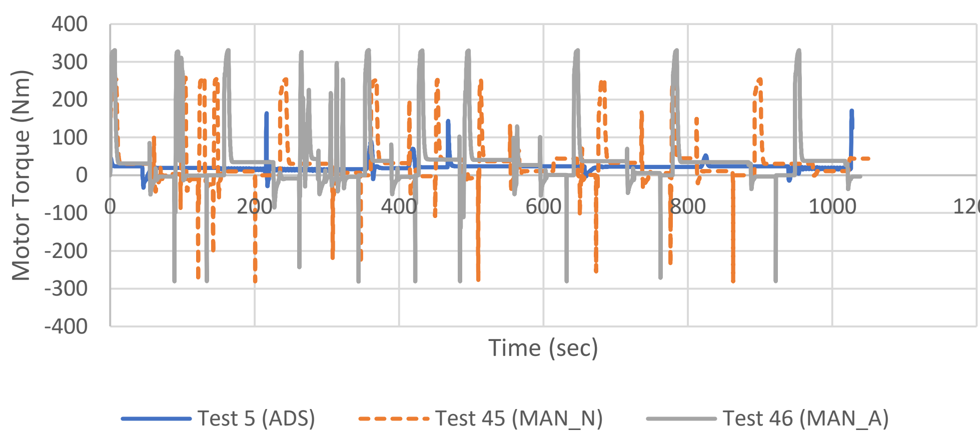

Fig. 6.85. Motor Torque for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

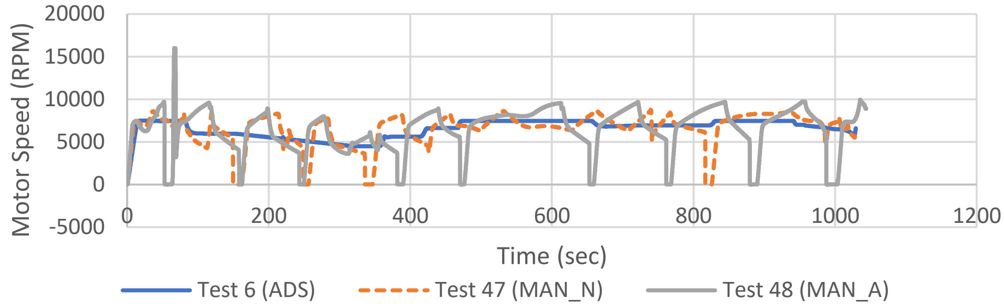

Fig. 6.86. Motor Speed for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

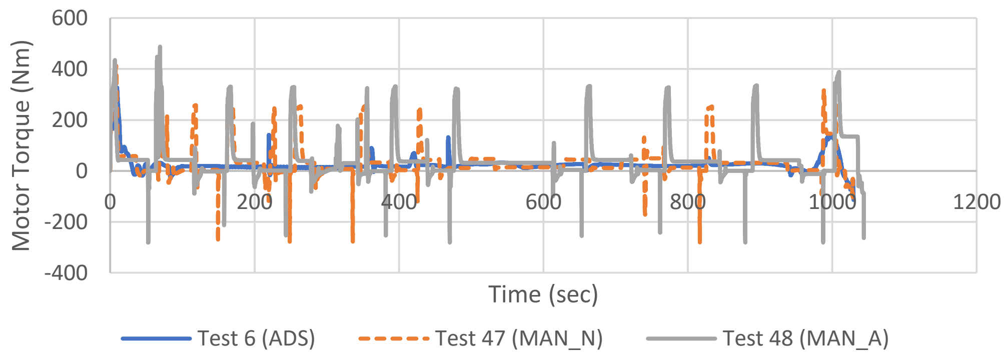

Fig. 6.87. Motor Torque for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

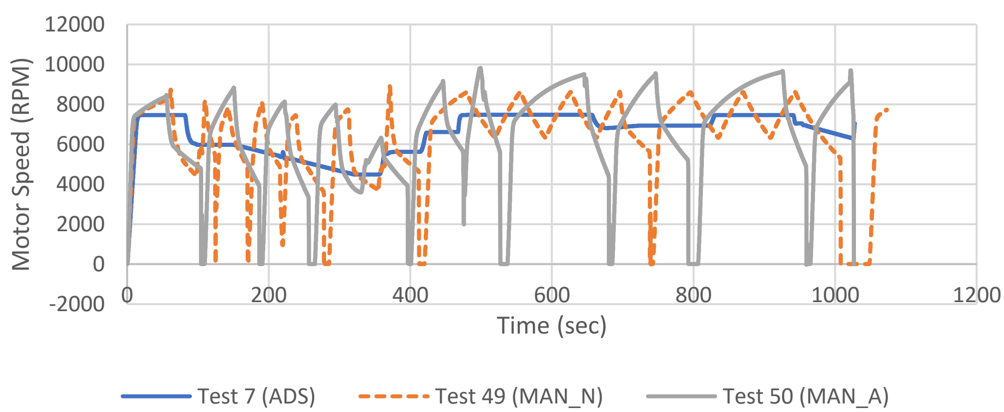

Fig. 6.88. Motor Speed for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

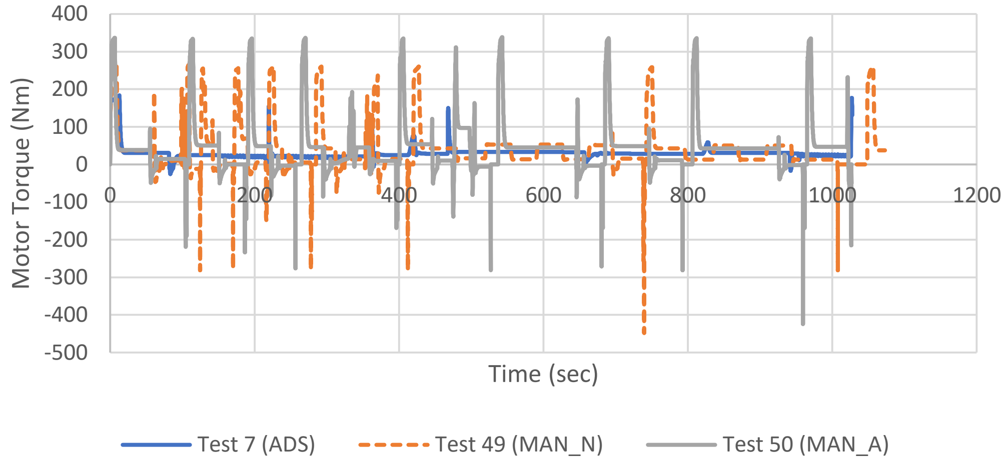

Fig. 6.89. Motor Torque for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

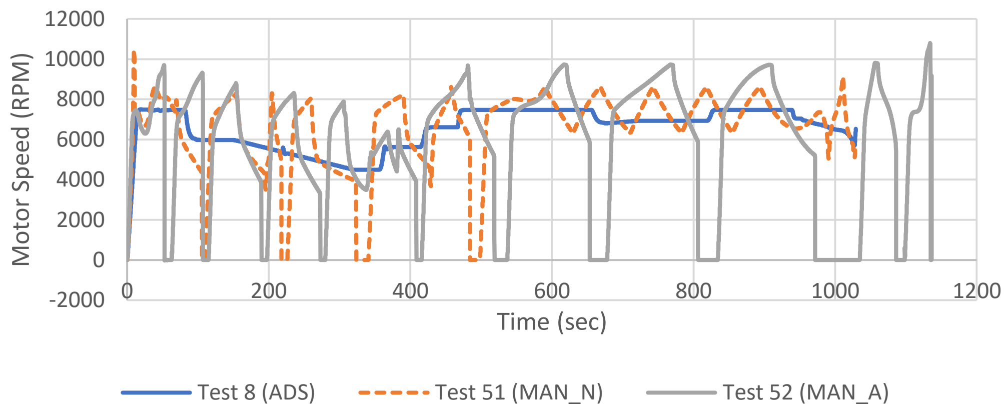

Fig. 6.90. Motor Speed for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

The aforementioned fluctuations for motor speed and torque are seen to be even higher for test cases with adverse external conditions demonstrating the extra demand on the Electrified Vehicle motor to meet the dynamic requirements of the driving environment.

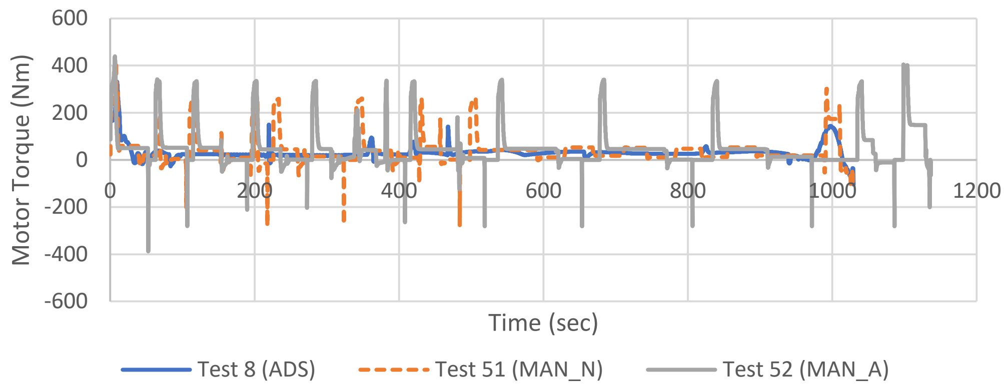

Fig. 6.91. Motor Torque for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

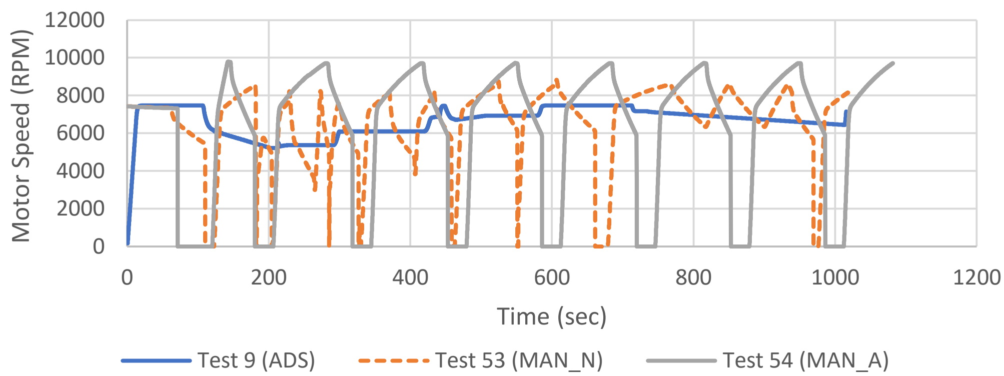

Fig. 6.92. Motor Speed for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

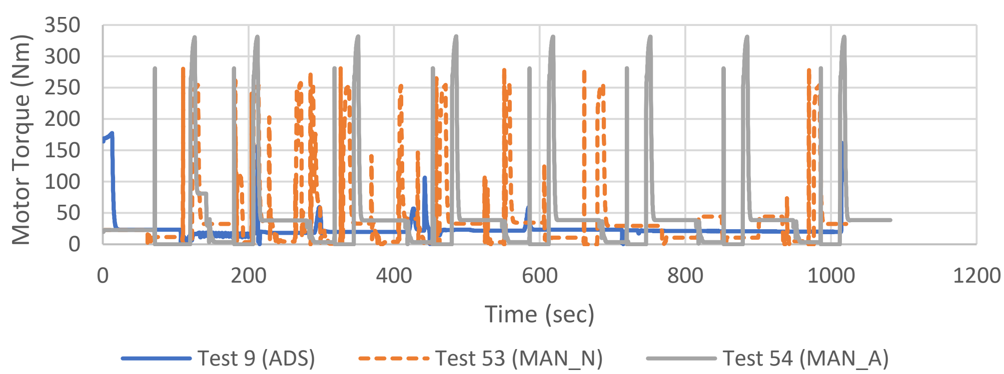

Fig. 6.93. Motor Torque for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

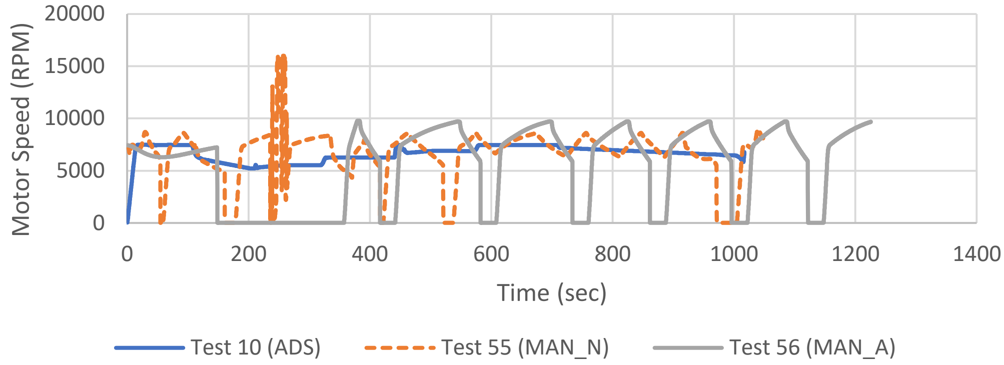

Fig. 6.94. Motor Speed for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

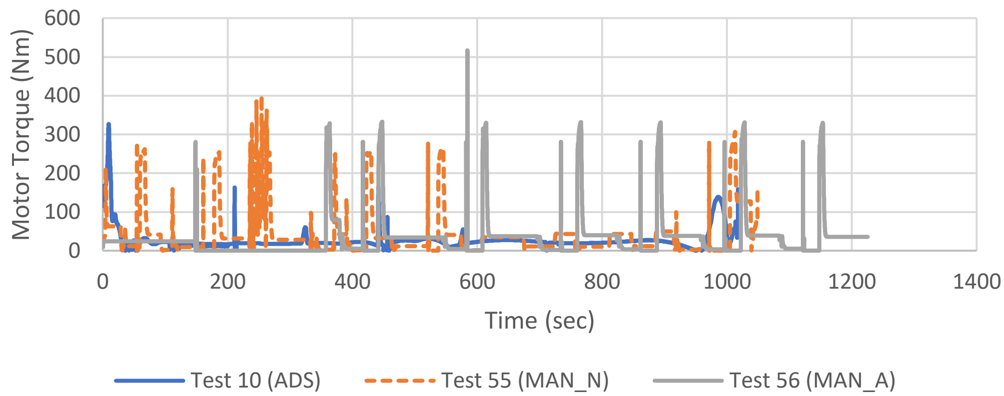

Fig. 6.95. Motor Torque for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

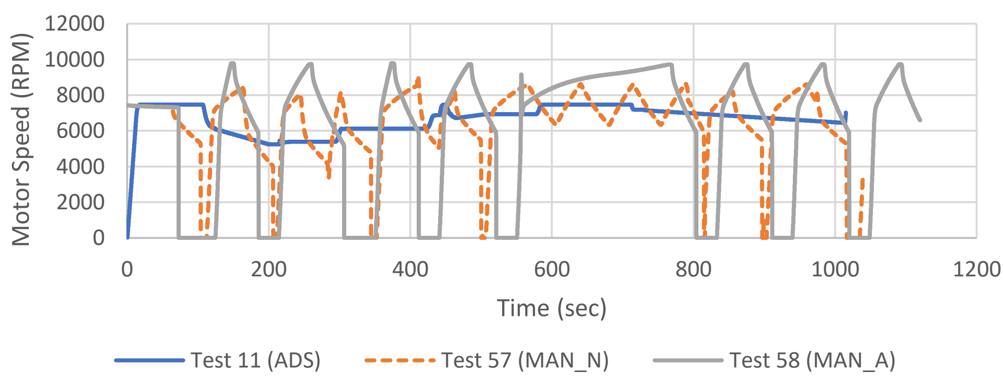

Fig. 6.96. Motor Speed for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

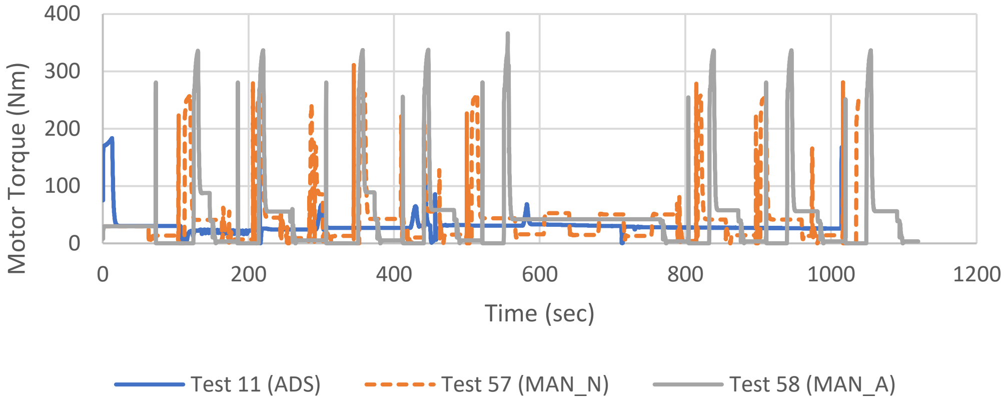

Fig. 6.97. Motor Torque for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

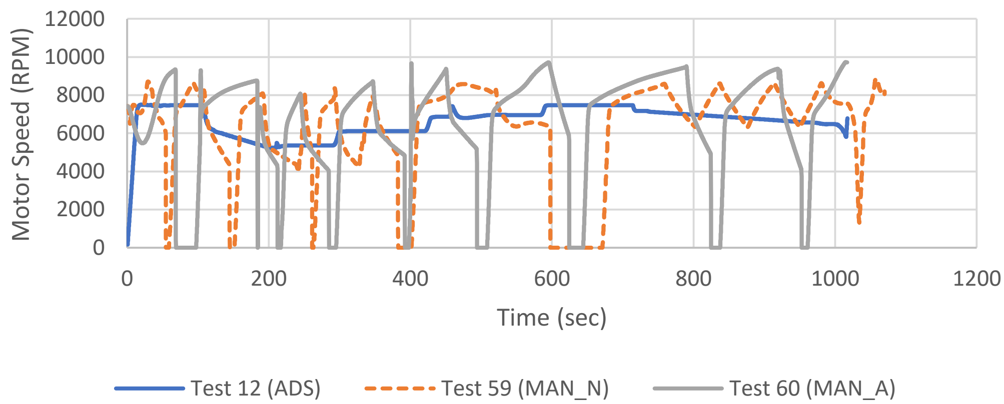

Fig. 6.98. Motor Speed for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

In overall, a more optimal operation of the Electrified Vehicle motor was seen during the test cases with ADS control offering semi-autonomous or autonomous vehicle control when compared to both the normal and the aggressive human driver. This in turn aids in having better Electrified Vehicle performance with increased autonomy.

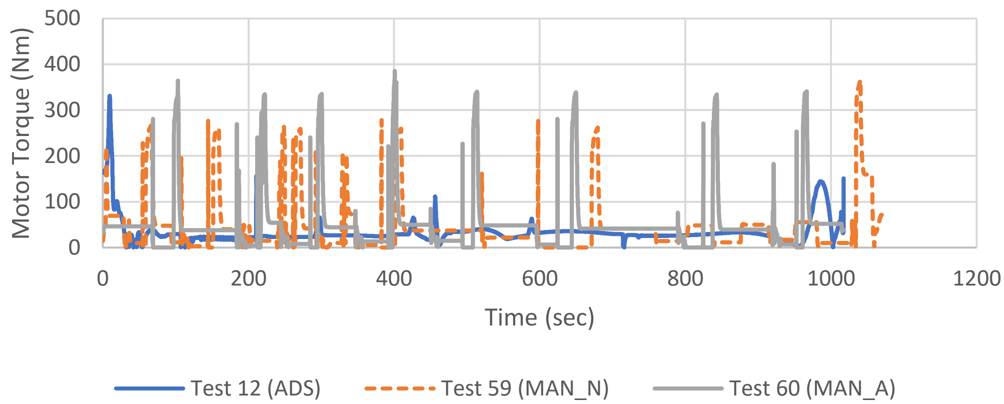

Fig. 6.99. Motor Torque for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

The motor speed and torque results for test cases with ACC and AEB control and the corresponding manual comparisons can be seen in Fig. 6.100 to 6.115. Similar to the results described in the previous sub-sections, the influence of external conditions is also considered in these results.

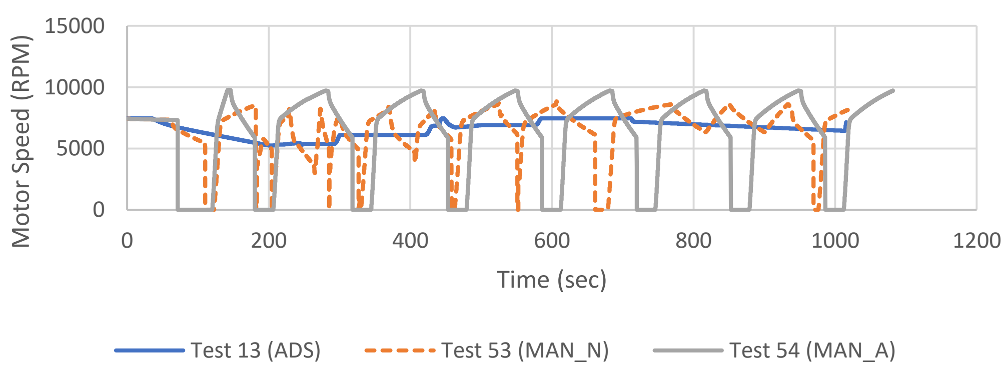

Fig. 6.100. Motor Speed for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

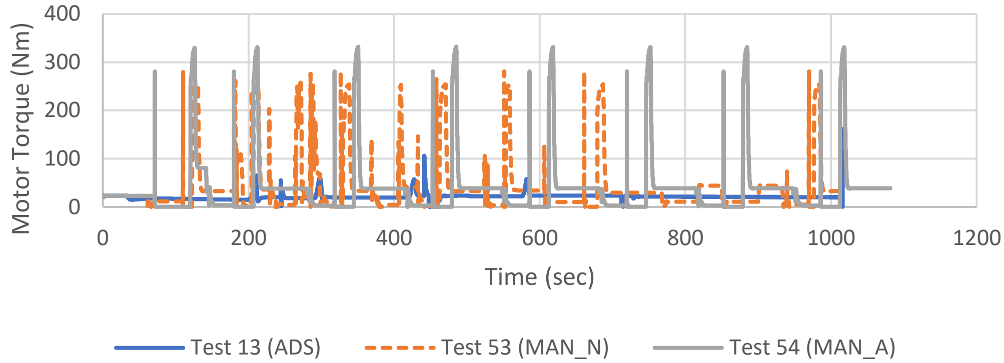

Fig. 6.101. Motor Torque for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

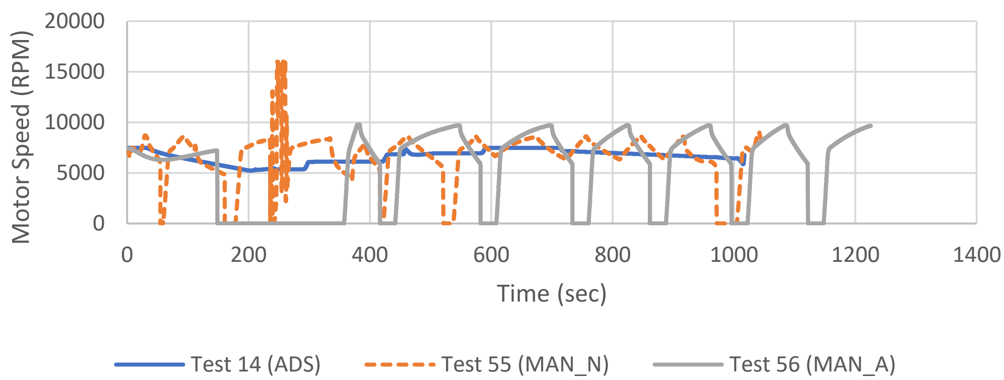

Fig. 6.102. Motor Speed for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

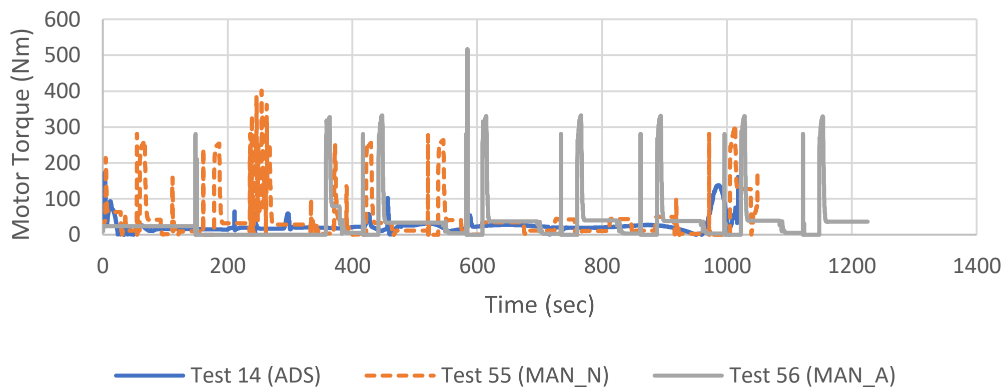

Fig. 6.103. Motor Torque for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

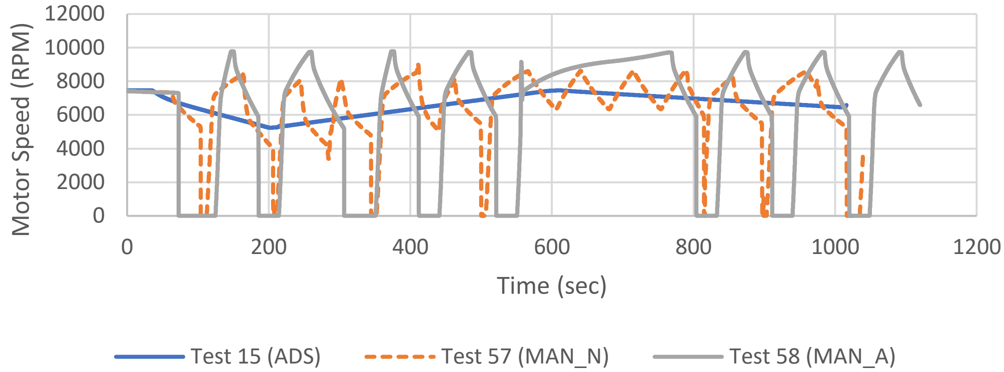

Fig. 6.104. Motor Speed for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

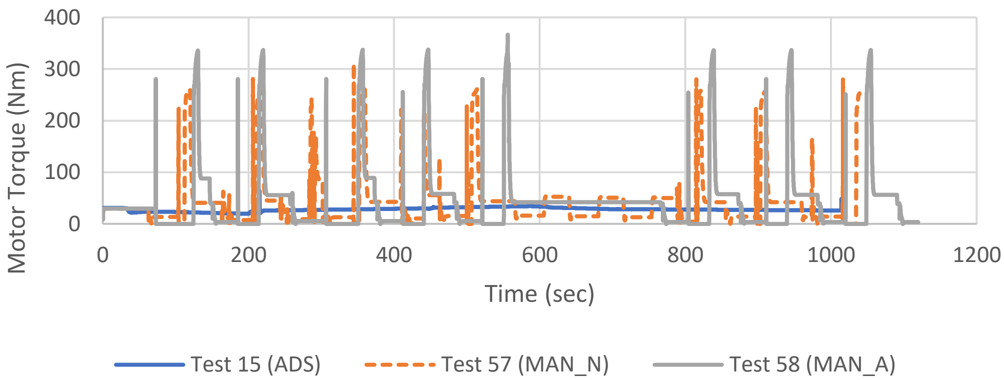

Fig. 6.105. Motor Torque for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

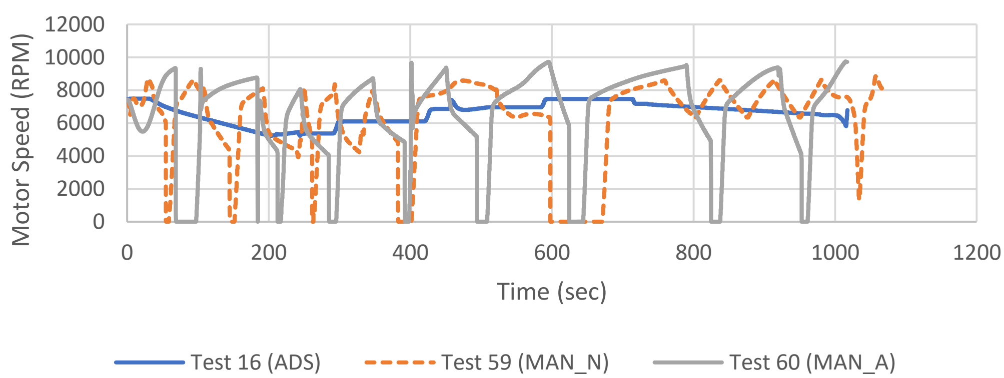

Fig. 6.106. Motor Speed for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

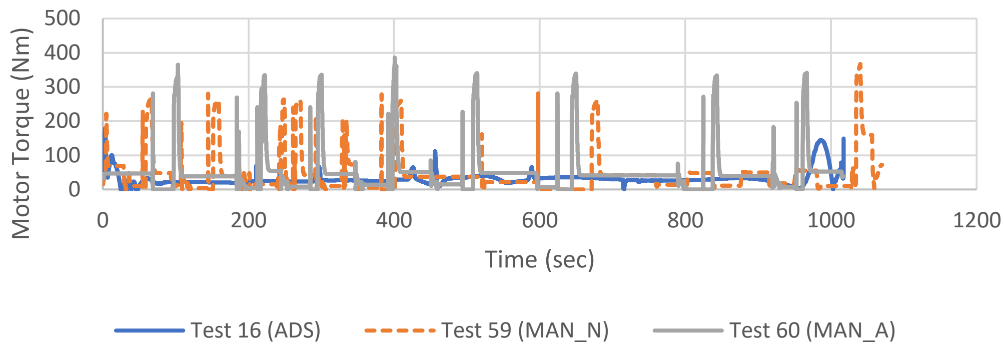

Fig. 6.107. Motor Torque for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

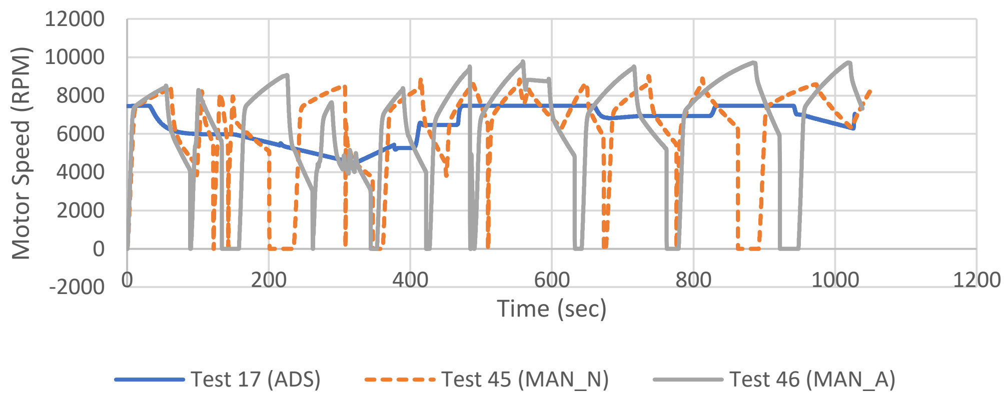

Fig. 6.108. Motor Speed for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

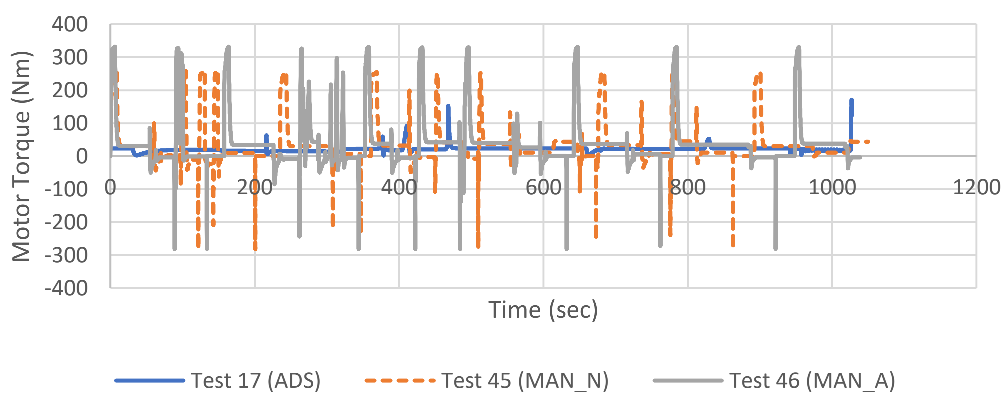

Fig. 6.109. Motor Torque for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

As it can be seen from the figures, the motor speed and torque fluctuations are significantly lower for ADS control compared to the normal and aggressive driver. Since, within the ACC control, the entire longitudinal vehicle control responsibility is taken by the ADS, an optimal Electrified Vehicle motor operation is evident.

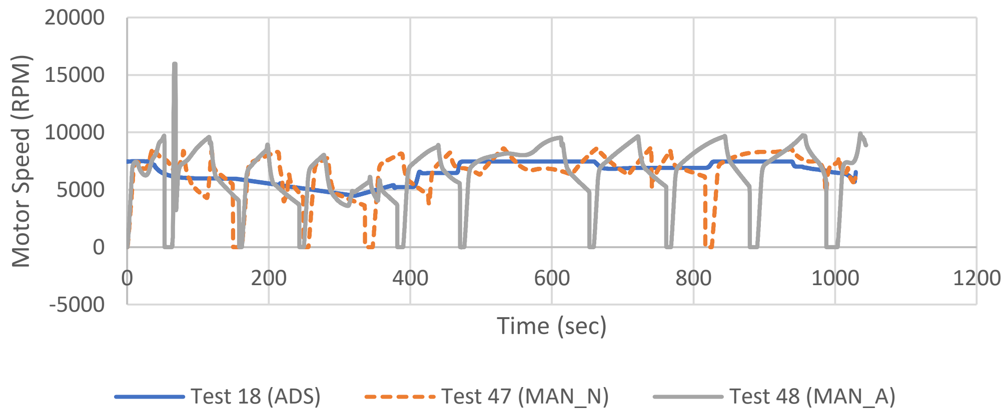

Fig. 6.110. Motor Speed for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

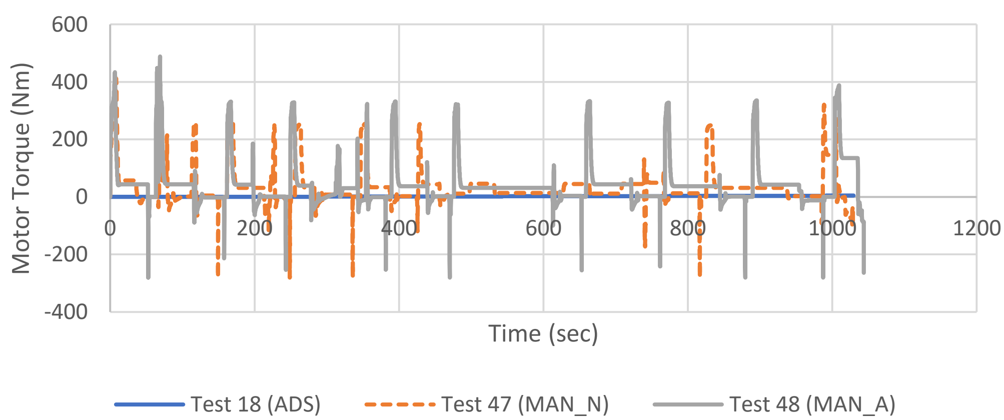

Fig. 6.111. Motor Torque for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

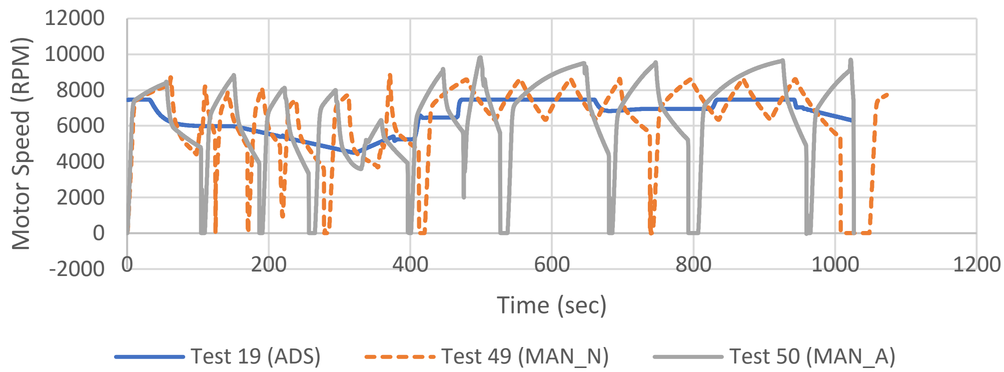

Fig. 6.112. Motor Speed for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

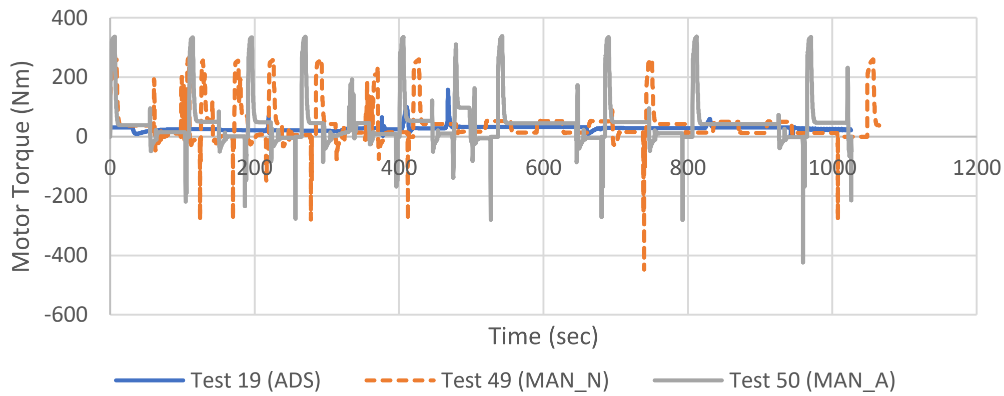

Fig. 6.113. Motor Torque for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

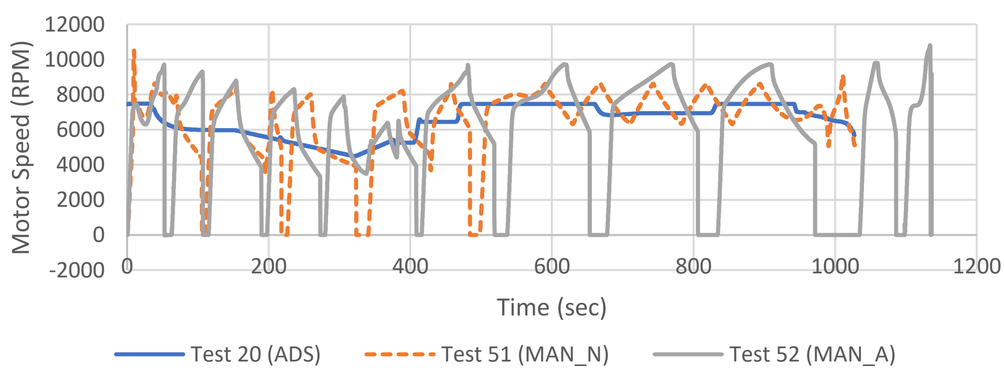

Fig. 6.114. Motor Speed for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

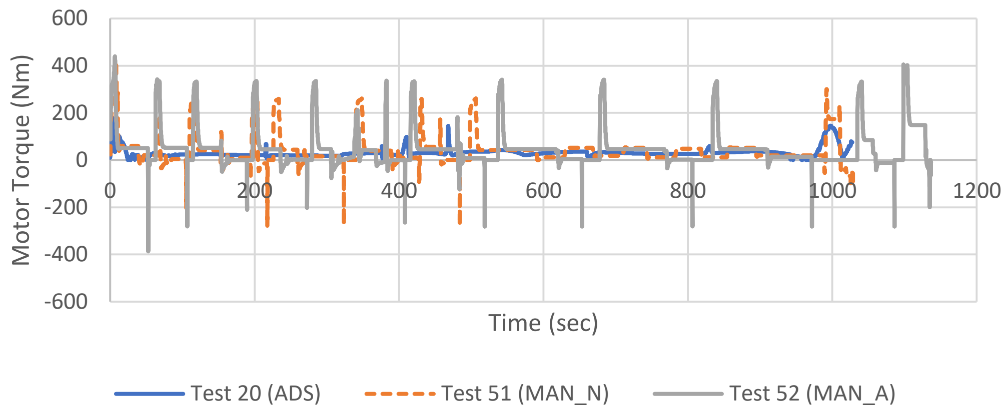

Fig. 6.115. Motor Torque for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

The Autonomous-capable Electrified Vehicle's motor results during the Active Lane Keep Assist functionality in addition to their human driver control comparisons can be seen in Fig. 6.116 to 6.131. As noticed in the previous energy consumption and vehicle dynamic results, the impact of autonomous lateral vehicle control on the Electrified Vehicle motor is also relatively low compared to the autonomous longitudinal vehicle control.

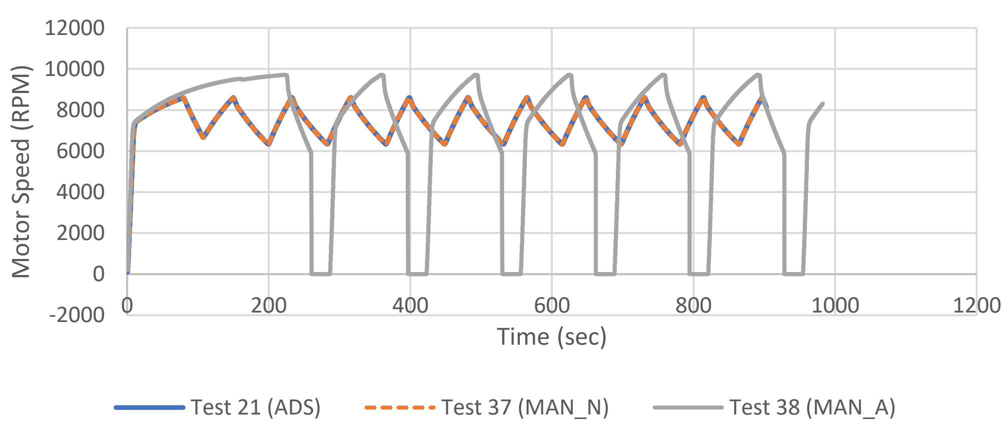

Fig. 6.116. Motor Speed for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

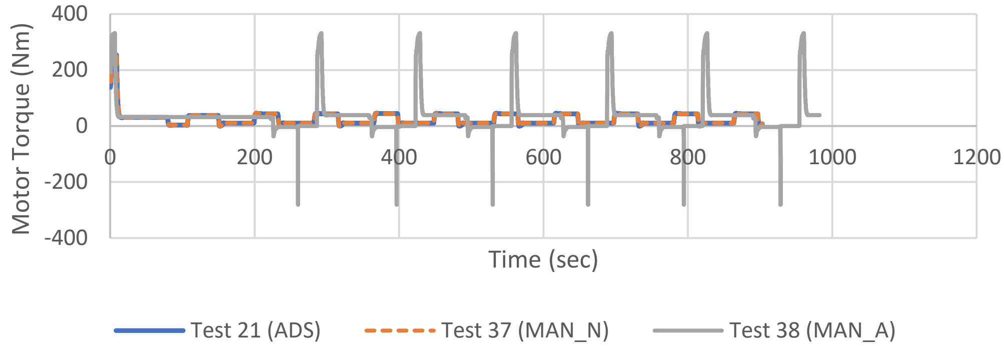

Fig. 6.117. Motor Torque for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

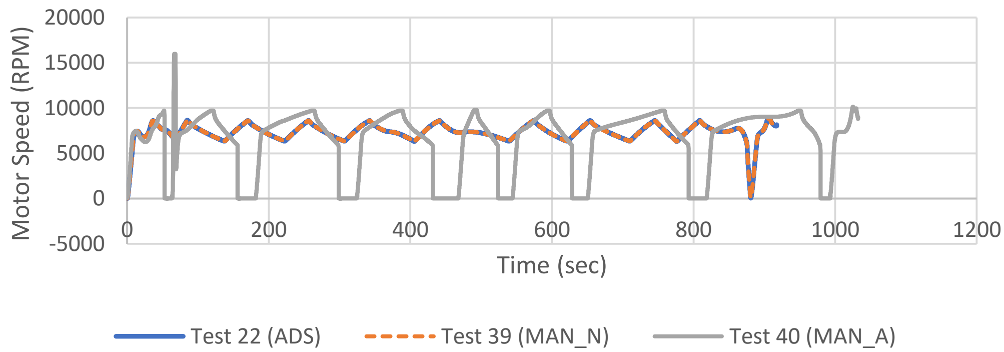

Fig. 6.118. Motor Speed for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

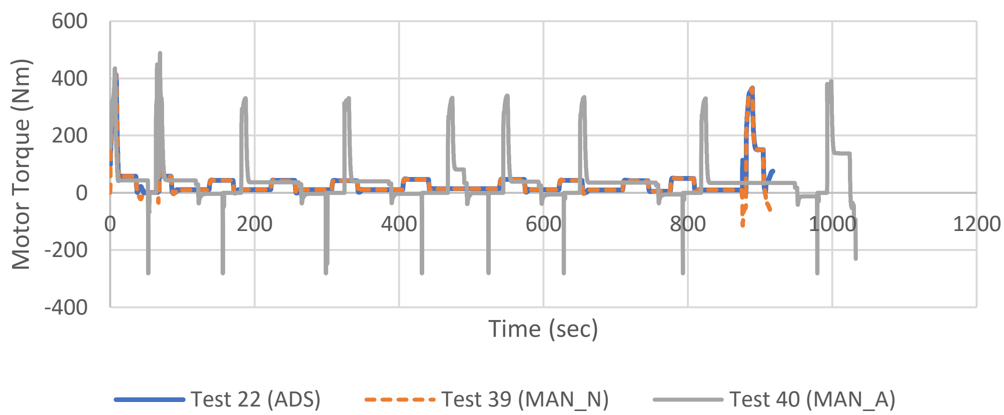

Fig. 6.119. Motor Torque for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

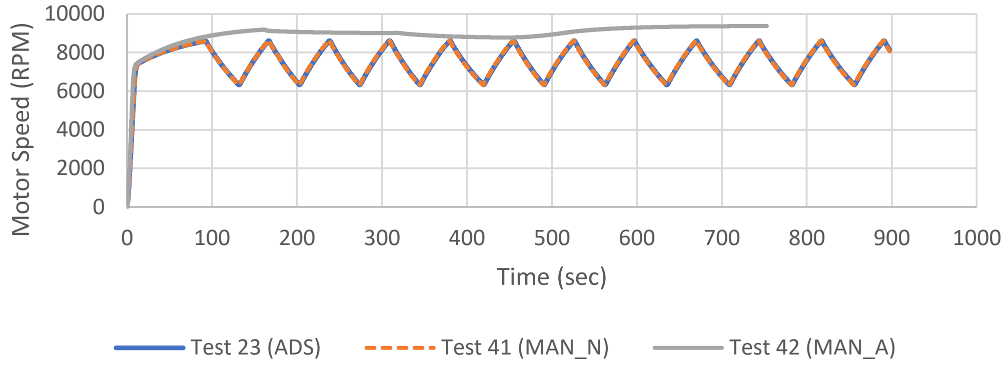

Fig. 6.120. Motor Speed for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

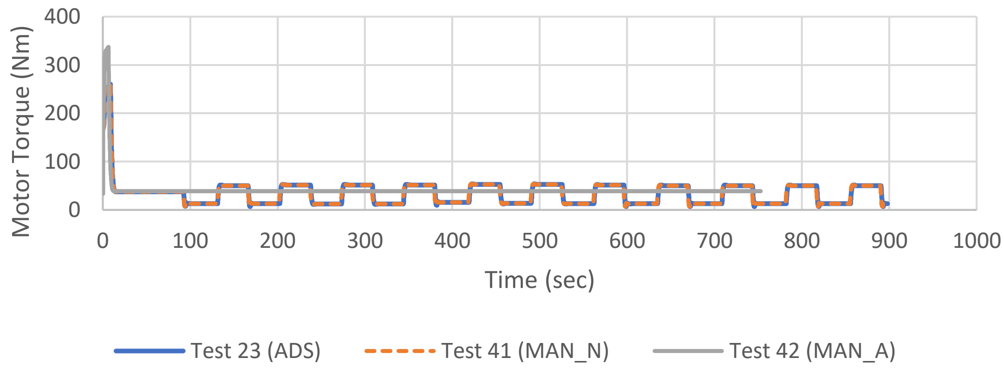

Fig. 6.121. Motor Torque for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

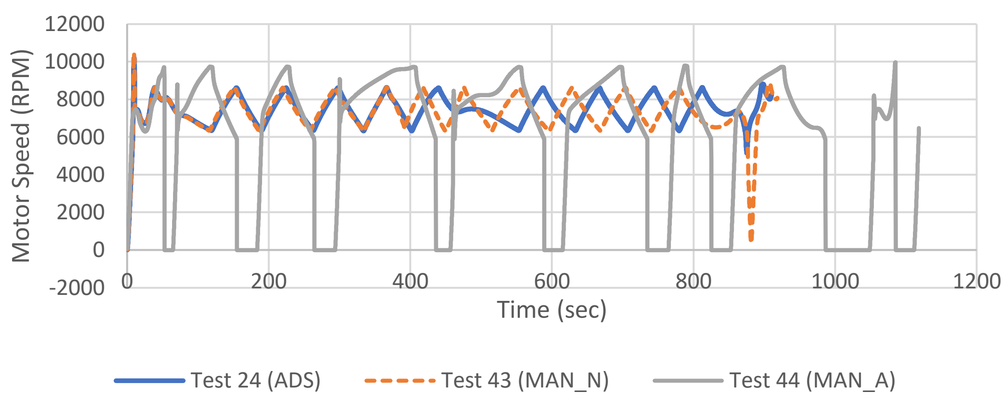

Fig. 6.122. Motor Speed for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

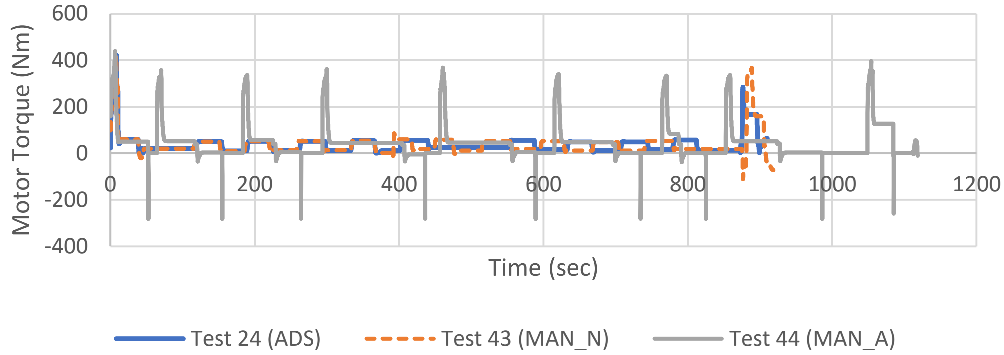

Fig. 6.123. Motor Torque for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

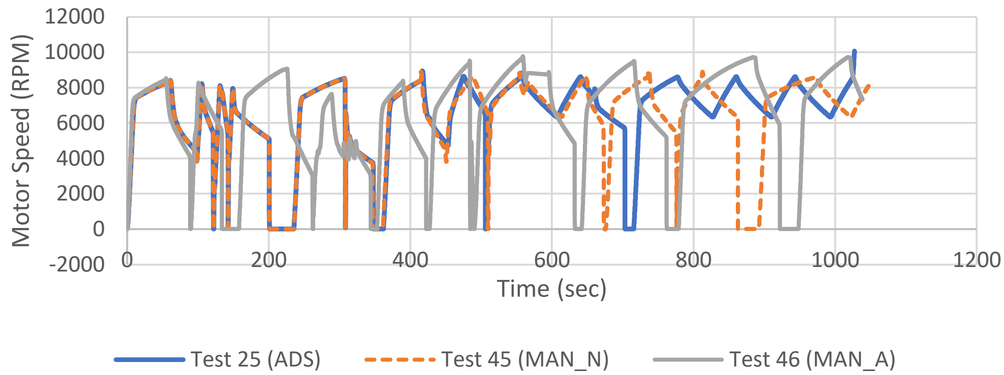

Fig. 6.124. Motor Speed for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

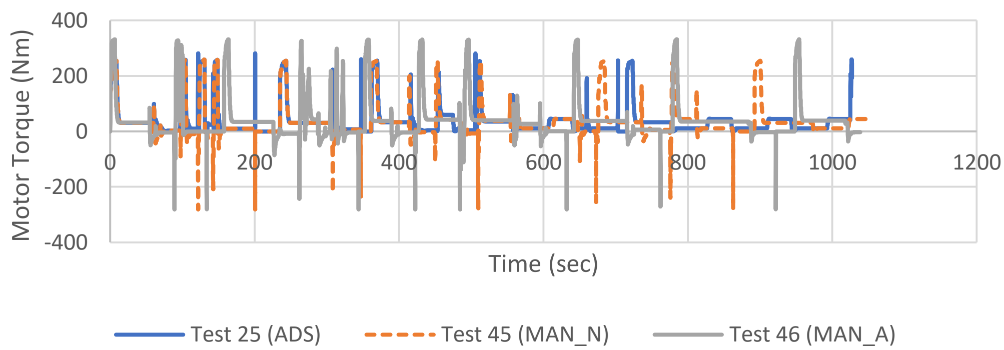

Fig. 6.125. Motor Torque for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

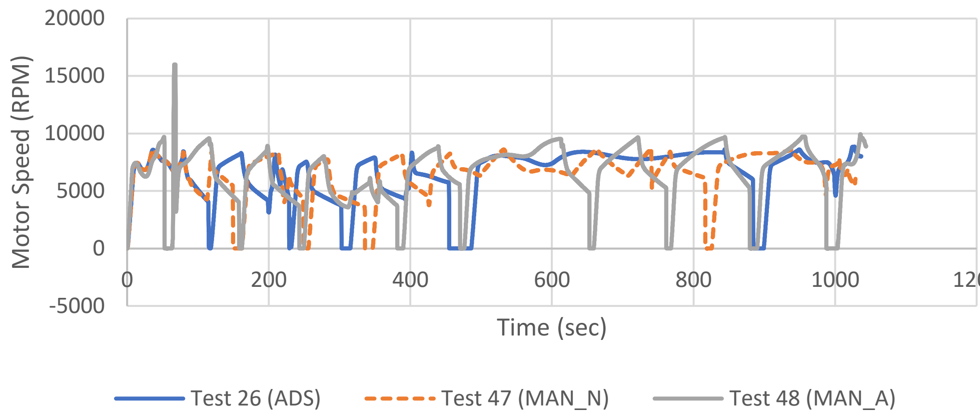

Fig. 6.126. Motor Speed for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

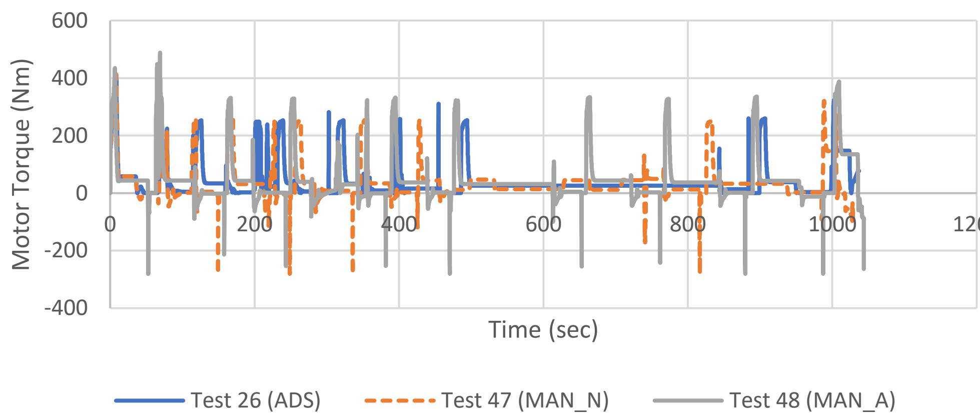

Fig. 6.127. Motor Torque for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

In overall, despite of a relatively lower influence of autonomous lateral vehicle control on the Autonomous-capable EV attributes studied, the fluctuations and overall magnitude are seen to be significantly higher for the aggressive driver test cases compared to the ADS control ones.

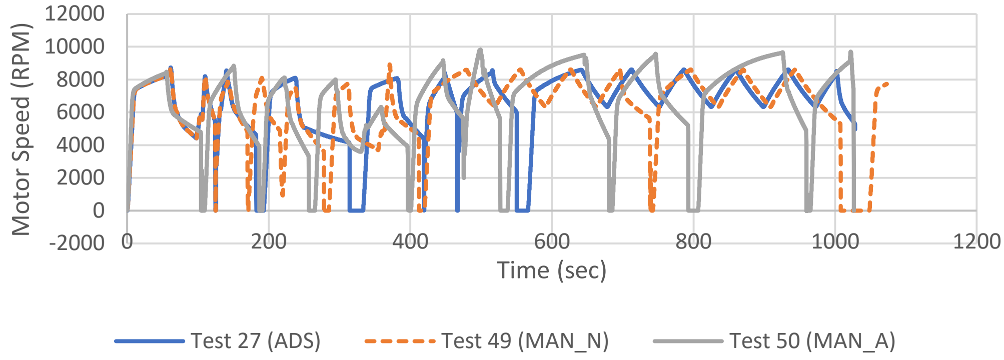

Fig. 6.128. Motor Speed for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

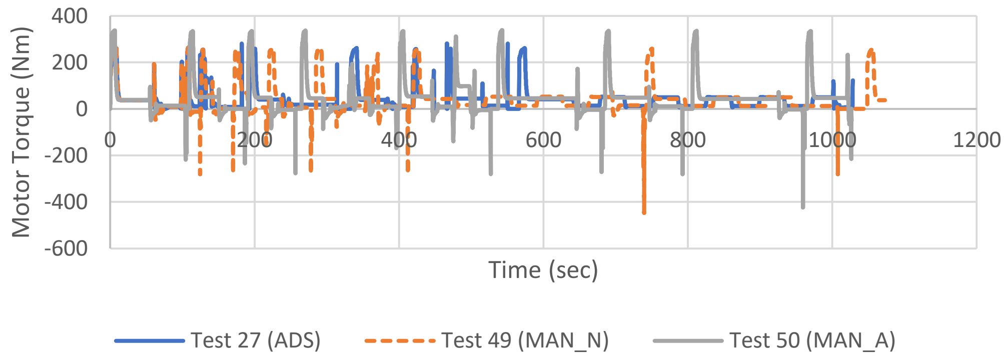

Fig. 6.129. Motor Torque for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

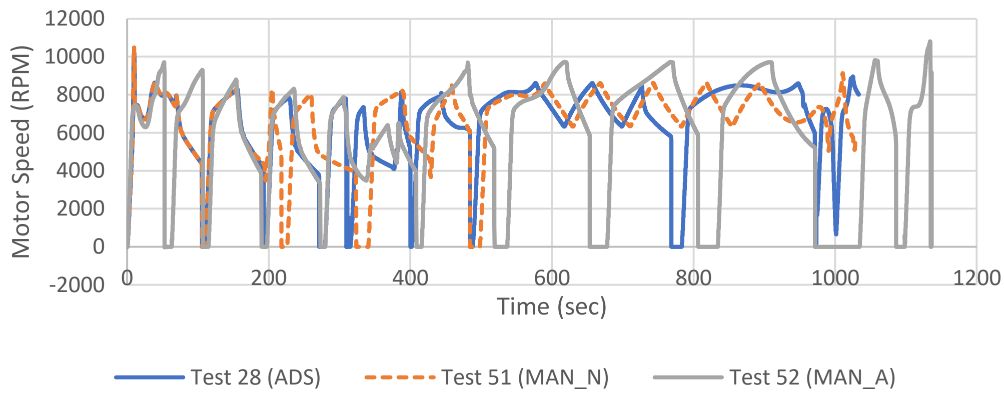

Fig. 6.130. Motor Speed for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

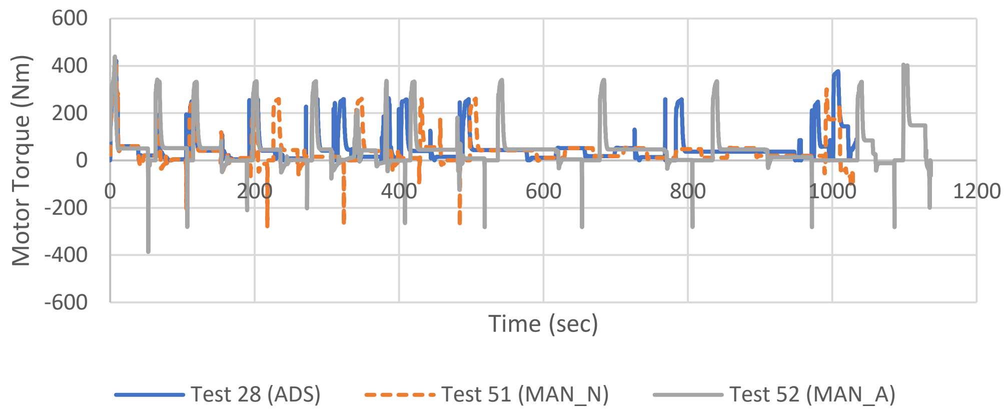

Fig. 6.131. Motor Torque for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

Lastly, the Autonomous-capable EV motor results for level 4 autonomous control can be seen in Fig. 6.132 to 6.147. Similar to previous results, Fig. 6.132 depicts the EV motor operation in ideal external conditions. Fig. 6.133 to 6.147 show the EV motor behavior for non-ideal or adverse external conditions.

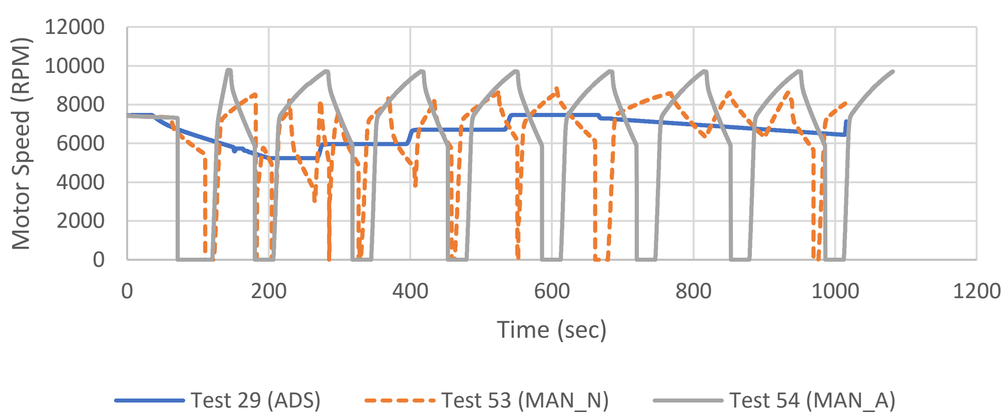

Fig. 6.132. Motor Speed for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

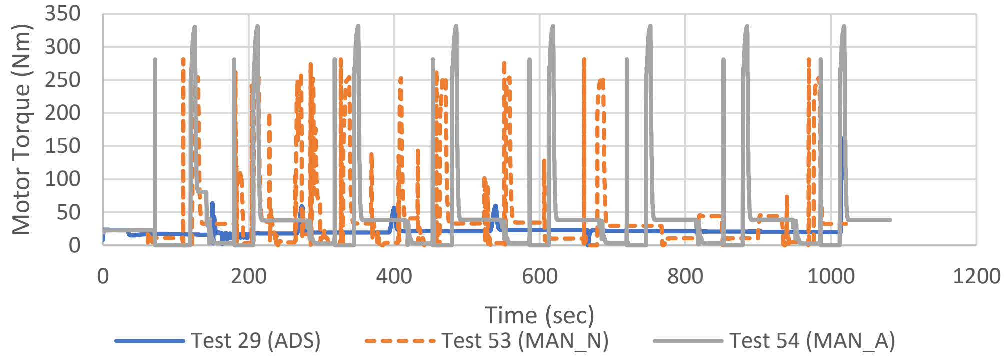

Fig. 6.133. Motor Torque for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

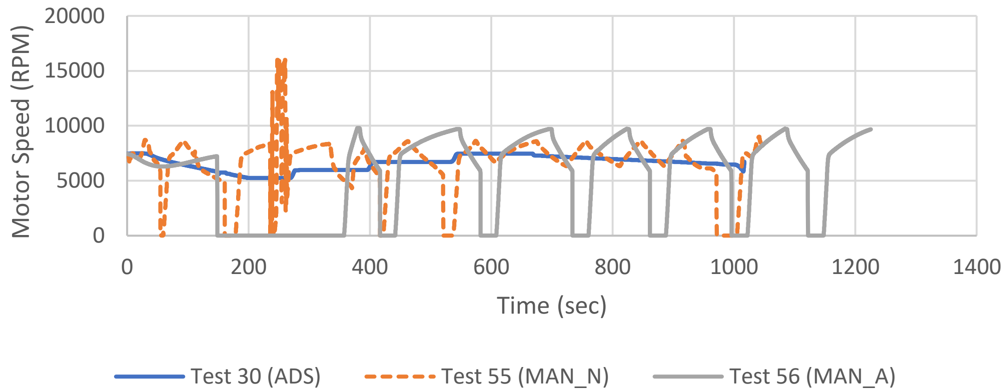

Fig. 6.134. Motor Speed for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

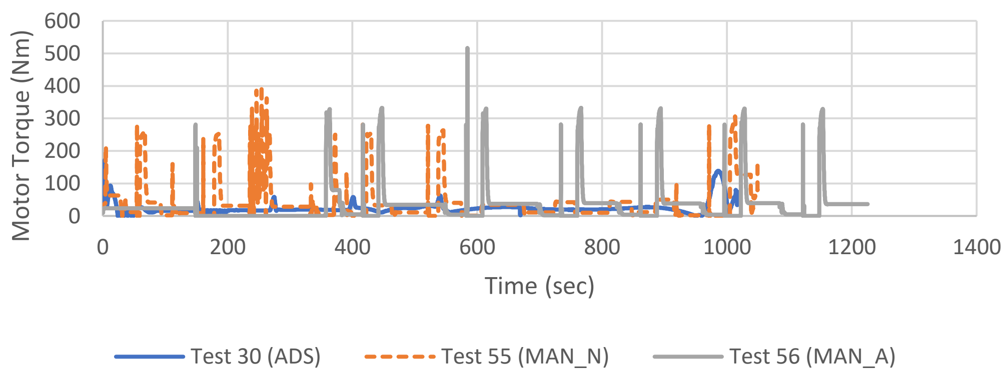

Fig. 6.135. Motor Torque for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

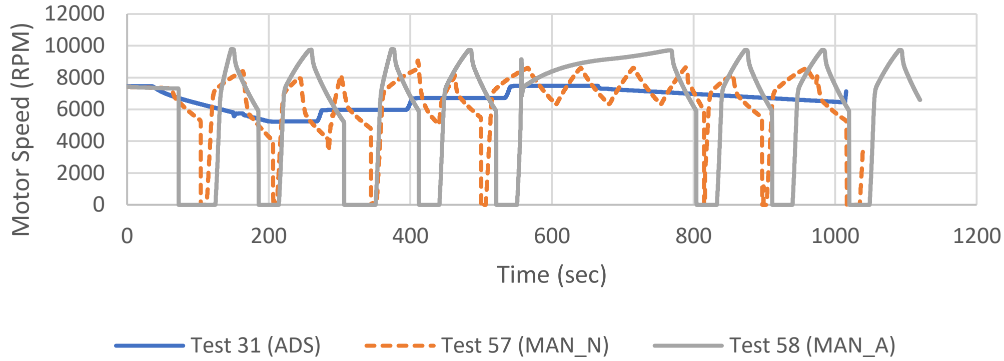

Fig. 6.136. Motor Speed for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

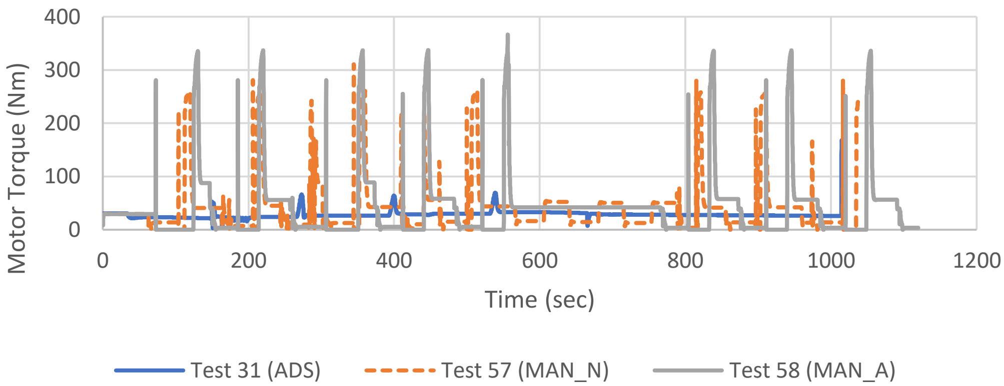

Fig. 6.137. Motor Torque for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

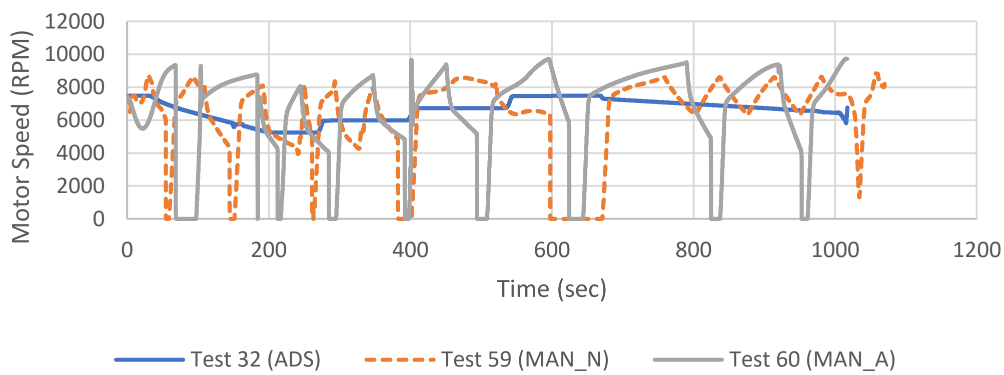

Fig. 6.138. Motor Speed for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

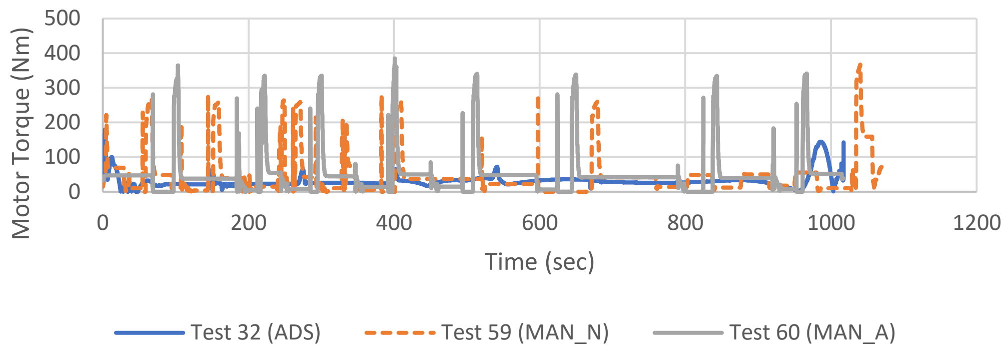

Fig. 6.139. Motor Torque for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

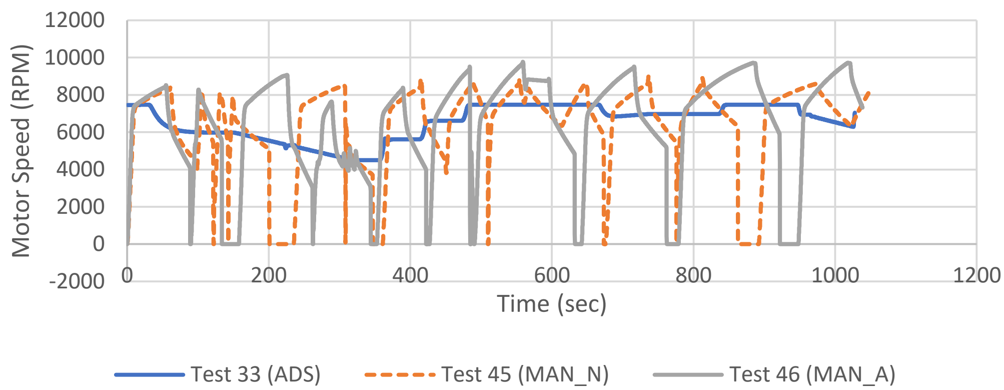

Fig. 6.140. Motor Speed for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

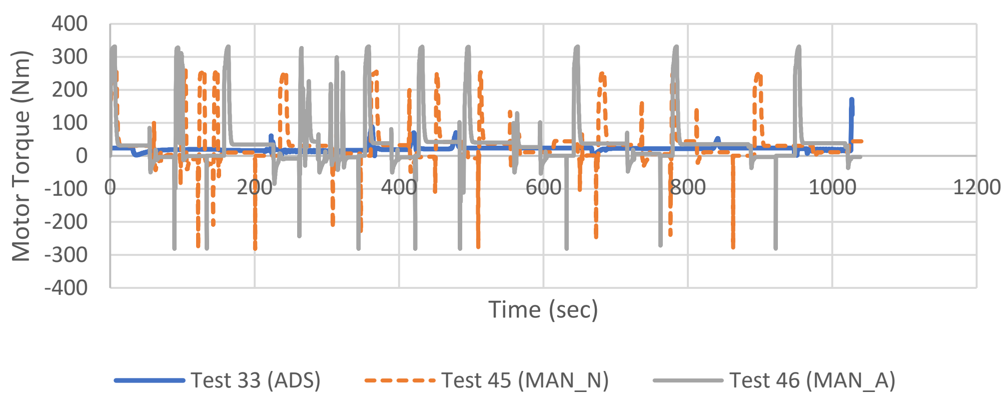

Fig. 6.141. Motor Torque for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

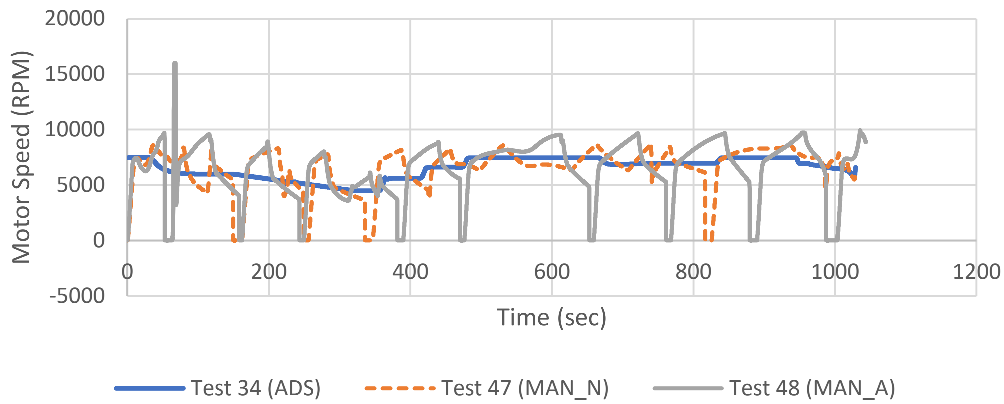

Fig. 6.142. Motor Speed for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

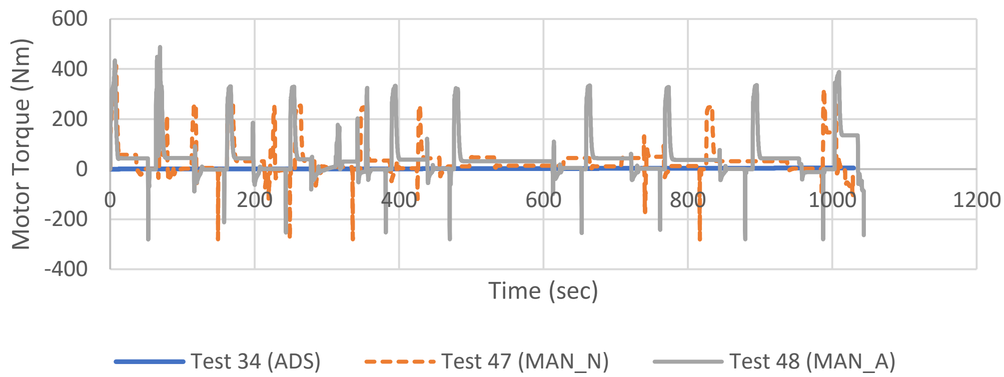

Fig. 6.143. Motor Torque for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

In overall, the Autonomous-capable EV motor speed and torque results evidently show a more uniform and streamlined profile for the ADS control compared to normal and aggressive driver control. This further demonstrates the optimal operation of the EV motor under level 4 autonomous control, where both the lateral and the longitudinal vehicle control is completely taken care of by the ADS. This impact on the EV motor is also expected to result in better vehicle performance when under autonomous control.

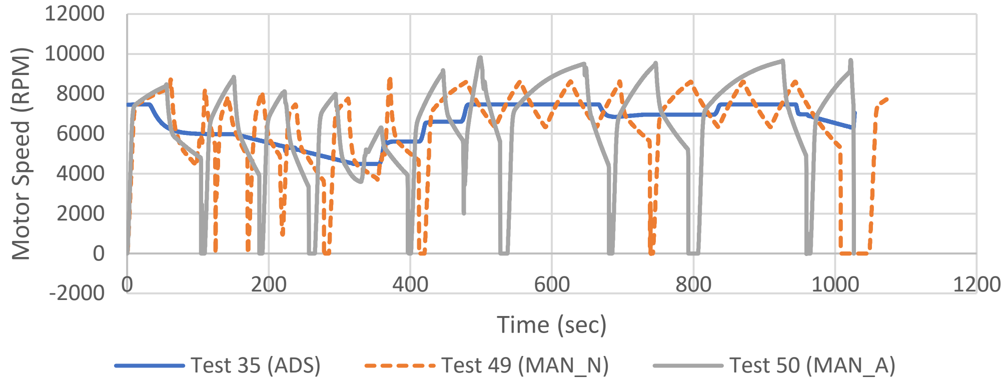

Fig. 6.144. Motor Speed for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

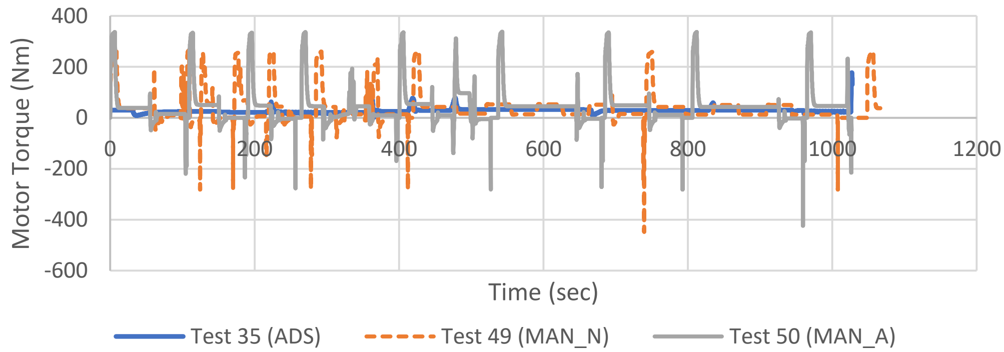

Fig. 6.145. Motor Torque for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

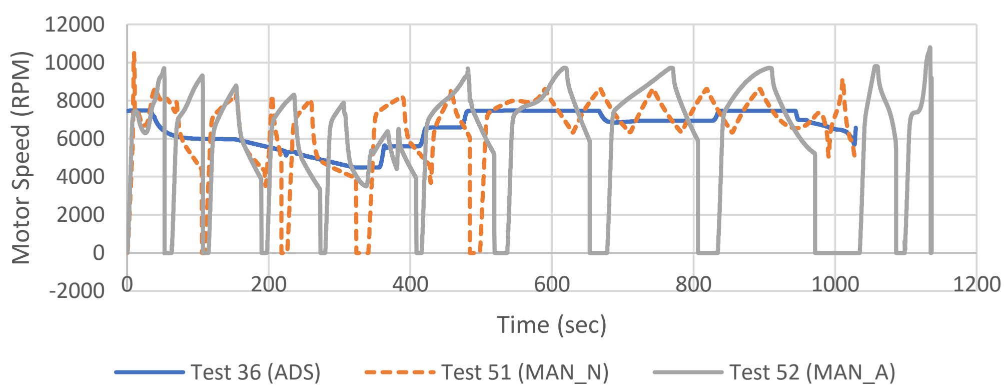

Fig. 6.146. Motor Speed for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

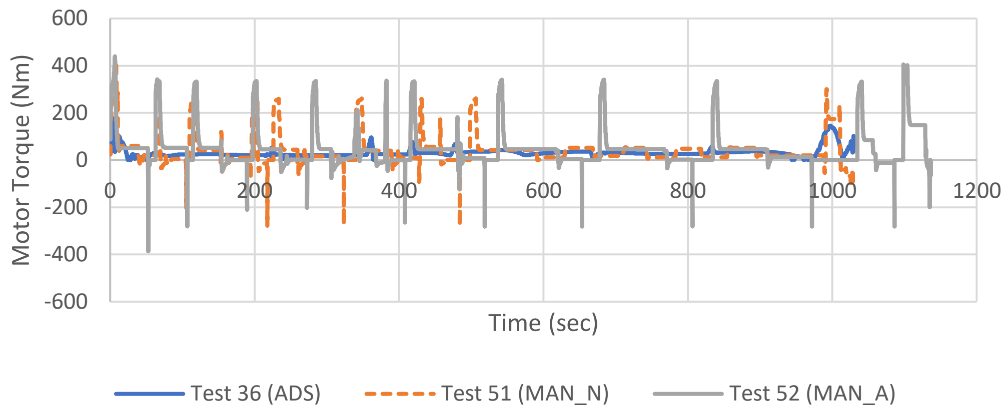

Fig. 6.147. Motor Torque for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

6.2.4 Electrified Vehicle Battery Results

This section presents the results for the Autonomous-capable Electrified Vehicle battery. Two different battery parameters including the State of Charge or SOC and the battery current have been shown here. The battery results for Cruise Control are shown in Fig. 6.148 to 6.171.

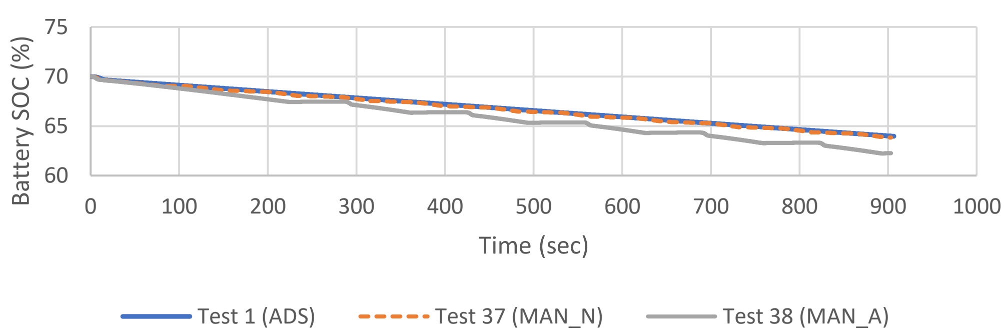

Fig. 6.148. Battery SOC for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

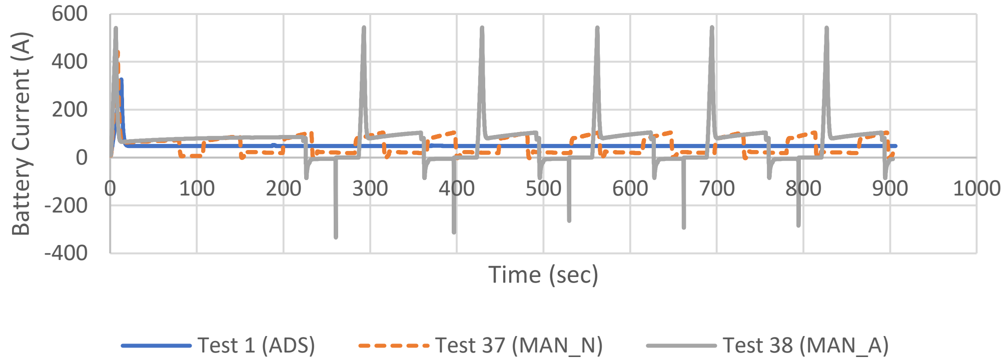

Fig. 6.149. Battery Current for Test 1 (CC with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

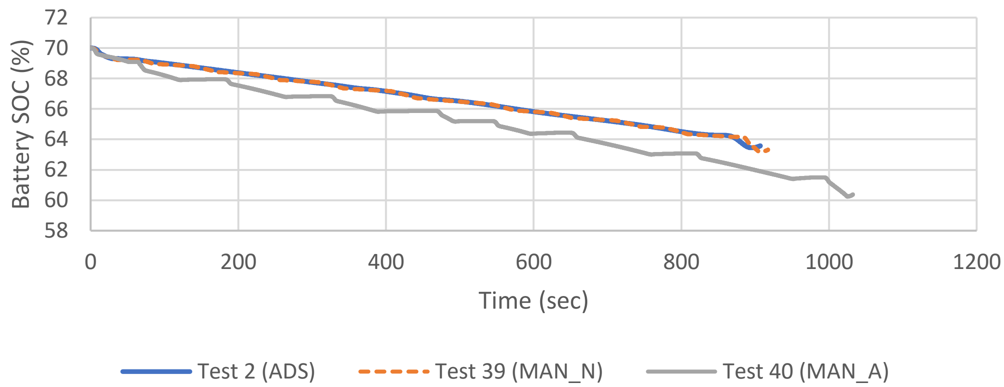

Fig. 6.150. Battery SOC for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

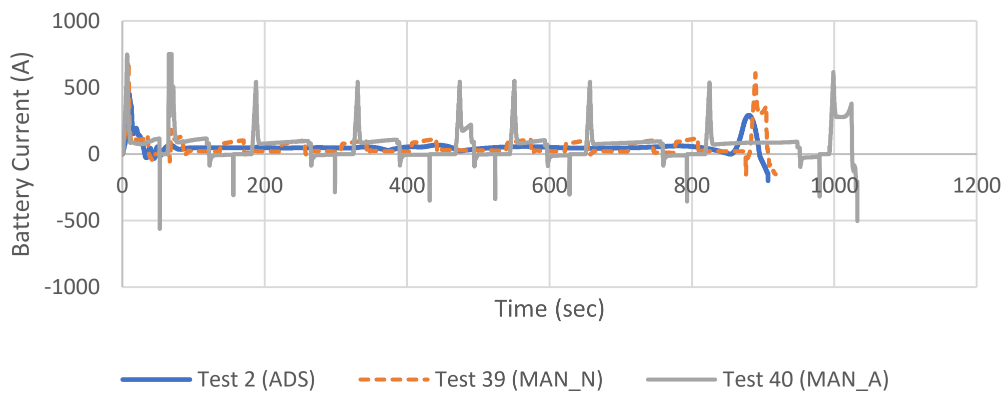

Fig. 6.151. Battery Current for Test 2 (CC with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

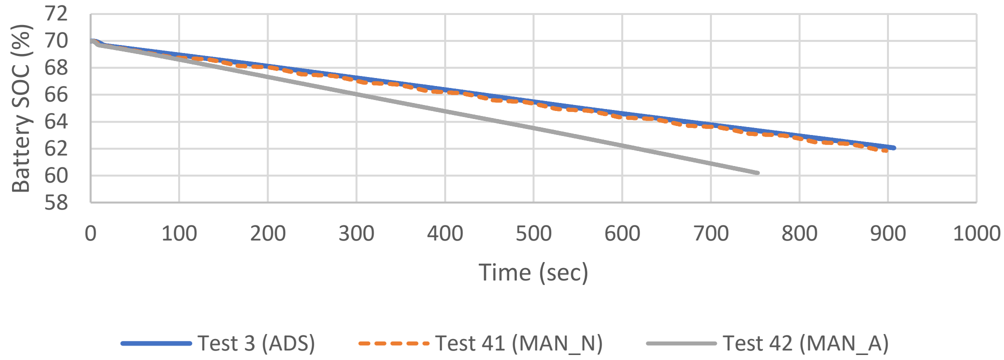

Fig. 6.152. Battery SOC for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

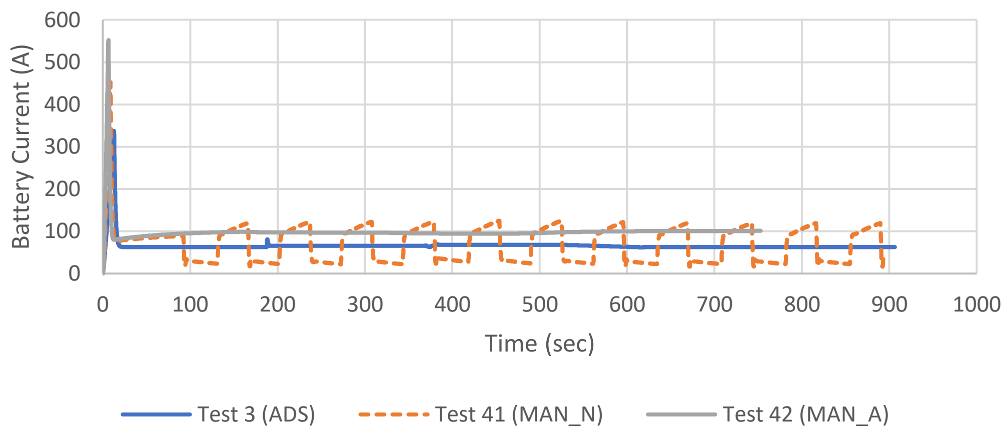

Fig. 6.153. Battery Current for Test 3 (CC with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

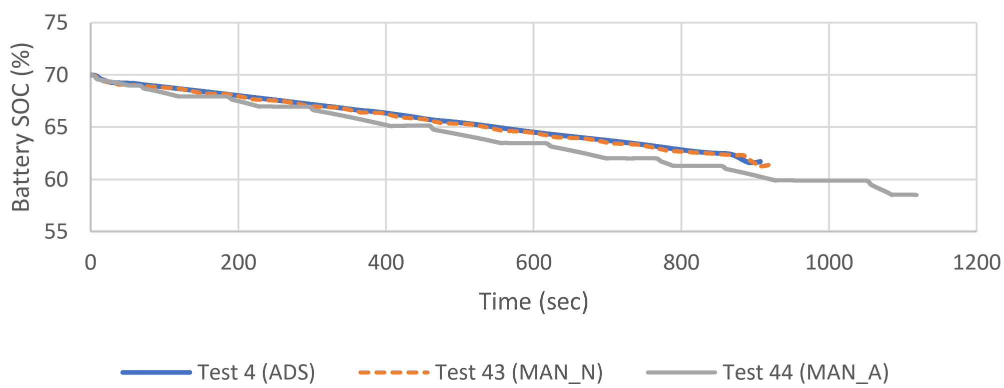

Fig. 6.154. Battery SOC for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

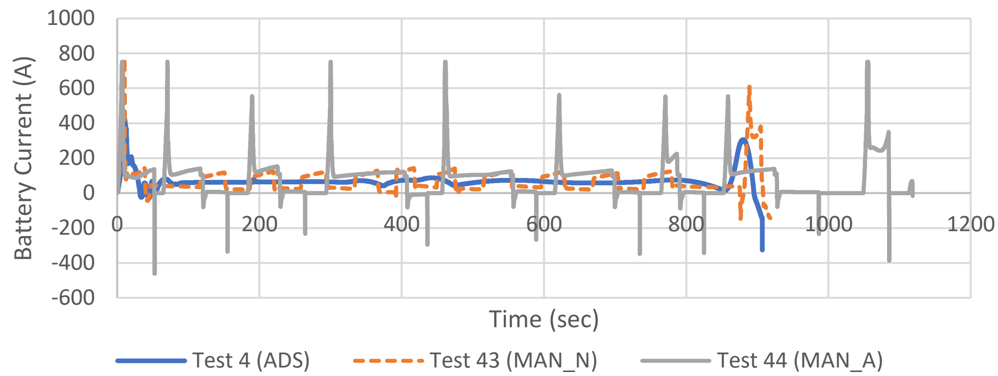

Fig. 6.155. Battery Current for Test 4 (CC with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

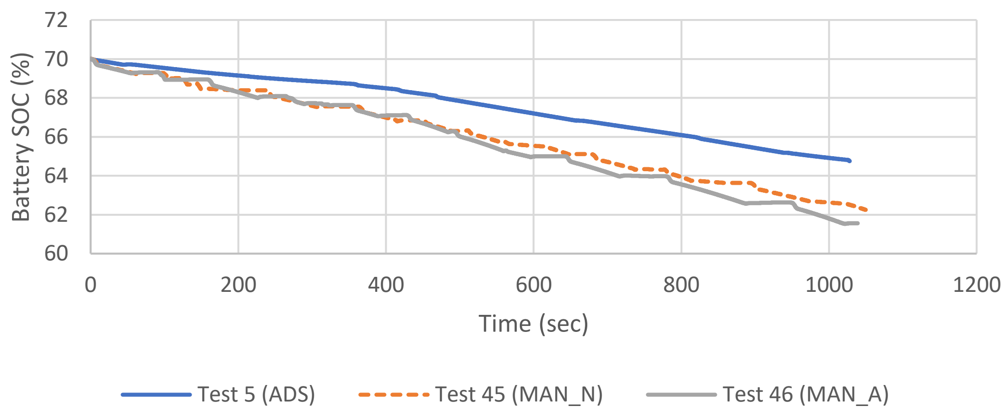

Fig. 6.156. Battery SOC for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

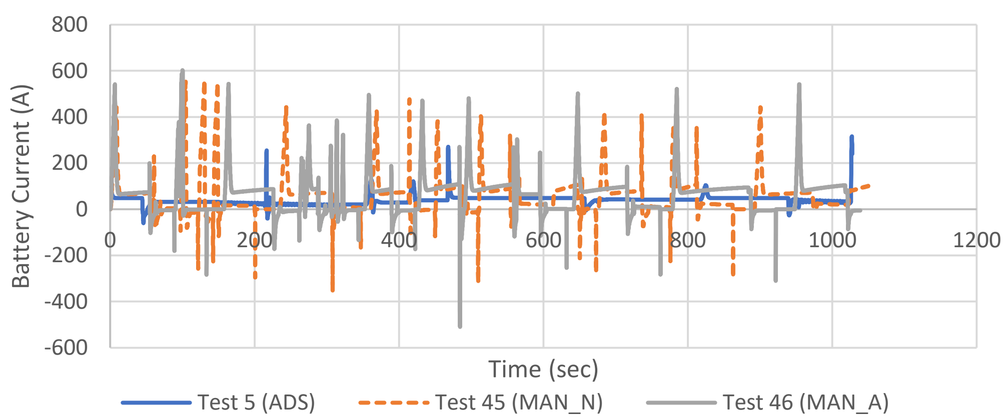

Fig. 6.157. Battery Current for Test 5 (CC with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

A comparison is provided in the battery results for the test cases with and without Autonomous Vehicle lateral and longitudinal control under the presence of varying external conditions. The optimal operation of the battery is equally important to that of the motor in order to produce better vehicle performance results.

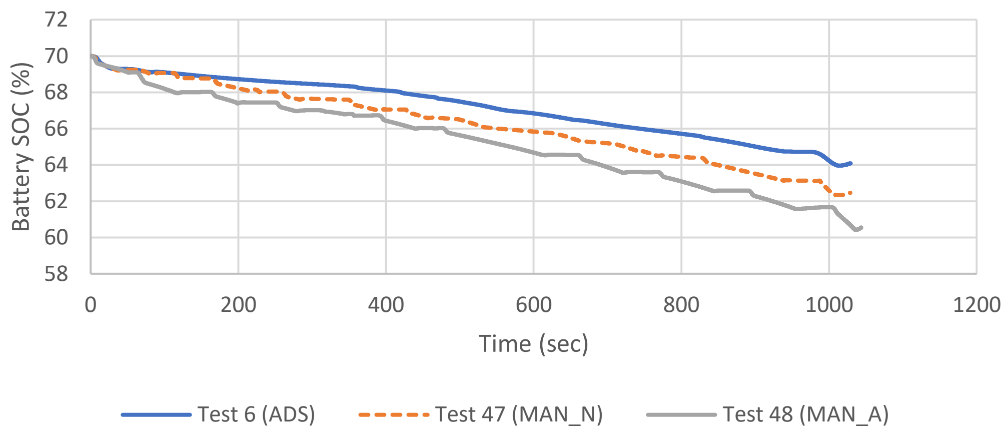

Fig. 6.158. Battery SOC for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

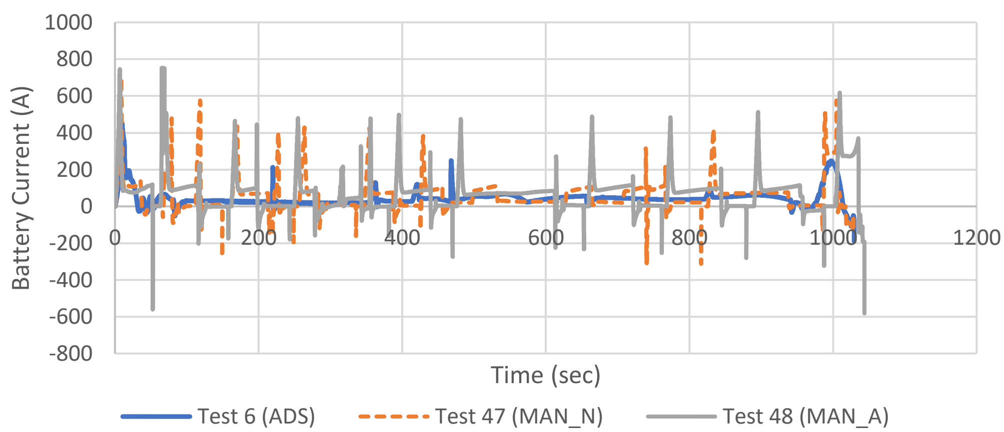

Fig. 6.159. Battery Current for Test 6 (CC with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

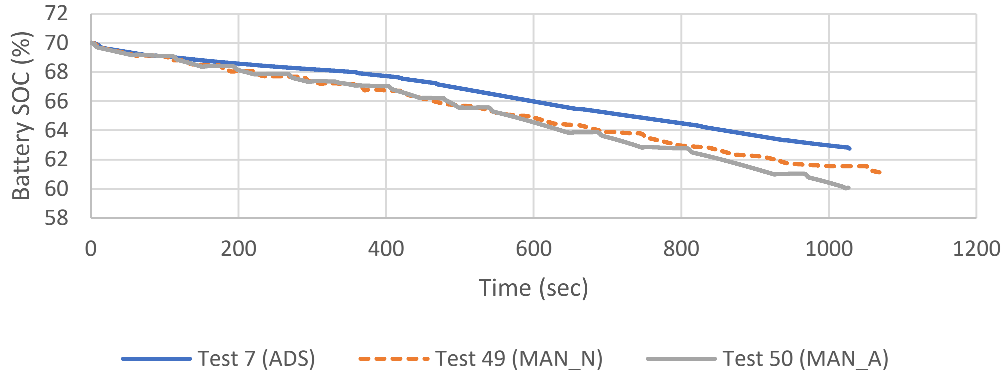

Fig. 6.160. Battery SOC for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

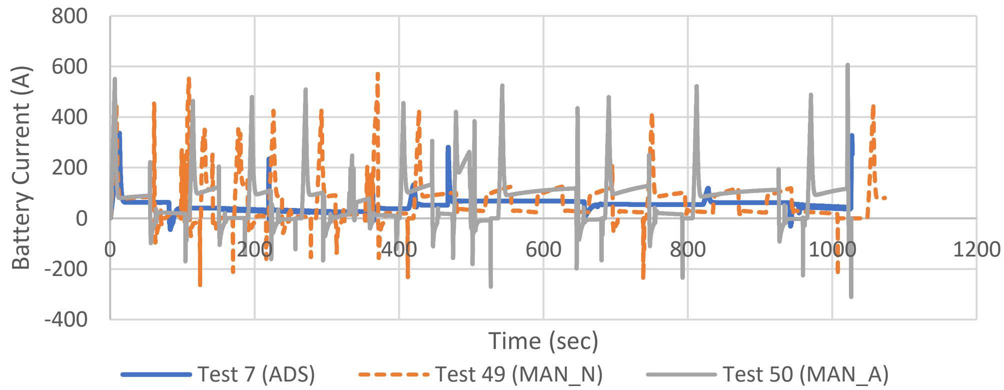

Fig. 6.161. Battery Current for Test 7 (CC with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

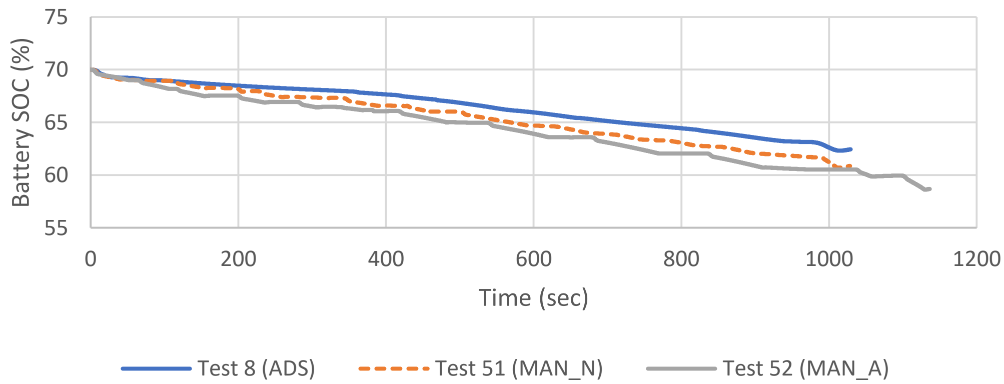

Fig. 6.162. Battery SOC for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

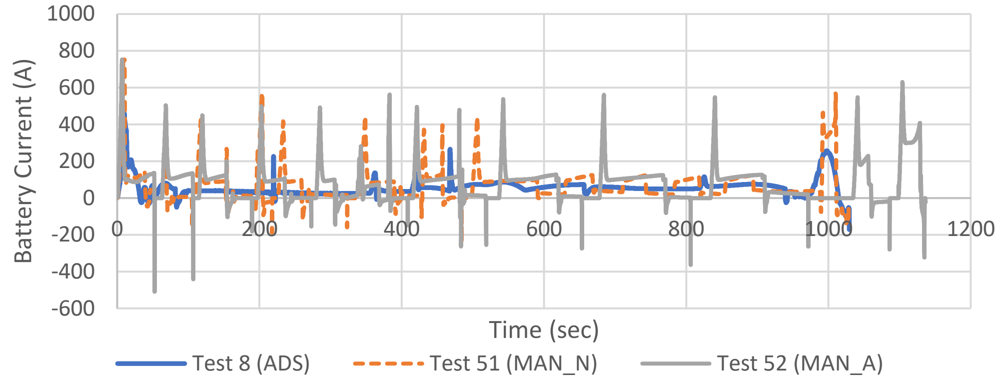

Fig. 6.163. Battery Current for Test 8 (CC with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

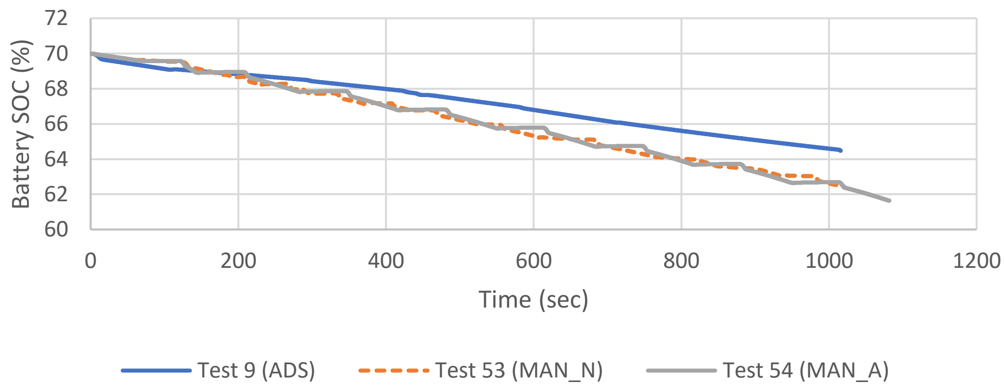

Fig. 6.164. Battery SOC for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

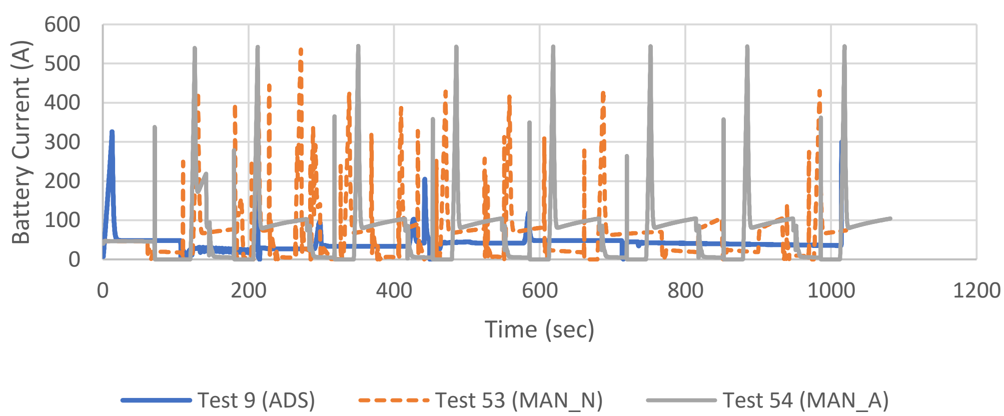

Fig. 6.165. Battery Current for Test 9 (CC with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

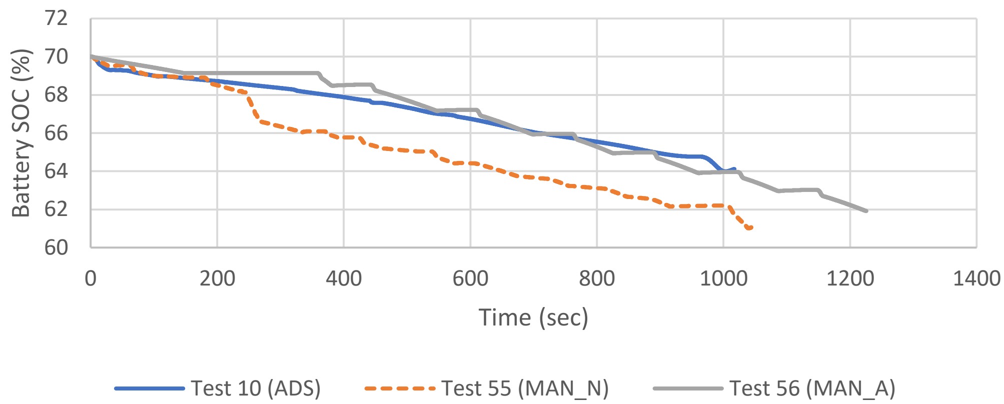

Fig. 6.166. Battery SOC for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

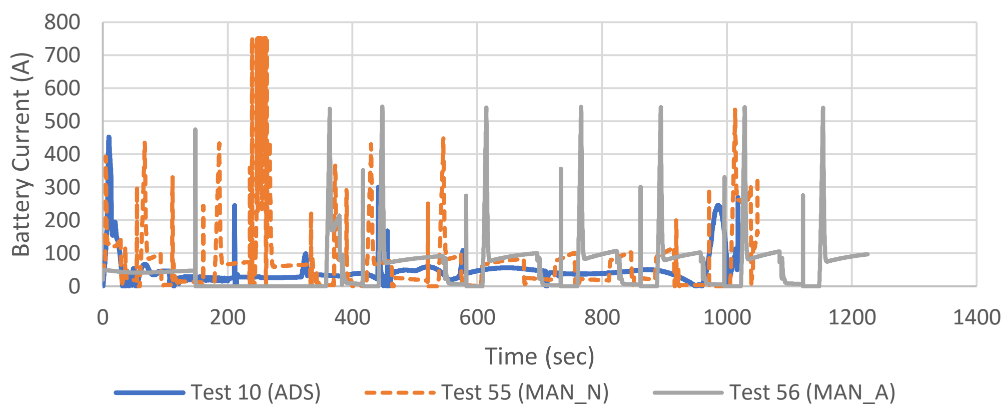

Fig. 6.167. Battery Current for Test 10 (CC with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

In overall, it was seen that the battery SOC was significantly higher for the ADS control test cases compared to the normal and aggressive human driving ones. Furthermore, the fluctuations in both the battery current and the SOC profiles were seen to be significantly lower with more streamlined profiles for the ADS control compared to the human driving test cases.

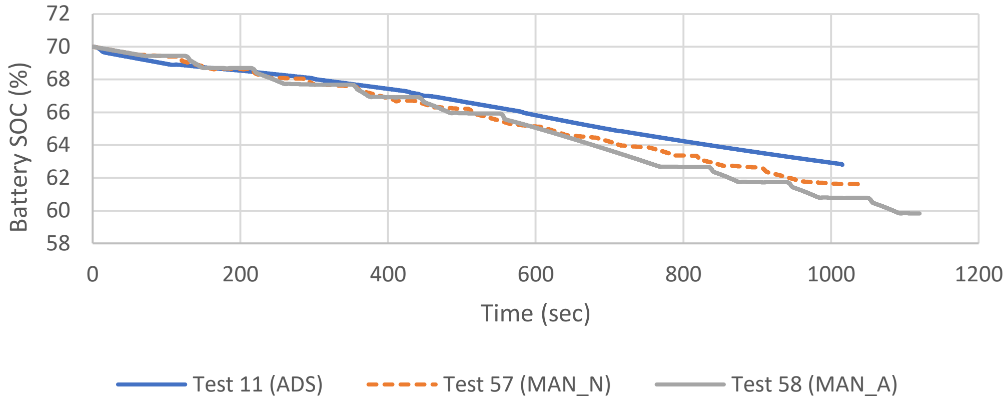

Fig. 6.168. Battery SOC for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

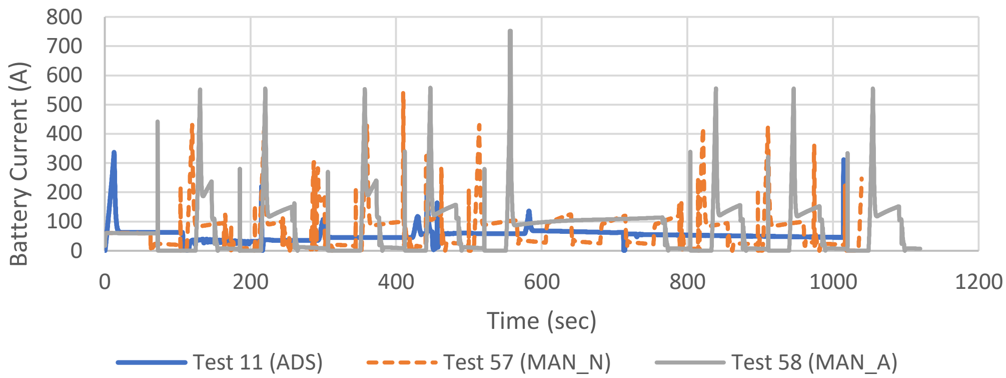

Fig. 6.169. Battery Current for Test 11 (CC with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

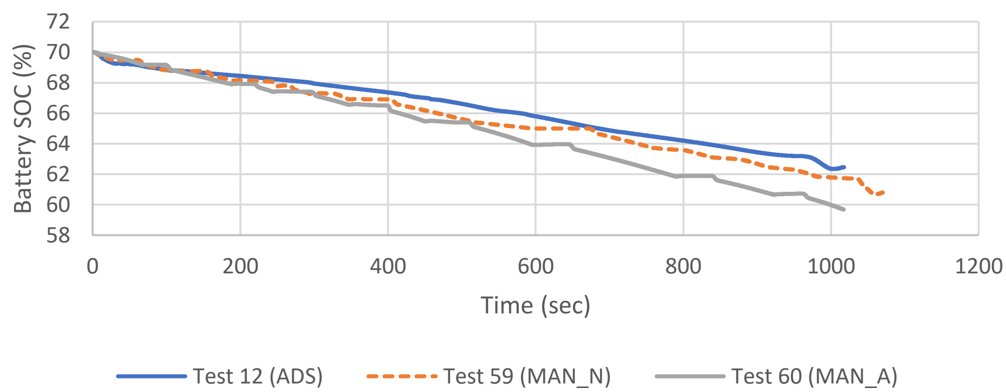

Fig. 6.170. Battery SOC for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

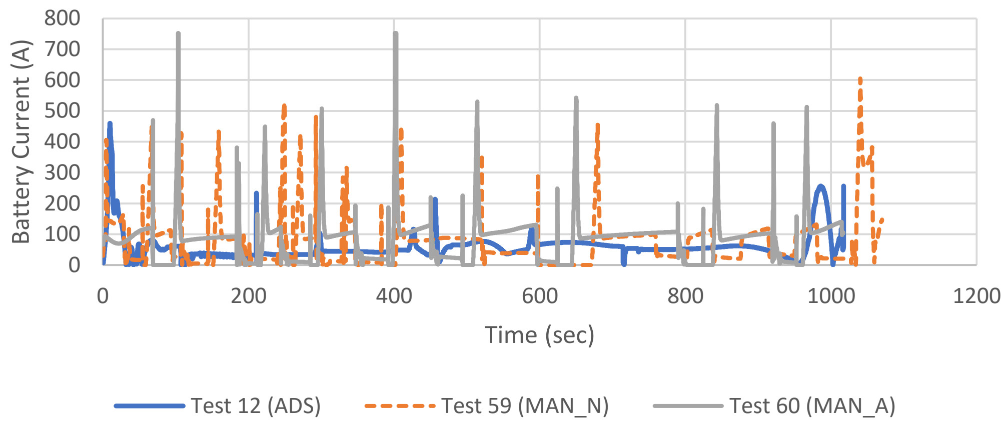

Fig. 6.171. Battery Current for Test 12 (CC with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

The autonomous-capable EV battery results for test cases with ACC and AEB control in addition to their manual comparisons under the presence of ideal and varying non-ideal external conditions can be seen in Fig. 6.172 to 6.187.

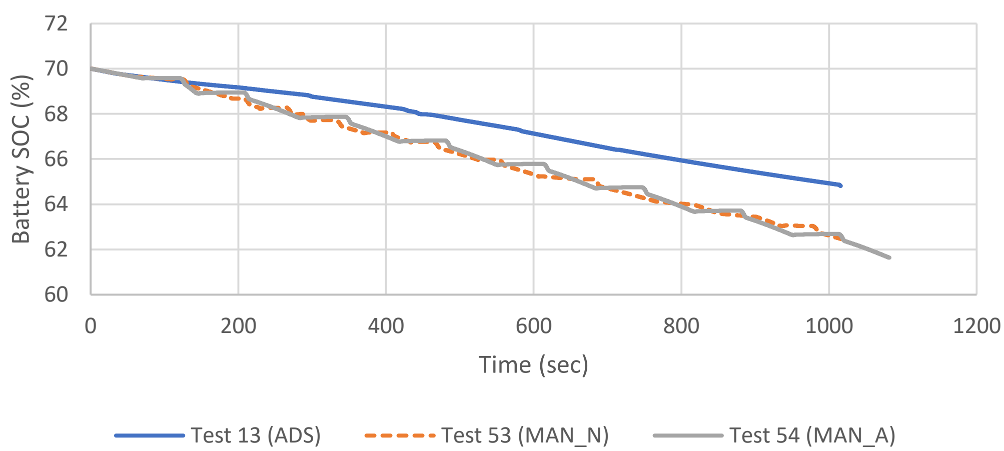

Fig. 6.172. Battery SOC for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

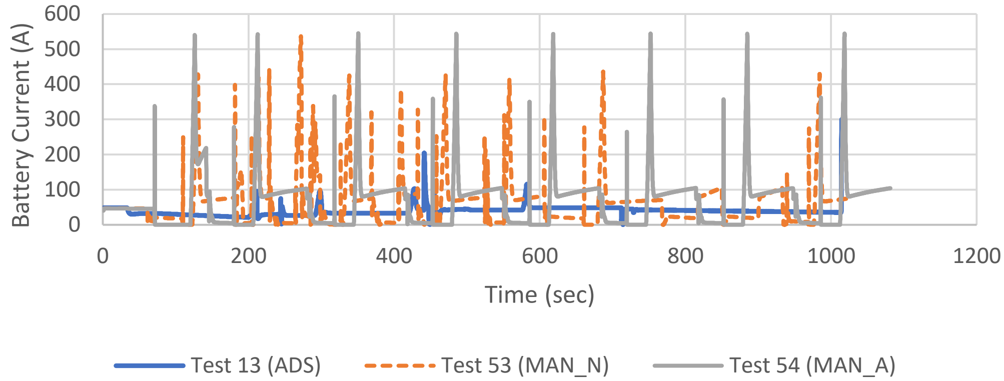

Fig. 6.173. Battery Current for Test 13 (ACC and AEB with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

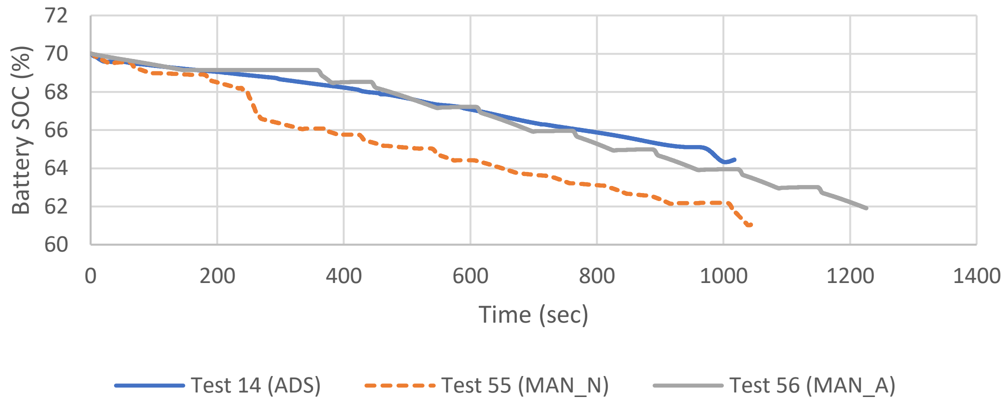

Fig. 6.174. Battery SOC for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

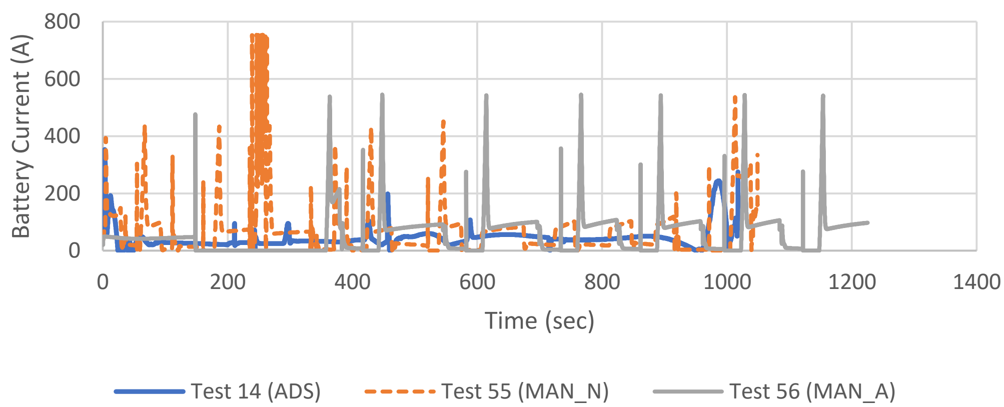

Fig. 6.175. Battery Current for Test 14 (ACC and AEB with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

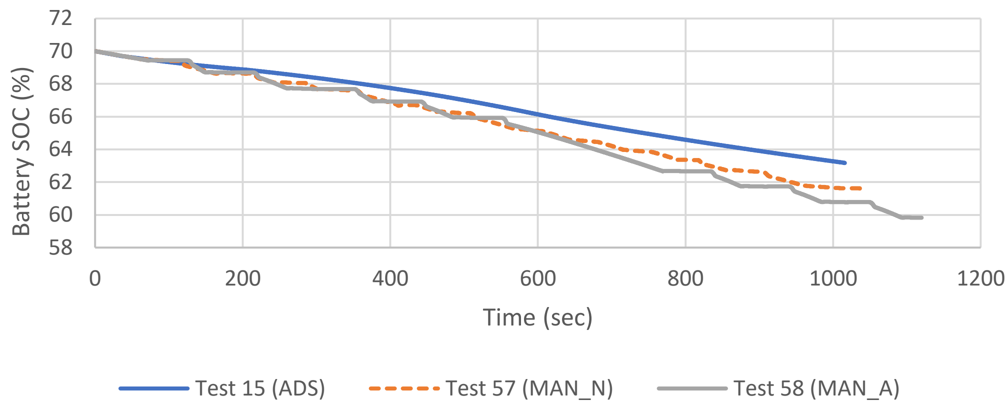

Fig. 6.176. Battery SOC for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

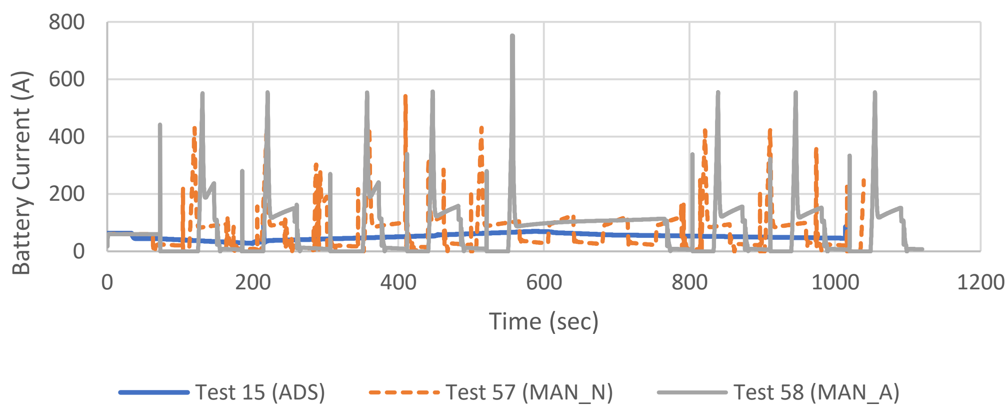

Fig. 6.177. Battery Current for Test 15 (ACC and AEB with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

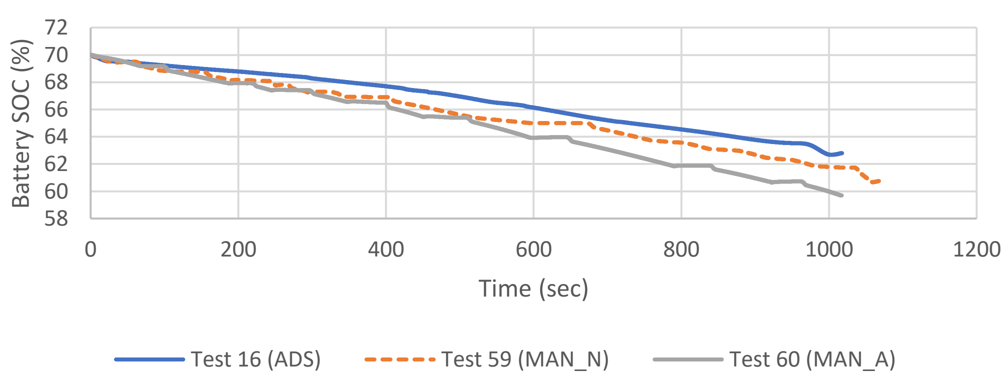

Fig. 6.178. Battery SOC for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

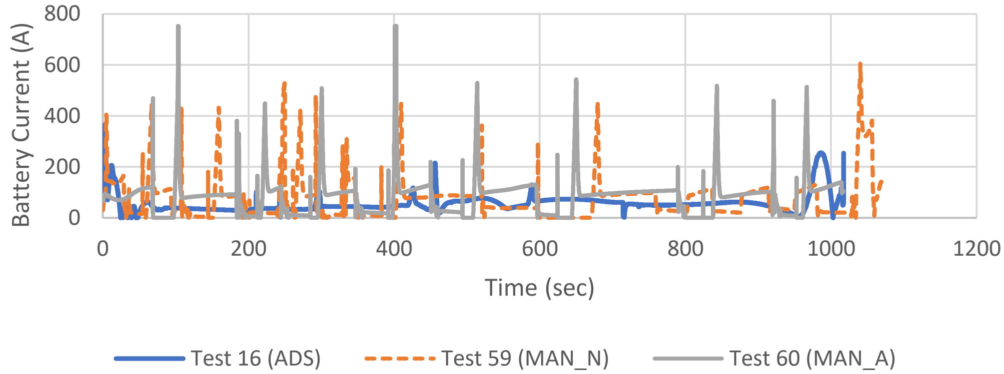

Fig. 6.179. Battery Current for Test 16 (ACC and AEB with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

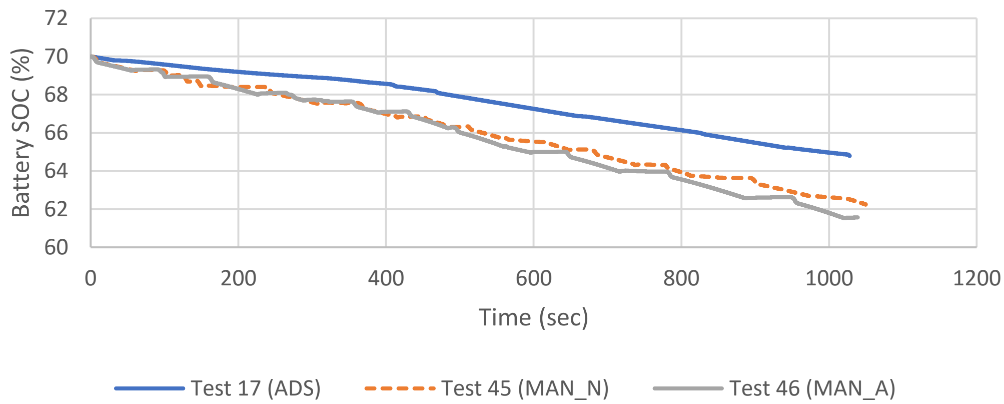

Fig. 6.180. Battery SOC for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

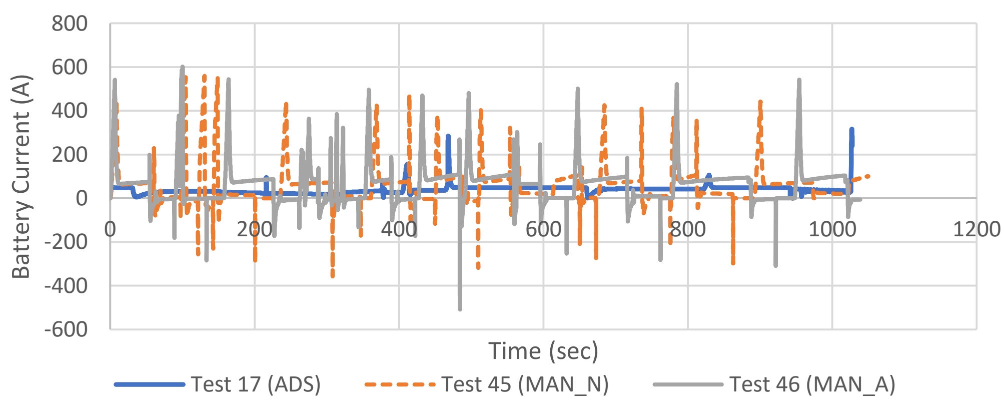

Fig. 6.181. Battery Current for Test 17 (ACC and AEB with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

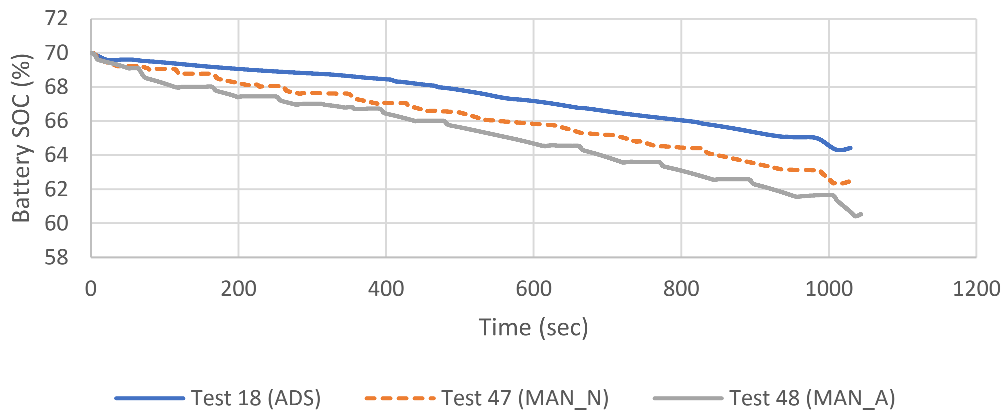

Fig. 6.182. Battery SOC for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

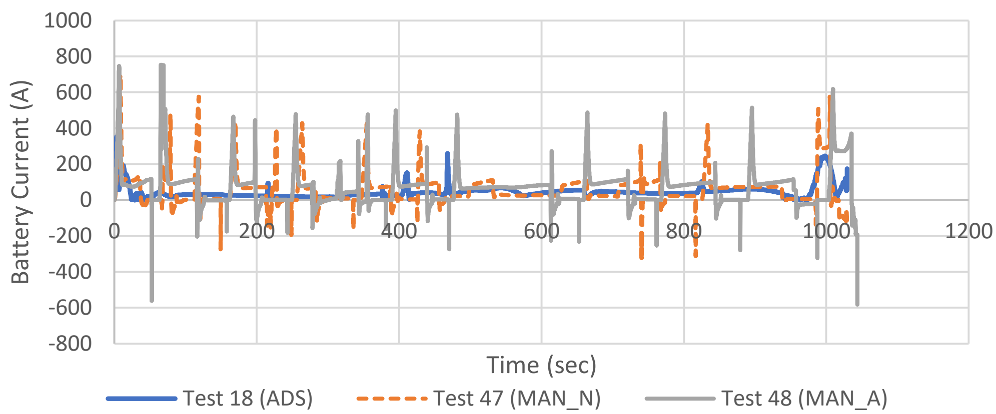

Fig. 6.183. Battery Current for Test 18 (ACC and AEB with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

The ADS based test cases with ACC and AEB control were again seen to produce Autonomous-capable EV battery current and SOC profiles with significantly lower fluctuations or instantaneous deviations compared to the normal and aggressive driving test cases. Similar to the CC test cases, the ACC and AEB test cases also resulted in a higher battery SOC throughout the drive cycle, on average.

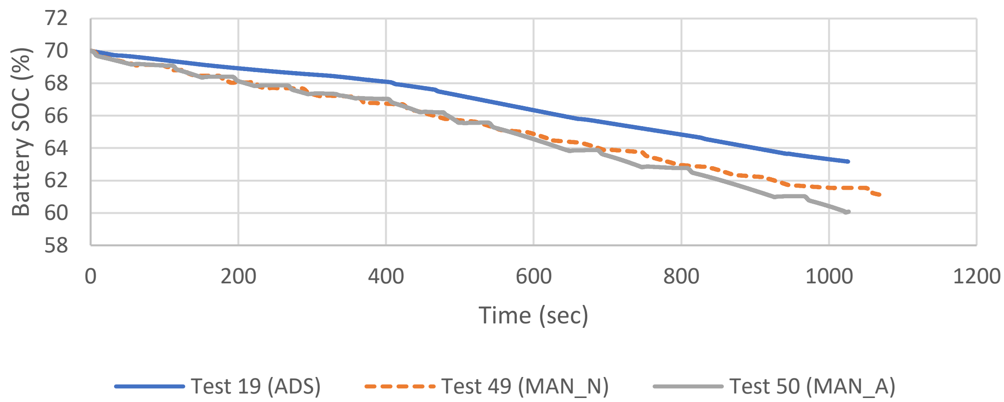

Fig. 6.184. Battery SOC for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

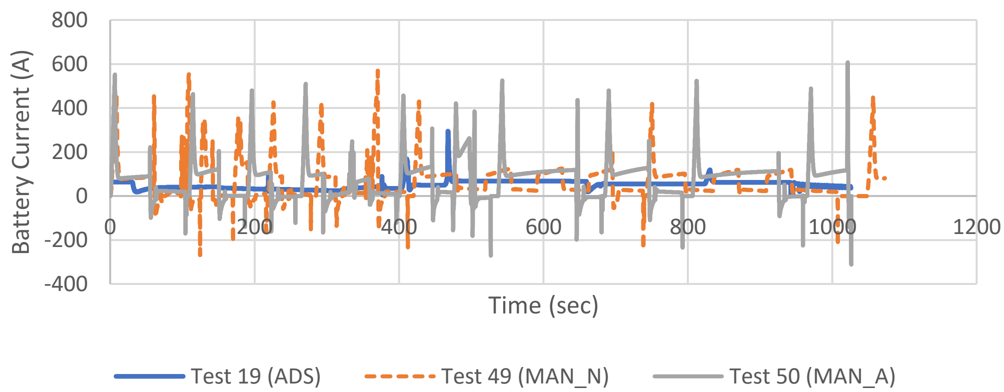

Fig. 6.185. Battery Current for Test 19 (ACC and AEB with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

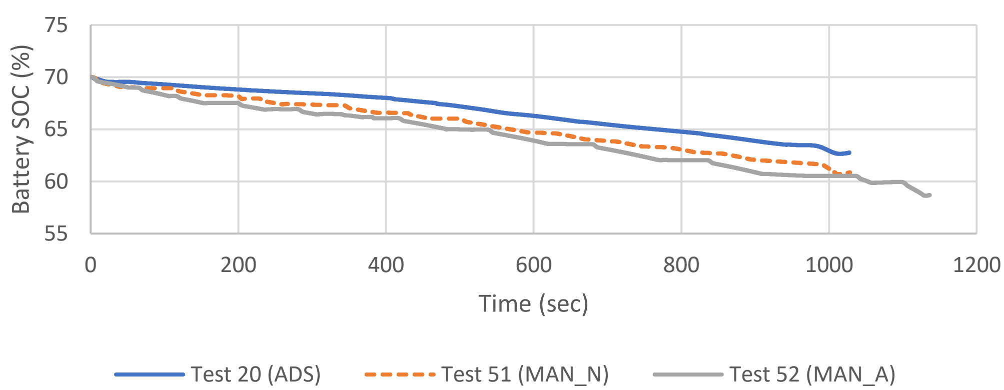

Fig. 6.186. Battery SOC for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

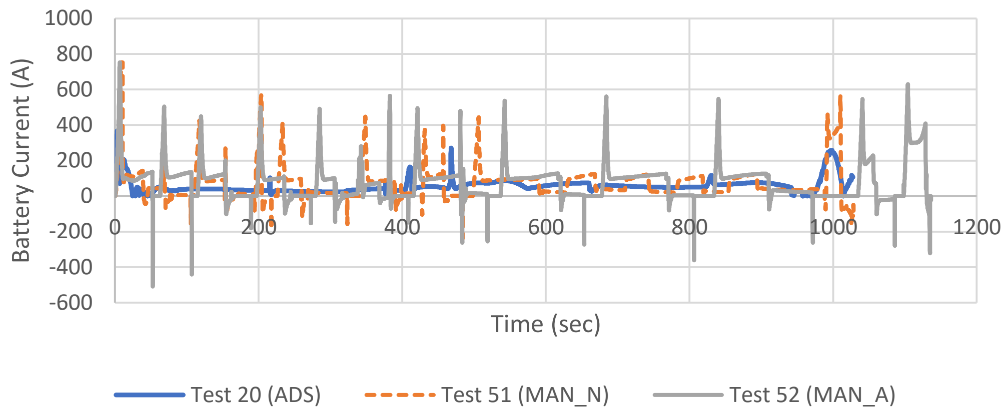

Fig. 6.187. Battery Current for Test 20 (ACC and AEB with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

The battery results for ALKA based test cases and their manual human driving comparisons are shown in Fig. 6.188 to 6.203. The patterns reflected for the Autonomous-capable EV motor results are also seen to be replicated for the battery results, as anticipated.

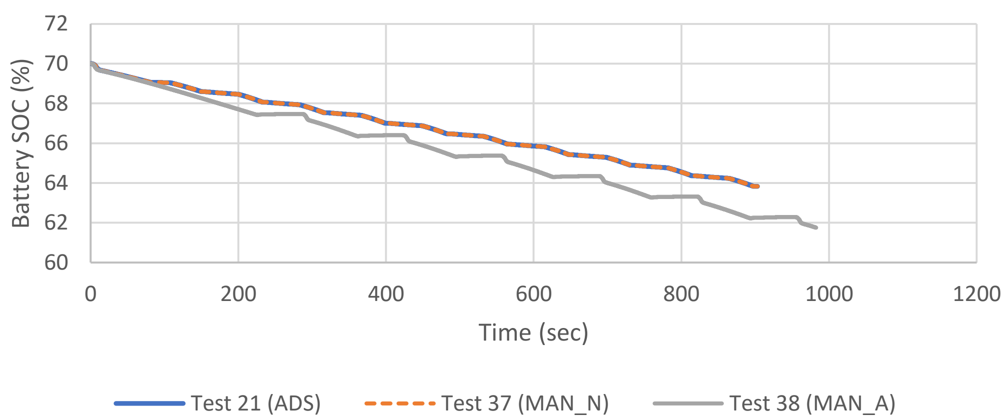

Fig. 6.188. Battery SOC for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

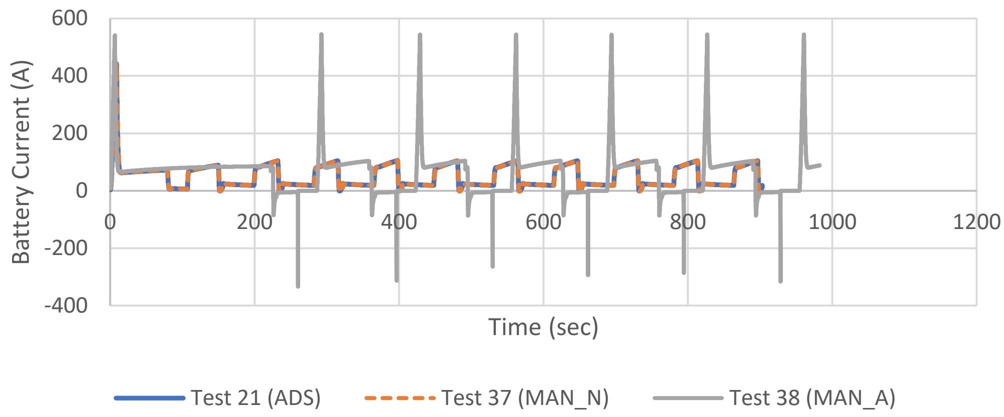

Fig. 6.189. Battery Current for Test 21 (ALKA with Road 1, Ideal Weather and No Traffic) and its Manual Comparisons.

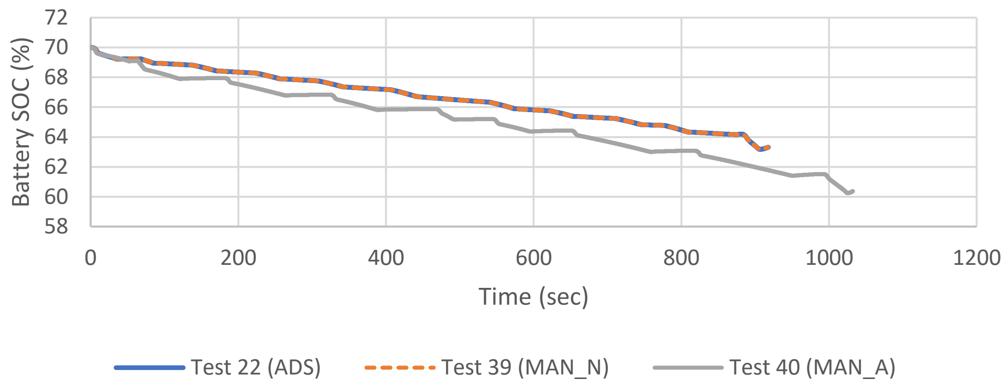

Fig. 6.190. Battery SOC for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

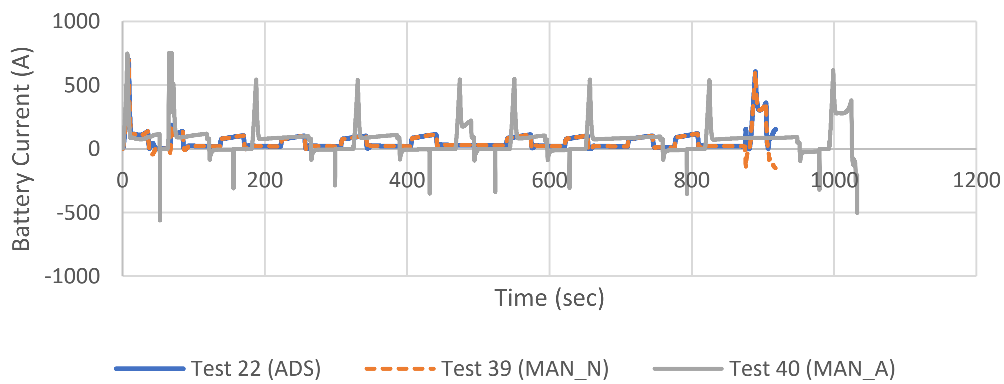

Fig. 6.191. Battery Current for Test 22 (ALKA with Road 2, Ideal Weather and No Traffic) and its Manual Comparisons.

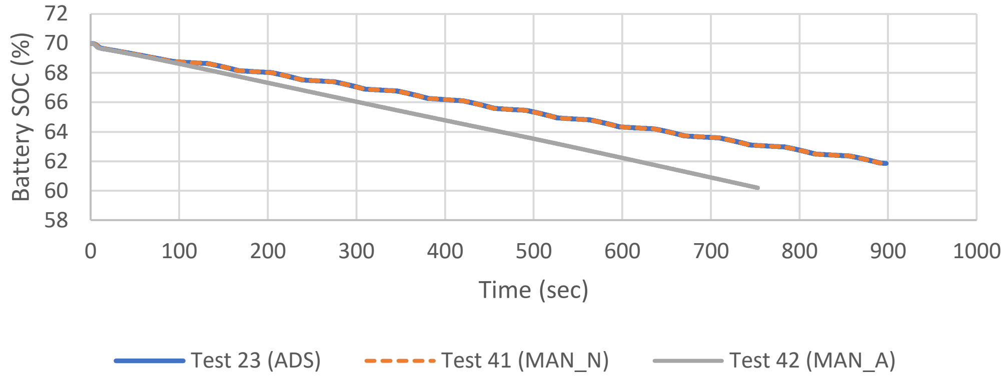

Fig. 6.192. Battery SOC for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

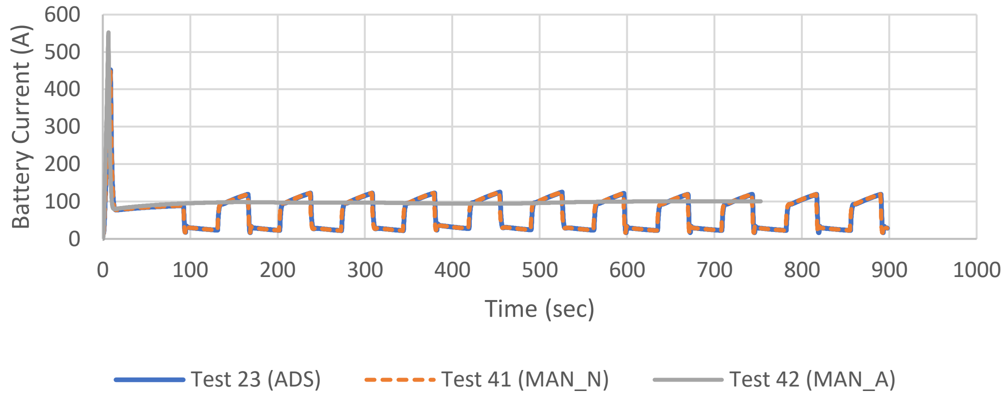

Fig. 6.193. Battery Current for Test 23 (ALKA with Road 1, Adverse Weather and No Traffic) and its Manual Comparisons.

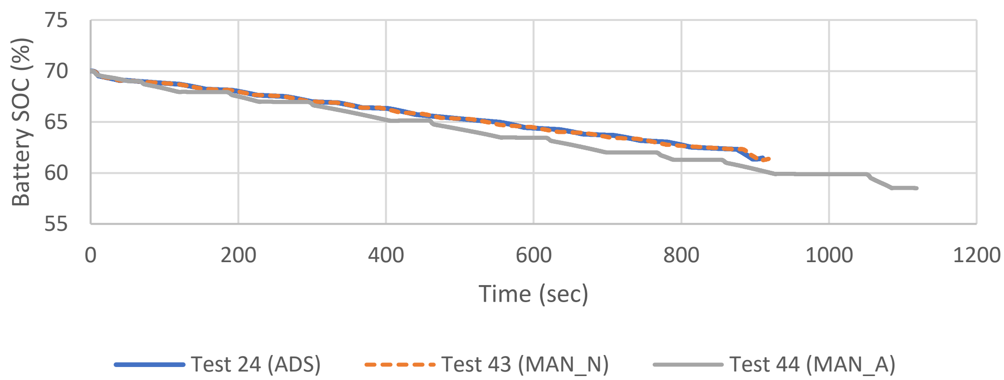

Fig. 6.194. Battery SOC for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

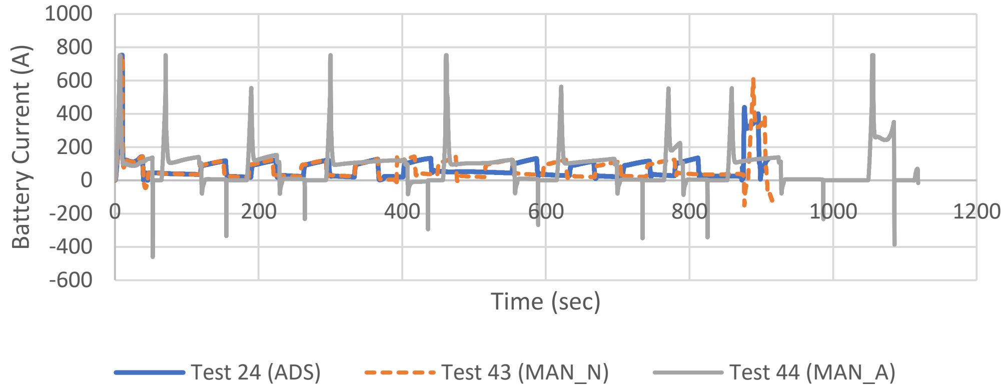

Fig. 6.195. Battery Current for Test 24 (ALKA with Road 2, Adverse Weather and No Traffic) and its Manual Comparisons.

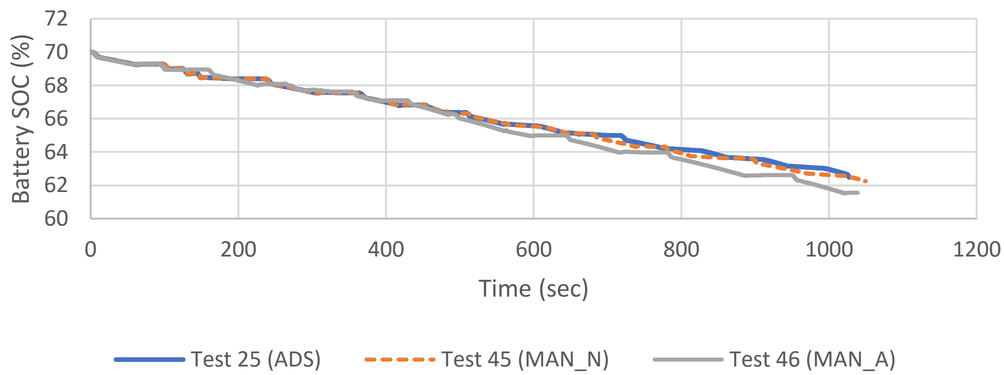

Fig. 6.196. Battery SOC for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

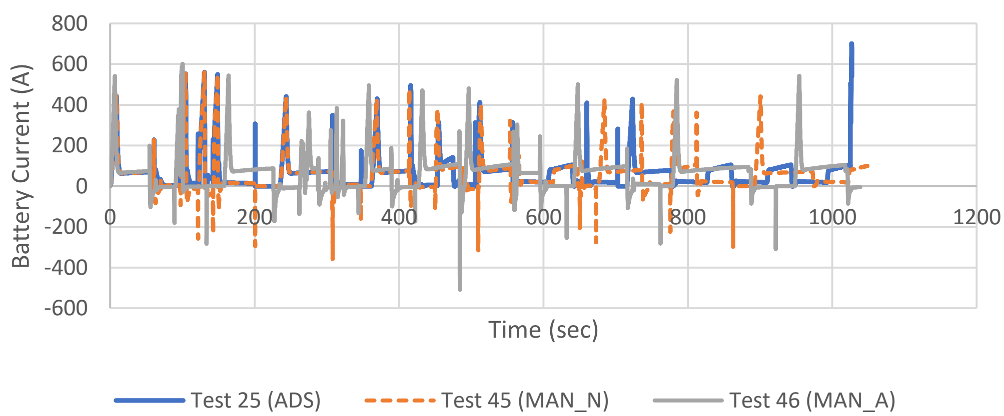

Fig. 6.197. Battery Current for Test 25 (ALKA with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

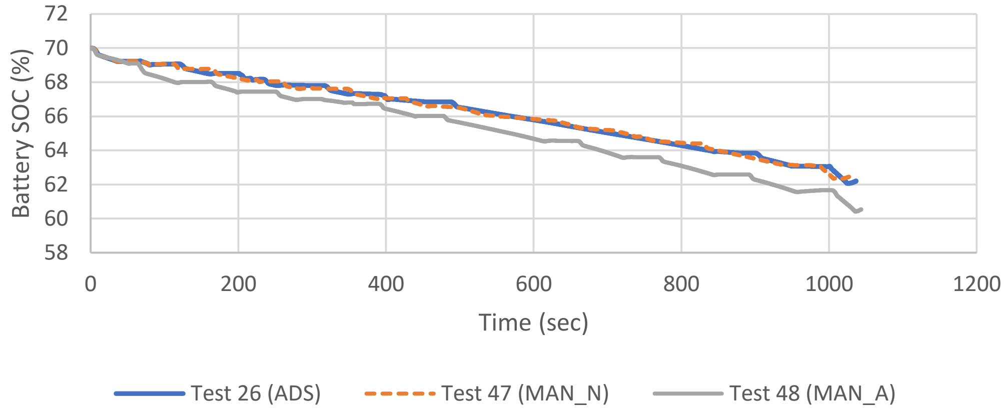

Fig. 6.198. Battery SOC for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

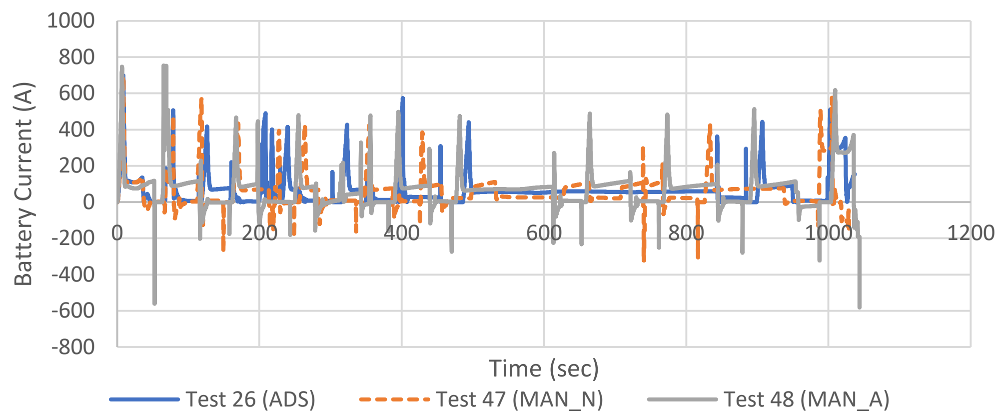

Fig. 6.199. Battery Current for Test 26 (ALKA with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

In overall, although once again the autonomous lateral control of the vehicle seems to have a relatively lower impact on the EV battery operation, it is evident that the battery performs optimally under the ADS lateral control in comparison to the aggressive driving control. This is seen through the drastically lower fluctuations under ADS control.

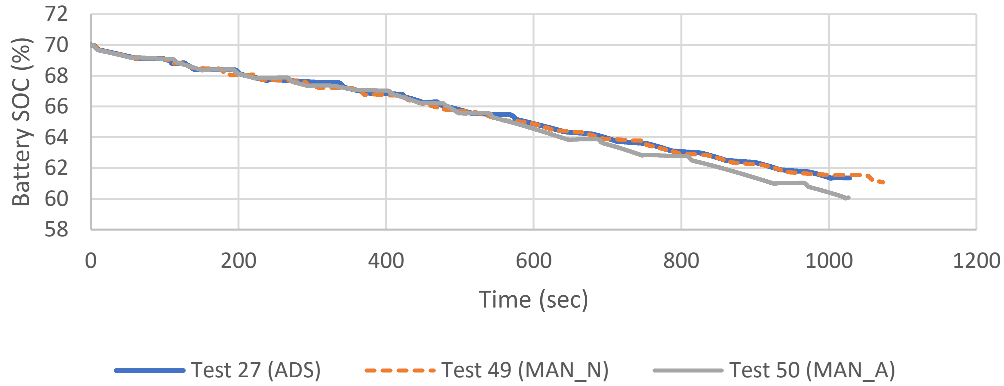

Fig. 6.200. Battery SOC for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

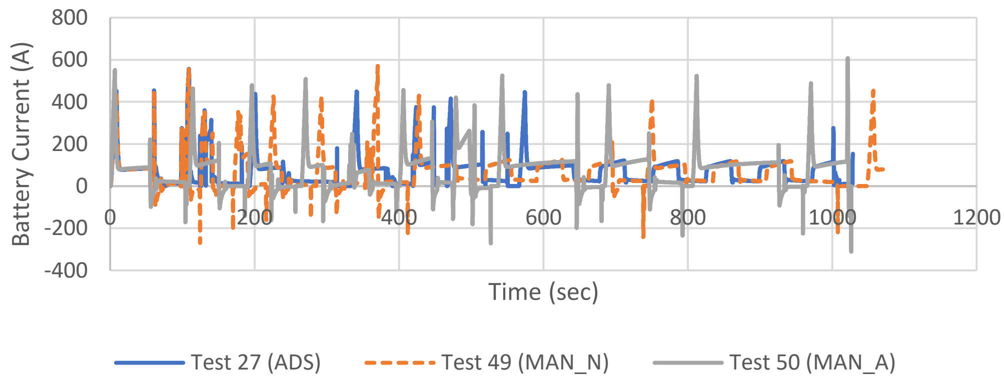

Fig. 6.201. Battery Current for Test 27 (ALKA with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

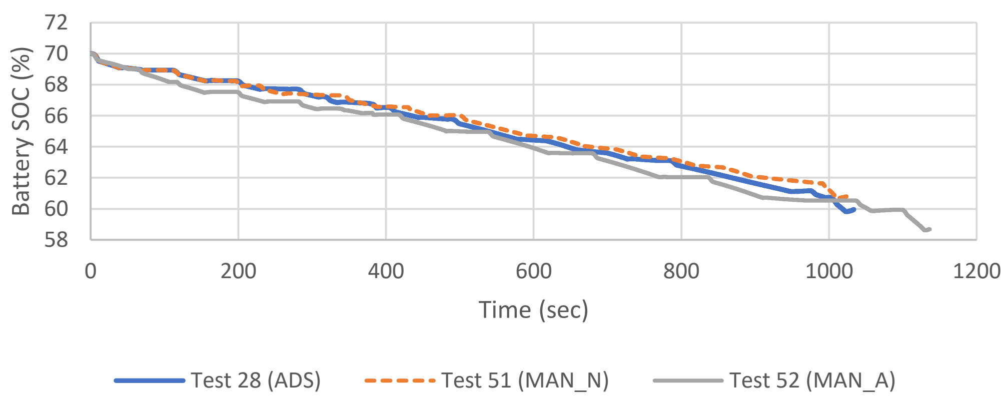

Fig. 6.202. Battery SOC for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

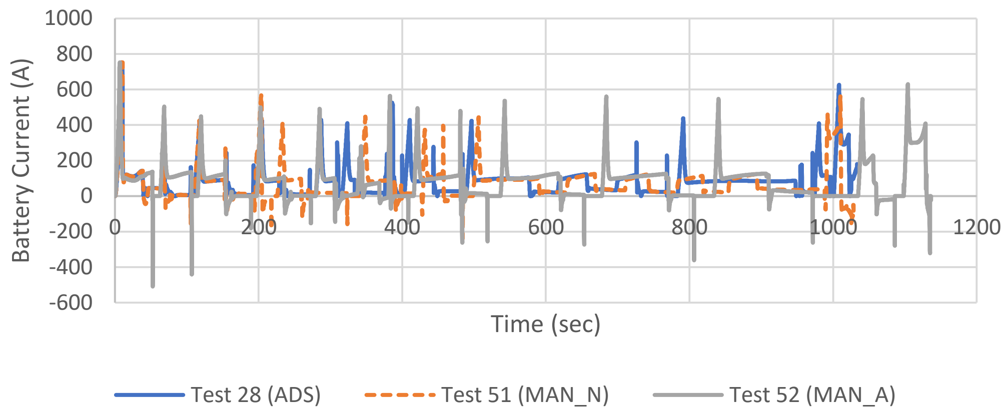

Fig. 6.203. Battery Current for Test 28 (ALKA with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

Lastly, the Autonomous-capable Electrified Vehicle battery SOC and current profiles for the level 4 autonomous control is presented through Fig. 6.204 to 6.219. Similar to the energy consumption, vehicle dynamics and motor results discussed in the previous sections for level 4 autonomous control, the battery results also demonstrate the optimal battery operation under the ADS control.

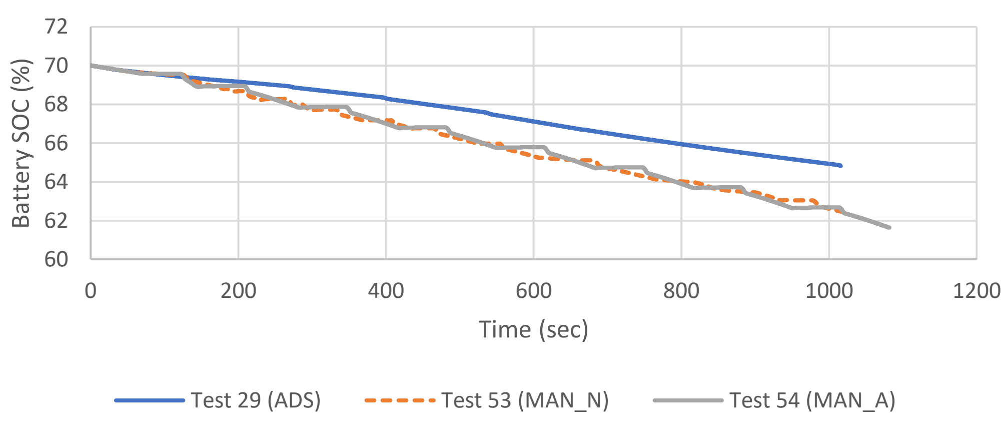

Fig. 6.204. Battery SOC for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

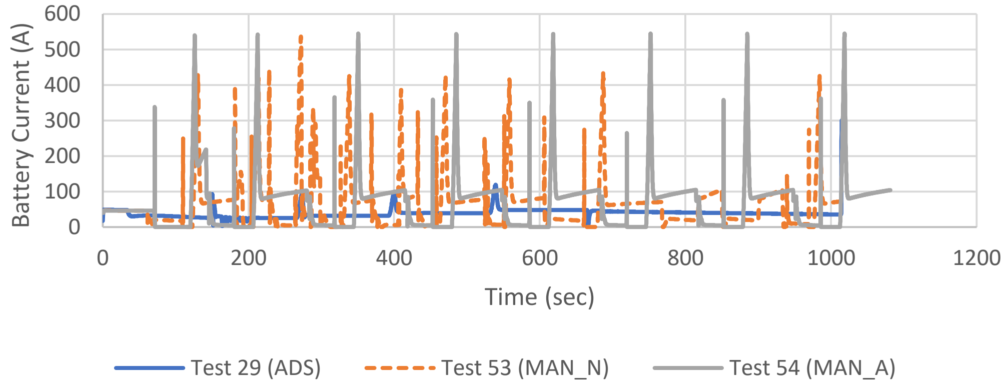

Fig. 6.205. Battery Current for Test 29 (L4 with Road 1, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

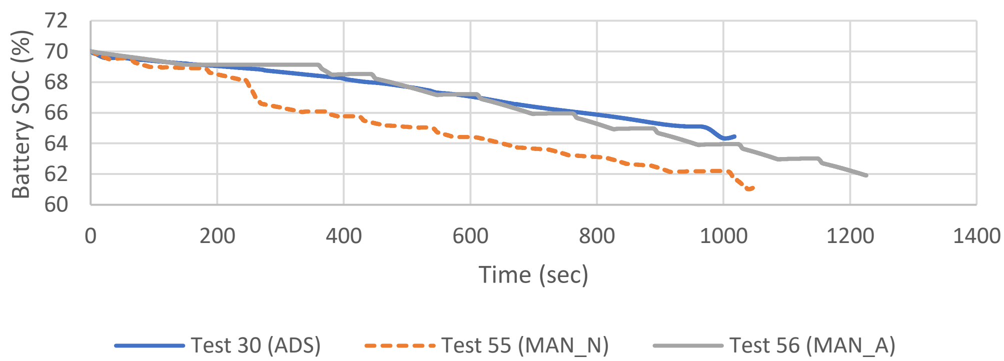

Fig. 6.206. Battery SOC for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

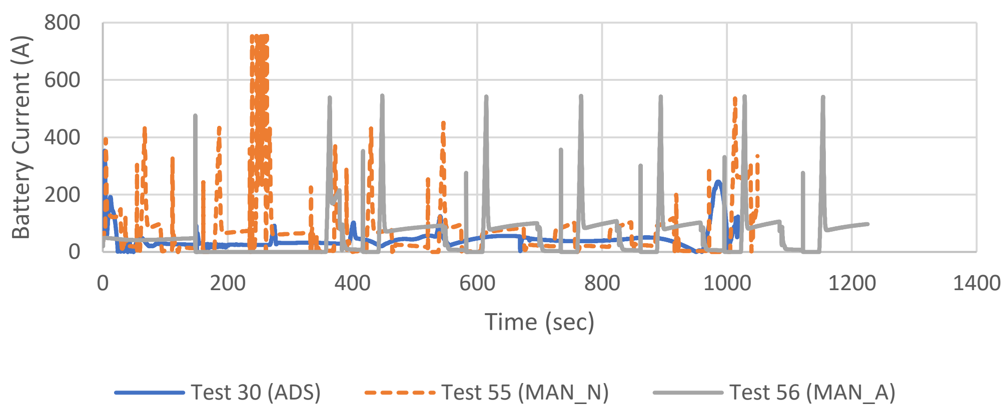

Fig. 6.207. Battery Current for Test 30 (L4 with Road 2, Ideal Weather and Lead Vehicle Only) and its Manual Comparisons.

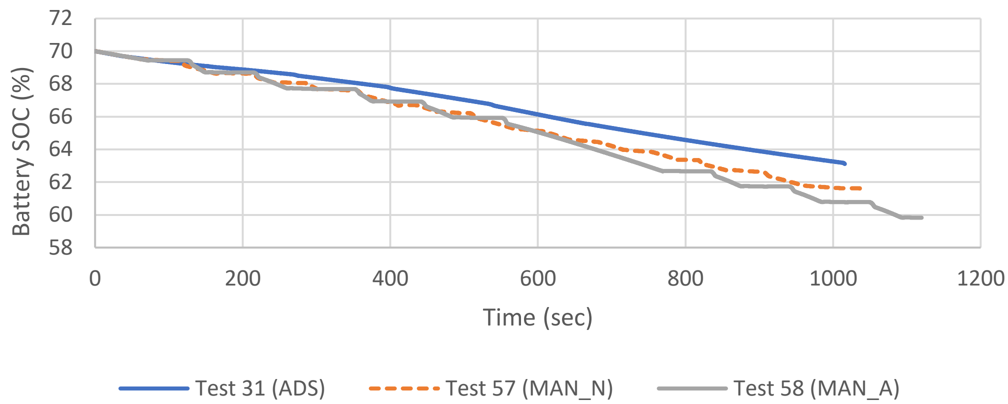

Fig. 6.208. Battery SOC for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

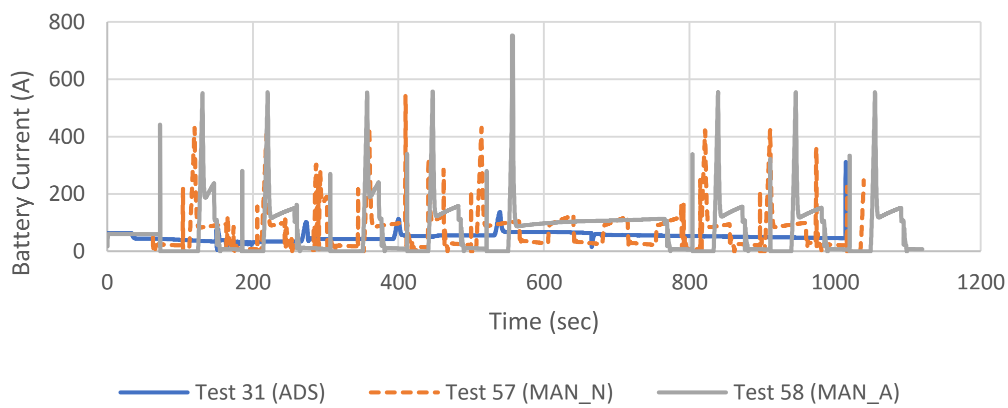

Fig. 6.209. Battery Current for Test 31 (L4 with Road 1, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

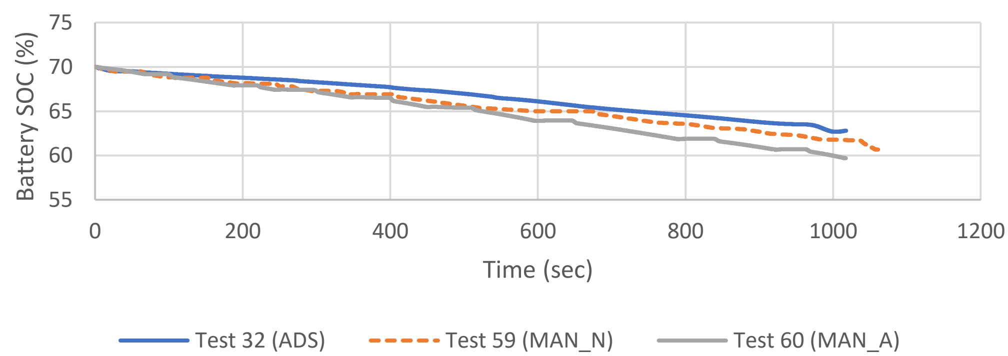

Fig. 6.210. Battery SOC for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

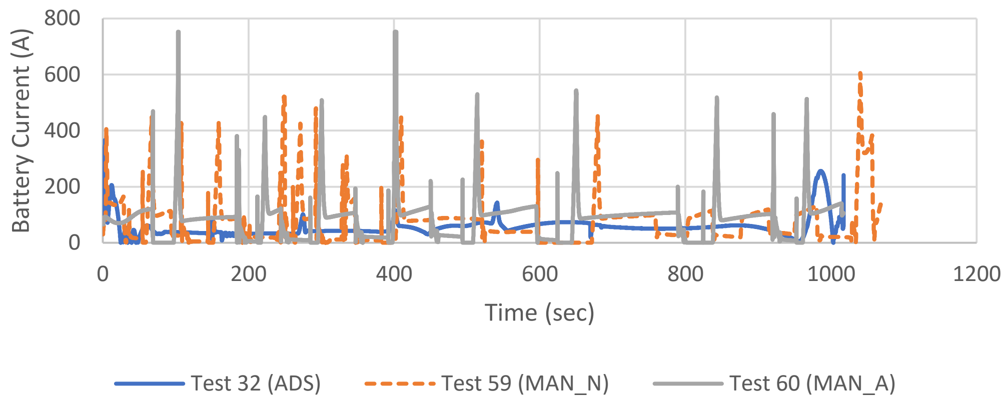

Fig. 6.211. Battery Current for Test 32 (L4 with Road 2, Adverse Weather and Lead Vehicle Only) and its Manual Comparisons.

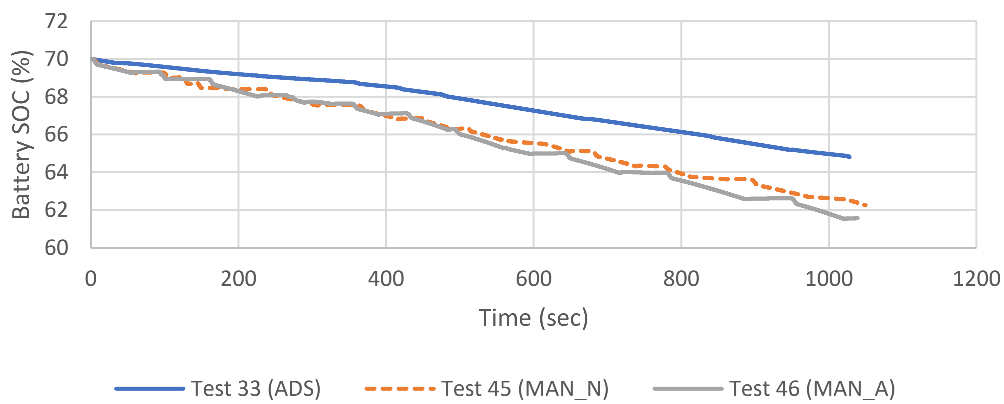

Fig. 6.212. Battery SOC for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

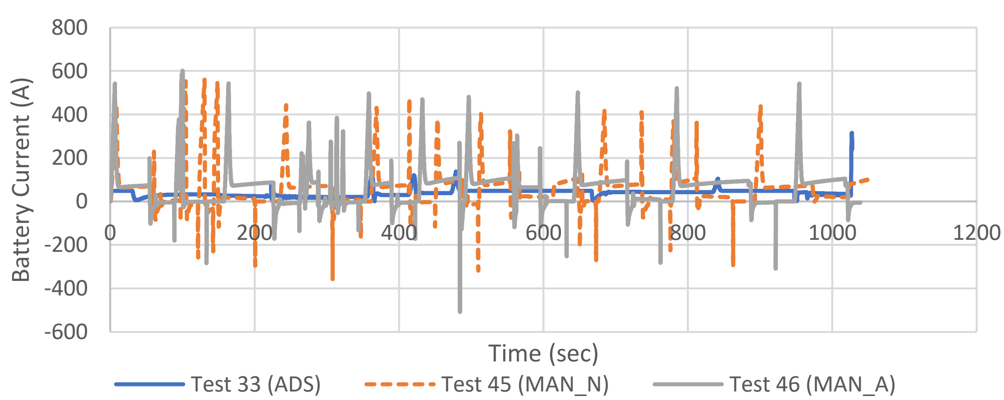

Fig. 6.213. Battery Current for Test 33 (L4 with Road 1, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

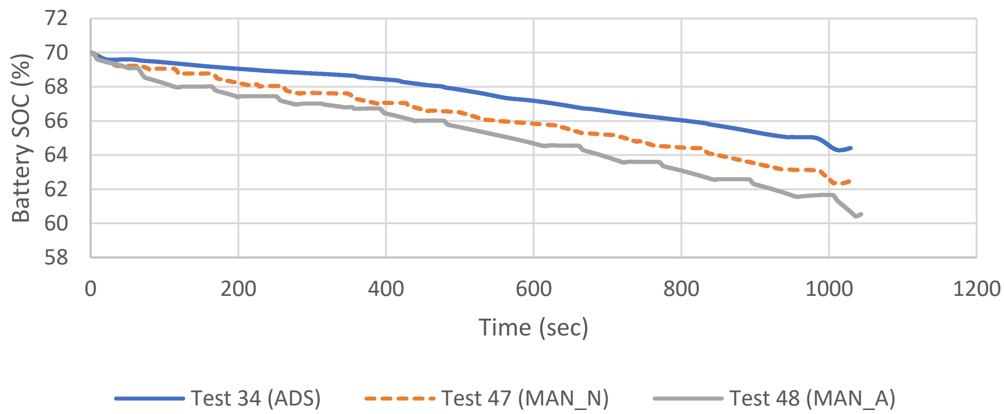

Fig. 6.214. Battery SOC for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

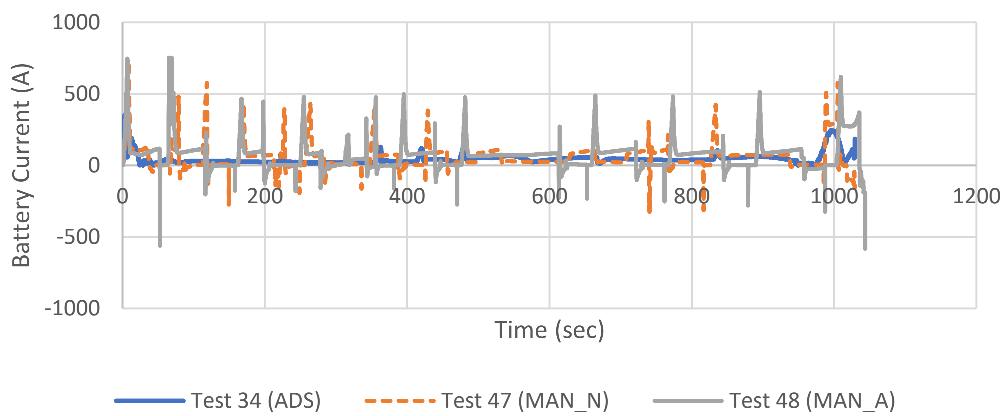

Fig. 6.215. Battery Current for Test 34 (L4 with Road 2, Ideal Weather and Multi-Object Traffic) and its Manual Comparisons.

In other words, the minimized instantaneous fluctuations and the streamlined profiles seen with the ADS control demonstrate the better operation of the EV battery during the level 4 autonomous control compared to its corresponding normal and aggressive driver control. These fluctuations and the established results will be further analyzed using a through quantitative sensitivity analysis in the next section of this thesis.

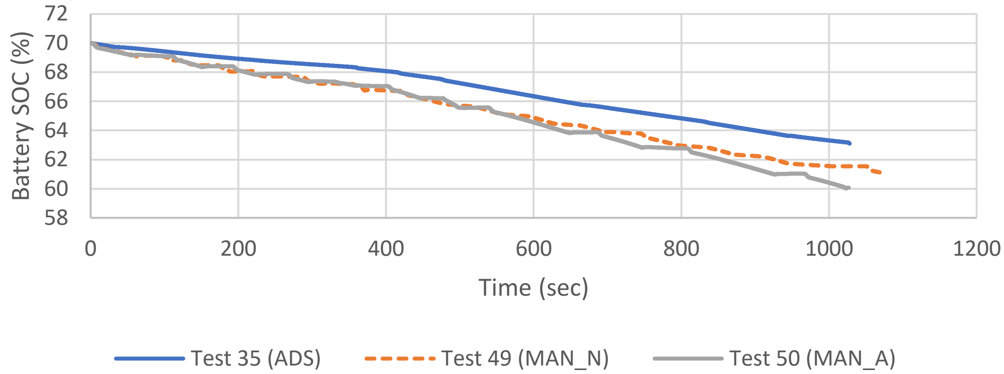

Fig. 6.216. Battery SOC for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

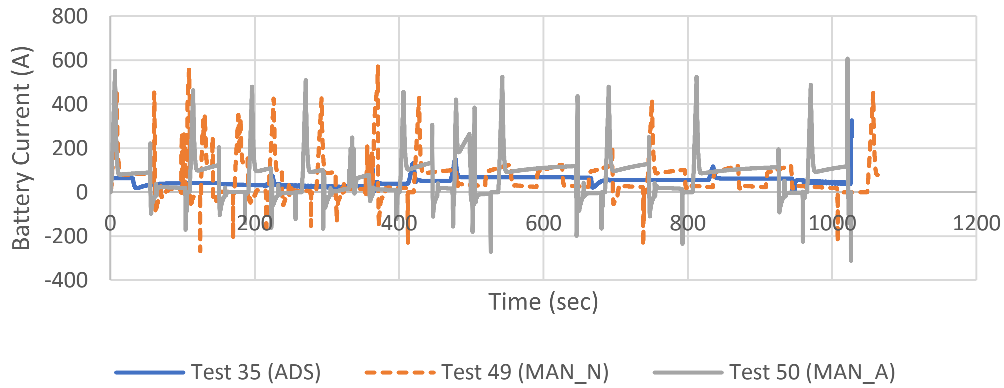

Fig. 6.217. Battery Current for Test 35 (L4 with Road 1, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

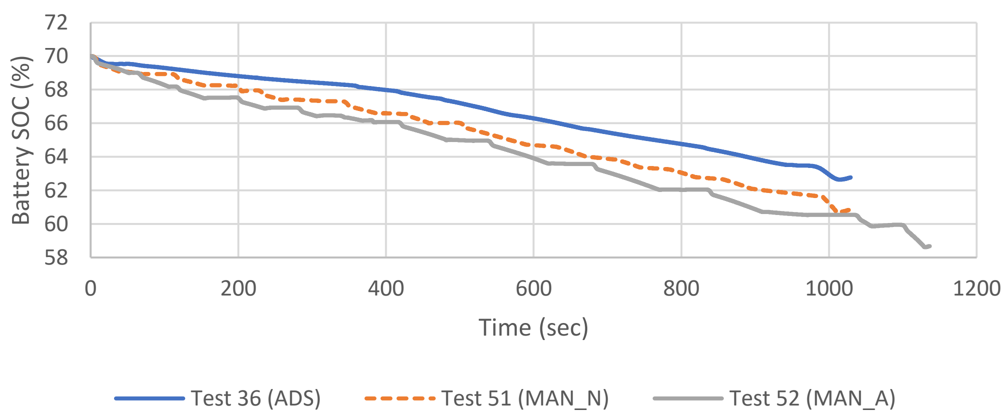

Fig. 6.218. Battery SOC for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

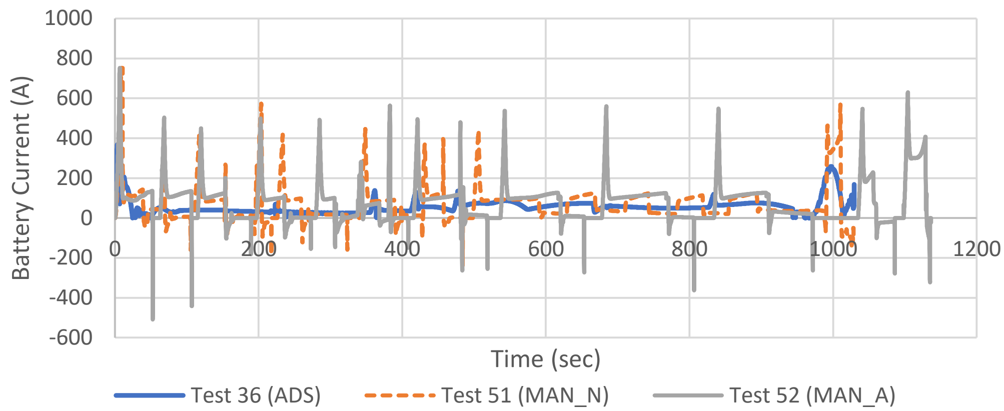

Fig. 6.219. Battery Current for Test 36 (L4 with Road 2, Adverse Weather and Multi-Object Traffic) and its Manual Comparisons.

6.3 Sensitivity Analysis on the Influence of Vehicle Autonomy

From the previous sections of this chapter, it is evident that the Electrified Vehicle performance is improved during the ADS control compared to the manual human driver control. This improved vehicle performance or a decrease in energy consumption, during an increase in vehicle autonomy, is intuitively expected to occur from an optimal eco-driving and energy management. Furthermore, one of the reasons is also anticipated to be the positive influence of vehicle autonomy on the various Electrified Vehicle components. It was briefly seen in the previous sections how the complete or partial autonomous control of Electrified Vehicle's driving functions aided in achieving steadier and streamlined profiles, with lower instantaneous fluctuations for the motor, battery and so on. This section attempts to quantify this impact of vehicle autonomy on various Electrified Vehicle components, properties, and dynamics through a rigorous sensitivity analysis. The average instantaneous deviations or fluctuations for every test case is studied through a systematic comparative analysis between the ADS, normal human driver and an aggressive human driver. In overall, the fluctuations can be seen to be the highest for an aggressive driver, followed by a normal driver and then by ADS. This precisely contributes to the highest energy economy offered during ADS control due to the least amount of fluctuations in the various Electrified Vehicle dynamics and the component operation.

Firstly, the average percent deviations for the various Electrified Vehicle properties such as host vehicle velocity, battery current, energy consumption and motor load, power, torque, voltage, and speed were studied. The results have been presented in Fig. 6.220. It can be seen that the battery current is the most sensitive parameter to variations in the vehicle control, followed by motor power. It can also be seen that for all of the properties analyzed, the average instantaneous fluctuations have been the least for ADS control offering semi or full autonomous control of the test Electrified Vehicle.

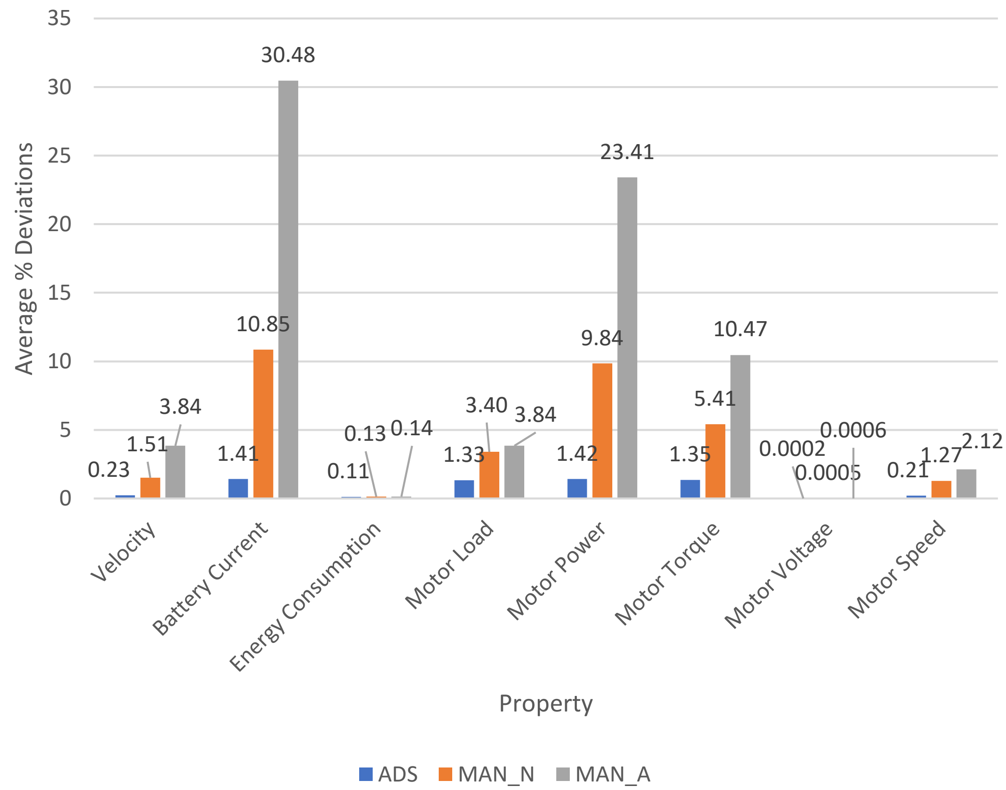

Fig. 6.220. Average percent deviations for the various EV properties.

The average percent fluctuations in the instantaneous velocity of the host vehicle is compared for the ADS, normal human driver and the aggressive human driver control. The results are represented in Fig.6.221. Similar to above, the fluctuations can be seen to be very low for the ADS control compared to the normal and the aggressive driving. Furthermore, the deviation cluster is seen to be mostly higher for the aggressive driver compared to the normal human driver. This, in turn, contributes to a better vehicle performance during ADS or autonomous/ semi-autonomous control, compared to a human driver, through optimal eco-driving.

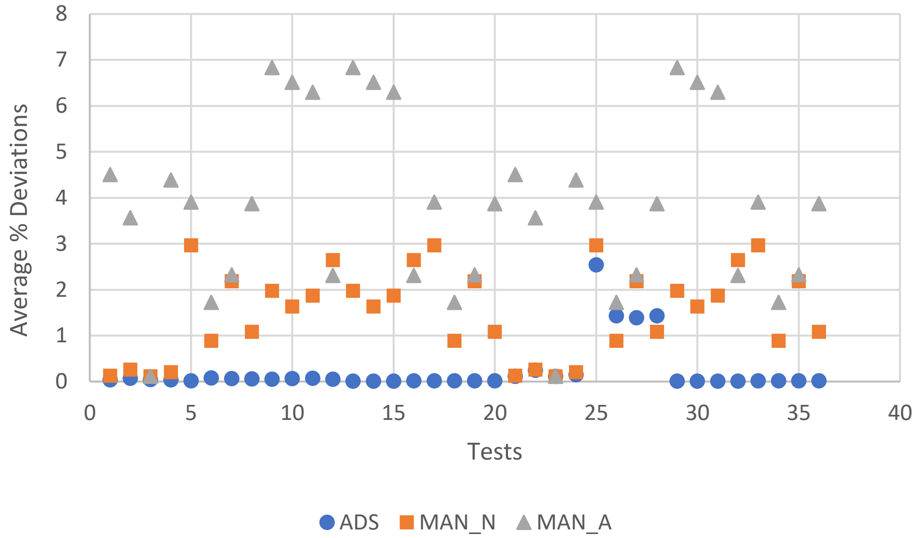

Fig.6.221. Average percent deviations in host vehicle velocity.

The fluctuations in the Electrified Vehicle battery current and the energy consumption are shown in Fig. 6.222 and 6.223 respectively. The optimal energy management is clearly seen through the least instantaneous deviations noticed for ADS control, followed by normal human driver control and then the aggressive human driver, on average.

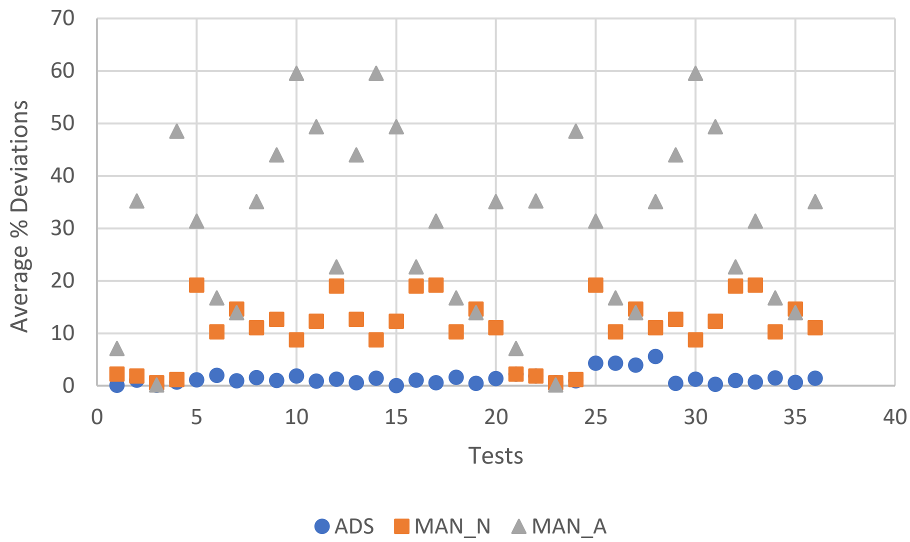

Fig.6.222. Average percent deviations in EV battery current.

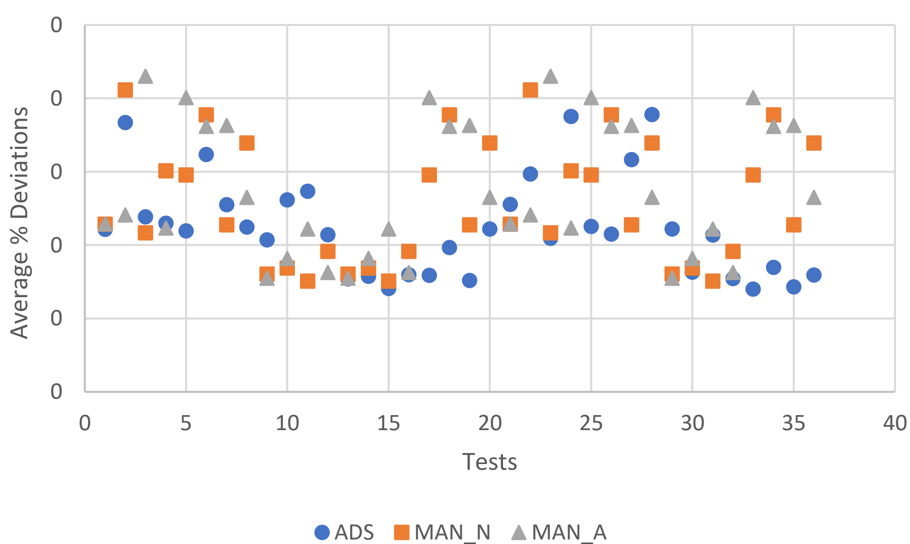

Fig.6.223. Average percent deviations in energy consumption.

The above-described trend is also evident from the motor load, power, torque, voltage and speed deviation profiles shown in Fig. 6.224, 6.225, 6.226, 6.227 and

6.228 respectively. These profiles, in overall, demonstrate a more optimal performance of the motor during semi-autonomous or autonomous control of the Electrified Vehicle, compared to normal or aggressive human driving, in turn resulting in better vehicle performance.

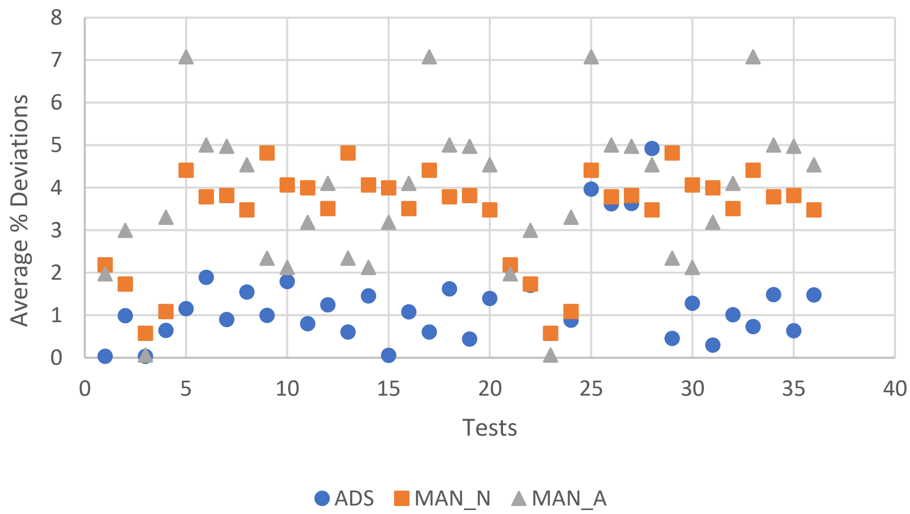

Fig.6.224. Average percent deviations in EV motor load.

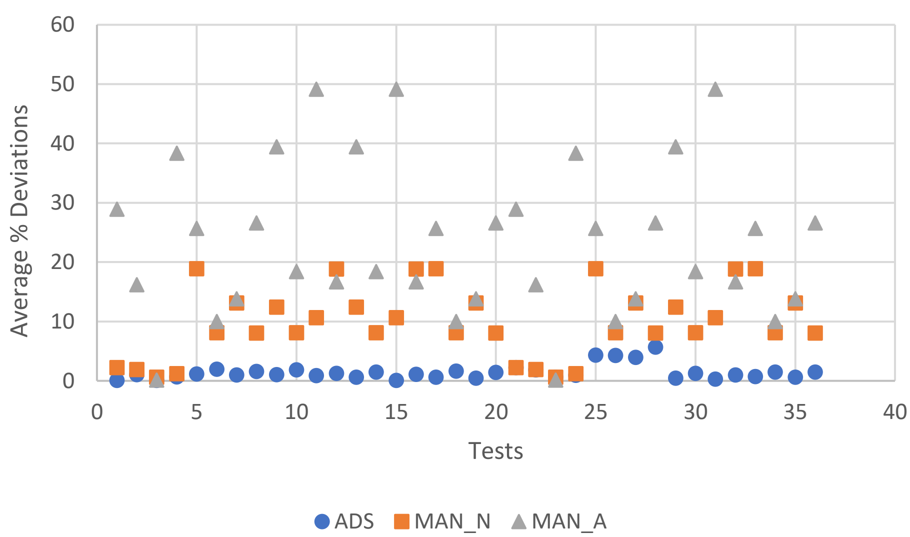

Fig.6.225. Average percent deviations in EV motor power.

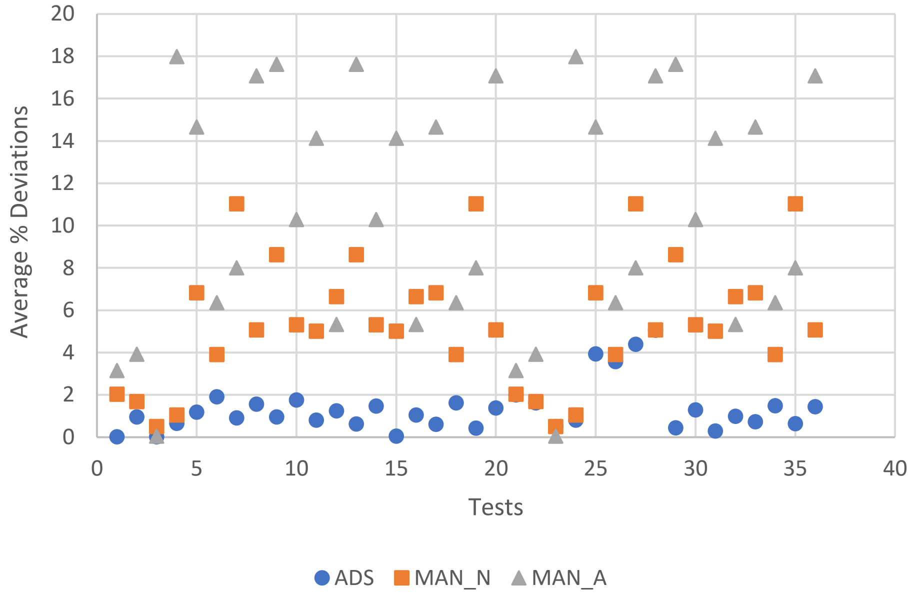

Fig.6.226. Average percent deviations in EV motor torque.

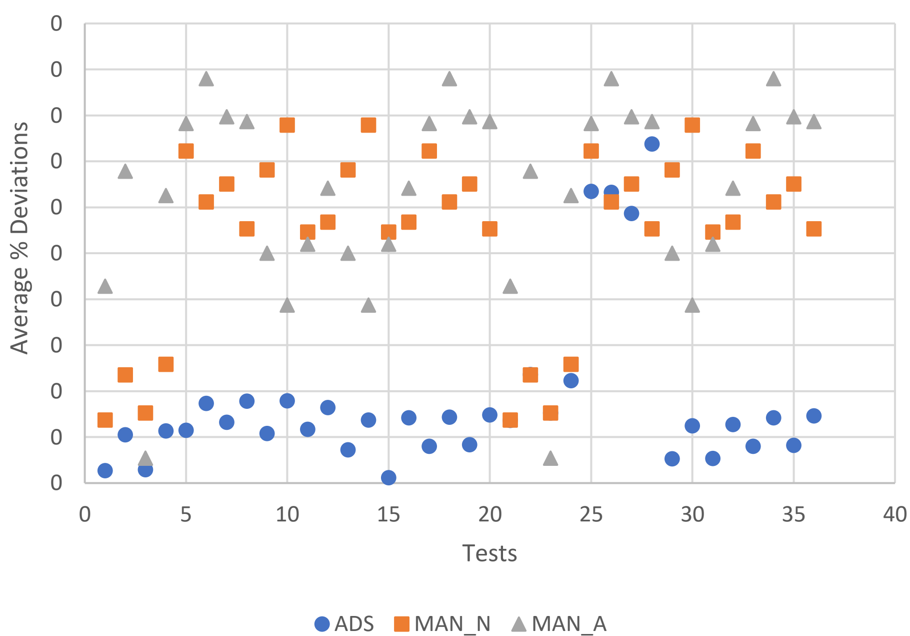

Fig.6.227. Average percent deviations in EV motor voltage.

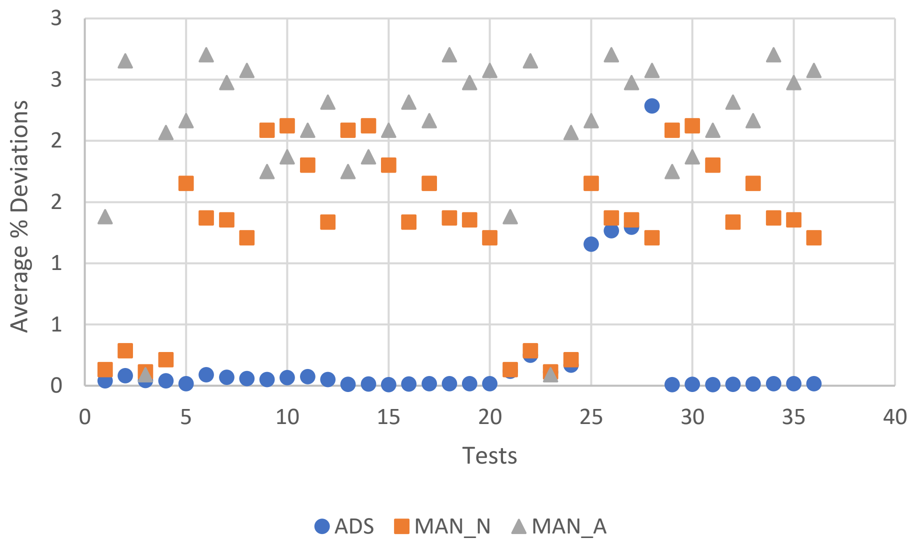

Fig.6.228. Average percent deviations in EV motor speed.

Furthermore, a quantitative comparative analysis was also performed to analyze the average percent increase or decrease in the fluctuations for the various Electrified Vehicle properties during autonomous or semi-autonomous control of the vehicle versus manual human driver control. The results of this analysis are presented in Table 6.4 below. In overall, it can be seen that the percent increase in fluctuations is drastically high for manual human control compared to the ADS control (semi-autonomous/ autonomous control), strongly signifying the optimal Electrified Vehicle component operation and energy management, thus offering an optimal eco-driving ability with higher energy economies during semi-autonomous/ autonomous control of the Electrified Vehicles.

Table 6.4 Average Percent Increase in Fluctuations for Manual human driver control compared to ADS

EV Properties	% increase in fluctuations for normal human driver control compared to ADS	% increase in fluctuations for aggressive human driver control compared to ADS
Vehicle Velocity	146	177
Battery Current	154	182
Energy Consumption	15	22
Motor Load	87	97
Motor Power	150	177
Motor Torque	120	154
Motor Voltage	101	112
Motor Speed	143	164

Chapter 7

Conclusions and Future Work

This chapter presents major conclusions derived from the research work conducted as part of this thesis. Discussion of the challenges faced, and methodology adopted to overcome them in addition to the limitations and scope for any future work is also presented.

7.1 Thesis Findings and Conclusions

This thesis addresses the limited technical literature available for ADAS architectures which are expected to form as a primary building block for the next generation of Highly Automated EVs by proposing a Cognitive ADAS Architecture for Autonomous-capable Electrified Vehicles. The proposed architecture is inspired by the human cognitive processes to represent a functional distribution of the various modules, sub-modules, component examples, interactions, and interfaces both internal and external to the vehicle. The proposed Cognitive ADAS Architecture is developed primarily for level 4 Autonomous-capable Vehicles. However, variations of the architecture are also offered for levels 3 and 3.5.

In addition, the proposed Cognitive ADAS Architecture is verified using vehicle-level simulations based on an enhanced 2014 Tesla Model S 85. 113 test cases with 108 for functional simulations and 5 for validation are setup with 60 different unique combinations of ADS, normal human driver and aggressive driver control. 7 different variations in the external conditions such as road, traffic and weather were also evaluated. This methodology adopted for simulations encompassing varying realistic external conditions as well as the validation of the simulation model utilizing the EPA standard 5 cycle adjustment method helped in ensuring robustness of the proposed model.

Based on the results acquired, it was evident that the ADS control-based test cases have outperformed both the normal and the aggressive driver control, on average, in terms of the various EV attributes studied. It could be seen that with the increase in Electrified Vehicle autonomy, the vehicle performance is also increased. This is mainly due to the optimal eco-driving, energy management and planning possible through the improved operation of the EV components such as the motor and battery under autonomous or semi-autonomous control of the EV compared to the complete human driver control. In other words, the Autonomous-capable EV, upon being exposed to the same driving environment conditions as the human driver model, showed an improved vehicle performance when partially or completely controlled by the ADS.

On average, a significant increase of about 28 percent was noticed for the Autonomous-capable EV energy economy under the ADS control compared to the human driver control. When this result was decomposed further, it was seen that there was a 22 and 35 percent increase, on average, for ADS control compared to the normal and the aggressive driver control respectively. A thorough sensitivity analysis was also carried out to further quantify the impact of EV autonomy on the various vehicle attributes. From this analysis it was seen that, on average, the instantaneous fluctuations were significantly lower, hence providing more uniform and streamlined profiles under ADS control, compared to the human driver control for the energy economy, vehicle dynamics, motor and battery results collected. The battery current, followed by the motor power, speed and then torque were seen to have the highest fluctuations, about 168, 163.5, 153.5 and 137 percent higher respectively under average human driver control compared to ADS, out of the various Autonomous-capable EV component parameters studied. In essence, the increase in autonomous control of the EV resulted in an increase in the vehicle performance and improved operation of the EV components in addition to the overall positive impact also on the vehicle dynamics.

In overall, the work presented in this thesis is believed to advance the current literature another step forward in terms of the ADAS architectures, modeling and simulation of highly Autonomous-capable EVs as well as systematically understanding the role played by autonomous driving in improving the Electrified Vehicle performance.

7.2 Discussion

This section will present a summary of the challenges faced during this research and how they were overcome to successfully accomplish the goals established. Firstly, the architecture development was faced with challenges due to the need for representing a vast amount of complex details about the different functions, components, interfaces and their interactions within an Advanced Driver Assistance System targeting Highly Automated Driving. To address this, the architecture was broken to provide a modular and systematic arrangement of the important attributes at the system-level. The breakdown between levels 3, 3.5 and 4 have been shown in separate diagrams. Further details about the different layers, modules, and sub-modules within the architecture have been described within Chapter 4.

In addition, the development of the simulation model by realizing the complex combination of autonomous and Electrified Vehicle concepts was also found to be challenging due to the very limited technical literature on this topic. Nevertheless, the systematic mapping offered between the proposed Cognitive ADAS Architecture and the CarMaker simulation model was very helpful for verifying both the architecture and the simulation model.

Furthermore, the most arduous challenge faced was the collection and analysis of the enormous amount of simulation results (collected with a time span of 0.1 seconds and simulated at a speed of 5X), acquired from the 113 test cases, which accounted for approximately 600,000 rows including vehicle dynamics, motor, battery and energy consumption results. This part of the research work was the most laborious and time-consuming. This was addressed through the systematic section-wise arrangement of the representative results and analysis in this thesis.

Lastly, the validation of the simulation model was also found to be challenging due to the commercial unavailability of level 4 Autonomous-capable EVs for experimental validation. Due to the proprietary nature of some of the on-going prototyping activities, very limited technical literature and physical resources are currently available. As such, given the extensive amount of validated simulation-based research work and quantitative analyses conducted, experimental validation was considered out of scope for this study, as already described previously. Thus, an alternative validation technique using the EPA 5-cycle adjustment method was presented in the previous chapter which demonstrated the validity of the simulation model and the acquired results in addition to the sound research methodology and thorough quantitative analysis techniques adopted for this study.

7.3 Limitations and Future Work

This section summarizes the limitations of the work presented in this thesis as well as scope for any future work. The proposed Cognitive ADAS Architecture is divided based on the targeted vehicle automation level giving a slightly different architecture for every level. Suggested future work includes further development of the proposed Cognitive ADAS Architecture to be scalable to represent the different levels of vehicle automation ranging from 0 to 5.

Furthermore, each of the individual sub-blocks of the proposed system level architecture could be broken down to represent a detailed architecture (similar to the one presented) at the next abstraction levels. The architecture could also be expanded to include different types of vehicles such as hybrid, ICE and so on. The current architecture only focuses on Electrified Vehicles.

In addition, experimental analysis to further support the evaluation of vehicle autonomy and its impact on the Electrified Vehicle dynamics, components and performance could be carried out. This has been out of scope for this thesis due to the commercial unavailability of the highly Autonomous-capable EVs at the time of this research.

The analysis of the results could also be expanded further, as part of future work, to understand the other reasons behind the improved vehicle performance during semi-autonomous/ autonomous control of EVs compared to manual human driving besides the studied attributes such as the optimal eco-driving, energy management and operation of the Electrified Vehicle components with decreased instantaneous fluctuations during ADS control. Also, evaluation of the simulation model against realistic driving cycles as described in 5, [178]-[181] would be very helpful in further improving the analysis use cases and for benchmarking through a rolling road dynamometer testing or a vehicle simulator. In addition, the impact of autonomy on vehicle's long-term aging, battery life, motor efficiency and power consumption could also contribute to advancement of the current work. A trade-off analysis looking at the different vehicle attributes as well as safety, cost, comfort, economic and societal impacts can also be carried out, based on a specific vehicle example, as part of the future work. Also, the benefits of ADS control combined with energy optimization (e.g. regenerative braking) in further improving the vehicle performance can be evaluated.

Furthermore, some of the growing trends in the field of Autonomous-capable Vehicles such as vehicle platooning (with at least one of the host vehicles demonstrating level 2 or above vehicle automation level), Vehicle to Vehicle and Infrastructure, and Cloud communication can also be explored further in the simulations based on the availability of applicable resources. Although V2V, V2I and Cloud communications have been included in the proposed Cognitive ADAS architecture, they were considered out of scope for the current simulations due to the limited infrastructure available at the time of this research.

Control of the Sensor Fusion and Integration functionality was limited due to the assumed default operations performed by CarMaker in the simulation's background. Future improvement on the tool side could be helpful in incorporating sensor fusion inaccuracies or realistic discrepancies among the different sensors. It was also observed from the simulation results that the normal and aggressive human driver models recommended in the tool provided more fluctuations in the velocity, motor and battery profiles than expected. Having the availability of additional human driver models, with varying parameter recommendations covering other possibilities in the human factors spectrum, could be helpful in further improving the reliability of human driver comparisons to ADS control.

Lastly, an online repository of the extensive amount of data collected can be developed for future vehicle analysis work in the field of Autonomous-capable Vehicles.

References

[1] NHTSA, “Distracted Driving", *NHTSA*, 2015. [Online]. Available: https://www.nhtsa.gov/risky-driving/distracted-driving. [Accessed: 01- Jan- 2018].

[2] NETS, NHTSA, OSHA, "Guidelines for Employers to Reduce Motor Vehicle Crashes", *Osha.gov*, [Online]. Available: https://www.osha.gov/Publications/motor_vehicle_guide.html. [Accessed: 01- Jan- 2018].

[3] *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems,* SAE J3016_201401, Society of Automotive Engineers (SAE), Jan 2014.

[4] Tesla Motors, “Model S”, *Teslamotors.com*, 2016. [Online]. Available: https://www.teslamotors.com/en_CA/models. [Accessed: 01- Feb- 2016].

[5] K. P. Divakarla, "Journey Mapping: a new approach for defining automotive drive cycles," M.A.Sc. Thesis, McMaster University, 2014.

[6] K. Bimbraw, “Autonomous cars: past, present and future – A review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology,” in *Proc. 2015 The International Conference on Informatics in Control, Automation and Robotics (ICINCO’15)*, Colmar, France, July 2015.

[7] R.R. Teetor, “Speed control device for resisting operation of the accelerator,” U.S. Patent US2519859A, Aug. 11, 1948.

[8] M. Cranswick, *Pontiac Firebird: The Auto-Biography*. Dorchester, England. Veloce Publishing Ltd., ISBN: 978-1-845845-97-1, Aug. 2013.

[9] M. Burgan, *The Pontiac Firebird*. New York: RiverFront Books, ISBN: 978-0-736801-82-9, Jan.1999.

[10] D. Temple and D. Adler, *GM's Motorama*. St. Paul, MN: MBI Pub., ISBN: 978-0-760328-2-62, Dec. 2006.

[11] Cardew, K. H. F. “The Automatic Steering of Vehicles: An Experimental System Fitted to a DS 19 Citroen Car”, UC Berkely Transportation Library, CA, RRL report. LR 340, 1970.

[12] J. Pressnell, *Citroen DS*. Ramsbury: Crowood, ISBN: 978-1861260550, June 1999.

[13] Toyota, “Intelligent Adaptive Front-lighting System (AFS)”, *Toyota-global.com,* 2016. [Online]. Available: http://www.toyota-global.com/innovation/safety_technology/safety_technology/technology_file/active/afs.html. [Accessed: 01- Feb- 2016].

[14] X.Ming, L. Trassoudaine, J. Alizon, M. Thonnat, and J. Gallice. “Active and intelligent sensing of road obstacles: Application to the European Eureka PROMETHEUS Project,” in *Proc. 1993 International Conference on Computer Vision*, Berlin, Germany, May 1993.

[15] G. Flyte, "Safe design of in-vehicle information and support systems: the human factors issues," *International journal of vehicle design*, vol. 16, no. 2-3, pp. 158-169, 1995.

[16] L.S. Davis, D. Dementhon, R. Gajulapalli, T. R. Kushner, J. LeMoigne, and P. Veatch. "Vision-based navigation: A status report," in *Proc. 1987 DARPA Image Understanding Workshop*, San Mateo, CA, Feb. 1987.

[17] W.J. Chundrlik, P.I. Labuhn, "Adaptive cruise system," U.S. Patent US5014200A, May 07, 1991.

[18] R. Leighty. "DARPA ALV (Autonomous Land Vehicle) Summary," Army Engineer Topographic Labs, Fort Belvoir, VA, No.ETL-R-085, Mar. 1986.

[19] J.W. Lowrie, T. Mark, K. Gremban, and M. Turk. "The autonomous land vehicle (ALV) preliminary road-following demonstration," in *Proc. 1985 International Society for Optics and Photonics Cambridge Symposium*, 1985.

[20] S. Chandran, L. S. Davis, D. Dementhon, S. J. Dickenson, and. S. Gajulapalli. "An Overview of Vision-Based Navigation for Autonomous Land Vehicles 1986," Maryland University College Park Center for Automation Research, MD, No. CAR-TR-285, Apr. 1987.

[21] R. Behringer and N. Muller, "Autonomous road vehicle guidance from autobahnen to narrow curves." *IEEE Transactions on Robotics and Automation*, vol. 14, no. 5, pp. 810-815, Oct. 1998.

[22] J. Wenger, "Automotive radar—Status and perspectives," in *Proc. IEEE Compound Semic. Integ. Circuit Symp.*, Palm Springs, CA, USA, Oct./Nov. 2005.

[23] U. Franke, S. Gorzig, F. Lindner, D. Mehren, and F. Paetzold. "Steps towards an intelligent vision system for driver assistance in urban traffic," in *Proc. 1997 IEEE Conference on Intelligent Transportation System (ITSC'97)*, Boston, MA, Nov. 1997.

[24] C. E. Thorpe, M. Hehert, T. Kanade and S. Shafer, "Toward Autonomous Driving: CMU Navlab." *IEEE Expert*, vol. 6, no. 4, Aug. 1991.

[25] D.A. Pomerleau, "Knowledge-based training of artificial neural networks for autonomous robot driving,"Carnegie Mellon University, Pittsburgh, PA, 1993.

[26] A. Broggi, M. Bertozzi, and A. Fascioli, "Architectural issues on visionbased automatic vehicle guidance: the experience of the argo project," *Real-Time Imaging Journal*, no. 6, pp. 313–324, 2000.

[27] S. E. Shladover, "Lane assist systems for bus rapid transit, Volume I:Technology Assessment," US Department of Transportation Publication, Washington, DC, RTA 65A0160, 2007.

[28] T. Panayotova, "People Movers: Systems and case studies," University of Florida, Gainesville, FL, 9, 2003.

[29] Andréasson, Ingmar. "Innovative transit systems: Survey of current developments," Vinnova, 2001.

[30] T.H. Hong, M. Abrams, T. Chang, and M. Shneier. “An intelligent world model for autonomous off-road driving.” Computer Vision and Image Understanding Journal, 2000.

[31] M. McFarland, "GM just introduced a self-driving car without a steering wheel", 2018. [Online]. Available: https://money.cnn.com/2018/01/12/technology/general-motors-cruise-self-driving-car/index.html. [Accessed: 01- Jun- 2018].

[32] J.M. Anderson, N.Kalra, K.D. Stanley, P.Sorensen, C.Samaras, O.A.Oluwatola. “Autonomous Vehicle Technology – A Guide for Policymakers,” RAND. Santa Monica, California, USA, 2016.[Online]. Available: https://www.rand.org/pubs/research_reports/RR443-2.html

[33] *Road Vehicles – Functional Safety*, ISO 26262, International Organization for Standardization (ISO), Nov 2011.

[34] National Instruments, "What is the ISO 26262 Functional Safety Standard?", *National Instruments*, 2014. [Online]. Available: http://www.ni.com/white-paper/13647/en/#top. [Accessed: 01- Jan- 2018].

[35] R. Messnarz, C. Kreiner, O. Bachmann, A. Riel, K. Dussa-Zieger, R. Nevalainen and S. Tichkiewitch, “Implementing Functional Safety Standards – Experiences from the Trials about Required Knowledge and Competencies (SafEUr),” in *Proc 2013 European Conference EuroSPI.*, Dundalk, Ireland, June 2013.

[36] *Road Vehicles – Safety of the Intended Functionality*, ISO/ WD PAS 21448, International Organization for Standardization (ISO), Under Development.

[37] Q. Li, L. Chen, M. Li, S. L. Shaw and A. Nüchter, "A Sensor-Fusion Drivable-Region and Lane-Detection System for Autonomous Vehicle Navigation in Challenging Road Scenarios," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 2, pp. 540-555, Feb. 2014.

[38] Y. L. Chen, M.R. Jahanshahi, P. Manjunatha, W. Gan, M. Abdelbarr, S.F. Masri, B.B. Gerber and J.P. Caffrey, "Inexpensive Multimodal Sensor Fusion System for Autonomous Data Acquisition of Road Surface Conditions," *IEEE Sensors Journal*, vol. 16, no. 21, pp. 7731-7743, Nov. 2016.

[39] M. Cunningham and M. A. Regan. (2015, Oct). Autonomous Vehicles: Human Factors Issues and Future Research. presented at Australasian Road Safety Conference. [Online]. Available: http://acrs.org.au/files/papers/arsc/2015/CunninghamM%20033%20Autonomous%20vehicles.pdf

[40] T. Victor, “System and method for monitoring and managing driver attention loads,” U.S. Patent *6 974 414 B2*, Abbrev. Dec, 13, 2005.

[41] NHTSA, "Vehicle Cybersecurity", *NHTSA*. [Online]. Available: https://www.nhtsa.gov/technology-innovation/vehicle-cybersecurity. [Accessed: 12- Mar- 2018].

[42] S. Plosz and P. Varga, "Security and safety risk analysis of vision guided autonomous vehicles," *2018 IEEE Industrial Cyber-Physical Systems (ICPS)*, St. Petersburg, 2018, pp. 193-198. doi: 10.1109/ICPHYS.2018.8387658

[43] T. Litman. “Autonomous Vehicle Implementation Predictions,” Victoria Transport Policy Institute. Victoria, British Columbia, Canada. Feb. 9, 2018. [Online] Available: https://www.vtpi.org/avip.pdf

[44] KPMG. “Marketplace of change: Automobile insurance in the era of autonomous vehicles,” KPMG. Oct., 2015. [Online] Available: https://assets.kpmg.com/content/dam/kpmg/pdf/2016/06/id-market-place-of-change-automobile-insurance-in-the-era-of-autonomous-vehicles.pdf

[45] NHTSA, "Federal Automated Vehicles Policy", Hsdl.org, [Online]. Available: https://www.hsdl.org/?view&did=795644. [Accessed: 01- Jun-2018].

[46] C. Bergenhem, Q. Huang, A. Benmimoun and T. Robinson, “Challenges Of Platooning On Public Motorways”, 2018. [Online] Available: https://www.researchgate.net/publication/228859487_Challenges_Of_Platooning_On_Public_Motorways. [Accessed: 10-Dec-2018].

[47] "The 15 Cheapest Cars With Adaptive Cruise Control", *U.S. News and World Report*, 2017. [Online]. Available: https://cars.usnews.com/cars-trucks/cheapest-cars-with-adaptive-cruise-control. [Accessed: 01- Jan- 2018].

[48] M. Monticello, "Guide to Automatic Emergency Braking", *Consumer Reports*, 2017. [Online]. Available: https://www.consumerreports.org/car-safety/automatic-emergency-braking-guide/. [Accessed: 01- Jan- 2018].

[49] Toyota, “Brake Assist”, *Toyota-global.com*, 2016. [Online]. Available: http://www.toyota-global.com/innovation/safety_technology/safety_technology/technology_file/active/brake.html. [Accessed: 01- Feb- 2016].

[50] Toyota, “Navigation-Brake Assist”, *Toyota-global.com*, 2016. [Online]. Available: http://www.toyota-global.com/innovation/safety_technology/safety_technology/technology_file/active/navi_brake.html. [Accessed: 01- Feb- 2016].

[51] Volvo,"Brake assist system", *Support.volvocars.com*, 2016. [Online]. Available: https://support.volvocars.com/en-CA/cars/Pages/owners-manual.aspx?mc=v526t8hbat&my=2016&sw=15w46&article=0188b0b265e9b2d5c0a8015138c15543. [Accessed: 01- Jan- 2018].

[52] Mercedes-Benz, "Mercedes-Benz Brake Assist System", *Mercedes-Benz of Massapequa*, 2015. [Online]. Available: https://www.mbofmassapequa.com/mercedes-benz-brake-assist-system/. [Accessed: 01- Jan- 2018].

[53] Toyota, “Lane Keeping Assist”, *Toyota-global.com*, 2016. [Online]. Available: http://www.toyota-global.com/innovation/safety_technology/safety_technology/technology_file/active/lka.html. [Accessed: 01- Feb- 2016].

[54] M. Monticello, "Guide to Lane-Departure Warning & Lane-Keeping Assist", *Consumer Reports*, 2017. [Online]. Available: https://www.consumerreports.org/car-safety/lane-departure-warning-lane-keeping-assist-guide/. [Accessed: 01- Jan- 2018].

[55] C. Threewitt, "10 Cars with Lane Change Assist Using Cameras or Sensors", *Autobytel.com*, 2018. [Online]. Available: https://www.autobytel.com/car-buying-guides/features/10-cars-with-lane-change-assist-using-cameras-or-sensors-130847/. [Accessed: 04- Mar- 2018].
[56] NHTSA, "Blind Spot Monitoring in Light Vehicles - System Performance", *Department of Trasnportation*, 2014. [Online]. Available: http://www.nhtsa.gov/DOT/NHTSA/NVS/Crash%20Avoidance/Technical%20Publications/2014/812045_Blind-Spot-Monitoring-in-Light-Vehicles-System-Performance.pdf. [Accessed: 01- Feb- 2016].
[57] Mercedes-Benz, "Safety", *Mercedes-Benz USA*, 2018. [Online]. Available: https://www.mbusa.com/mercedes/benz/safety#module-4. [Accessed: 11- Mar- 2018].
[58] Nissan, "Blind Spot Intervention and Warning System", *Nissan News*, 2018. [Online]. Available: http://nissannews.com/en-US/nissan/usa/channels/us-infiniti-technology/releases/blind-spot-intervention-and-warning-system. [Accessed: 11- Mar- 2018].
[59] C. Threewitt, "The 8 Best Self-Parking Cars", *U.S. News and World Report*, 2017. [Online]. Available: https://cars.usnews.com/cars-trucks/best-self-parking-cars. [Accessed: 01- Jan- 2018].
[60] Audi, "Audi Q2 rear cross traffic assist", *Audi Technology Portal*, 2016. [Online]. Available: https://www.audi-technology-portal.de/en/electrics-electronics/driver-assistant-systems/audi-q2-rear-cross-traffic-assist. [Accessed: 01- Jan- 2018].
[61] Lexus, "Safety", *Lexus USA*, 2018. [Online]. Available: http://www.lexus.com/models/RX/safety. [Accessed: 11- Mar- 2018].
[62] D. DeMuro, "7 New Technologies You Didn't Know You Could Get in a Car", *Autotrader*, 2014. [Online]. Available: https://www.autotrader.com/best-cars/7-new-technologies-you-didnt-know-you-could-get-in-a-car-225723. [Accessed: 01- Jan- 2018].
[63] C. Krome, "10 Cars with Adaptive Headlights", *Autobytel*, 2018. [Online]. Available: https://www.autobytel.com/car-buying-guides/features/10-cars-with-adaptive-headlights-131125/. [Accessed: 11- Mar- 2018].
[64] Gillian Yeomans, "Autonomous Vehicles Handing Over Control: Opportunities and Risks for Insurance", Lloyd's, 2014.
[65] The Economist, "Game of drones", *The Economist*, 2013. [Online]. Available: http://www.economist.com/news/business/21591862-some-see-privacy-threats-civilian-drones-others-see-profits-game-drones. [Accessed: 01- Feb- 2016].
[66] P. Murray, "Drones Close In On Farms, The Next Step In Precision Agriculture - Singularity HUB", *Singularity Hub*, 2013. [Online]. Available: http://singularityhub.com/2013/05/28/drones-close-in-on-farms-the-next-step-in-precision-agriculture/. [Accessed: 01- Feb- 2016].

[67] G. Wozniacka, “Agriculture the most promising market for drones”, *Phys Org*, 2013. [Online]. Available: http://phys.org/news/2013-12-agriculture-drones.html. [Accessed: 01- Feb- 2016].
[68] Cbsnews.com, “New use for drones: Sports photography”, *CBS News*, 2012. [Online]. Available: http://www.cbsnews.com/news/new-use-for-drones-sports-photography/. [Accessed: 01- Feb- 2016].
[69] C. Taibi, “WATCH: Drone Helicopter Delivers Dry Cleaning”, *The Huffington Post*, 2013. [Online]. Available: http://www.huffingtonpost.com/2013/07/09/manayunk-cleaners-drone_n_3567804.html. [Accessed: 01- Feb- 2016].
[70] Financial Times, “Drone industry divided over Amazon plans for aerial deliveries - FT.com”, *Financial Times*, 2013. [Online]. Available: http://www.ft.com/cms/s/0/e0208130-5bc6-11e3-848e-00144feabdc0.html?siteedition=uk#axzz2q6jWnUri. [Accessed: 01- Feb-2016].
[71] Airhighway, “Air Highway”, *Airhighway.org*, 2016. [Online]. Available: http://airhighway.org/. [Accessed: 01- Feb- 2016].
[72] XL Catlin, “Catlin Seaview Survey”, *Catlinseaviewsurvey.com*, 2016. [Online]. Available: http://catlinseaviewsurvey.com/. [Accessed: 01- Feb-2016].
[73] MUNIN, “Maritime Unmanned Navigation through Intelligence in Networks”, *MUNIN*, 2016. [Online]. Available: http://www.unmanned-ship.org/munin/. [Accessed: 01- Feb- 2016].
[74] D. Kushner, "Drug-Sub Culture: The Latest Way to Get Cocaine Out of Colombia? Underwater.", *The New York Times Magazine*, 2009. [Online]. Available: http://www.nytimes.com/2009/04/26/magazine/26drugs-t.html?pagewanted=all&_r=1&. [Accessed: 01- Feb- 2016].
[75] R. Ambrose, B. Wilcox, B. Reed, L. Matthies, D. Lavery, D. Korsmeyer, “Robotics, tele-robotics and autonomous systems roadmap”, NASA, Apr. 2012.
[76] Railway Gazette, "Driverless metros poised to expand", *Railway Gazette*, 2000. [Online]. Available: http://www.railwaygazette.com/news/single-view/view/driverless-metros-poised-to-expand.html. [Accessed: 01- Feb-2016].
[77] G. Xiong, H. Li, Y. Jin, J. Gong and H. Chen, "Collision avoidance system with cooperative adaptive cruise control in highway entrance ramp environment," in *Proc. 2017 18th International Conference on Advanced Robotics (ICAR)*, Hong Kong, July 2017.
[78] J. Fingas, "Airbus unveils an autonomous, modular flying car concept", *Engadget*, 2017. [Online]. Available: https://www.engadget.com/2017/03/08/airbus-pop-up-flying-car-concept/. [Accessed: 01- Jan- 2018].
[79] A. Kautonen, "Hyundai takes fully autonomous fuel cell vehicles on 70 mph road trip", *Autoblog*, 2018. [Online]. Available:

https://www.autoblog.com/2018/02/05/hyundai-autonomous-fuel-cell-vehicles-trip/. [Accessed: 12- Mar- 2018].
[80] J. Walker, "The Self-Driving Car Timeline - Predictions from the Top 11 Global Automakers", *TechEmergence*, 2017. [Online]. Available: https://www.techemergence.com/self-driving-car-timeline-themselves-top-11-automakers/. [Accessed: 01- Jan- 2018].
[81] "Driverless car market watch", *Driverless-future.com*. [Online]. Available: http://www.driverless-future.com/?page_id=384. [Accessed: 12- Mar- 2018].
[82] M. Moon, "GM plans to release cars with no steering wheel in 2019", *Engadget*, 2018. [Online]. Available: https://www.engadget.com/2018/01/12/gm-fully-autonomous-car-no-wheel-2018/. [Accessed: 12- Mar- 2018].
[83] A. Hawkins, "Nissan plans to launch its own self-driving taxi service in Japan", *The Verge*, 2018. [Online]. Available: https://www.theverge.com/2018/2/23/17044088/nissan-self-driving-taxi-dena-easy-ride-japan. [Accessed: 12- Mar- 2018].
[84] Ford, "Looking Further", *Ford*, 2017. [Online]. Available: https://corporate.ford.com/innovation/autonomous-2021.html. [Accessed: 12- Mar- 2018].
[85] "2018 Self-Driving Safety Report," General Motors. 2018. [Online] Available: https://www.scribd.com/document/369005282/Gm-Safety-Report#fullscreen&from_embed
[86] A. Davies, "Mercedes Promises Self-Driving Taxis in Just Three Years", *WIRED*, 2017. [Online]. Available: https://www.wired.com/2017/04/mercedes-promises-self-driving-taxis-just-three-years/. [Accessed: 01- Jan- 2018].
[87] A. Padeanu, "Volkswagen To Launch Fully Autonomous Electric Vehicles Starting In 2021", *Inside EVs*, 2017. [Online]. Available: https://insideevs.com/volkswagen-launch-fully-autonomous-electric-vehicles-starting-2021/. [Accessed: 12- Mar- 2018].
[88] P. Sigal, "PSA plans 'hands off' self-driving cars after 2020", *Automotive News*, 2017. [Online]. Available: http://www.autonews.com/article/20170628/COPY01/306289965/psa-plans-hands-off-self-driving-cars-after-2020. [Accessed: 12- Mar- 2018].
[89] C. Payne, "Driverless Cars - The Race to Level 5 Autonomous Vehicles", *Engineering.com*, 2017. [Online]. Available: https://www.engineering.com/DesignerEdge/DesignerEdgeArticles/ArticleID/15478/Driverless-Cars--The-Race-to-Level-5-Autonomous-Vehicles.aspx. [Accessed: 12- Mar- 2018].
[90] Kia, "DRIVEWiSE: Autonomous", *Kia Motors*. [Online]. Available: http://www.kia.com/worldwide/experience_kia/drive_wise/autonomous_driving.do. [Accessed: 12- Mar- 2018].
[91] G. B, "Autonomous cars: Everything you need to know about market and research trends - GreyB", *GreyB Services*, 2017. [Online]. Available:

https://www.greyb.com/autonomous-cars/#_Toc484626670. [Accessed: 12- Mar- 2018].

[92] K. Lee, "Toyota Won't Make A Self-Driving Car Until It's 100 Percent Safe", *Jalopnik*, 2017. [Online]. Available: https://jalopnik.com/toyota-wont-make-a-self-driving-car-until-its-100-perce-1820326849. [Accessed: 12- Mar- 2018].

[93] S. Edelstein, "Volvo Slows Down Its Self-Driving Car Development Program", *The Drive*, 2017. [Online]. Available: http://www.thedrive.com/tech/17002/volvo-slows-down-its-self-driving-car-development-program. [Accessed: 01- Jan- 2018].

[94] A. Stoklosa, "Kia Promises to Commercialize Level 4 Autonomous Cars by 2021", *Car and Driver*, 2018. [Online]. Available: https://blog.caranddriver.com/kia-promises-to-commercialize-level-4-autonomous-cars-by-2021/. [Accessed: 12- Mar- 2018].

[95] D. Etherington, "Baidu plans to mass produce Level 4 self-driving cars with BAIC by 2021", *TechCrunch*, 2017. [Online]. Available: https://techcrunch.com/2017/10/13/baidu-plans-to-mass-produce-level-4-self-driving-cars-with-baic-by-2021/. [Accessed: 01- Jan- 2018].

[96] D. Muoio, "RANKED: The 18 companies most likely to get self-driving cars on the road first", *Business Insider*, 2017. [Online]. Available: http://www.businessinsider.com/the-companies-most-likely-to-get-driverless-cars-on-the-road-first-2017-4. [Accessed: 01- Jan- 2018].

[97] M. Zhao, "Advanced Driver Assistant System Threats, Requirements, Security Solutions," Security & Privacy Research, Intel Labs, [Online]. Available: https://www.intel.com/content/dam/www/public/us/en/documents/white-papers/advanced-driver-assistant-system-paper.pdf. [Accessed 01-May-2018].

[98] Hitachi Automotive Systems Americas, Inc., "Advanced Driver Assistance System," *Hitachi Automotive Systems Americas, Inc.,* 1995 – 2018. [Online] Available: http://www.hitachi-automotive.us/Products/oem/DCS/ADAS/index.htm. [Accessed 01-May-2018].

[99] B. Siller, "Complex Trends and Challenges in Designing ADAS Systems," *Embedded Vision Alliance,* 2011 – 2018. [Online]. Available: https://www.embedded-vision.com/industry-analysis/technical-articles/2014/09/30/complex-trends-and-challenges-designing-adas-systems. [Accessed 01-May-2018].

[100] NGAN GIANG Technology & Trading Co. Ltd., "Automotive: The Total Solution for Next-Generation Automotive Applications," *NGAN GIANG Technology & Trading Co. Ltd.,* 2015. [Online] Available: http://oegalaxy.com.vn/en/tin-cong-nghe/oegalaxy/automotive/73/1. [Accessed 01-May-2018].

[101] inLane, "Overall architecture: Lane-level accuracy via fusion and hybridization algorithms for GNSS, IMU, Map and Computer Vision signal,"

inLane. [Online] Available: https://inlane.eu/inlane-solution/architecture/. [Accessed 01-May-2018].

[102] T. Gage, J. Morris, and M. Pacific, “The Coming Revolution in Vehicle Technology and its BIG Implications,” Xilinx, 2018. [Online]. Available: https://forums.xilinx.com/t5/Xcell-Daily-Blog/The-Coming-Revolution-in-Vehicle-Technology-and-its-BIG/ba-p/644922. [Accessed 01-May-2018].

[103] M. Nukala, “A constellation of innovations is needed for Autonomous Driving…,” *Medium,* 2016. [Online]. Available: https://medium.com/@murthynukala/a-constellation-of-innovations-is-needed-for-autonomous-driving-4b3cf6f98148. [Accessed 01-May-2018].

[104] Renesas Electronics Corporation, “Advanced Driver Assistance System (ADAS),” *Renesas Electronics Corporation,* 2010 – 2018. [Online] Available: https://www.renesas.com/en-us/solutions/automotive/adas.html. [Accessed 01-May-2018].

[105] R. Kastner, T. Michalke, J. Adamy, J. Fritsch, and C. Goerick, "Task-Based Environment Interpretation and System Architecture for Next Generation ADAS," *IEEE Intelligent Transportation Systems Magazine*, vol. 3, no. 4, pp. 20-33, Oct. 2011.

[106] W. Zong, C. Zhang, Z. Wang, J. Zhu, and Q. Chen, "Architecture Design and Implementation of an Autonomous Vehicle," *IEEE Access, Apr. 2018*.

[107] X. Liu-Henke, S. Scherler, and M. Goellner, "System architecture of a full active autonomous electric vehicle," in *Proc. 2017 IEEE Transportation Electrification Conference and Expo (ITEC),* Chicago, IL, USA, Jun. 2017.

[108] J. Pyper, "Self-Driving Cars Could Cut Greenhouse Gas Pollution", *Scientific American*, 2014. [Online]. Available: https://www.scientificamerican.com/article/self-driving-cars-could-cut-reenhouse-gas-pollution/. [Accessed: 01- Jan- 2017]

[109] J. Snyder, "Study: autonomous vehicles could improve MPG 10% in EPA tests", *Autoblog*, 2016. [Online]. Available: http://www.autoblog.com/2016/03/24/study-autonomous-vehicles-improve-mpg-epa-tests/. [Accessed: 02- Jan- 2017].

[110] K. Bullis, "How Vehicle Automation Will Cut Fuel Consumption", *MIT Technology Review*, 2017. [Online]. Available: https://www.technologyreview.com/s/425850/how-vehicle-automation-will-cut-fuel-consumption/. [Accessed: 02- Jan- 2017].

[111] Movimento, "OTA Technology Will Make Cars More Environment Friendly", *Movimento Group*, 2017. [Online]. Available: https://movimentogroup.com/blog/ota-technology-will-make-cars-environment-friendly/. [Accessed: 29- Jul- 2018].

[112] M. Strong, "Autonomous Vehicles Improve Fuel Economy by 10 Percent | TheDetroitBureau.com", *Thedetroitbureau.com*, 2016. [Online]. Available: http://www.thedetroitbureau.com/2016/03/autonomous-vehicles-improve-fuel-economy-by-10-percent/. [Accessed: 02- Jan- 2017].

[113] J. Anderson, N. Kalra, K. Stanley, P. Sorensen, C. Samaras and O. Oluwatola, "Autonomous Vehicle Technology: A Guide for Policy Makers", 2016.
[114] A. Rezaei and J. Burl, "Prediction of Vehicle Velocity for Model Predictive Control", *IFAC-PapersOnLine*, vol. 48, no. 15, pp. 257-262, 2015.
[115] Z.D.Asher *et al.*, "Increasing the Fuel Economy of Connected and Autonomous Lithium-Ion Electrified Vehicles," in *Behaviour of Lithium-Ion Batteries in Electric Vehicles*, USA: Springer International Publishing, 2018, pp. 129–151.
[116] J. Tunnell, Z. Asher, S. Pasricha and T. Bradley, "Towards Improving Vehicle Fuel Economy with ADAS", *SAE Technical Paper 2018-01-0593*, 2018. Accessed on: Jul. 23, 2018, DOI:10.4271/2018-01-0593.
[117] P. Michel, D. Karbowski and A. Rousseau, "Impact of Connectivity and Automation on Vehicle Energy Use", *SAE Technical Paper 2016-01-0152*, 2016. Accessed on: Jul. 23, 2018, DOI:10.4271/2016-01-0152.
[118] J. Gonder, M. Earleywine and W. Sparks, "Analyzing Vehicle Fuel Saving Opportunities through Intelligent Driver Feedback", *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, vol. 5, no. 2, pp. 450-461, 2012. Accessed on: Jul. 23, 2018, DOI:10.4271/2012-01-0494.
[119] S. G. Wirasingha and A. Emadi, "Classification and review of control strategies for plug-in hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 111–122, Jan. 2011.
[120] C. Manzie, H. Watson and S. Halgamuge, "Fuel economy improvements for urban driving: Hybrid vs. intelligent vehicles", *Transportation Research Part C: Emerging Technologies*, vol. 15, no. 1, pp. 1-16, 2007.
[121] K.P. Divakarla, A. Emadi and S.Razavi, "A Cognitive Advanced Driver Assistance Systems (ADAS) Architecture for Autonomous-capable Electrified Vehicles", *IEEE Transactions on Transportation Electrification*, 2018. Accessed on: Sep. 17, 2018, DOI: 10.1109/TTE.2018.2870819.
[122] S. Kato, E. Takeuchi, Y. Ishiguro, Y. Ninomiya, K. Takeda, T. Hamada, "An Open Approach to Autonomous Vehicles," *IEEE Micro*, vol.35, no.6, pp.60-68, Nov.-Dec. 2015.
[123] C. Patchett. (2015, Nov). A common systems architecture for autonomous vehicles. presented at Advanced Engineering. [Online]. Available:
http://www.easyfairs.com/fileadmin/groups/8/Advanced_Engineering/Advanced_Engineering_2016/AE_2015_presentations/Wednesday_-_Forum_5_-_13.30-14.00_-_Charles_Patchett_-_V2.pdf
[124] S. Haykin, *Cognitive Dynamic Systems*, 1st ed. Cambridge: Cambridge University Press, 2012.
[125] S. Haykin, J. M. Fuster, D. Findlay, and S. Feng, "Cognitive Risk Control for Physical Systems," *IEEE Access*, vol. 5, pp. 14664-14679, Jul. 2017.
[126] M. Montemerlo, J. Becker, S. Bhat, H. Dahlkamp, D. Dolgov, S. Ettinger, D. Haehnel, T. Hilden, G. Hoffmann, B. Huhnke, D. Johnston, S. Klumpp, D.

Langer, A. Levandowski, J. Levinson, J. Marcil, D. Orenstein, J. Paefgen, I. Penny, A. Petrovskaya, M. Pflueger, G. Stanek, D. Stavens, A. Vogt, and S.Thrun, "Junior: The Stanford entry in the Urban Challenge", *Journal of Field Robotics*, vol. 25, no. 9, pp. 569-597, 2008. Accessed on: Jul. 23, 2018, DOI: 10.1002/rob.20258.

[127] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian and P. Mahoney, "Stanley: The robot that won the DARPA Grand Challenge", *Journal of Field Robotics*, vol. 23, no. 9, pp. 661-692, 2006. Accessed on: Jul. 23, 2018, DOI: 10.1002/rob.20147.

[128] C. Molina, J. Almeida, L. Vismari, R. Gonzalez, J. Naufal and J. Camargo, "Assuring Fully Autonomous Vehicles Safety by Design: The Autonomous Vehicle Control (AVC) Module Strategy", in *Proc. 2017 47th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W)*, Denver, CO, USA, Jun. 2017.

[129] H. Lipson and M. Kurman, *Driverless - intelligent cars and the road ahead*. Cambridge, MA, USA: The MIT Press, 2017, ISBN: 978-0262534475.

[130] M. Maurer, J. Gerdes, B. Lenz and H. Winner, *Autonomous Driving*. Heidelberg, Germany: Springer, 2016, ISBN: 978-3-662-48845-4.

[131] S. Liu, L. Li, J. Tang, S. Wu and J. Gaudiot, *Creating autonomous vehicle systems*. Williston, VT, USA: Morgan & Claypool Publishers, 2018, ISBN: 978-1681730073.

[132] T. Fossen, K. Pettersen and H. Nijmeijer, *Sensing and Control for Autonomous Vehicles*. Cham, Switzerland: Springer International Publishing, 2017, ISBN: 978-3319553719.

[133] S. Darbha, S. Konduri and P. Pagilla, "Benefits of V2V Communication for Autonomous and Connected Vehicles", *IEEE Transactions on Intelligent Transportation Systems*, pp. 1-10, 2018.

[134] P. Felzenszwalb, R. Girshick, D. McAllester, and D. Ramanan, "Object Detection with Discriminatively Trained Part-Based Models", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 9, pp. 1627-1645, Sept. 2010.

[135] Matthew McNaughton. Parallel algorithms for real-time motion planning. 2011.

[136] M. Magnusson, A. Lilienthal and T. Duckett, "Scan Registration for Autonomous Mining Vehicles Using 3DNDT," *Journal of Field Robotics*, vol. 24, no. 10,pp. 803–827, May 2007.

[137] N. McNaughton, C. Urmson, J.M. Dolan, and J.W. Lee, "Motion Planning for Autonomous Driving with a Conformal SpatiotemporalLattice," in Proc 2011 IEEE International Conference on Robotics and Automation, Shanghai, China, May, 2011.

[138] R. Coulter, “Implementation of the Pure Pursuit Path Tracking Algorithm”, Robotics Institute, tech. report CMURI-TR-92-01, 1992.

[139] M. Amarasinghe, S. Muramudalige, S. Kottegoda, A. Arachchi, H. Bandara and A. Azeez, "Cloud-based Driver Monitoring and Vehicle Diagnostic with OBD2 Telematics", *International Journal of Handheld Computing Research*, vol. 6, no. 4, pp. 57-74, 2015. DOI: 10.4018/IJHCR.2015100104.

[140] M.V. Rajasekhar and A.K. Jaswal, “Autonomous vehicles: The future of automobiles,” in *Proc. 2015 IEEE International Transportation Electrification Conference (ITEC’15),* Chennai, India, Aug. 2015.

[141] C. Gilbertsen, "Here's How The Sensors in Autonomous Cars Work", *The Drive*, 2017. [Online]. Available: http://www.thedrive.com/tech/8657/heres-how-the-sensors-in-autonomous-cars-work. [Accessed: 01- Jan- 2018].

[142] "Three Sensor Types Drive Autonomous Vehicles", *Sensorsmag*, 2017. [Online]. Available: https://www.sensorsmag.com/components/three-sensor-types-drive-tonomous-vehicles. [Accessed: 01- Jan- 2018].

[143] R. A. McKinney, M. J. Zapata, J. M. Conrad, T. W. Meiswinkel and S. Ahuja, "Components of an autonomous all-terrain vehicle," in *Proc. 2010 IEEE SoutheastCon (SoutheastCon)*, Concord, NC, Mar 2010.

[144] M. Harris, "Night Vision for Self-Driving Cars", *IEEE Spectrum*, 2017. [Online]. Available: https://spectrum.ieee.org/cars-that-think/transportation/self-driving/do-selfdriving-cars-need-night-vision. [Accessed: 01- Jan- 2018].

[145] X. Yang et al., “A Vehicle-to-Vehicle Communication Protocol for Cooperative Collision Warning,” Proc. 1st Annual Int’l. Conf. Mobile and Ubiquitous Syst: Net - working and Services, 2004.

[146] J. Bell, "Network protocols used in the automotive industry", 2002. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.558.6159&rep=rep1&type=pdf. [Accessed: 19- Jul- 2018].

[147] B.K. Ramesh and K.S. Murthy, "In-Vehicle Networking", 2004. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.610.7222&rep=rep1&type=pdf. [Accessed: 19- Jul- 2018].

[148] A. Neumann, M. Mytych, D. Wesemann, L. Wisniewski and J. Jasperneite, "Approaches for In-vehicle Communication – An Analysis and Outlook", *Computer Networks*, pp. 395-411, 2017. Accessed on: Jul. 19, 2018, DOI: 10.1007/978-3-319-59767-6_31.

[149] R. Hamilton, H. Seager, K.P. Divakarla, A. Emadi and S.Razavi, "Modeling and Simulation of an Autonomouscapable Electrified Vehicle: A Review," in *Proc. IEEE Canada Electrical Power and Energy Conference (EPEC 2018)*, Toronto, October 2018.

[150] “User Manual Version 6.3”, IPG Automotive GmbH, 2009–2011.

[151] "Reference Manual", IPG Automotive GmbH, 2011.

[152] Bureau of Transportation Statistics, U.S. Department of Transportation, "Freight Facts & Figures 2017 - Chapter 3 The Freight Transportation System," *Bureau of Transportation Statistics, U.S. Department of Transportation.* [Online] Available:https://www.bts.gov/bts-publications/freight-facts-and-figures/freight-facts-figures-2017-chapter-3-freight. [Accessed 01-May-2018].

[153] G. Li, S. Li, L. Jia, W. Wang, B. Cheng and F. Chen, "Driving Maneuvers Analysis Using Naturalistic Highway Driving Data", in *Proc. 2015 IEEE 18th International Conference on Intelligent Transportation Systems*, Las Palmas, Spain, Sept. 2015.

[154] T. Weiss, B. Schiele and K. Dietmayer, "Robust Driving Path Detection in Urban and Highway Scenarios Using a Laser Scanner and Online Occupancy Grids", in *Proc. 2007 IEEE Intelligent Vehicles Symposium*, Istanbul, Turkey, Jun. 2007.

[155] "Product Examples Version 6.0.2", IPG Automotive GmbH, 1999–2017.

[156] United States Department of Energy, Office of Energy Efficiency & Renewable Energy, "Detailed Test Information," *United States Department of Energy, Office of Energy Efficiency & Renewable Energy.* [Online] Available: https://www.fueleconomy.gov/feg/fe_test_schedules.shtml. [Accessed 01-May-2018].

[157] Engineers Edge, LLC, "Air Density and Specific Weight Table, Equations and Calculator," *Engineers Edge, LLC.* [Online] Available: https://www.engineersedge.com/calculators/air-density.htm. [Accessed 01-May-2018].

[158] Central Weather Bureau, Government of Taiwan, "Precipitation Classification," *Central Weather Bureau, Government of Taiwan.* [Online] Available: https://www.cwb.gov.tw/V7e/observe/rainfall/define.htm. [Accessed 01-May-2018].

[159] National Oceanic and Atmospheric Administration, National Weather Service, "Beaufort Wind Chart – Estimating Winds Speeds", *National Oceanic and Atmospheric Administration, National Weather Service*. [Online]. Available:http://www.crh.noaa.gov/Image/iwx/publications/Beaufort_Wind_Chart.pdf. [Accessed: 14-Aug-2018].

[160] R. Ghandour, A. Victorino, M. Doumiati, and A. Charara, "Tire/road friction coefficient estimation applied to road safety," *18th Mediterranean Conference on Control and Automation, MED'10*, Marrakech, 2010, pp. 1485-1490. doi: 10.1109/MED.2010.5547840.

[161] D.S. Berry and D.M. Belmont, "Distribution of Vehicle Speeds and Travel Times," in *Proc. Second Berkeley Symposium on Mathematical Statistics and Probability*, Berkeley, USA, Aug. 1950.

[162] M. Gemou, "Transferability of driver speed and lateral deviation measurable performance from semi-dynamic driving simulator to real traffic conditions," *European Transport Research Review*, vol. 5, no. 4, pp. 217-233, Dec. 2013, DOI. 10.1007/s12544-013-0105-1.

[163] NHTSA, "National Survey of Speeding and Unsafe Driving Attitudes and Behavior:2002", *U.S. Department of Trasnportation*, 2004. [Online]. Available: https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/hs809730_0.pdf. [Accessed: 14-Aug-2018].

[164] J. Chai and G. Zhao, "Effect of exposure to aggressive stimuli on aggressive driving behavior at pedestrian crossings at unmarked roadways.", *Accident Analysis & Prevention*, vol. 88, pp.159-168, 2016, DOI: 10.1016/j.aap.2015.12.026.

[165] K.R. Agent, "Guidelines for the Use of Protected/ Permissive Lefi-TurnPhasing," *ITE Journal*, pp. 37 – 42, Jul. 1987, [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.417.4550&rep=rep1&type=pdf

[166] SAFETY 1N NUM3ERS, "Why your reaction time matters at speed", *National Highway Traffic Safety Administration,* Aug.2015. [Online] Available: https://one.nhtsa.gov/nhtsa/Safety1nNum3ers/august2015/S1N_Speeding-August2015_812008.pdf. [Accessed 23-Jul-2018].

[167] QUEENSLAND GOVERNMENT, "Stopping distances: speed and braking", *Queensland Government*, 2018. [Online] Available: https://www.qld.gov.au/transport/safety/road-safety/driving-safely/stopping-distances. [Accessed 23-Jul-2018].

[168] M. Green, ""How Long Does It Take to Stop?" Methodological Analysis of Driver Perception-Brake Times," *Transportation Human Factors*, vol. 2, no. 3, pp. 195-216, 2000, DOI. 10.1207/STHF0203_1.

[169] A. Emadi, *Advanced Electric Drive Vehicles*. Boca Raton, FL, USA: CRC Press, Oct. 2014.

[170] T. J. Barlow, S. Latham, I. S. McCrae, and P. G. Boulter, "A reference book of driving cycles for use in the measurement of road vehicle emissions," Jun. 2009. TRL Limited. [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/4247/ppr-354.pdf

[171] A. Emadi, M. Ehsani, and J.M.Miller, *Vehicular Electric Power Systems: Land, Sea, Air, and Space Vehicles*. New York, NY, USA: Marcel Dekker, Dec. 2003.

[172] United States Department of Energy, Office of Energy Efficiency & Renewable Energy, "EPA Test Procedures for Electric Vehicles and Plug-in Hybrids," *United States Department of Energy, Office of Energy Efficiency & Renewable Energy*. [Online] Available: https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. [Accessed 01-May-2018].

[173] United States Department of Energy, Office of Energy Efficiency & Renewable Energy, "2014 Tesla Model S," *United States Department of Energy, Office of Energy Efficiency & Renewable Energy.* [Online] Available: https://www.fueleconomy.gov/feg/bymodel/2014_Tesla_Model_S.shtml. [Accessed 01-May-2018].

[174] K.P. Divakarla, *ALKA - ADS - Gradient Road - Adverse Weather - NoTraffic*. Dec. 12, 2018. Accessed on: Dec. 12, 2018 [Video file]. Available: https://www.youtube.com/watch?v=1vChLxwR4so

[175] K.P. Divakarla, *L4 ADS - Flat Road - Ideal Weather - Lead Traffic*. Dec. 12, 2018. Accessed on: Dec. 12, 2018 [Video file]. Available: https://www.youtube.com/watch?v=gX4Y5OVdExI

[176] K.P. Divakarla, *L4 ADS - Flat Road - Ideal Weather - Multi-Traffic*. Dec. 12, 2018. Accessed on: Dec. 12, 2018 [Video file]. Available: https://www.youtube.com/watch?v=b4ph54kKcVI

[177] K.P. Divakarla, *L4 ADS - Gradient Road - Adverse Weather - Multi-Traffic*. Dec. 12, 2018. Accessed on: Dec. 12, 2018 [Video file]. Available: https://www.youtube.com/watch?v=KmUCR9eUHeA

[178] K. P. Divakarla, A. Emadi, and S. N. Razavi, "Journey mapping, re-defined drive cycle: an accurate vehicle performance prediction tool," *International Journal of Electric and Hybrid Vehicles*, vol. 9, no. 2, pp. 169-186, July 2017, Digital Object Identifier 10.1504/IJEHV.2017.10006174.

[179] K. P. Divakarla, A. Emadi, and S. N. Razavi, "Journey mapping—a new approach for defining automotive drive cycles," *IEEE Transactions on Industry Applications*, vol. 52, no. 6, pp. 5121-5129, Nov./Dec. 2016.

[180] K. P. Divakarla, S. Nalakath, M. Drennan, R. Ahmed, A. Emadi, and S. Razavi, "Battery characterization and state-of-charge prediction for different journey conditions with the help of the journey mapping concept," in *Proc. 41st Annual Conference of the IEEE Industrial Electronics Society (IECON'15)*, Yokohama, Japan, Nov. 2015.

[181] K. P. Divakarla, A. Emadi, and S. Razavi, "Journey mapping: a new approach for defining automotive drive cycles," in *Proc. 2015 IEEE Transportation Electrification Conference and Expo (ITEC'15)*, Dearborn, MI, June 2015.