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AN ECLECTIC DESIGN AND ADAS-ORIENTED REALTIME SIMULATION OF AEB WITH ADAPTIVE BRAKE ALGORITHM UNDER EURO NCAP PROTOCOL

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Master's Thesis

Supervisor

Assoc. Prof. Dr. Doğu Çağdaş ATİLLA

İstanbul, 2025

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The thesis titled AN ECLECTIC DESIGN AND ADAS-ORIENTED REALTIME SIMULATION OF AEB WITH ADAPTIVE BRAKE ALGORITHM UNDER EURO NCAP PROTOCOL prepared by AYAZ İSRAFİL TAŞTAN and submitted 01/07/2025 has been **accepted unanimously** for the degree of Master of Science in Electric and Computer Engineering.

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ABSTRACT

AN ECLECTIC DESIGN AND ADAS-ORIENTED REALTIME SIMULATION OF AEB WITH ADAPTIVE BRAKE ALGORITHM UNDER EURO NCAP PROTOCOL

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This thesis presents the development and evaluation of an adaptive braking algorithm integrated into an Autonomous Emergency Braking system, designed in accordance with Euro NCAP scenario protocols. The primary objective is to improve collision avoidance performance and driving comfort compared to classical fixed deceleration models.

A total of seven critical driving scenarios including car to car, pedestrian, and bicyclist interactions were modeled using MATLAB/Simulink. The simulations were conducted under three different road surface conditions: dry, wet, and icy. While the classical braking model applies pre-defined deceleration values once the AEB system is triggered, the proposed adaptive model continuously calculates and applies optimal braking force in real time, based on factors such as time to collision, ego vehicle speed, relative distance, target speed, and road friction coefficient.

The results show that the adaptive braking system achieves full collision avoidance in all tested scenarios and surfaces. It demonstrates a clear advantage in avoiding unnecessary braking, maintaining passenger comfort, and minimizing stress on the vehicle's mechanical components. The adaptive model also provides better responsiveness in complex or low-traction environments compared to the fixed model.

This research highlights the importance of real-time, environment-aware braking strategies for next-generation Advanced Driver Assistance Systems, and suggests that data-driven AI-based decision models could further enhance the flexibility and reliability of emergency braking systems.

Keywords: Autonomous Emergency Braking, Adaptive Braking Strategy, Advanced Driver Assistance Systems, Simulation-Based Safety Evaluation

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ABBREVIATIONS

ACC	:	Adaptive Cruise Control
AEB	:	Autonomous Emergency Braking
ADAS	:	Advanced Driver Assistance Systems
ABS	:	Anti-lock Braking System
AI	:	Artificial Intelligence
CCFtap	:	Car to Car Front turn-across-path
CCRb	:	Car to Car Rear braking
CCRm	:	Car to Car Rear moving
CCRs	:	Car to Car Rear stationary
CNN	:	Convolutional Neural Network
ECU	:	Electronic Control Unit
ESC	:	Electronic Stability Control
Euro NCAP	:	European New Car Assessment Program
FB	:	Full Braking
FCW	:	Forward Collision Warning
GVT	:	Global Vehicle Target
HiL	:	Hardware in the Loop
HMI	:	Human Machine Interface
ICS	:	Inevitable Collision States
LDW	:	Lane Departure Warning
LKA	:	Lane Keeping Assist
MAEB	:	Motorcycle Autonomous Emergency Braking
MIO	:	Most Important Object
ML	:	Machine Learning
MPC	:	Model Predictive Control
NCAP	:	New Car Assessment Program
PB1	:	Partial Braking - Stage 1
PB2	:	Partial Braking - Stage 2
PID	:	Proportional Integral Derivative
TAEB	:	Time of Automatic Emergency Braking
TTC	:	Time To Collision

V2I	:	Vehicle to Infrastructure
V2P	:	Vehicle to Pedestrian
V2V	:	Vehicle to Vehicle
VRU	:	Vulnerable Road User
VUT	:	Vehicle Under Test

1. INTRODUCTION

Traffic accidents continue to be a serious public safety problem worldwide, causing approximately 1.3 million people to lose their lives each year [1].The main causes of these accidents include driver errors, inattention, and delayed reaction times of drivers. As a solution to these problems, the automotive industry and scientific researchers have begun to develop smart safety technologies that aim to reduce driver errors and their effects.

In this context, a comprehensive set of systems has been developed under the title of Advanced Driver Assistance Systems that aims to provide support to the driver during the journey. ADAS includes many subsystems such as lane departure warning, blind spot detection, adaptive cruise control, and autonomous emergency braking. These systems use various sensors such as radar, LiDAR, camera, and ultrasonic sensors to perceive the vehicle's surroundings in real time and interpret environmental conditions by processing this data with sensor fusion algorithms [2]. Based on these interpretations, it takes steps to ensure driver and environmental safety by taking action together with the driver or on its own depending on the decision algorithm.

ADAS technologies aim not only to increase the driver's environmental awareness, but also to predict and prevent possible accidents and minimize the damage that may occur in the event of a collision. Autonomous Emergency Braking systems, in particular, are an important component developed to prevent frontal collisions and have the ability to automatically brake if the driver cannot react in time[3].

This thesis aims to model the AEB system in the MATLAB/Simulink environment and evaluate its performance. A simulation infrastructure that creates conditions similar to real traffic scenarios is developed, and the reactive behavior and limitations of the AEB system are analyzed. The findings obtained aim to contribute to the optimization of ADAS components and shed light on the future development of vehicle safety systems.

1.1 EVOLUTION OF VEHICLE SECURITY SYSTEMS

Vehicle safety systems have shown great development with the advancing time and developing technological momentum. While the automotive sector developed together with the industry, at first there were passive safety systems (such as seat belts and airbags) aimed at reducing the effects of car accidents, today active safety systems aimed at preventing accidents have been developed and continue to be developed. Automotive safety is addressed under two subheadings to ensure the protection of the driver, passenger and pedestrians. These are passive and active safety systems. These systems have been developed with the aim of preventing accidents or minimizing the effects of accidents that occur.

Passive safety systems are activated after a collision and focus on reducing loss of life and injuries, while active safety systems are all technologies that affect the vehicle or driver in the pre-accident process in order to prevent a collision. With developing sensor technologies and software solutions, active safety systems have become much smarter today and have given vehicles the ability to predict with the help of artificial intelligence technology[4].

1.1.1 Passive Safety

Passive safety systems are systems developed not to prevent an accident but to reduce the loss of life and property after the accident occurs. These systems actively aim to minimize the risk of injury to the driver and passengers during or immediately after the accident. The most well-known passive safety elements include seat belts, airbags, head restraints, reinforced cabin structure, crumple zones and child seat attachment systems.

Passive safety systems are directly related to the structural strength and interior design of the vehicle. For example, while the crumple zones absorb the impact energy of the vehicle and prevent it from reaching the passenger cabin, airbags reduce trauma by spreading the impact force to the body.[4]

1.1.2 Active Safety

Active safety systems are a set of advanced technologies designed to prevent an accident. These systems are activated before the accident, warn the driver, support them or in some cases directly intervene. The main purpose here is to minimize the risk of the driver making a mistake and prevent possible collisions. Active safety systems operate multi-operationally in modern cars by developing a fusion technology with sensor technologies, radar, camera systems, lidar, and artificial intelligence-supported software. Thanks to these systems, vehicles gain environmental awareness, can predict risky situations and can automatically perform braking, speed reduction or trajectory correction when necessary[5]. These technologies include:

a. ABS (Anti-lock Braking System)
b. ESC/ESP (Electronic Stability Control)
c. AEB (Automatic Emergency Braking)
d. LDW/LKA (Lane Departure Warning / Lane Keeping Assist)
e. Adaptive Cruise Control (ACC)
f. Blind Spot Detection
g. Driver Drowsiness Monitoring
h. Pedestrian Detection Systems

1.2 ADVANCED DRIVER ASSISTANT SYSTEM

Advanced Driver Assistance Systems are integrated systems that combine sensor technologies, communication systems and artificial intelligence-supported software developed to increase driving safety and ensure traffic efficiency. These systems aim to increase the driver's environmental awareness, detect potential dangers in advance, warn the driver and prevent accidents by intervening in the vehicle when necessary. ADAS systems include many sub-technologies such as lane tracking assistant, adaptive cruise control, pedestrian detection, collision warning systems and autonomous emergency braking.

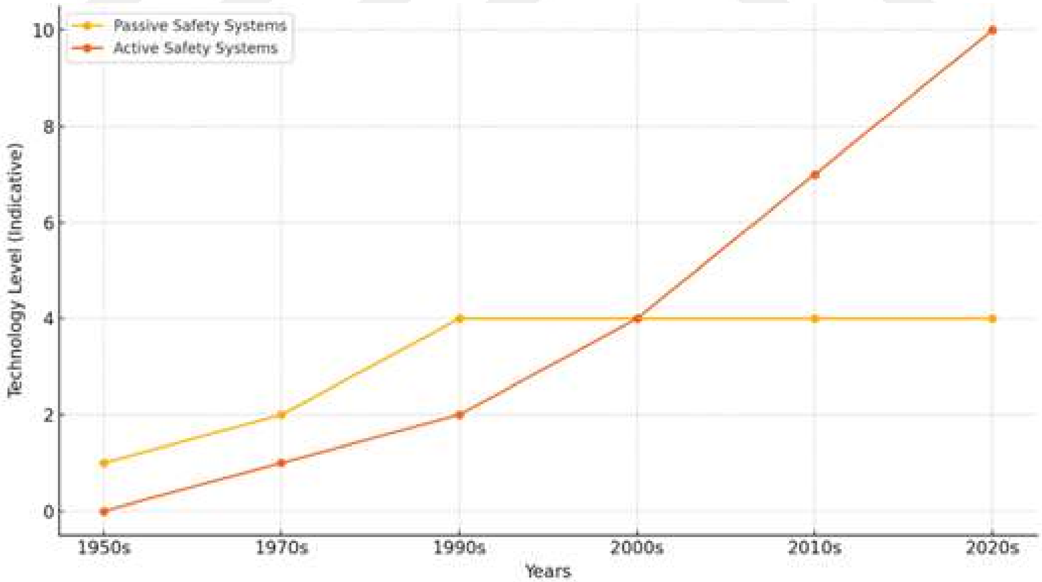


Figure 1.1: Evolution of Vehicle Safety Over Decades

The basic building block of ADAS is the sensor fusion architecture created by combining the data collected by multiple sensors on the vehicle (camera, radar, LIDAR, ultrasonic sensors, etc.)[6]. This architecture enables real-time detection of surrounding objects, road users and road structure. However, ADAS systems are not limited to detection and warning mechanisms; they can also perform autonomous actions directed to the vehicle (for example, braking or steering maneuver) in case the driver does not react appropriately. Especially in rural and intercity roads, the importance of ADAS systems is increasing due to unstructured environmental conditions and variable traffic conditions. In such environments, the possibility of driver error is higher and the risk of accidents leading to fatal consequences is high. In this context, ADAS systems aim to increase not only safety but also efficiency in terms of fuel consumption and traffic flow. In addition, the next generation of ADAS technologies focuses on cooperative systems, which include communication between multiple vehicles and infrastructure elements, not just a single vehicle. In these systems, vehicles optimize driving decisions by exchanging information with other vehicles (V2V), infrastructure (V2I) and road users (V2P) via wireless communication[7]. Thus, a more comprehensive safety and efficiency network is created, going beyond environmental perception.

1.3 AUTONOMOUS EMERGENCY BRAKING SYSTEM

Autonomous emergency braking systems are activated when the driver cannot detect a potential collision or cannot react in time and aim to prevent or reduce the severity of the collision. This system continuously monitors the traffic in the front area while driving, evaluates the risk of collision with vehicles, pedestrians and other road users, and automatically applies the brakes if necessary [8]. AEB systems consist of three basic components: detection, decision making and application (braking). The vehicle's surroundings are detected through sensors such as radar, camera and LIDAR, the risk assessment is made and if a collision is unavoidable, the system intervenes by determining the appropriate braking strategy [8].

AEB systems generally consist of three stages:

i. Warning stage: The system detects a potential collision and warns the driver audibly/visually.
ii. Partial braking: If the driver does not react to the current situation, braking is initiated gradually by the system.

iii. Full braking: If the critical threshold for the collision duration is exceeded, the system applies the maximum brake force.

The success of the braking system; sensor type, braking delay, detection accuracy and environmental conditions[9].

According to real-world data, AEB systems have been shown to reduce the risk of rear-end collisions by 38% to 50%. For example, in a study conducted by Cicchino in the USA; FCW alone provided a 27% reduction, Low-speed AEB system provided a 43% reduction, FCW + AEB together provided a 50% reduction [10]. The same study also emphasized that these systems provide a 45-56% reduction in injury accidents. These effects are particularly evident in urban traffic. On roads where the speed limit is 50 km/h or below, AEB systems are 54-57% more effective. However, although the system's effect decreases at high speeds, it does not completely disappear; for example, 12-25% effectiveness has been observed even at speeds above 80 km/h [10]. In addition to their crash prevention performance, these systems have also been shown to be effective in reducing the severity of injuries. It is estimated that approximately 1 million rear-end crashes and more than 400,000 injuries could have been prevented in the United States alone in 2014 if all vehicles had an effective AEB system [10].

1.4 EURO NCAP TEST PROTOCOLS AND THEIR APPLICATION IN THIS THESIS

Euro NCAP is an independent and consumer-focused test program established in 1997 to assess the safety performance of cars sold in Europe. The program is not limited to crash tests alone but also evaluates active safety technologies such as driver assistance systems, providing a comprehensive safety scoring system. Euro NCAP's star-based assessment system is calculated according to the performance of vehicles in the categories of adult occupant, child occupant, pedestrian and safety assistance systems, and plays an important role in shaping both consumer awareness and manufacturer standards.

Today, the effectiveness of collision prevention systems, especially the performance of Autonomous Emergency Braking systems, has become a decisive factor in Euro NCAP assessments. AEB systems detect frontal collisions and warn the driver or, if necessary, apply automatic braking to reduce the impact of the collision or prevent it completely. Euro NCAP evaluates not only the presence of these systems in the vehicle, but also how effectively they work in various realistic scenarios. In this context, Euro NCAP has defined two main protocols for AEB systems: a protocol that evaluates vehicle-to-car (C2C) scenarios and a protocol that includes collision scenarios for vulnerable road users (VRU).

The AEB Car-to-Car test protocol[11] evaluates the performance of systems under different vehicle-to-vehicle interactions in four main scenarios: CCRs (Car-to-Car Rear stationary), CCRm (Car-to-Car Rear moving), CCRb (Car-to-Car Rear braking) and CCFtap (Car-to-Car Front turn-across-path). These scenarios evaluate situations such as the vehicle being tested approaching a stationary vehicle, a vehicle moving at a constant speed or braking suddenly. In addition, in some cases, situations where the vehicle turns at an intersection and poses a risk of collision with an oncoming vehicle are also considered. In the tests, speed ranges are generally determined between 10–80 km/h, and lateral overlap rates are configured as –50%, 0%, +50%. The Global Vehicle Target (GVT) used as the target vehicle is a fake vehicle designed to be detectable by sensors such as radar, camera and LIDAR.

The AEB VRU protocol[12] measures the system's response to pedestrians and cyclists. Pedestrian scenarios include longitudinal (same direction), nearside/farside (side crossing), encounter during a turn and a child coming out from behind an obstacle, while cyclist scenarios include interactions such as longitudinal and crossing. In these tests, the system's target detection, decision-making and intervention processes are measured using physical models such as EPT (Euro NCAP Pedestrian Target) and EBT (Euro NCAP Bicyclist Target). Lateral positions are varied with overlaps such as 25%, 50% and 75%, and the system's performance against different perception difficulties is evaluated.

In this thesis, based on Euro NCAP's Car-to-Car and VRU scenarios, an AEB simulation model Dynamic Brake Force algorithm was developed in MATLAB/Simulink environment and the AEB model was updated and tested in real time. The following parameters were measured and analyzed within the scope of the simulation: time to collision (TTC), automatic braking initiation time (TAEB), collision moment speed (Vimpact), applied brake force, stopping distance and collision avoidance rate. These data were evaluated and compared to reveal the effectiveness of the system according to the scenarios.

A total of 7 representative scenarios were modeled and tested within the scope of the thesis, selected from the Euro NCAP protocol to reflect diverse collision types and traffic conditions. Thanks to the developed simulation infrastructure, the high cost, time and safety limitations of physical tests were eliminated; a controlled and repeatable digital test environment was obtained. This approach aims to provide a reference analysis infrastructure that can be used in the design of AEB systems in the future.

1.5 PURPOSE AND SCOPE OF THE THESIS

The main purpose of this thesis is to analyze the structure, operation and performance of Autonomous Emergency Braking systems in real traffic scenarios by modeling them in a simulation environment and to evaluate the effectiveness of the system through the obtained outputs. Today, AEB systems, which are offered as standard or optional in many vehicles, are expected to prevent accidents or reduce their effects by activating without driver intervention. However, how successful these systems are in which situations, the effect of environmental conditions on performance and the optimization requirements of the system's design parameters are still subjects of research.

In this direction, an AEB system model operating under conditions similar to real-world scenarios was developed in the MATLAB/Simulink environment within the scope of the thesis. The model consists of a radar/camera/sensor-based detection module, a logic structure that decides according to the probability of collision and application components that manage the braking response. The behavior of the system was observed at different vehicle speeds, obstacle distances and reaction time scenarios and performance metrics were derived.

The thesis study covers the following sub-objectives:

i. Testing under Euro-NCAP test scenarios reflecting real traffic conditions
ii. Measuring parameters such as timing, response time and braking power of the AEB system under these scenarios
iii. Analyzing the system architecture in terms of control and decision-making algorithms
iv. Interpreting the outputs and contributing to the design and improvement processes of AEB systems.

The findings obtained within this scope not only contribute to the production of academic knowledge but also serve as an important reference source for researchers and engineers interested in ADAS design in the automotive industry.

2. LITERATURE REVIEW

2.1 ADVANCED DRIVER ASSISTANCE SYSTEMS OVERVIEW

Advanced Driver Assistance Systems are integrated systems developed to increase safety in modern vehicles, improve driver awareness and prevent traffic accidents. Since approximately 90% of accidents today are caused by human error, these systems play a critical role in preventing accidents and reducing their effects[13]. ADAS systems do not only provide information to the driver but also support driving control by intervening directly in the vehicle when necessary and aim to prevent possible accidents and loss of life.

ADAS systems have gone beyond passive safety systems (e.g. seat belts, airbags) and have strengthened the safe area of vehicles and other elements. The purpose of active safety systems is for the system to step in and take preventive interventions before an accident or collision occurs[14]. The technology developed with these systems uses a large number of sensor technologies (Radar, LiDAR, Camera, Ultrasonic) to perceive and interpret the vehicle's surroundings. Thanks to these sensors, the intelligent system in the vehicle can recognize other vehicles, pedestrians, traffic signs and traffic lane lines around it.

ADAS systems consist of different subsystems according to their functions. These include:

i. Lane Keeping and Lane Departure Warning Systems: Warns the driver or corrects with steering input when the vehicle is about to leave the lane.
ii. Blind Spot Warning Systems: Detects vehicles in areas that the side mirrors cannot see and informs the driver.
iii. Adaptive Cruise Control: Automatically adjusts the speed to maintain a safe distance from the vehicle in front.
iv. Collision Warning and Autonomous Emergency Braking: Warns the driver when a risk of collision with the vehicle or pedestrian in front is detected and applies the brakes if necessary.
v. Driver Attention and Fatigue Detection Systems: Detects inattention or drowsiness based on eye movement and head position.
vi. Traffic Sign Recognition Systems: Recognizes traffic signs such as speed limits and no-overtaking through cameras.

vii. Night Vision and Pedestrian Sensitive Systems: Includes thermal cameras and artificial intelligence-supported analysis mechanisms for the detection of pedestrians, especially in low light.

Most of these systems are generally evaluated within Level 1 (support) and Level 2 (partial automation) in the 5-level automation structure defined by the Society of Automotive Engineers (SAE) [13]. The developed driver assistance systems also form the building blocks for the transition to fully autonomous driving Figure 2.1[15] shows a diagram explaining the use of ADAS in a car. The basic sensors used in ADAS technologies are as follows:

i. Radar: The location and speed of vehicles are determined using both short and long range radars. Radars can operate stably even in bad weather conditions [13].
ii. LiDAR: Laser-based and determines the distance and shape of surrounding objects in three dimensions but is costly.
iii. Cameras: Used in functions such as traffic sign recognition, lane tracking and object detection by providing visual information.
iv. Ultrasonic Sensors**:** Used especially in close-range detection (e.g. parking assistant).

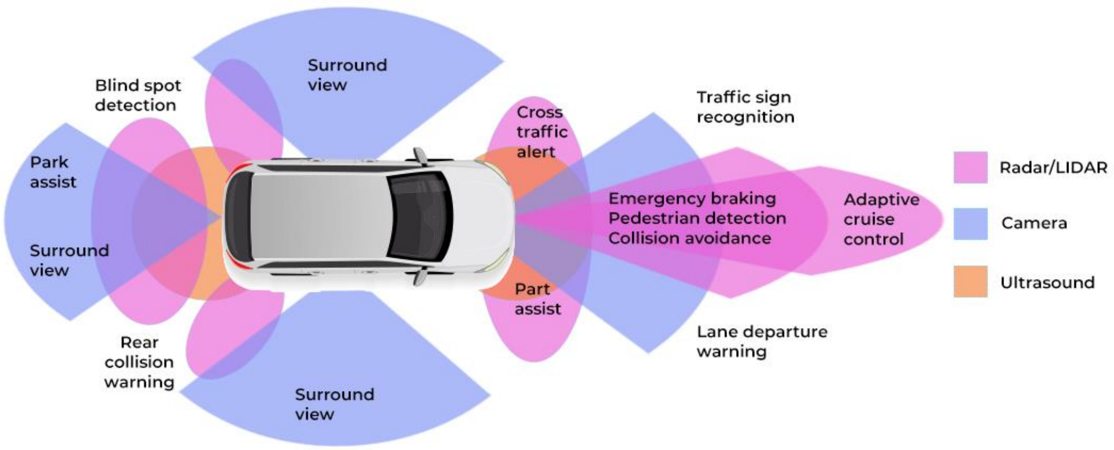


Figure 2.1: Locations and Functional Scopes of Sensors Used in Advanced Driver Assistance Systems

Today ADAS systems have ceased to be single solutions and have become more reliable, environmentally aware systems with sensor fusion. Thanks to these approaches, the system can analyze the environment more accurately, independent of the limitations of a single sensor[13].

It should not be forgotten that ADAS technologies are not only high-tech systems but also carry a social responsibility in terms of reducing traffic accidents and ensuring life safety. The development of ADAS solutions is driven by public policies and consumer safety ratings (e.g. Euro NCAP) as well as vehicle manufacturers.

2.2 AUTONOMOUS EMERGENCY BRAKING SYSTEM APPROACHES IN LITERATURE

Autonomous Emergency Braking systems are among the active safety technologies that are activated against the risk of collision without driver intervention. Academic studies on AEB systems have deepened with advancing technology in areas such as decision-making strategies, brake control algorithms, sensor integration and environmental adaptation. In this section, studies on AEB systems are classified by taking into account both chronological and technical evolution.

2.2.1 Early Algorithms and Basic Approaches

The first studies on Autonomous Emergency Braking systems generally focused on deterministic models and simple time-based thresholding algorithms to estimate the risk of collision. The main purpose of the systems developed in this period was to estimate the risk of collision by evaluating the distance and speed difference to the object in front with the data obtained from the sensors integrated into the vehicle (especially radar) and to automatically initiate the braking process.

One of the basic approaches that emerged in this period was the decision algorithms based on Time-to-Collision calculation. Kaempchen et al. proposed one of the first AEB models that evaluated different vehicle-to-vehicle collision scenarios. In this study, the collision risk was classified and the braking trigger conditions were defined with the radar-assisted situation assessment method[16].

Savino et al. evaluated the accident reduction potential of autonomous braking systems (MAEB-Motorcycle AEB) developed for motorcycles. In this study, which was conducted with simulations based on detailed accident data, the speed ranges and braking delays in which the AEB system is effective were analyzed[17]. The subsequent study of the same research group, Savino et al., proposed a new triggering algorithm for MAEB systems based on the concept of Inevitable Collision States (ICS), which defines situations where a collision becomes inevitable. The ICS-based approach makes the braking decision depending on multiple variables such as not only distance but also driving direction and speed difference[18].

Another approach proposed by Stellet et al. and which can be evaluated at early stage limits is the mathematical derivation of the performance limits of the AEB system by considering parameters such as maximum braking capacity, detection errors and braking delay. This study defined the design lower limits such as the minimum detection distance and reaction time at which AEB systems can react safely[19].

Early literature reveals that AEB systems are based on front vehicle detection, distance measurement, and brake triggering based on fixed threshold values. These studies generally aim to avoid collisions at low speeds or reduce collision speed; dynamic environmental conditions or artificial intelligence-supported decision mechanisms have not yet been introduced.

2.2.2 Road Conditions, Friction and Environmental Effects

The performance of Autonomous Emergency Braking systems depends not only on decision algorithms but also on vehicle-road interaction to a great extent. The braking behaviors of vehicles under external variables such as road surface conditions, friction coefficient, road slope, and weather conditions directly affect the reliability of the system. Studies conducted between 2014 and 2020 focused on algorithms that enable AEB systems to dynamically adapt to these environmental parameters.

Han et al. proposed a control strategy that takes into account parameters such as friction coefficient (μ) and road slope in order to increase the braking efficiency of the AEB system under different road surface conditions. In this model, the information received from the road surface is processed by the system in real time to determine the appropriate braking force and timing. The results showed that the system optimizes the stopping distance, especially on low-grip surfaces[20].

Kim et al. also analyzed the behavior of AEB systems under sloped road conditions and different braking surfaces; an AEB control algorithm was developed that takes into account the effect of road slope on vehicle kinetics. In the MATLAB/Simulink-based model, it was shown that the braking response was delayed on positive slope roads; on negative slope (downhill) roads, the system should intervene earlier[21].

Sevil et al. took these two approaches even further and developed an adaptive AEB algorithm. Real-time estimates were made with Kalman filters using parameters such as friction coefficient, vehicle mass and road slope, and the braking response of the system was updated according to these estimates. In the simulations, more successful results were obtained in terms of both stopping distance and braking comfort compared to classical fixed threshold-based systems[22].

Koglbauer et al. focused on driver perception rather than the technical success of the system and showed that when AEB systems are used in snow-covered road conditions, drivers' confidence in these systems increases significantly. This study reveals that AEB affects not only physical but also psychological safety factors[23].

Studies from this period show that environmental variables must be monitored in real time and integrated into the model in order for AEB systems to operate safely and effectively not only in ideal conditions but also in variable and difficult road conditions. These findings, in particular, paved the way for Euro NCAP to require testing system performances according to different surface types in its test protocols.

2.2.3 Model Predictive Control and Dynamic Braking Structures

Model Predictive Control (MPC) based methods stand out among the models developed to make the decision mechanisms of Autonomous Emergency Braking systems more flexible, time-sensitive and predictive. MPC continuously runs a forward-looking optimization process to predict the dynamic behavior of the system and selects the most appropriate braking decision at each time point. In the literature after 2020, this method has become frequently preferred in the control strategies of AEB systems.

Mu et al. developed a deceleration strategy that continuously optimizes the speed and brake force parameters of the AEB system using a nonlinear MPC structure. The study aimed to provide both short response time and comfortable braking against sudden collision threats. The model was tested in the Simulink environment and it was stated that significant gains were achieved in stopping distance compared to classical methods[24].

Ribeiro developed an AEB system that integrates the MPC structure with not only braking but also lane tracking and longitudinal speed control. This multi-target control structure ensures that vehicles both continue at a safe distance and maintain the correct lane position, especially in highway scenarios. In this respect, the system, unlike classical AEB architectures, offers not only emergency braking but also continuous safety optimization[25].

Gounis and Bassiliades designed the AEB system with a multi-layered control architecture. A high-level rule-based control module (RBSC) and lower-level slip control algorithms were integrated; the aim was to prevent the system from giving unstable reactions during sudden braking. This architecture showed a more controlled and stable braking behavior, especially in slippery ground and high-speed braking scenarios[26].

Han et al. developed the AEB system with a structure that automatically adapts to environmental variables (especially road grip conditions). The target road adhesion coefficient was estimated in real time and the limit values of the MPC were updated, and thus the system was able to provide safer and more effective braking against dynamic road conditions. The study showed that the system can provide early and controlled braking even on low-friction surfaces that carry a risk of freezing [27].

Studies conducted in this period show that, unlike classical threshold-based AEB systems; systems that operate with predictive, multivariable, environmentally sensitive and real-time optimized control strategies provide higher success. In particular, the adaptation of the MPC to dynamic braking behaviors stands out as an important development that increases both safety and driving comfort.

2.2.4 Sensor Fusion and Stereo Vision Based Detection Systems

The success of AEB systems depends not only on decision-making algorithms, but also on how accurately they can perceive the environment. In this context, sensor fusion and stereo vision techniques are widely used in AEB systems to increase environmental awareness. The main goal of these technologies is to overcome the limitations of single sensors and produce more reliable decisions by combining different types of data.

Rajendar et al. proposed a model that allows the AEB system to predict the stopping distance by performing stereo camera-based pedestrian detection. In the study, the location of pedestrians was determined by creating a depth map from the stereo image and it was calculated when the system should brake in the event of a possible collision. The system, tested in the MATLAB environment, was evaluated over a stopping distance threshold value of 3.3 meters and it was shown that the response sensitivity towards pedestrians could be increased[28].

Alsuwian et al. developed an AEB algorithm based on multi-sensor fusion combining radar and camera data. In this algorithm, beyond the classical data fusion methods, the control strategy uses Super-Twisting Sliding Mode Control. This hybrid structure has increased the responsive accuracy of the AEB system by reducing sensor delays and measurement uncertainties. The system's intervention stability has been strengthened, especially in near-collision situations[29].

Coelingh et al., in their study introducing the AEB system developed by Volvo, presented a practical system application where camera and radar are used together. The system can detect both vehicles in front and pedestrians, evaluate the risk of collision, and perform full braking in appropriate situations. The findings obtained in real vehicle tests revealed that the radar is strong in distance determination, while the camera is more effective in object classification. These results show that fusion combines the strengths of the two technologies[30].

These studies show that sensor fusion and stereo vision applications in AEB systems increase the system's environmental awareness, reduce the response time and provide more effective protection, especially against sensitive road users such as pedestrians and cyclists. In addition, the fact that evaluation organizations such as Euro NCAP have started to measure the performance of such detection systems in AEB test protocols has further increased the importance of these technologies.

2.2.5 Deep Learning, Reinforcement Learning and Artificial Intelligence Based Methods

While AEB systems are generally based on physical models and threshold-based decision-making rules, in recent years, with the integration of machine learning and deep learning-based models into AEB systems, these systems have become more intelligent, adaptable, and structures that can interact with the environment. These approaches provide significant advantages, especially in complex traffic scenarios, pedestrian-specific behavior predictions, and multivariate decision processes.

Fu et al. developed a deep reinforcement learning approach for a system that makes emergency braking decisions. In this structure, a reward-based learning was performed to observe the traffic situation in which a vehicle is located and make the most appropriate braking decision at each step. The vehicle not only avoided the collision, but also learned to produce a comfortable braking profile. This approach enabled the decision-making module to develop human-like reflexes[31].

Yang et al. proposed a multi-layer AEB decision mechanism by combining deep learning with fuzzy logic and PID control structures. In this architecture, variables such as the distance and speed between the vehicle and the pedestrian were fuzzified and transferred to a decision network, and then these outputs were converted into a PID-based braking action. The results showed that a faster and more stable braking response was obtained compared to classical algorithms [32].

Gounis and Bassiliades developed a multi-layered brake control system supported by a rule-based intelligent decision maker (RBSC) instead of an artificial intelligence-supported system. In this system, decision-making is made at a high level according to the rules of the environment, while the focus is on physical parameters such as skid control at a lower level. This structure offers a deterministic but flexible decision infrastructure, unlike classical artificial intelligence methods[26].

Thanks to these studies, it is shown that AEB systems are no longer systems that only respond to physical situations, but are intelligent structures that can learn, generalize and respond strategically. Additionally, these methods pave the way for advanced applications such as driver personalization, adaptation to variable traffic scenarios, and advanced environmental perception.

2.2.6 System Performances, Limitations and Safety Assessments

The reliability of AEB systems is determined not only by the existence of the system but also by its performance in real traffic scenarios, its physical limits and its success in different environmental conditions. For this reason, in recent years, studies focusing on testing AEB systems, conducting impact analysis and evaluating different limiting factors have gained intensity.

Stellet et al. mathematically analyzed the performance limits of AEB systems and modeled how factors such as detection uncertainties, brake response delays and algorithm response times limit the system success. The study revealed the minimum sensor accuracy and brake response time thresholds required for the systems to operate safely. This analysis contributed to the determination of basic engineering requirements for system design[19].

Edwards et al. modeled the benefits that could be achieved if AEB systems were to be widespread in Europe and showed that up to 57% of fatalities and serious injuries could potentially be prevented in pedestrian collisions. The simulations used in such studies are based on Euro NCAP scenarios as well as European accident databases[33].

Rajendar et al. analyzed whether AEB correctly calculates the stopping distance and intervenes in time in stereo camera-assisted systems. The stopping distance in the study was determined as 3.3 meters and it was shown that the system can brake at this threshold with over 90% accuracy. This result shows that the AEB system can meet the requirements of precise reaction time, especially in VRU scenarios[28].

Kovaceva et al. considered the cases where AEB systems work together with steering-assisted evasive maneuvers and stated that this combination is more effective in reducing collisions with pedestrians and cyclists. However, the success of the system is affected by multiple parameters, especially detection delay, road type, speed and angular position[34].

Santos-Cuadros et al. evaluated the effect of autonomous braking on interior passengers; by examining the effects on body dynamics of passengers who are not wearing seat belts during braking, they presented important results regarding interior safety scenarios. Such studies advocate that system performance should be evaluated in a way that covers not only external hazards but also interior passenger safety[35].

In general, these studies reveal that the conditions under which AEB systems are tested should become more complex; factors such as environmental uncertainty, passenger safety, physical boundaries and post-crash effects should be taken into account in system design. It is also emphasized that tests should include not only laboratory but also real road conditions and human factor variables.

2.2.7 Autonomous Braking for Motorcycles

Although AEB systems were initially developed for automobiles, it has become a necessity to design similar systems for motorcycles due to the high-risk positions of motorcycle users in traffic. The systems developed for this purpose are called Motorcycle Autonomous Emergency Braking (MAEB). MAEB systems aim to slow down the motorcycle by activating without the intervention of the driver; however, the design of these systems is much more complex than that of automobiles in terms of sensitivity to vehicle balance and braking stability.

Savino et al. revealed that MAEB systems have the potential to significantly reduce deaths and serious injuries based on the examination of motorcycle accidents in the first MAEB study. In the comparative analyses conducted with accident data in this study, it was shown that systems that intervene at low speed are especially effective in urban accidents[17]. Another study developed by Savino et al. designed the triggering logic of MAEB systems based on the "Inevitable Collision States" (ICS). In this approach, the system initiates braking when the moment when a collision is inevitable is determined, considering not only the distance ahead but also the speed and direction[18]. In 2016, Savino et al. evaluated the real-world applications of MAEB systems with open field experiments conducted under different test conditions, and analyzed the extent to which motorcycle stability can be maintained during braking. In this study, both brake trigger delays and driver balance responses were tested. In addition, another analysis using Australian accident data predicted that MAEB systems could reduce the accident fatality rate by up to 25%[36], [37].

Lucci et al. analyzed the biomechanical limitations, driver-vehicle interaction and brake stability that should be considered during the design of MAEB systems and evaluated how the system can be operated effectively without harming the driver. In this study, it is emphasized that the system should be soft-started and the braking profile should be fine-tuned[38].

The main limitations for MAEB systems include; the balance of the motorcycle, the danger of sudden braking in turning movements, the perception of the driver's riding position, and human factors such as whether the braking is expected by the driver. Therefore, current research aims to regulate not only the technical adequacy of MAEB systems but also their interaction with the driver in a safe way.

In this context, MAEB systems focus on fully automatic braking, especially in urban low-speed scenarios and linear movements, and semi-automatic or assisted braking in more complex turning maneuvers. This may enable motorcycle safety systems to be included in active safety standards in the future, as in automobiles.

2.3 ALGORITHMS AND SENSORS

The effectiveness of AEB systems is not only critical to the accurate perception of environmental data, but also to how these data are processed and interpreted with which algorithms. The sensors used in AEB systems provide information to the system's decision-making processes by observing environmental factors. The data processed by these sensors generally includes elements such as distance measurement, speed difference, road type and target's motion profile. Algorithms produce outputs such as collision risk, braking requirement and intervention timing from this data.

Sensors such as radar, LiDAR and camera are the basic sensors used in AEB systems. While radar can provide reliable data especially in low light conditions and bad weather conditions; cameras perform object recognition and traffic sign detection functions with high resolution. LiDAR provides high-accuracy distance measurements by performing 3D modeling of the environment. However, a single sensor may be insufficient in many cases. Therefore, sensor fusion techniques are used to combine data from different sensors and enable more robust decisions to be made.

Rajendar et al. developed an AEB model that detects pedestrians using a stereo camera. After determining the pedestrian position through depth maps and evaluating the collision risk, the system made a timely decision to brake by estimating the stopping distance in advance. In the tests conducted in the simulation environment, it was reported that this system offered higher sensitivity than classical methods [28].

Gounis and Bassiliades proposed an AEB architecture with a multi-layered decision structure. In this structure, the upper-level decision module analyzed the environmental conditions, while the lower-level slip control performed the braking intervention according to the road holding. This structure, together with sensor fusion, enabled the system to respond more balancedly to sudden situations[26].

Yang et al. aimed to enable the system to respond more flexibly to environmental variables by integrating methods such as fuzzy logic and PID control into AEB decision processes. Thanks to this structure, the system performed comfortable braking at low speeds and fast and stable braking at high speeds[32].

Ribeiro integrated MPC (Model Predictive Control) algorithms not only with braking but also with longitudinal speed control and lane tracking, enabling the AEB system to provide more comprehensive driving support in highway scenarios. Such predictive algorithms provide a critical structure for the vehicle to adapt to changing conditions around it [25].

In modern AEB systems, not only physical sensor accuracy but also flexible and multi-layered algorithms that process this data to produce optimum braking decisions are of great importance. It is envisaged that artificial intelligence and learning-based algorithms will contribute more to the stability of these systems in the future.

2.4 TEST AND EVALUATION METHODS OF AEB SYSTEMS

In order to determine the extent to which AEB systems are effective in real traffic conditions, standardized test protocols and scenario-based evaluation methods are needed. In this context, the most widely used and internationally valid test framework is the AEB test protocols developed by Euro NCAP.

Euro NCAP is an independent organization that evaluates vehicle safety and measures not only the hardware presence of AEB systems, but also the performance of these systems in different traffic scenarios. Euro NCAP tests include both Car-to-Car (C2C) and Vulnerable Road Users (VRU), i.e. pedestrians and cyclists encounter scenarios [1].

The C2C protocol includes three main test scenarios:

i. CCRs (Car-to-Car Rear stationary): Approaching a stationary target
ii. CCRm (Car-to-Car Rear moving): Approaching a moving vehicle ahead
iii. CCRb (Car-to-Car Rear braking): Following a vehicle that is braking suddenly

In addition, in some cases intersection turning scenarios such as CCFtap (Front turn-across-path) are also considered[11]. Each test scenario is systematically conducted using different speed ranges (10–80 km/h), lateral overlap rates (–50%, 0%, +50%) and target object types (GVT – Global Vehicle Target).

The VRU protocol aims to measure the AEB response to pedestrians and cyclists. The protocol covers the following basic scenarios:

i. CPNC (Child Nearside Crossing): Child exiting from behind the obstacle
ii. CPNA/CPFA (Adult Nearside/Farside Crossing): Adult pedestrians crossing in front of the vehicle
iii. CPLA (Longitudinal Adult Pedestrian): Pedestrian walking in the same direction as the vehicle
iv. CBNA (Cyclist Crossing from Nearside): Cyclist crossing from the side
v. CBLA (Longitudinal Cyclist): Cyclist moving in the same direction[11]

The pedestrian and cyclist targets used in these tests are physical models defined by Euro NCAP. Each of the scenarios is run on moving platforms to provide a realistic assessment of vehicle-sensor interaction.

Schram et al. have examined the gradual development of Euro NCAP tests and have detailed how AEB systems are scored according to the test protocols. The study states that the tests are becoming increasingly complex and that in the future, criteria such as collisions during turning, evaluation according to environmental conditions, and adaptability according to driving style are expected to be included[11].

Kim and Lee conducted real tests on a special platform to test AEB systems for VRU scenarios and compared the stopping point, braking time, and collision avoidance performance of the systems at different pedestrian speeds. This study showed that real field tests can produce results consistent with simulations[39].

2.5 AEB AND THE USE OF ARTIFICIAL INTELLIGENCE

With the evolution of advanced driver assistance systems, the integration of artificial intelligence-based methods such as machine learning, deep learning, and reinforcement learning has accelerated in AEB systems, moving beyond classical decision algorithms. These developments have increased the environmental awareness level of systems and have also enabled the development of customizable, learning, and predictive models.

Fu et al. designed a structure that can learn emergency braking decisions in AEB systems and used the deep reinforcement learning method for this structure. This architecture, in which the vehicle evaluates the environmental situation at each step and makes a braking decision according to a reward function, is an important example in terms of modeling human-like reactions[31].

Yang et al. developed a model that combines classical control structures with artificial intelligence, bringing together fuzzy logic, artificial neural networks, and PID control systems under a single roof. Thanks to this multi-layered structure, the vehicle was able to interpret both the distance from the pedestrian and the speed changes and make a braking decision adapted to the variable road conditions[32].

Alsuwian et al. developed a hybrid structure that controls the AEB algorithm on multi-sensor data with the Super Twisting Sliding Mode Control (STS-SMC) method. This model increases the stability of the AEB system, especially in scenarios with sudden speed changes and sensor uncertainties[29].

In the approach proposed by Gounis and Bassiliades, a rule-based controller (RBSC) that manages high-level decisions and modules that perform low-level sliding control are integrated. Although this structure is different from classical artificial intelligence approaches, it shows how multi-layered intelligent control systems can be applied to AEB architectures[26].

These studies show the use of artificial intelligence in AEB systems:

i. Target detection and tracking (with camera, radar data)
ii. Optimizing decision-making processes
iii. Making human-like decisions in complex scenarios
iv. Developing real-time adaptive braking strategies

provides successful results in functions such as. Especially thanks to advanced applications such as stereo vision, learning-based braking curve estimation, scenario-based driver modeling and real-time adaptation, AEB systems are taking shape as structures that not only prevent collisions but also become sensitive to road conditions, driver style and environmental variables[26], [29], [31], [32].

2.6 CONTRIBUTION OF THE THESIS TO LITERATURE

Although studies on AEB systems have shown significant progress in recent years, it is seen that there are still various limitations and areas open to development in literature. Issues such as test coverage, flexibility of decision algorithms and adaptation of the system to different conditions are among the prominent deficiencies.

The fact that many studies have been conducted only in certain speed ranges and with a limited number of scenarios is insufficient to reflect the diversity of real-world traffic interactions. Although the C2C (Car-to-Car) and VRU (Vulnerable Road Users) protocols defined by organizations such as Euro NCAP systematically address this diversity, simulations based on all of these protocols are rarely encountered in academic studies[8], [40].

Another important shortcoming is that AEB systems are largely based on decision algorithms that use constant braking force. This approach may be inadequate in responding appropriately to the dynamic nature of the collision risk, thus offering limited performance in terms of both safety and driving comfort[24], [27].

In addition, in many literature studies, simulations are evaluated on narrow scenarios, special test platforms or only a single metric (e.g. stopping distance), which makes comparative analysis of systems difficult[18], [28].

In this thesis study, one of the important limitations frequently encountered in the literature, which is the use of constant braking force without considering the variability in traffic and environmental conditions, is directly addressed. As an alternative to this limitation, an adaptive braking force algorithm sensitive to five different parameters has been developed. The algorithm dynamically determines the braking level based on critical data that can change in real time, such as time to collision, road conditions (dry, wet, icy), speed of the test vehicle, speed of the target vehicle and distance to the target vehicle.

In order to evaluate the performance of the developed algorithm, a total of seven basic scenarios representing different types of collisions, determined by reference to the Euro NCAP protocol, were modeled in the MATLAB/Simulink environment. These scenarios were carefully selected to represent various types of collisions that may occur with both vehicle-to-vehicle and vulnerable road users (pedestrians and cyclists) with different speeds, overlap rates and target motion profiles.

The performance of the adaptive braking algorithm was evaluated comparatively with the traditional constant braking force approach. In the comparison; Basic criteria such as braking start time, collision speed, stopping distance and comfort level of deceleration were used. The aim of the developed system is not only to prevent collisions, but also to protect passenger comfort by intervening when and as much as necessary, and to minimize the disruption of traffic flow and secondary collision risks that may occur due to unnecessary braking.

The original contribution of the thesis is the proposal of an adaptive, scenario-based control approach that evaluates the braking performance of the AEB system in different traffic scenarios in terms of both safety (collision speed, stopping distance) and system response (braking time, decision moment). This contribution provides a valuable basis for studies on designing AEB systems in a more flexible and environmentally sensitive manner.

3. METHODOLOGY

In this thesis, a control algorithm has been developed that can dynamically adjust the braking force of Autonomous Emergency Braking systems in a way that is sensitive to the collision risk and environmental conditions. This developed adaptive braking algorithm has a decision-making mechanism based on five basic parameters that can change in real time: time to collision, road conditions (dry, wet, icy), test vehicle speed, target vehicle speed, and distance between the test vehicle and the target vehicle.

The constant brake force approach, which is frequently encountered in classical AEB systems, is insufficient in some scenarios; in some cases, it can lead to early or late braking reactions. This can negatively affect both passenger comfort and disrupt traffic flow, causing chain accidents. For this reason, the developed algorithm is designed to brake only when and as much as necessary. Thus, the system aims to provide the optimum balance between passenger comfort and traffic safety while intervening at a level that will prevent collisions.

In order to evaluate the algorithm, 7 basic scenarios representing different types of collisions were selected in accordance with the Euro NCAP protocol and these scenarios were modeled in the MATLAB/Simulink environment. The selected scenarios include vehicle-to-vehicle collisions, sudden braking of the vehicle in front, approaching a fixed target, encountering a cyclist and a pedestrian. Each scenario was tested separately with both the classical fixed braking approach and the proposed adaptive braking algorithm.

Thanks to this approach, not only whether the collision was prevented or not, but also performance criteria such as braking timing, collision speed, stopping distance, impact on the passenger and suitability for the traffic scenario were analyzed in detail. The obtained results show that the adaptive brake control algorithm provides a more balanced, safe and comfortable driving experience compared to the classical fixed braking approach.

3.1 TEST PROTOCOLS AND SCENARIOS USED

In this thesis, seven representative scenarios were determined in accordance with the AEB test protocols defined by Euro NCAP and the system performance was evaluated on these scenarios. The selected scenarios cover different collision types such as vehicle-to-vehicle collisions (CCRs, CCRm, CCRb), intersection scenario (CCFtap), encounters with cyclists and pedestrians. This selection was made by considering the scenarios that best reflect different types of risks and the system's response to various situations from the wide range of scenarios in the Euro NCAP protocol.

The scenarios are generally divided into the following categories:

i. CCFtap: Collision risk caused by the turning of the oncoming vehicle at the intersection
ii. CCRs: Moving towards a stationary target vehicle
iii. CCRm: Approaching the vehicle in front at a constant speed
iv. CCRb: Situation where the vehicle in front brakes suddenly
v. Pedestrian - Child: Child pedestrian leaving the obstruction of vision
vi. Pedestrian - Turning: Encountering a pedestrian proceeding in the direction of the turn
vii. Cyclist - Longitudinal: High overlap approach with a cyclist proceeding in the same direction as the vehicle

All of these scenarios were modeled in MATLAB/Simulink environment and run via Simulink Test Manager. During the tests, system performance was analyzed via numerical output and evaluation metrics; most of the simulations did not require any visual animation production.

Among these scenarios, scenario_AEB_CCFtap scenario was staged in the RoadRunner environment in order to express the vehicle direction change dynamics more clearly and a visual simulation output was created. This scenario, like the others, was run on Simulink basis; RoadRunner was used only for staging and obtaining visual video output.

Similarly, other scenarios can also be staged in the RoadRunner environment; however, since visual output was not needed in this study and numerical simulation was sufficient for analysis, no additional staging process was needed.

Thanks to these seven scenarios, the collision avoidance performance of the system, intervention timing, effectiveness of brake force, effect on passenger comfort and suitability for traffic scenarios were evaluated in a multidimensional manner.

Table 3.1: Selected Representative Euro NCAP Scenarios

Scenario Type	Scenario Name	Description
CCFtap	Car-to-Car Front Turn Across Path	Oncoming vehicle turning across the path of the test vehicle (visual simulation)
CCRs	Car-to-Car Rear Stationary	Approaching a stationary vehicle with 100% lateral overlap
CCRm	Car-to-Car Rear Moving	Approaching a vehicle moving at constant speed with full overlap
CCRb	Car-to-Car Rear Braking	Approaching a vehicle performing 6 m/s^2 braking from 40 m initial distance
Pedestrian Child Crossing	Pedestrian Child Nearside	Child pedestrian emerging from occlusion at nearside
Pedestrian Turning	Pedestrian Turning Farside	Pedestrian turning into vehicle path from farside
Bicyclist Longitudinal	Bicyclist Longitudinal	Cyclist traveling in same direction with 75% lateral overlap

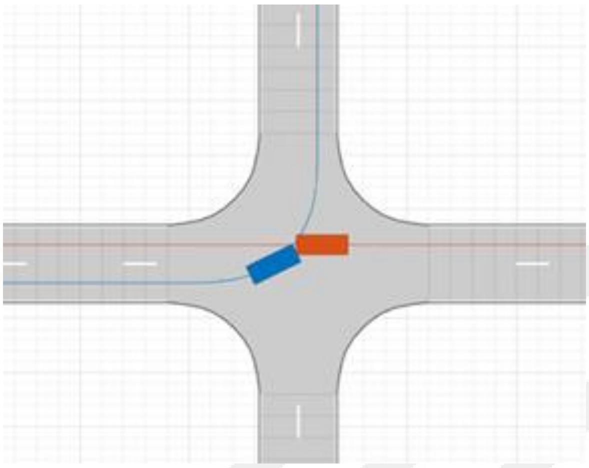
3.1.1 Scenario Car-to-Car Front Turn Across Path

This scenario was designed based on Euro NCAP's Front Turn Across Path (CCFtap) test protocol[11]. In the scenario, the tested vehicle (VUT) is driving straight at 15 km/h, while another oncoming vehicle (GVT) approaches at 55 km/h and after a short waiting period, turns left with 50% overlap and enters the VUT's path. Such collisions are of critical importance, especially in intersection accidents.

The scenario was created in MATLAB/Simulink environment using Automated Driving Toolbox tools and staged using RoadRunner integration. In addition to visual simulation, system analysis was performed via Simulink Test Manager.

RoadRunner is a visual scenario and scene design tool developed by MathWorks that allows the creation of 3D scenes and simulation environments for automotive systems. This platform allows detailed design of environmental elements such as road geometries, traffic patterns, buildings and pedestrian structures. It works integrated with Automated Driving Toolbox and Simulink, allowing the creation and testing of realistic test environments for autonomous driving systems and advanced driver assistance systems[11].

Table 3.2: Scenario CCFtap VUT15kph GVT 55kph Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
Collision Course of VUT (blue) and GVT (red) in Car-to-Car Front Turn Across Path Scenario 	Global Vehicle Target (GVT): The Global Vehicle Target travels in a straight line in the opposite direction from the adjacent lane in which the vehicle under test is traveling and at a constant speed of 55 km/h. Event: A collision in which the front bumper of the GVT engages in a lateral position covering 50% of the width of the VUT.	Travel at a constant speed: 15 km/h. Expected behavior: The collision avoidance system will be triggered, and the autonomous braking system will be activated, stopping the ego vehicle.

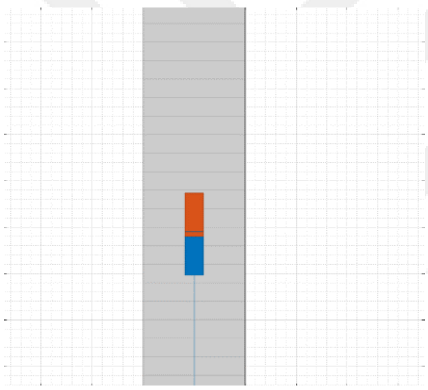
3.1.2 Scenario Car-to-Car Rear Stationary

This scenario is designed in accordance with the Car-to-Car Rear Stationary (CCRs) protocol defined by Euro NCAP[11]. In the scenario, the tested vehicle (VUT) approaches a stationary target vehicle (GVT) at a constant speed on a straight path with 100% overlap. The target vehicle is stationary in the middle of the road and does not make any movement.

The scenario is modeled using Automated Driving Toolbox tools in MATLAB/Simulink environment, and control mechanisms such as collision detection, braking decision and brake force application are integrated into the AEB Test Bench structure. The aim of this test is to evaluate whether the system detects a stationary target in a timely manner and activates the forward collision warning system (FCW) and then the AEB system at the right time before the collision.

This scenario represents the situations of approaching a suddenly stopped vehicle, which is commonly encountered especially in urban traffic density. In the simulations, the adaptive braking algorithm is compared with the classical stationary braking method, and metrics such as braking timing, collision speed and stopping distance are analyzed.

Table 3.3: Scenario CCRs %100 Overlap Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
VUT (blue) and GVT (red) Positions in Car-to-Car Rear Braking Scenario 	Stationary Vehicle: Target vehicle is stationary on the road. Event: The ego vehicle indicates a collision that matches the target vehicle by 100% of its width.	It moves at a constant speed: 30 km/h. Expected behavior: The collision avoidance system will be triggered and the autonomous braking system will be activated, stopping the ego vehicle.

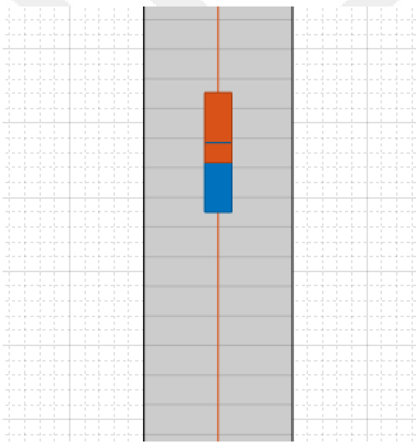
3.1.3 Scenario Car-to-Car Rear Moving

This scenario is structured in accordance with Euro NCAP's Car-to-Car Rear Moving (CCRm) test protocol[11]. In the test, the tested vehicle (VUT) is on a collision course with another vehicle (GVT) in front of it, which is also moving at a constant speed, with 100% lateral overlap. This scenario represents the constant speed pursuit situations that are frequently encountered especially in urban and highway traffic.

The scenario was modeled using Automated Driving Toolbox in MATLAB/Simulink environment; collision detection, braking control and sensor responses were run integrated with AEB Test Bench infrastructure. Whether VUT detects GVT in front and brakes in time; It was evaluated comparatively between the classical constant brake force approach and the developed adaptive algorithm.

Within the scope of the scenario, how VUT reacts as the collision time (TTC) decreases according to the speed of the vehicle in front was analyzed. The system is expected to activate AEB by giving a forward collision warning (FCW) under a certain TTC threshold value. This scenario is critical to assess the crash prevention role of the AEB system, especially in situations where the driver is distracted.

Table 3.4: Scenario CCRm %100 Overlap Test Parameters

Test Description	Target Actor	Requirements on Vehicle Under Test
Car-to-Car Rear Moving Scenario Full Overlap Between Moving Vehicles 	Moving Vehicle: Moving at a constant speed of 20 km/h. Event: A collision in which the ego vehicle rear-ends a moving vehicle. At the moment of collision, the ego vehicle covers an area 100% of the width of the moving vehicle. The ego vehicle moves to rear-end the moving target vehicle. The area in which the collision occurs covers 100% of the width of the target vehicle.	Travels at a constant speed: 30 km/h Expected behavior: The collision avoidance system will be triggered, and the autonomous braking system will be activated, stopping the ego vehicle.

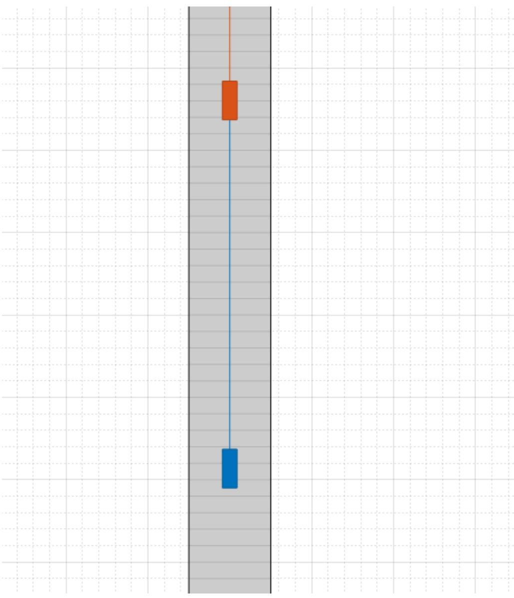
3.1.4 Scenario Car-to-Car Rear Braking

This scenario is structured in accordance with the Car-to-Car Rear Braking (CCRb) test protocol defined by Euro NCAP[11]. In this scenario, the preceding vehicle (GVT) is simulated to brake suddenly at a certain point while proceeding at a constant speed, while the test vehicle (VUT) follows this vehicle at a constant speed. The aim of the scenario is to evaluate the collision prevention effectiveness of the AEB system in the event of sudden braking.

In the scenario, the GVT vehicle brakes with a negative acceleration of 6 m/s^2 after proceeding at a speed of 50 km/h. The VUT follows at a constant speed of 50 km/h with a following distance of approximately 40 meters. The overlap between the vehicles is 100%. This situation represents the situation where the driver cannot detect the sudden deceleration of the vehicle in front.

The simulation is modeled using the Automated Driving Toolbox in MATLAB/Simulink environment and the control algorithm is integrated on the AEB Test Bench architecture. The aim of the scenario is for the system to detect the speed change of the vehicle in front in time and intervene with the forward collision warning (FCW) and AEB system.

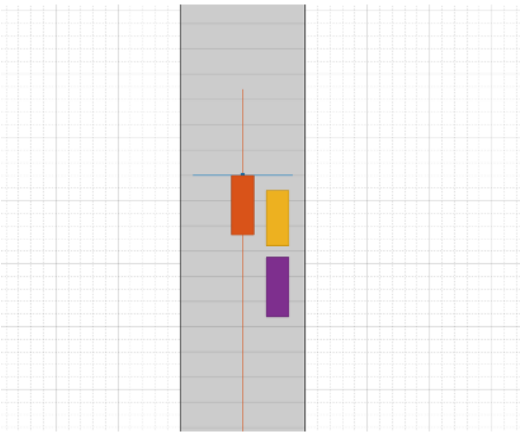
Table 3.5: Scenario Car-to-Car Rear Braking 40 Meter Initial Gap %100 Overlap Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
Car-to-Car Rear Stationary Scenario Linear Approximation of VUT to negatively accelerating GVT 	Braking Vehicle: Initially moves at a constant speed of 50km/h. Then starts to slow down at 6m/s2. Initial interval = 40 meters. Event: A collision where the ego vehicle hits the moving target vehicle from behind while moving at a constant speed	Travels with constant velocity: 50 km/h Expected behavior: The collision avoidance system will be triggered and the autonomous braking system will be activated, stopping the ego vehicle.

3.1.5 Scenario Pedestrian-Child Nearside

This scenario is based on Euro NCAP's Pedestrian Nearside-Child test protocol[11]. In the scenario, a child pedestrian exiting from behind a visual obstacle (e.g. a parked vehicle or wall) suddenly enters the path of the test vehicle (VUT) with a 50% overlap from the right to the left of the road. This situation is representative of sudden pedestrian exits, which are especially common in school surroundings or residential areas. The scenario was modeled using the Automated Driving Toolbox in the MATLAB/Simulink environment. The aim is for the VUT to detect the child pedestrian and activate the forward collision warning (FCW) and then the AEB system. In the simulation environment, the scenario was run with the AEB Test Bench infrastructure; the dynamics between the VUT and the pedestrian were modeled according to the sensor data. The pedestrian was structured in a way that it can be observed how the system reacts to the pedestrian entering the vehicle's path at a certain speed and angle.

Table 3.6: Scenario Pedestrian-Child Nearside %50 Overlap Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
Nearside Pedestrian Scenario Intersection of VUT (orange) with Visibility Obstruction (yellow, purple) in Front and Pedestrian (black) Coming Out from Behind 	Child pedestrian: A pedestrian is crossing the road from the right (near side) at a constant speed of 1.39 m/s. Blocking Vehicles: Two vehicles are stationary on the road obstructing the pedestrian's view for VUT. Incident: A collision in which the pedestrian travels 50% of the width of the ego vehicle.	Travels with constant velocity: 20 km/h Expected behavior: The collision avoidance system will be triggered and the autonomous braking system will be activated, stopping the ego vehicle.

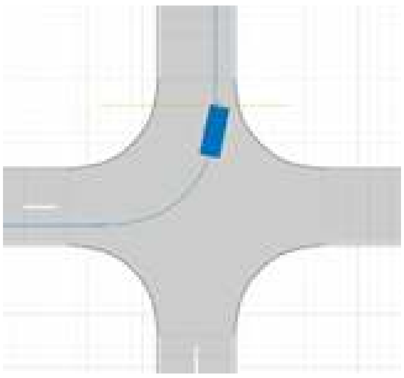
3.1.6 Scenario Pedestrian Turning Farside

This scenario is based on Euro NCAP's Pedestrian Turning-Farside test protocol[11]. In the scenario, the test vehicle (VUT) is making a left turn at an intersection while a pedestrian on the opposite side of the road (farside) is crossing the road at a constant speed. The VUT's path intersects with the pedestrian's movement, creating a risk of collision at this point.

The scenario is defined in MATLAB/Simulink. While the vehicle is making the turn, the system is expected to detect the pedestrian in time and activate the forward collision warning (FCW) and then the AEB system.

In the scenario, the moment of collision occurs at the position where the pedestrian crosses 50% of the VUT's width. This allows the system to evaluate how early it can detect and respond to the pedestrian movement.

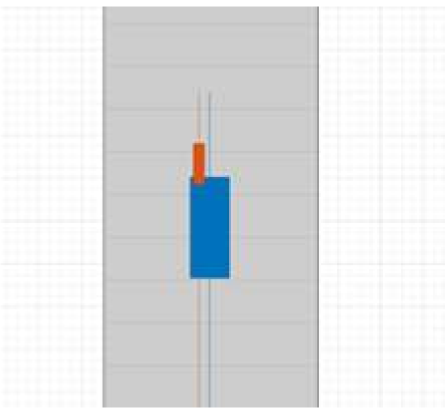
Table 3.7: Scenario Pedestrian Farside %50 Overlap Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
Farside Pedestrian Turn Scenario VUT (blue) Left Turn Movement at Intersection 	Pedestrian: A pedestrian crosses the road at a constant speed while the ego vehicle turns left at the intersection. Incident: A collision scene with a pedestrian at 50%	Travels with constant velocity: 10 km/h. Expected behavior: The collision avoidance system will be triggered and the autonomous braking system will be activated, stopping the ego vehicle.

3.1.7 Scenario Bicyclist Longitudinal

This scenario is based on the Cyclist Longitudinal test protocol defined by Euro NCAP [1]. In the scenario, the test vehicle (VUT) approaches a cyclist in front of it, traveling at a constant speed on a flat road, at a slower speed in the same direction. This simulates a common interaction in urban traffic conditions. In the scenario, the cyclist target is traveling at a constant speed of 15 km/h. The vehicle under test is traveling at a constant speed of 25 km/h, and at the time of the collision, the cyclist has passed 75% of the width of the vehicle under test. The scenario is defined in MATLAB/Simulink. Both objects are traveling in the same direction and in the same lane, and the system must detect the cyclist in time and initiate the necessary braking. This structure aims to evaluate the response of the AEB system to moving, weakly perceptible targets (such as cyclists). In the test, the system's sensor and decision mechanisms are activated by paying attention to the cyclist's position at the moment of the collision.

Table 3.8: Scenario Bicyclist Longitudinal %75 Overlap Test Parameters

Test Description	**Target Actor**	**Requirements on Vehicle Under Test**
Cyclist Longitudinal Scenario Tracking Status Between VUT (blue) and Cyclist (orange) 	Cyclist: Travels at a constant speed of 15 km/h. Event: The ego vehicle travels at a constant speed toward the cyclist in front of it. Before the collision, the cyclist and the ego vehicle are moving in the same direction along the longitudinal axis. At the moment of collision, the bicycle has covered 75% of the width of the ego vehicle.	Travels with constant velocity: 25 km/h. Expected behavior: The collision avoidance system will be triggered and the autonomous braking system will be activated, stopping the ego vehicle.

3.2 SIMULATION ENVIRONMENT AND TECHNICAL INFRASTRUCTURE

3.2.1 AEB Test Bench Structure

The simulation infrastructure used in this study is based on the Autonomous Emergency Braking (AEB) Test Bench architecture, which is configured in the MATLAB/Simulink environment. This structure is a modular test environment that enables modeling of test scenarios defined by Euro NCAP testing of control algorithms and evaluation of system outputs[41], [42].

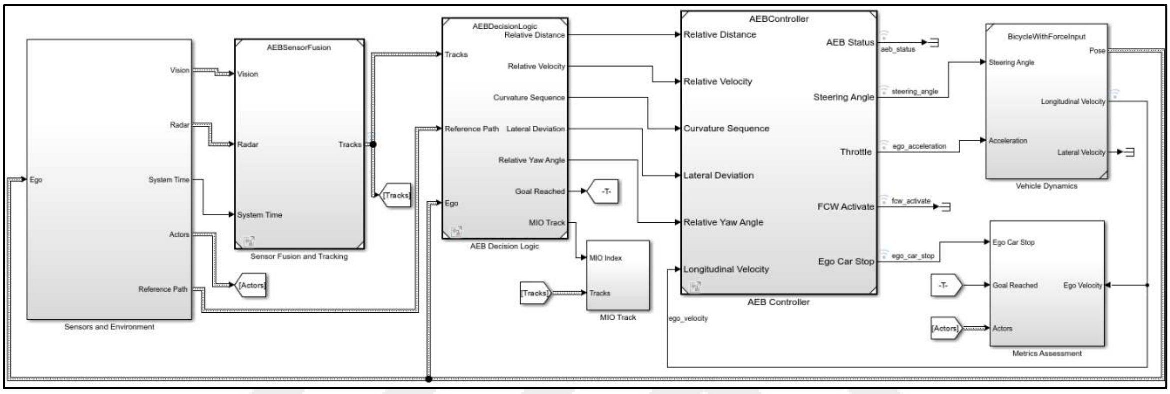


Figure 3.1: AEB Test Bench System General Block Diagram

3.2.1.1 Sensors and environmental modeling

The behaviors and positions of actors such as vehicles, pedestrians and cyclists are defined through RoadRunner scenarios. Environmental perception is created through sensors such as cameras and radars. These sensors are configured with defined fields of view and ranges to recognize objects around the vehicle.

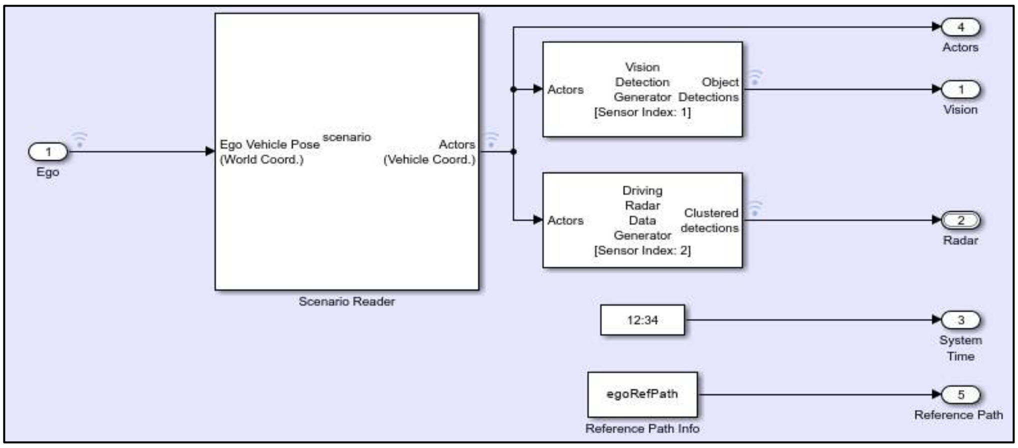


Figure 3.2: Sensor and Environmental Modeling Structure (Vision–Radar–Path) Block Diagram

3.2.1.2 Sensor fusion and tracking

Target objects are tracked by combining data from sensors. In this module, the most critical target for the system, the Most Important Object (MIO), is determined. Tracking algorithms continuously monitor the speed, position and direction changes of the targets.

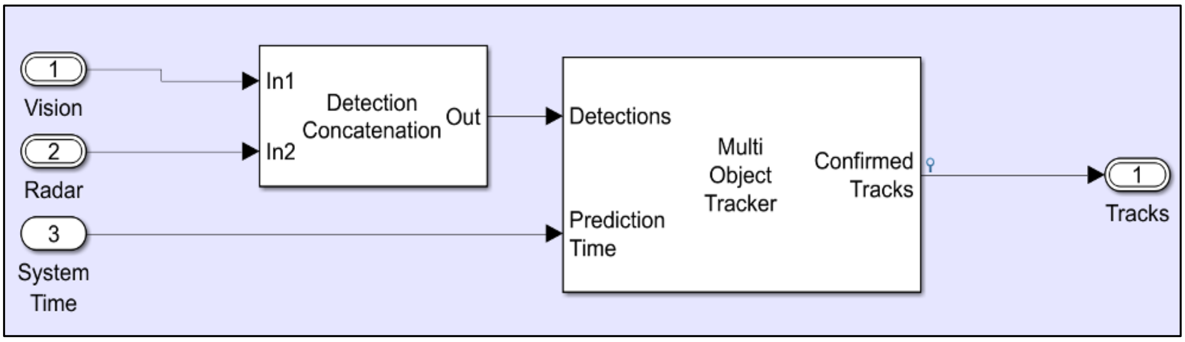


Figure 3.3: Integration of Vision and Radar Detections into the Tracking System

3.2.1.3 AEB decision logic

By analyzing variables such as the distance between VUT (Vehicle Under Test) and MIO, speed difference and collision time (TTC), it is determined whether the system will produce a braking decision. This decision structure is sensitive to both longitudinal and lateral scenario analyses.

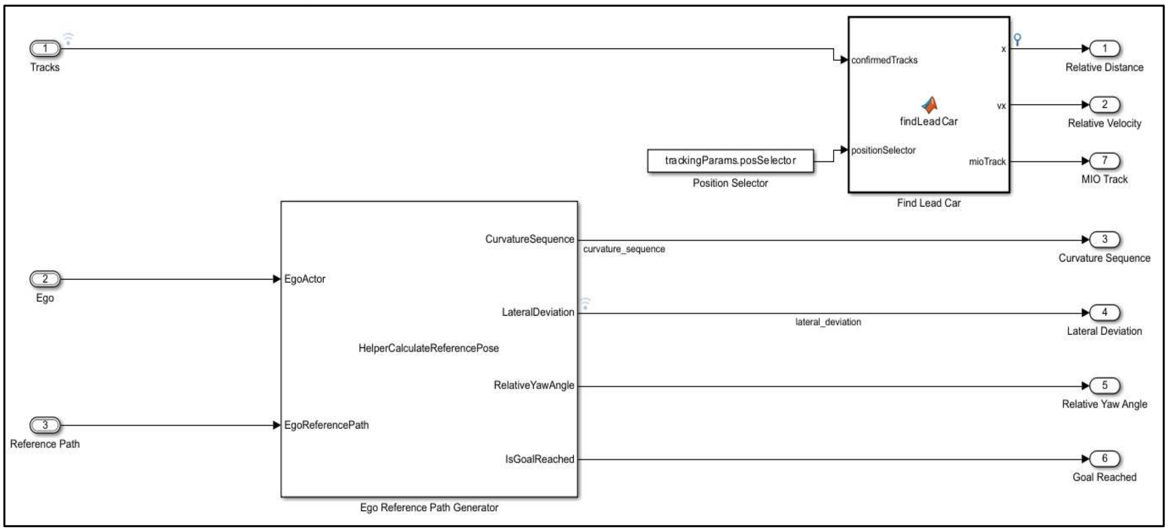


Figure 3.4: Block Diagram of MIO Determination and Decision Inputs of AEB Decision Logic

3.2.1.4 AEB controller

The deceleration that the system will apply depending on the braking decision is calculated. The controller calculates the brake force and sends it to the vehicle model.

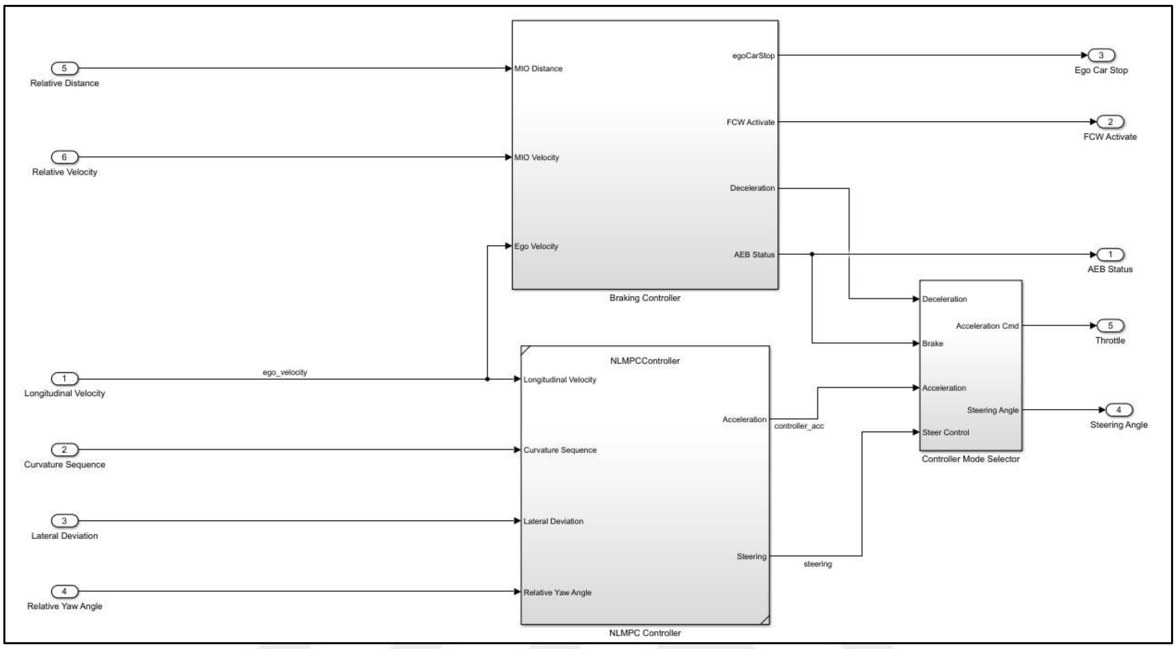


Figure 3.5: Block Diagram of AEB Braking and Steering Control Mechanisms

3.2.1.5 Vehicle dynamics

As a result of braking, the physical parameters of the vehicle such as speed, direction, position and stopping distance are updated. This component is the basic layer that provides the physical accuracy of the system.

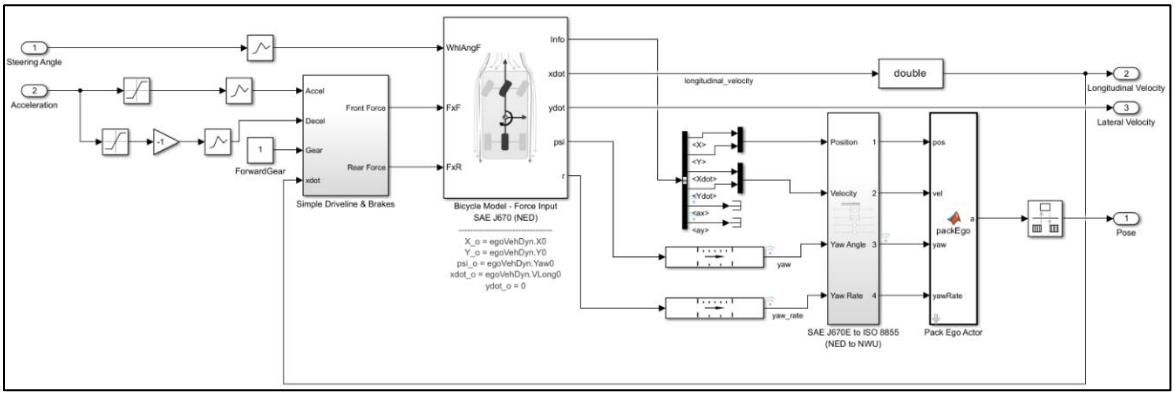


Figure 3.6: Physical Vehicle Dynamics Block Diagram Integrated into AEB System

3.2.1.6 Performance metrics

During the simulation the behavior of the system is monitored with certain metrics. These include metrics such as braking initiation time, stopping distance, collision moment speed. These values are the basic evaluation tools for comparing the tested algorithms.

3.2.2 Automated Driving Toolbox

Automated Driving Toolbox is a comprehensive toolkit developed on the MATLAB platform that supports the simulation, development and testing processes of autonomous driving systems. This toolbox offers basic functions such as environmental modeling, actor definition, road geometry creation and sensor simulation, which play a critical role in modeling advanced driver assistance systems such as AEB (Autonomous Emergency Braking) systems.

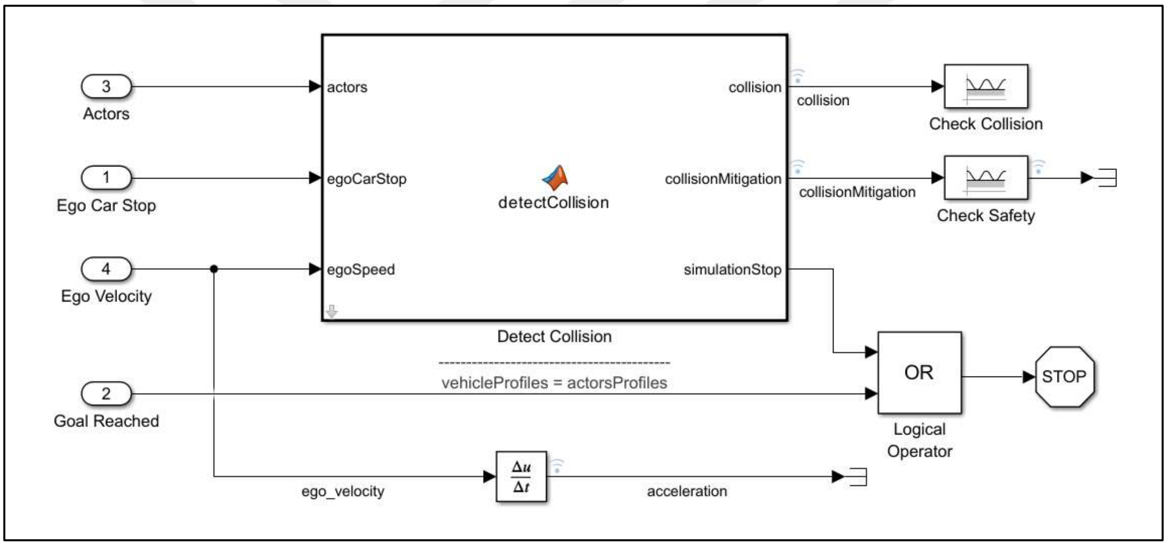


Figure 3.7: Block Structure Calculating AEB Performance Evaluation and Collision Metrics

In the test environment used within the scope of this study, the definition of scenarios, the configuration of sensors and the execution of the simulation were carried out directly through the Automated Driving Toolbox components. Thanks to the Toolbox, actors such as vehicles (ego vehicles), target vehicles, pedestrians and cyclists could be placed in the scene, and their initial positions, speeds, directions and follow-up routes could be defined. These actors move according to the scenario time in a way that they physically interact throughout the scenario.

Road geometries were also created through this toolbox; They were configured with parameters such as the number of lanes, lane width, road length and turn curves. In particular, blocks such as Scenario Reader, Vision Detection Generator and Radar Data Generator have enabled the production of real-time detections by processing road scene and sensor data synchronously within Simulink.

Toolbox also offers a wide flexibility in sensor modeling. Radar and camera sensors are customized with parameters such as viewing angle, range, resolution and location. The data obtained from these sensors is used for the system to detect and track objects in its environment, and the object tracks produced from this data constitute the basic inputs of the AEB decision mechanism.

Automated Driving Toolbox also provides accurate interpretation of data by performing transformations between the world (World), vehicle (Vehicle) and sensor (Sensor) coordinate systems. Thanks to all these components, it has been possible to model situations similar to real traffic scenarios in a simulation environment and the AEB system has been tested in these scenes[43].

3.2.3 Matlab Test Manager

The AEB system developed within the scope of this thesis was tested using the Simulink Test Manager interface under defined scenarios. Simulink Test Manager is a test execution and verification platform integrated into the Simulink environment that allows the configuration, execution, observation and comparative analysis of test scenarios[44].

Seven basic scenarios defined according to Euro NCAP protocols were systematically run in this environment; initial speeds, target distances, braking profiles and environmental variables were configured for each test. In this process, both the classical fixed braking algorithm and the developed dynamic braking algorithm were applied in parallel under the same scenario and their performances were compared.

Simulink Test Manager; It allowed the analysis of system responses with outputs such as stopping distance, braking start time, collision moment speed and passenger comfort, thus playing a critical role in measuring the effectiveness of the developed algorithm. In addition, thanks to its graphical interface, scenario management and result comparison processes were carried out in a simple and repeatable structure.

3.2.4 RoadRunner

In this thesis study, simulations were mainly carried out in the MATLAB Test Manager environment. However, only scenario CCFtap was additionally staged in the MathWorks RoadRunner platform[45]. With this visual staging, how the scenario works within the realistic intersection geometry and the timing of the collision scenario can be observed more clearly. This application does not contribute to the numerical accuracy of the simulation results and is only for visualization purposes. All other scenarios were modeled in the MATLAB environment and executed through the Test Manager interface. The use of RoadRunner was limited to this single scenario in order not to add additional visual load to the scope of the study and not to affect the verification results.

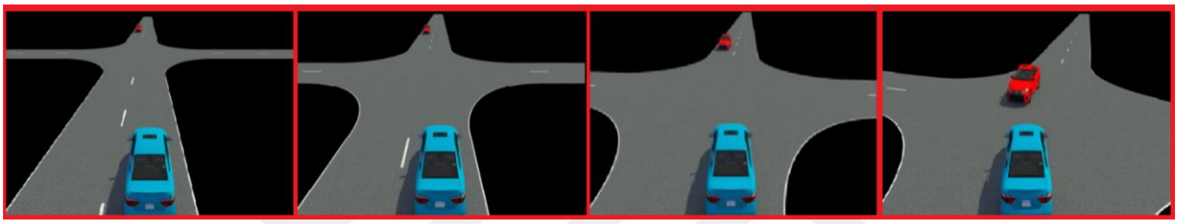


Figure 3.8: Time-Sequenced Visual Representation of Car-to-Car Front Turn Across Path Scenario on Intersection Geometry

3.3 CONSTANT BRAKE FORCE BRAKING APPROACH

In classical AEB systems, braking decelerations are predetermined fixed values and do not change according to driving conditions. The braking decelerations used in the Simulink model[46] established for this test bench are as follows:

i. Partial Brake 1 (PB1):

$$a_{PB1} = 3.8\, m\, /\, s^2 \tag{3.1}$$

ii. Partial Brake 2 (PB2):

$$a_{PB2} = 5.3\, m\, /\, s^2 \tag{3.2}$$

iii. Full Brake (FB):

$$a_{FB} = 9.8\, m\, /\, s^2 \tag{3.2}$$

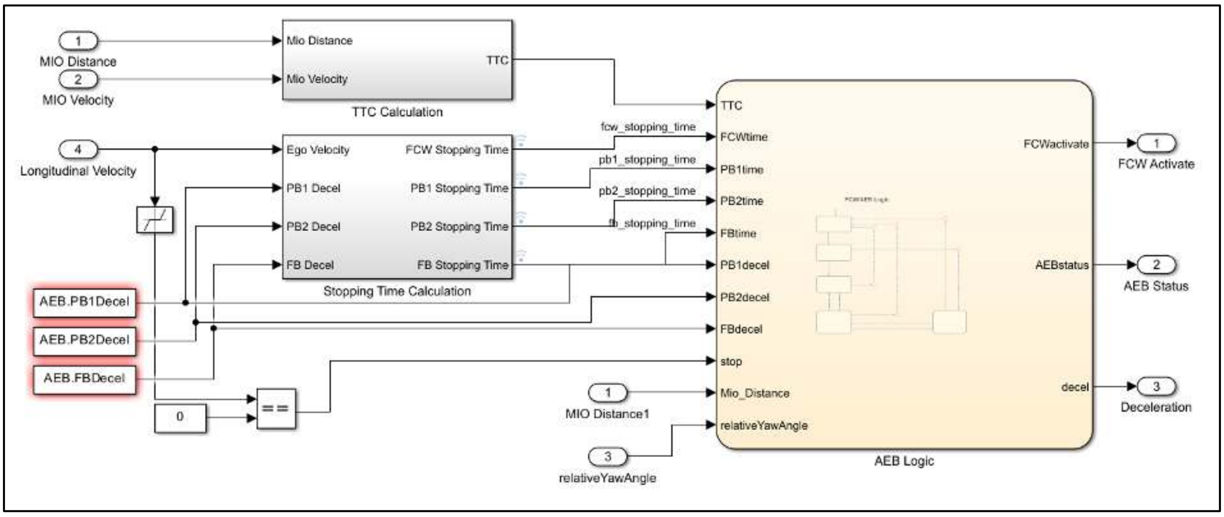


Figure 3.9: Block Diagram of AEB Logic Working with Constant Deceleration Values of PB1, PB2 and FB

3.4 DYNAMIC BRAKING FORCE ALGORITHM MODEL

The dynamic brake force algorithm developed in this thesis study is designed as an alternative to the classical fixed braking approach. This model, integrated into the AEB system, carries out the braking process in three stages in collision risk situations: Partial Brake 1, Partial Brake 2 and Full Brake. In each braking stage, instead of applying a constant deceleration; the system calculates instantaneous and appropriate braking deceleration depending on parameters such as collision time (TTC), vehicle and target vehicle speeds, distance between two vehicles, ABS status and road friction coefficient. This structure not only focuses on preventing collisions but also aims to protect passenger comfort by preventing unnecessary or excessive braking. The system determines which braking stage will be activated and the deceleration level to be applied at that stage completely according to the current driving conditions.

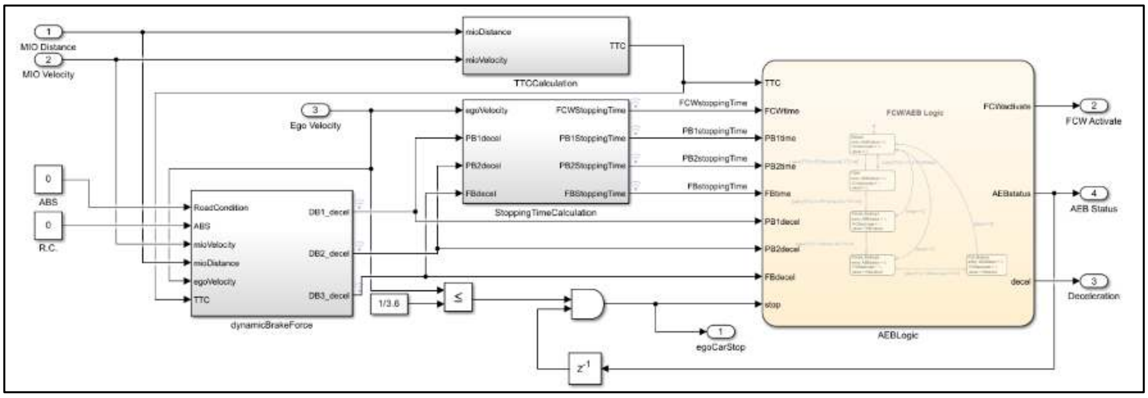


Figure 3.10: Block Diagram of AEB Logic Working with Dynamic Brake Algorithm

Input data is obtained through sensors and processed in various modules of the system to calculate the appropriate brake force level. The high-level block structure of the model is presented in Figure 3.18.

There are four modules on the upper layer of the block diagram:

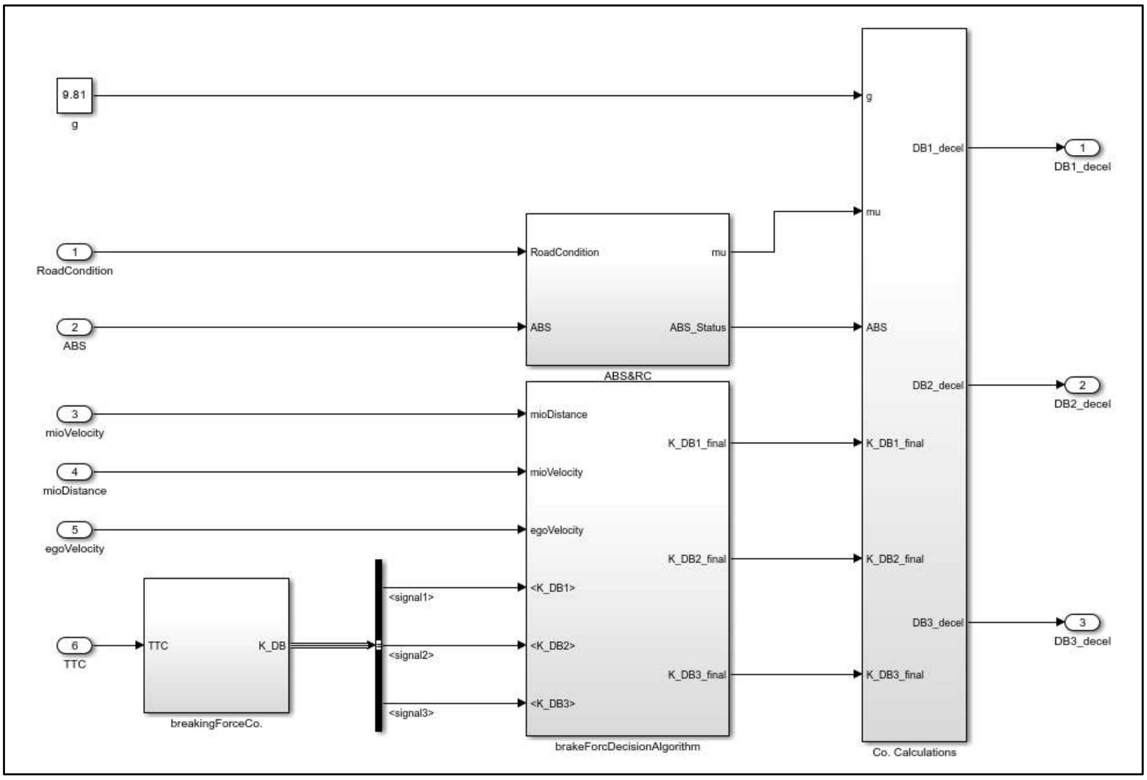


Figure 3.11: Overall Block Diagram of the Dynamic Braking Force Algorithm

i. TTC based Brake Coefficient Selection Block: Creates the initial coefficients of the pre-braking decisions based on TTC.
ii. Mu & ABS Status Decision Block: Evaluates whether the ABS is active in the vehicle and the surface condition of the road (dry, wet, icy). In this module, the physical limits of the braking force are determined using the friction coefficient (μ). The coefficient values corresponding to the road conditions are taken from the experimental data presented by Gustafsson[47].
iii. State Decision Block: Evaluates the data from other modules and determines the most appropriate K_DB1, K_DB2 and K_DB3 braking coefficients according to the current driving conditions.
iv. Final Deceleration Calculation Block: Calculates the braking decelerations using the decided coefficients and sends these values as output to the AEB system.

In the developed dynamic braking algorithm, the braking deceleration for each braking stage (DB1, DB2, DB3) is calculated with the following general formula:

$$a_{brake} = k \cdot \mu \cdot g \tag{3.3}$$

i. a_{brake} : Applied braking deceleration (m/s²)
ii. k: Dynamic braking coefficient (determined separately for DB1, DB2, DB3)
iii. μ: Road surface friction coefficient variable for ground:

$$dry_{\mu} \approx 0.92 \tag{3.4}$$

$$wet_{\mu} \approx 0.37 \tag{3.5}$$

$$ice_{\mu} \approx 0.19 \tag{3.6}$$

iv. g: Gravitational acceleration (9.81 m/s²)

This formula makes it possible to dynamically adjust the required braking deceleration according to the road conditions and the braking stage. The coefficients for each braking stage are represented as follows:

i. Dynamic Brake 1 (DB1):

$$a_{PB1} = k_{PB1} \cdot \mu \cdot g \tag{3.7}$$

ii. Dynamic Brake 2 (DB2):

$$a_{PB2} = k_{PB2} \cdot \mu \cdot g \tag{3.8}$$

iii. Dynamic Brake 3 (DB3):

$$a_{FB} = k_{FB} \cdot \mu \cdot g \tag{3.9}$$

4. ANALYSIS OF BRAKING BEHAVIORS IN AEB SCENARIOS

In order to evaluate the effectiveness of the dynamic brake force algorithm developed in this study, seven different scenarios defined by Euro NCAP were used[11],[12]. These scenarios cover various traffic situations in order to model the collision risks from different perspectives. The applied scenarios are grouped under the following headings:

i. Car-to-Car scenarios: CCRs, CCRm, CCRb
ii. Intersection scenario: CCFtap
iii. Pedestrian scenarios: Pedestrian Longitudinal
iv. Cyclist scenario: Cyclist Longitudinal

A total of four different variations were applied for each scenario:

i. Classic constant braking force (reference model)
ii. Dynamic braking algorithm – dry ground
iii. Dynamic braking algorithm – wet ground
iv. Dynamic braking algorithm – icy ground

Thanks to this structure, both the comparison between the algorithms and the effect of road surface conditions on braking performance were evaluated. Dynamic braking variations produce variable braking force depending on parameters such as collision time (TTC), vehicle speed, target speed, following distance and road friction coefficient whereas the classical fixed algorithm applies a fixed deceleration value.

The friction coefficient values used in road condition variations were determined based on experimental data published by Gustafsson [47]. Thus, the response differences of the system on dry, wet and icy surfaces were modeled within realistic physical limits.

Each test scenario was run in the MATLAB Simulink Test Manager environment; comparative data production was provided by applying the relevant variations under the same conditions. A total of 7 scenarios and 4 variations, 28 different test combinations were created and the performance metrics related to them were analyzed in detail in the following headings.

4.1 AEB OUTPUT EVALUATION UNDER CONSTANT VS ADAPTIVE BRAKING STRATEGIES

4.1.1 Scenario CCFtap Outputs

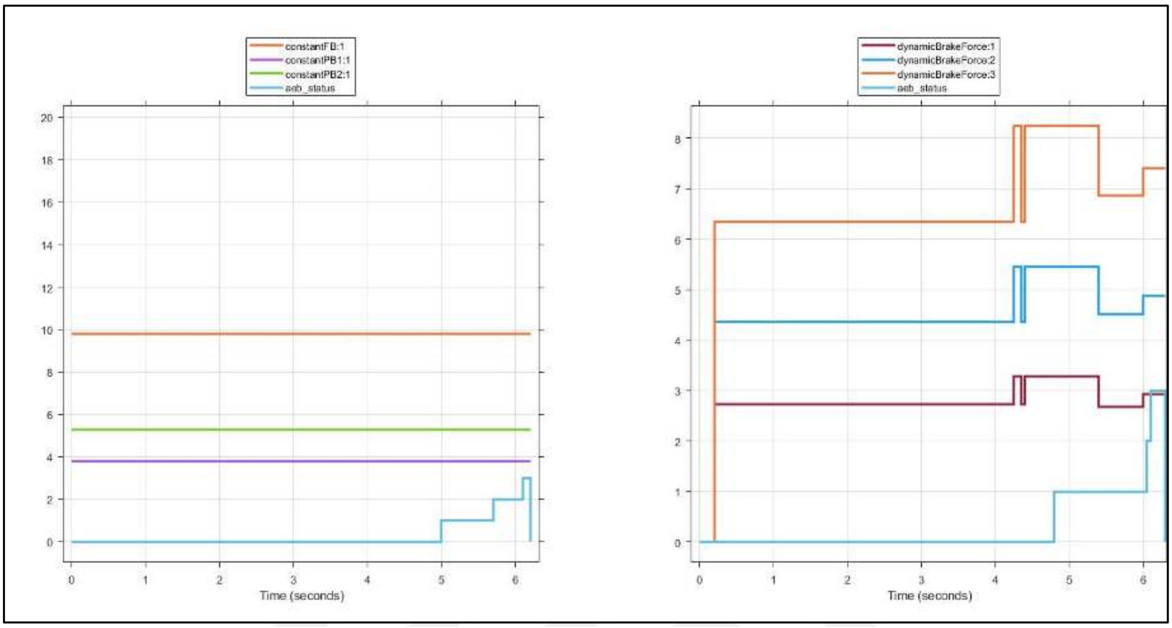


Figure 4.1: Comparison of Constant vs Dynamic Braking Force Patterns in CCFtap Scenario under Dry Road Conditions

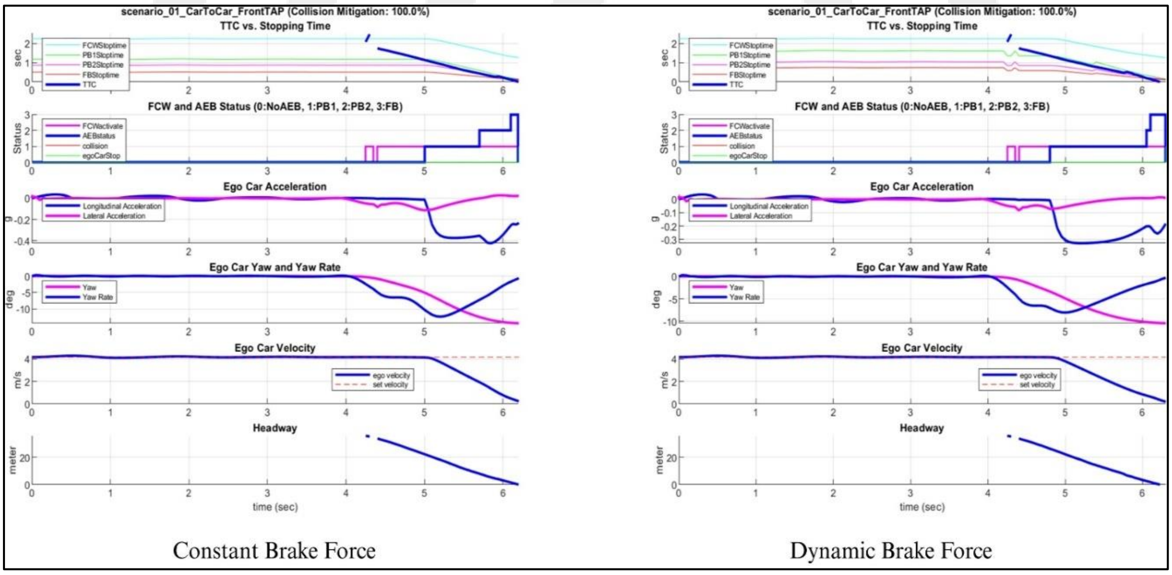


Figure 4.2: Comparative AEB Response in CCFtap Scenario Using Constant and Dynamic Brake Forces

Table 4.1: Braking Behavior Data for CCFtap Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	4.20	4.20
AEB 1 Activation Time	5.00	4.85
AEB 2 Activation Time	5.60	6.05
AEB 3 Activation Time	6.15	6.10
Ego Velocity Decrease Start Time	5.05	4.90
Ego Stop Time	6.20	6.30
Total Braking Time	1.15	1.40

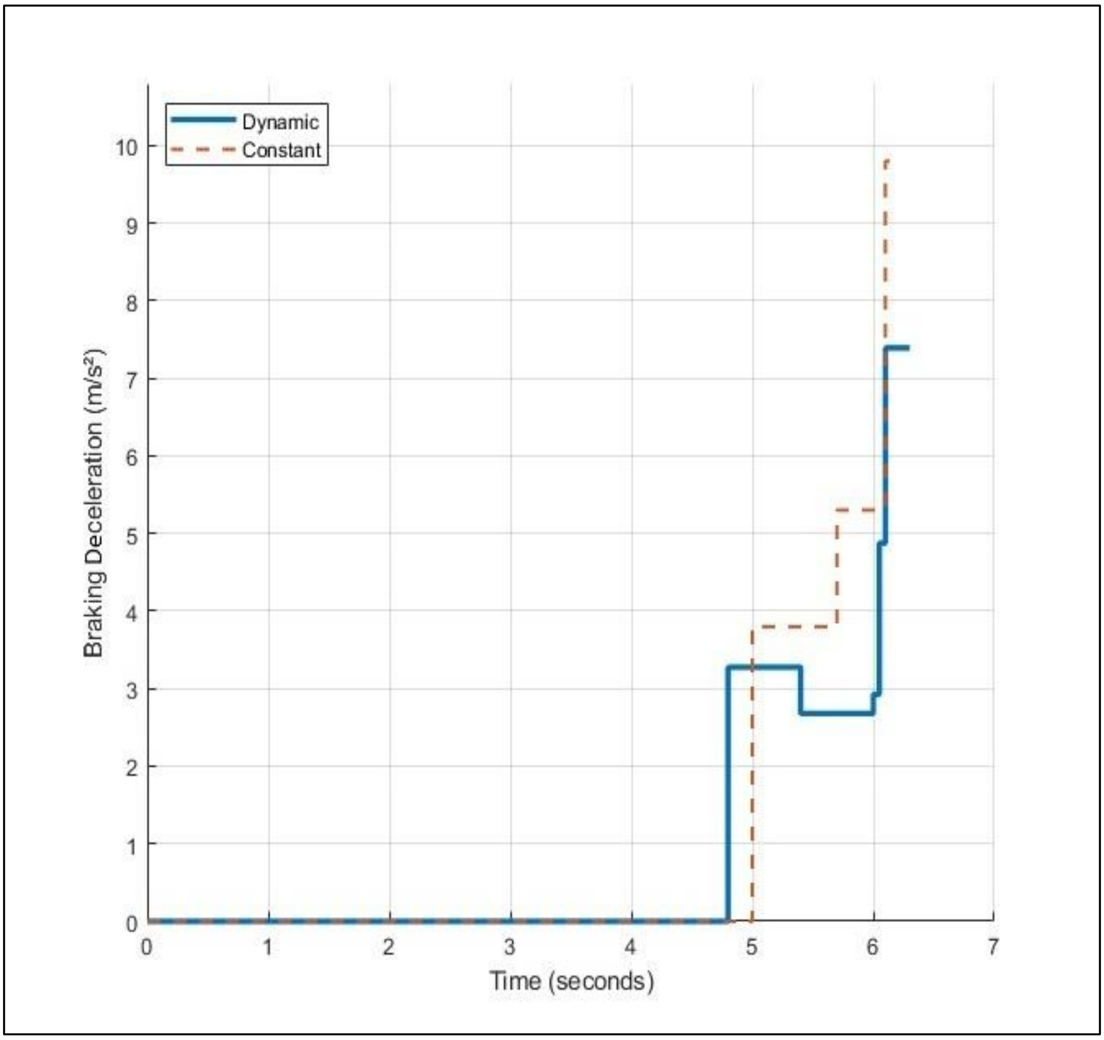


Figure 4.3: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in CCFtap scenario

4.1.2 Scenario CCRs Outputs

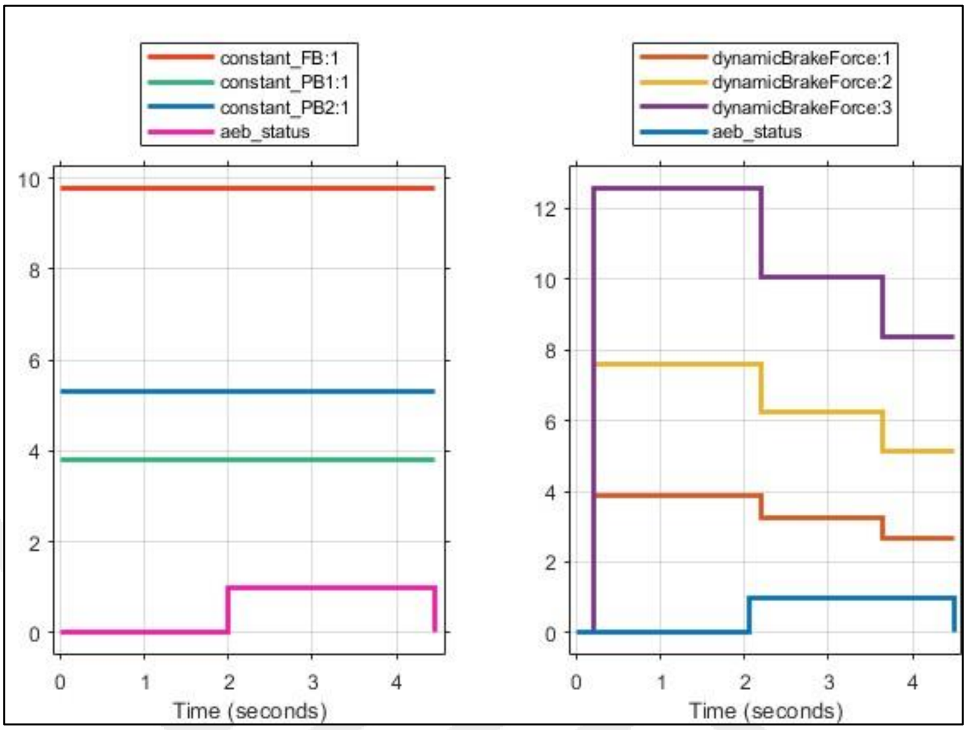


Figure 4.4: Comparison of Constant vs Dynamic Braking Force Patterns in CCRb Scenario under Dry Road Conditions

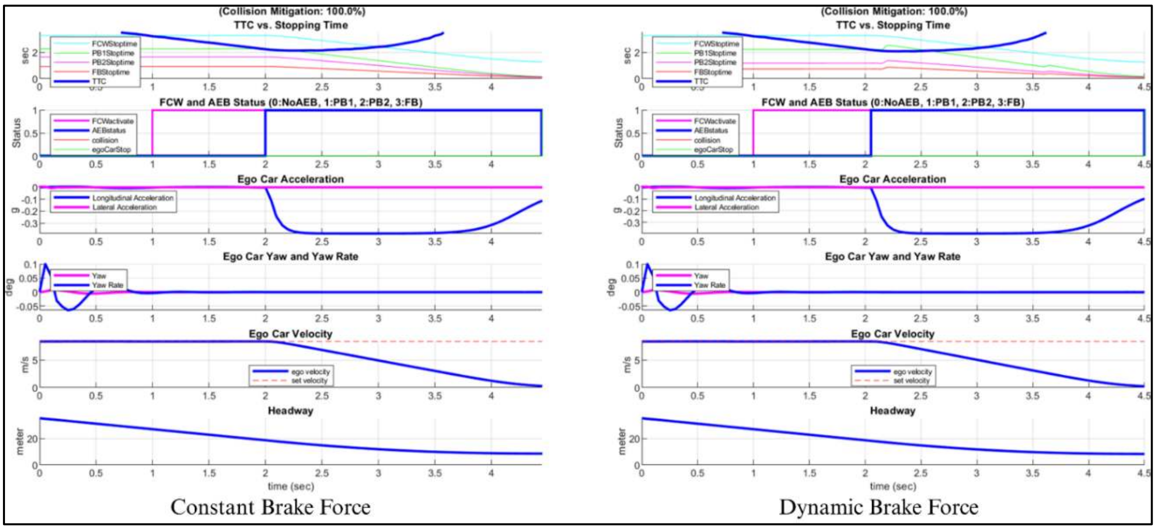


Figure 4.5: Comparative AEB Response in CCRb Scenario Using Constant and Dynamic Brake Forces

Table 4.2: Braking Behavior Data for CCRs Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	1.00	1.00
AEB 1 Activation Time	2.00	2.05
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	2.10	2.10
Ego Stop Time	4.45	4.50
Total Braking Time	2.35	2.40

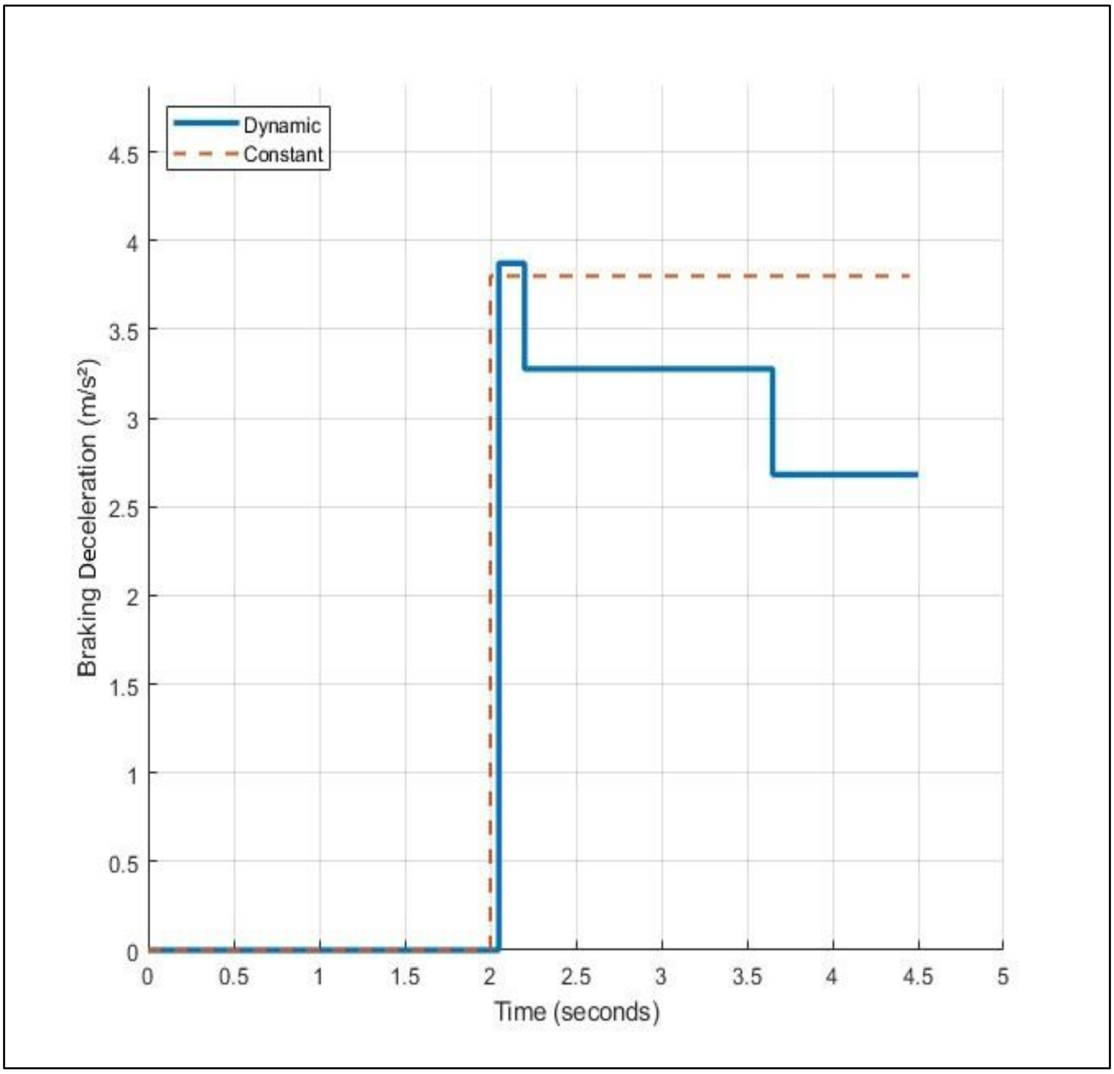


Figure 4.6: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in CCRs scenario

4.1.3 Scenario CCRm Outputs

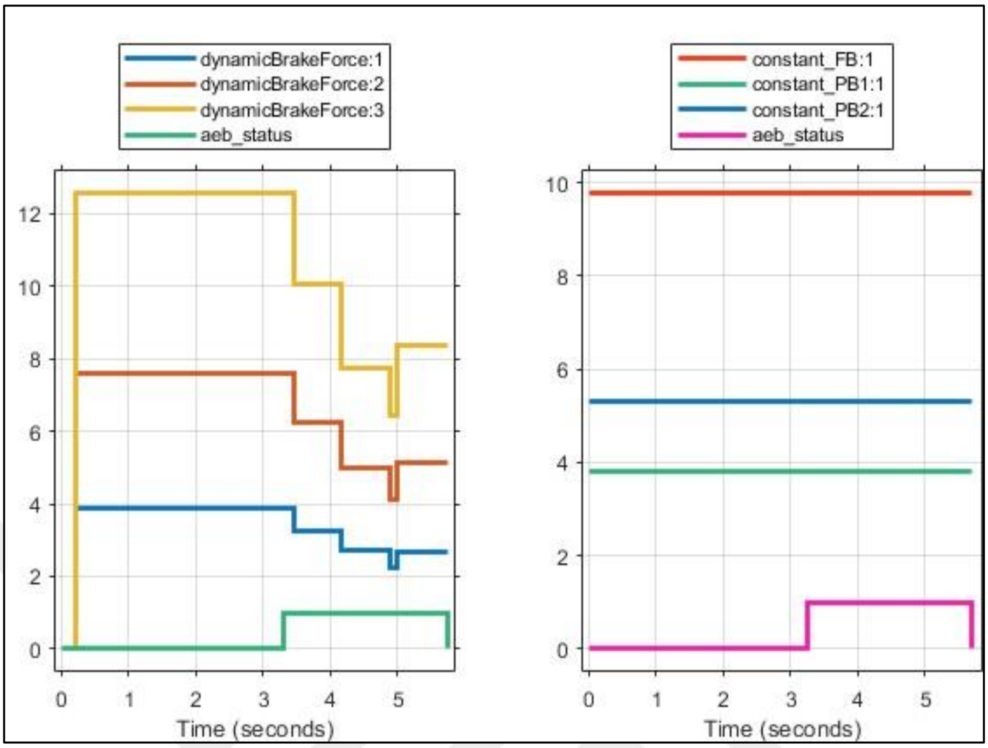


Figure 4.7: Comparison of Constant vs Dynamic Braking Force Patterns in CCRm Scenario under Dry Road Conditions

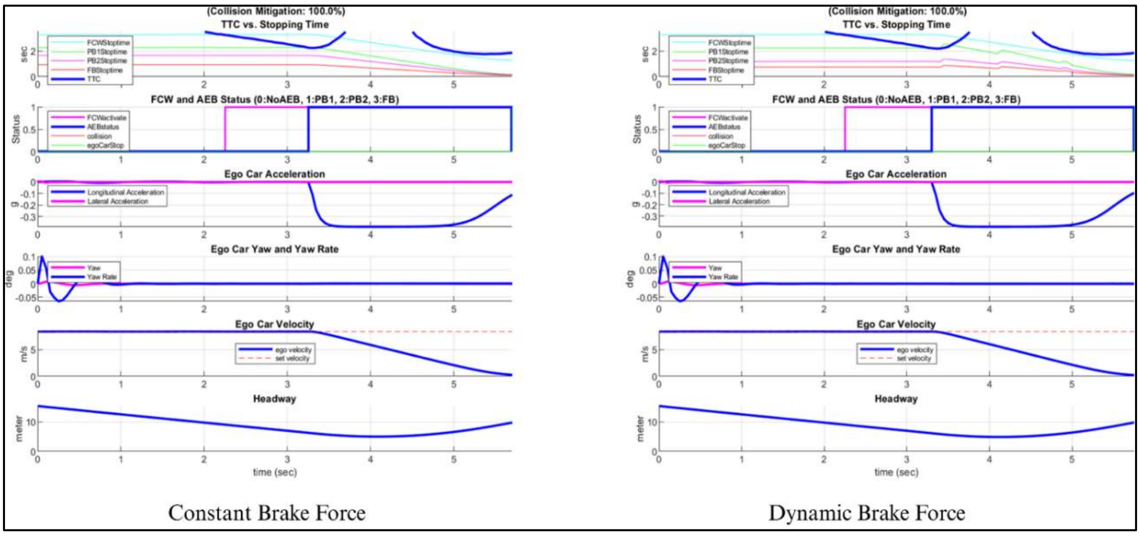


Figure 4.8: Comparative AEB Response in CCRm Scenario Using Constant and Dynamic Brake Forces

Table 4.3: Braking Behavior Data for CCRm Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	3.25	3.25
AEB 1 Activation Time	3.20	3.20
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	3.30	3.30
Ego Stop Time	5.70	5.75
Total Braking Time	2.40	2.45

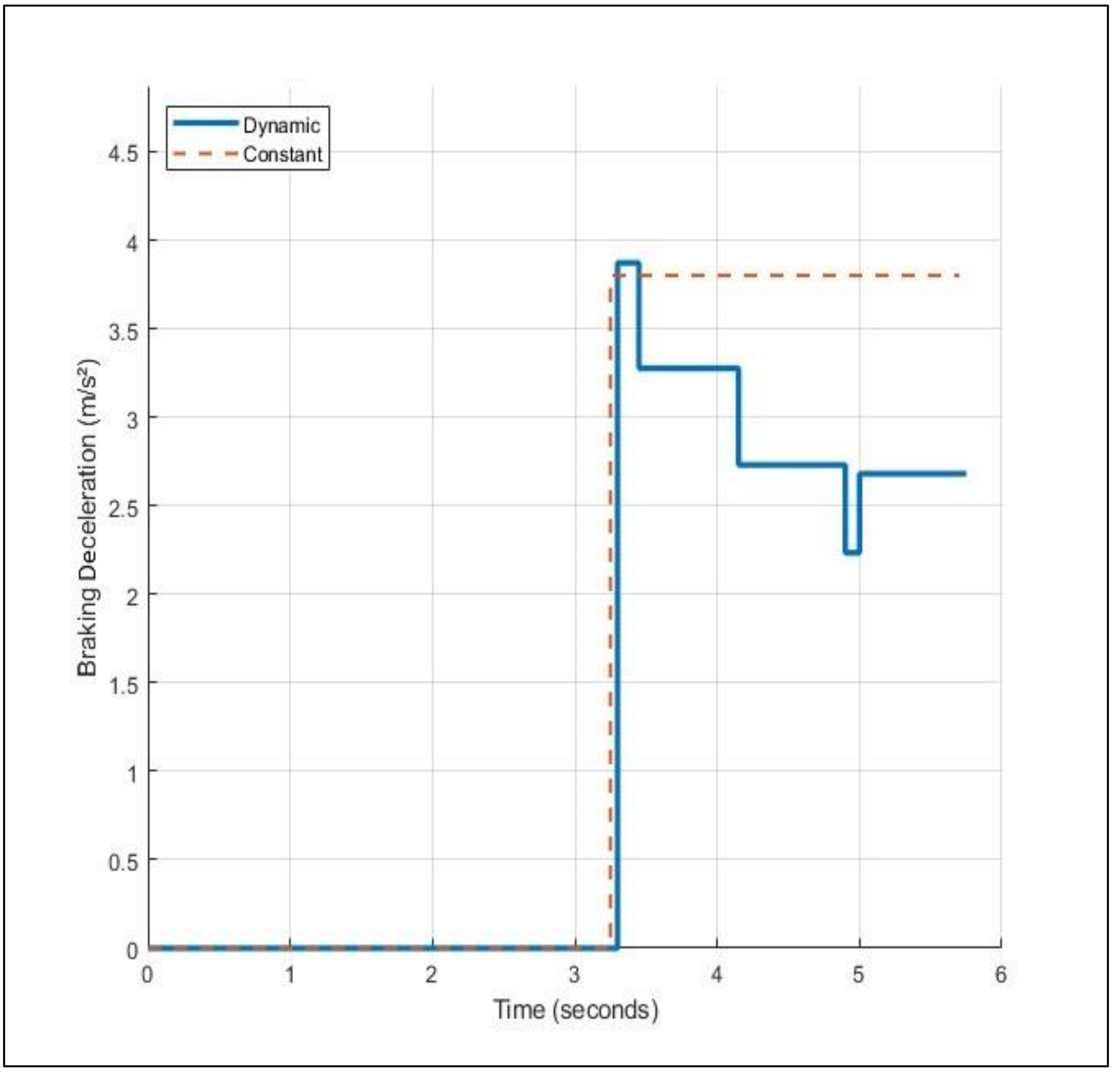


Figure 4.9: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in CCRm Scenario

4.1.4 Scenario CCRb Outputs

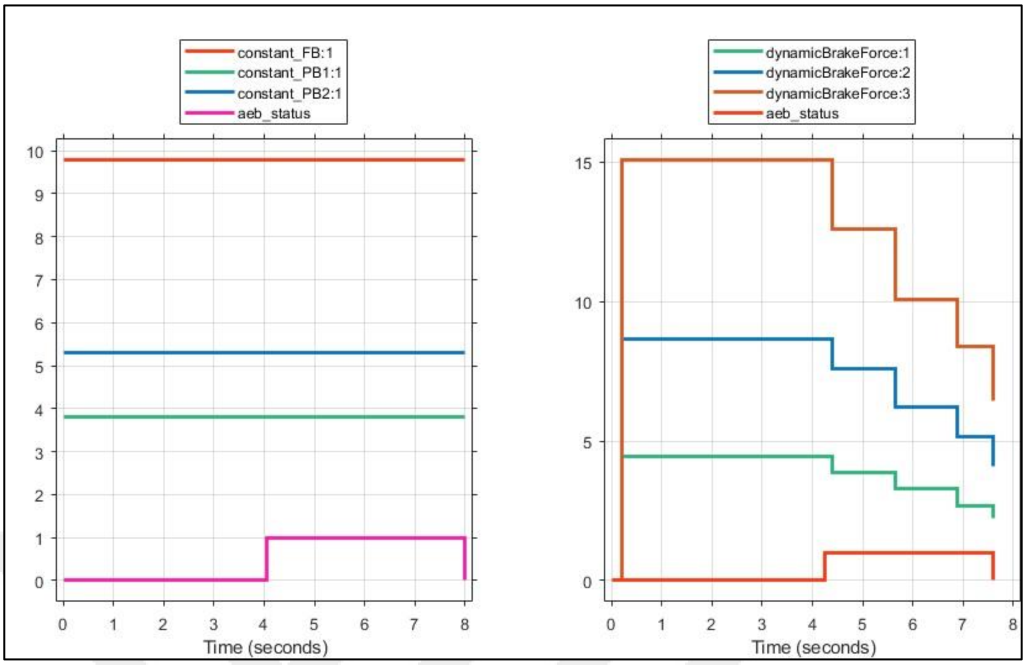


Figure 4.10: Comparison of Constant vs Dynamic Braking Force Patterns in CCRb Scenario under Dry Road Conditions

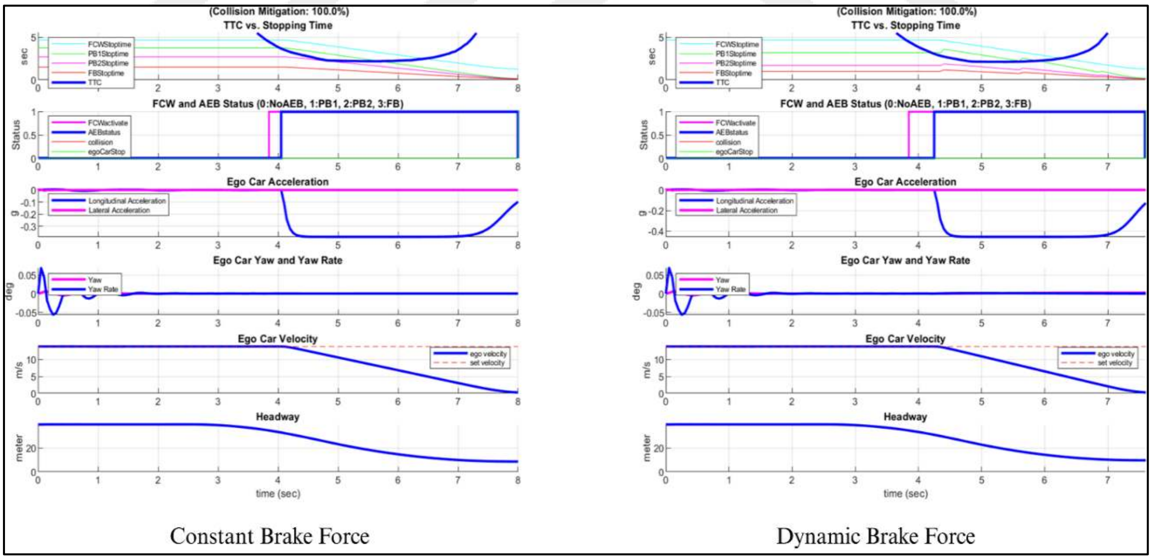


Figure 4.11: Comparative AEB Response in CCRb Scenario Using Constant and Dynamic Brake Forces

Table 4.4: Braking Behavior Data for CCRb Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	3.85	3.85
AEB 1 Activation Time	4.00	4.2
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	4.05	4.25
Ego Stop Time	8.00	7.60
Total Braking Time	3.95	3.35

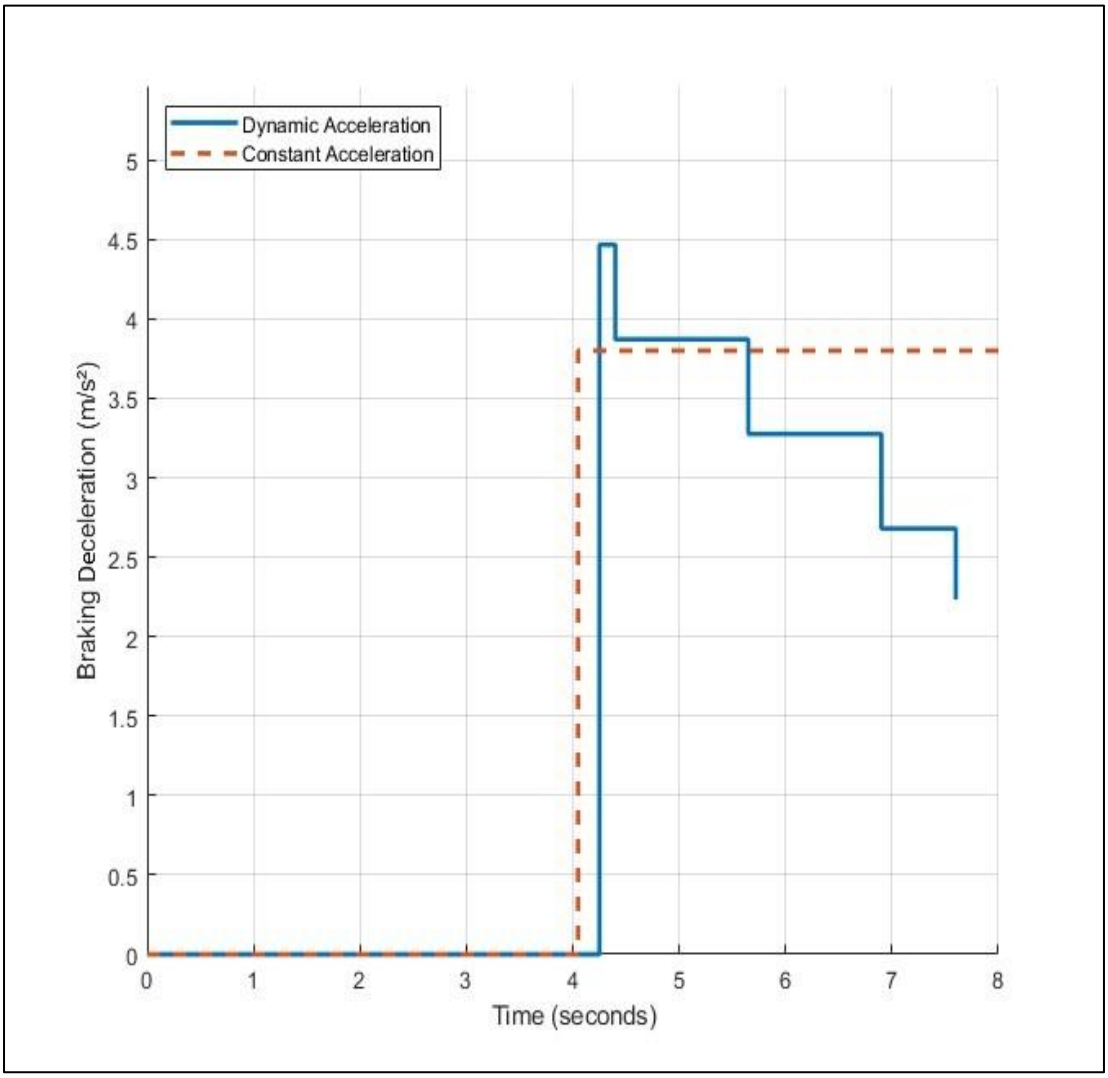


Figure 4.12: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in CCRb Scenario

4.1.5 Scenario Pedestrian-Child Nearside Outputs

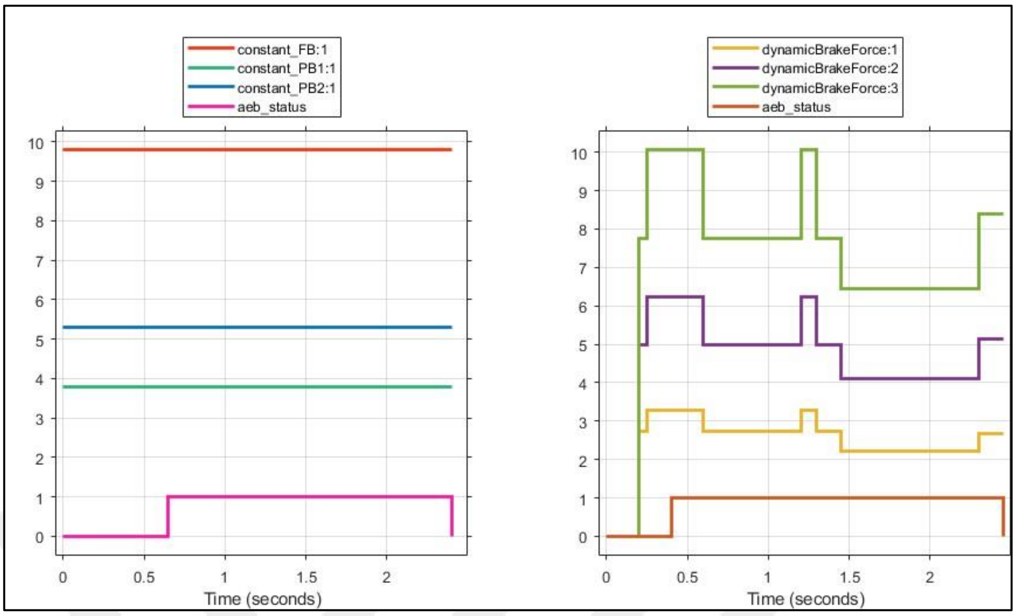


Figure 4.13: Comparison of Constant vs Dynamic Braking Force Patterns in Pedestrian-Child Nearside Scenario under Dry Road Conditions

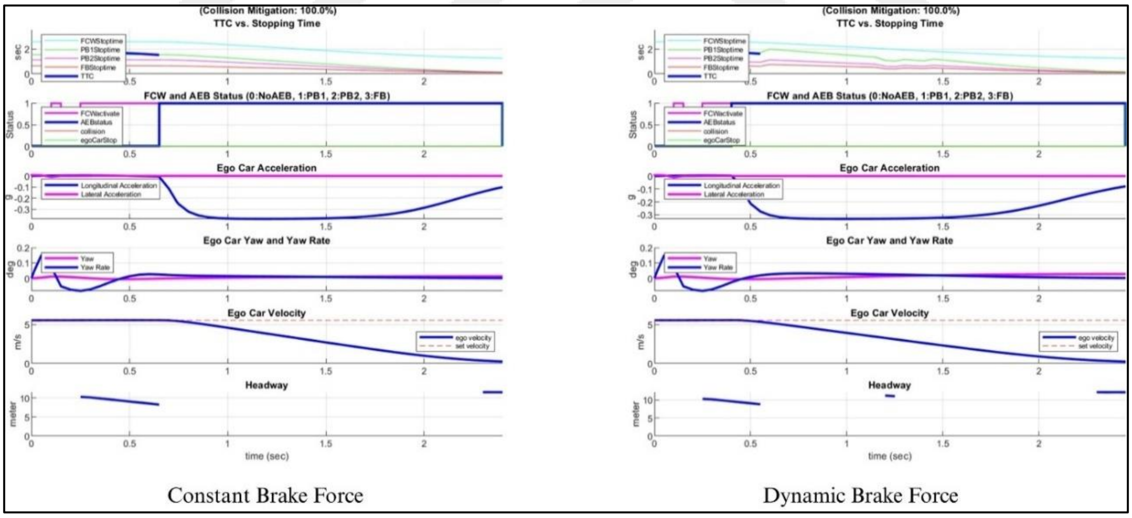


Figure 4.14: Comparative AEB Response in Pedestrian-Child Nearside Scenario Using Constant and Dynamic Brake Forces

Table 4.5: Braking Behavior Data for Pedestrian-Child Nearside Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	0.10	0.10
AEB 1 Activation Time	0.65	0.40
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	0.70	0.45
Ego Stop Time	2.40	2.45
Total Braking Time	1.70	2.00

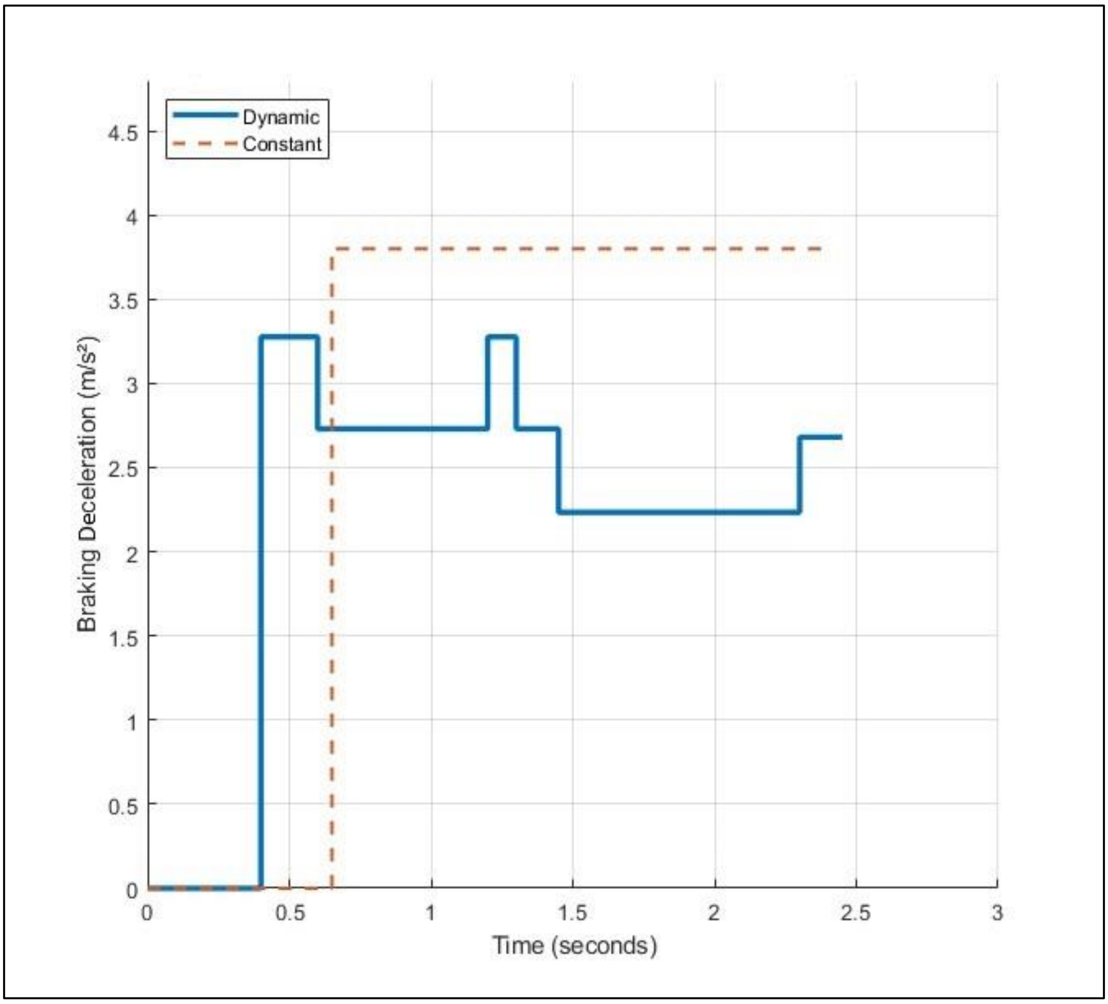


Figure 4.15: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in Pedestrian-Child Nearside Scenario

4.1.6 Scenario Pedestrian Turning Farside Outputs

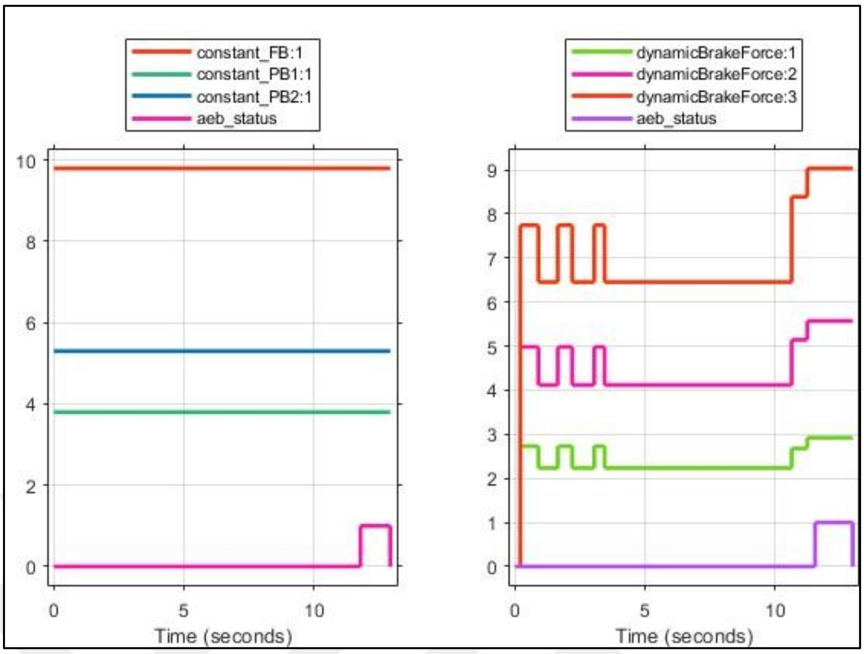


Figure 4.16: Comparison of Constant vs Dynamic Braking Force Patterns in Pedestrian Turning Farside Scenario under Dry Road Conditions

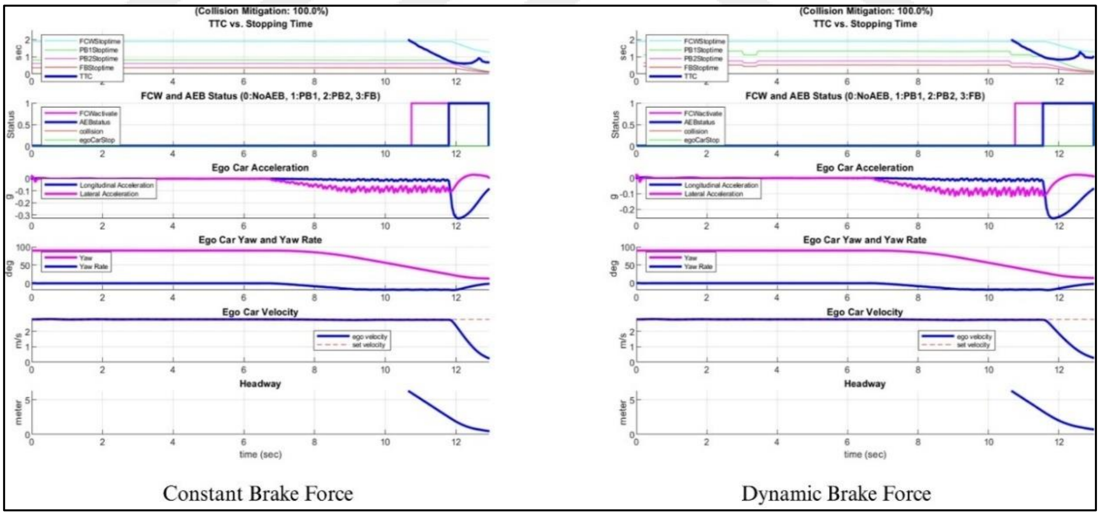


Figure 4.17: Comparative AEB Response in Pedestrian Turning Farside Scenario Using Constant and Dynamic Brake Forces

Table 4.6: Braking Behavior Data for Pedestrian Turning Farside Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	10.90	10.90
AEB 1 Activation Time	11.90	11.70
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	11.95	11.75
Ego Stop Time	12.95	13.00
Total Braking Time	1.00	1.25

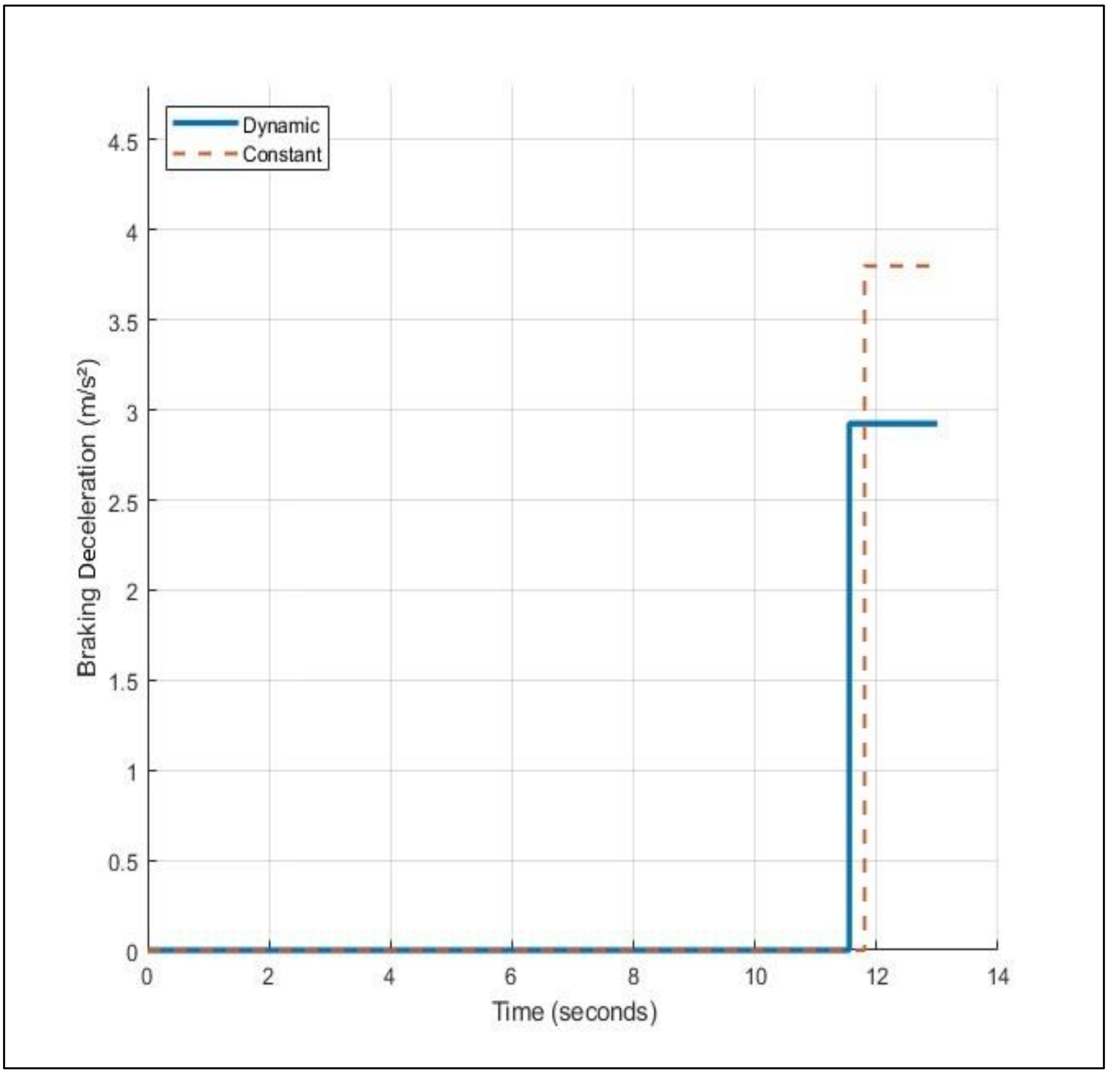


Figure 4.18: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in Pedestrian Turning Farside Scenario

4.1.7 Scenario Bicyclist Longitudinal Outputs

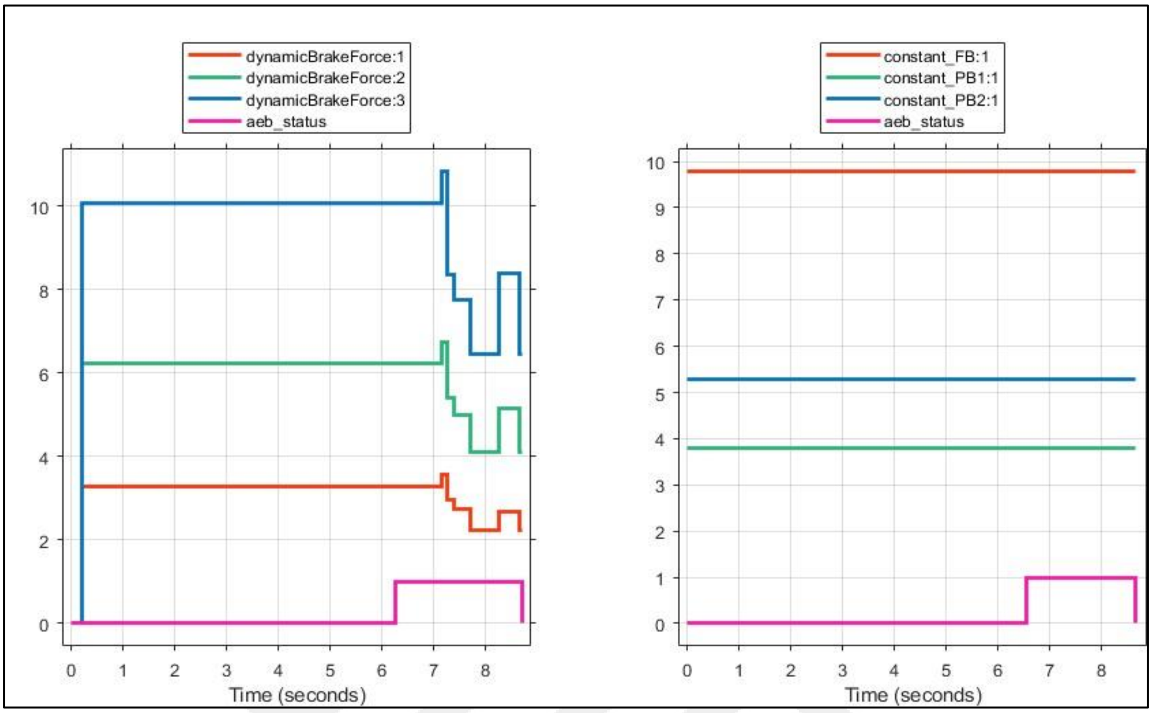


Figure 4.19: Comparison of Constant vs Dynamic Braking Force Patterns in Bicyclist Longitudinal Scenario under Dry Road Conditions

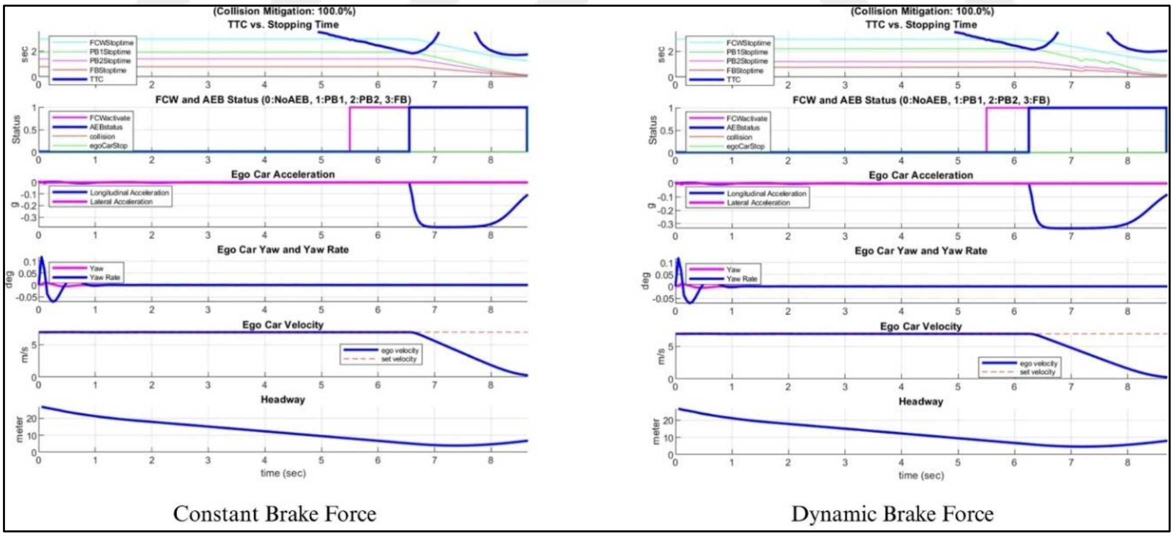


Figure 4.20: Comparative AEB Response in Bicyclist Longitudinal Scenario Using Constant and Dynamic Brake Forces

Table 4.7: Braking Behavior Data for Bicyclist Longitudinal Scenario

Variable	Constant Braking(s)	Dynamic Braking(s)
FCW Activation Time	5.50	5.50
AEB 1 Activation Time	6.55	6.15
AEB 2 Activation Time	-	-
AEB 3 Activation Time	-	-
Ego Velocity Decrease Start Time	6.60	6.20
Ego Stop Time	8.65	8.70
Total Braking Time	2.05	2.50

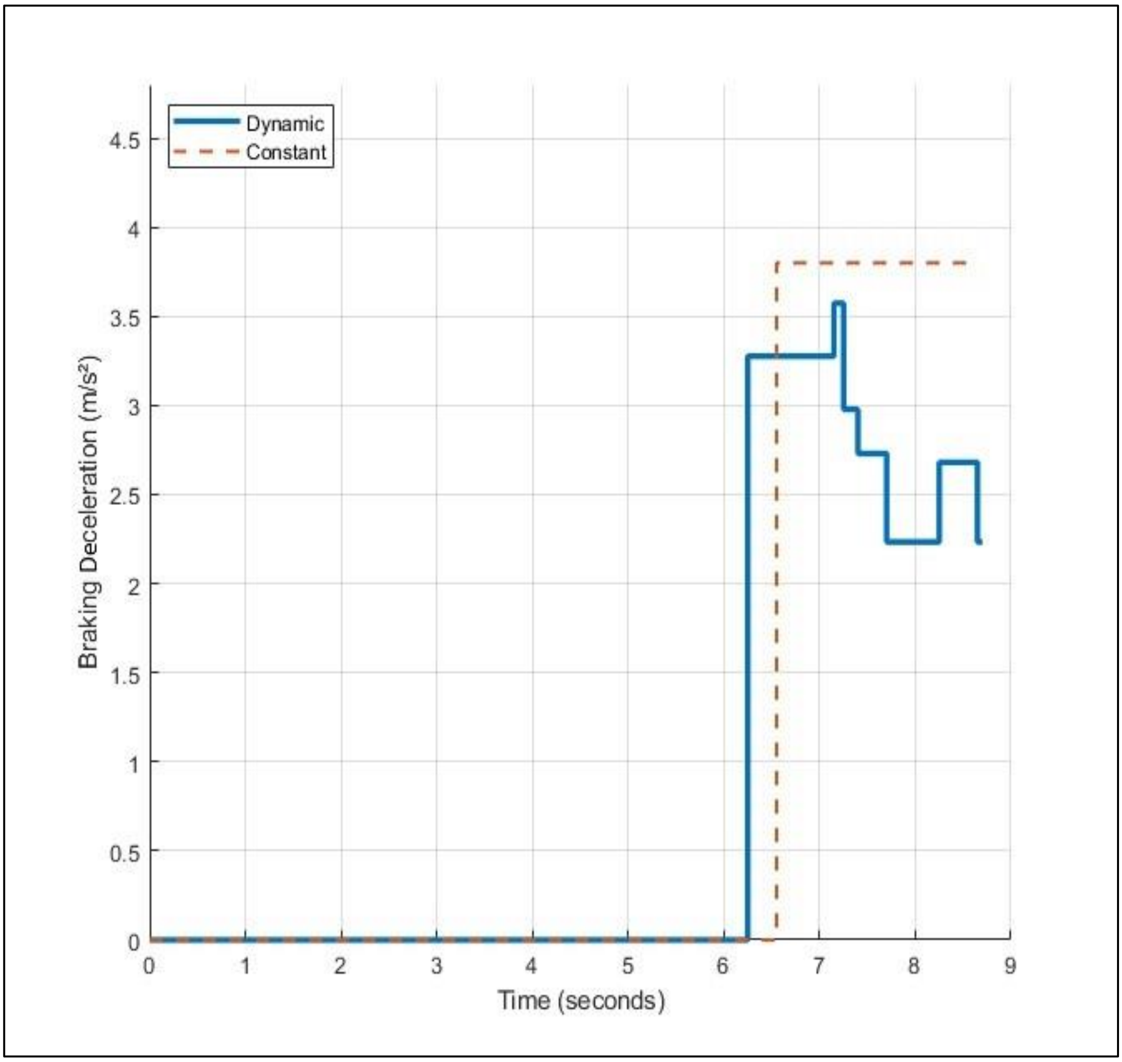


Figure 4.21: Comparison of Deceleration Behavior under Adaptive and Constant Braking Models in Bicyclist Longitudinal Scenario

4.2 AEB OUTPUT BEHAVIOR UNDER VARYING ROAD CONDITIONS IN SCENARIO BASED SIMULATIONS

4.2.1 Scenario CCFtap Outputs

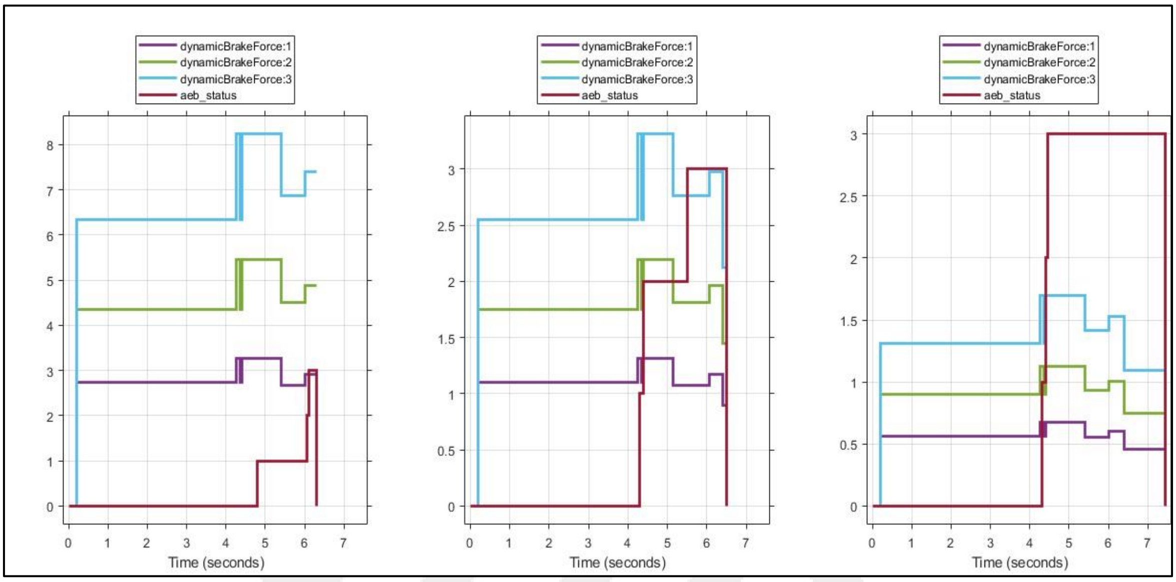


Figure 4.22: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the CCFtap Scenario

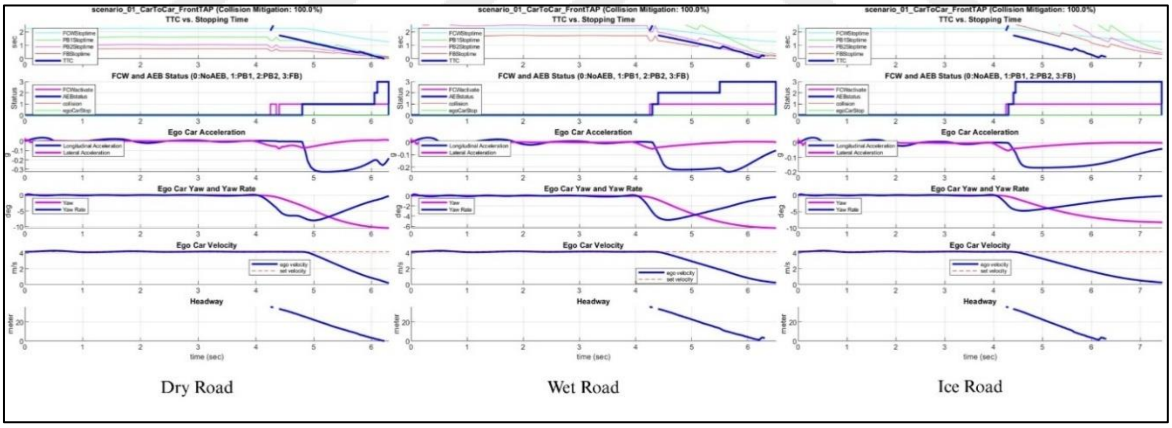


Figure 4.23: Comparative AEB Response in the CCFtap Scenario Using Varying Road Conditions

Table 4.8: Braking Behavior Data for CCFtap Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	4.20	4.20	4.20
AEB 1 Activation Time	4.80	4.30	4.30
AEB 2 Activation Time	6.05	4.40	4.40
AEB 3 Activation Time	6.10	5.50	4.45
Ego Velocity Decrease Start Time	4.85	4.35	4.30
Ego Stop Time	6.30	6.50	7.45
Total Braking Time	1.50	2.20	3.15

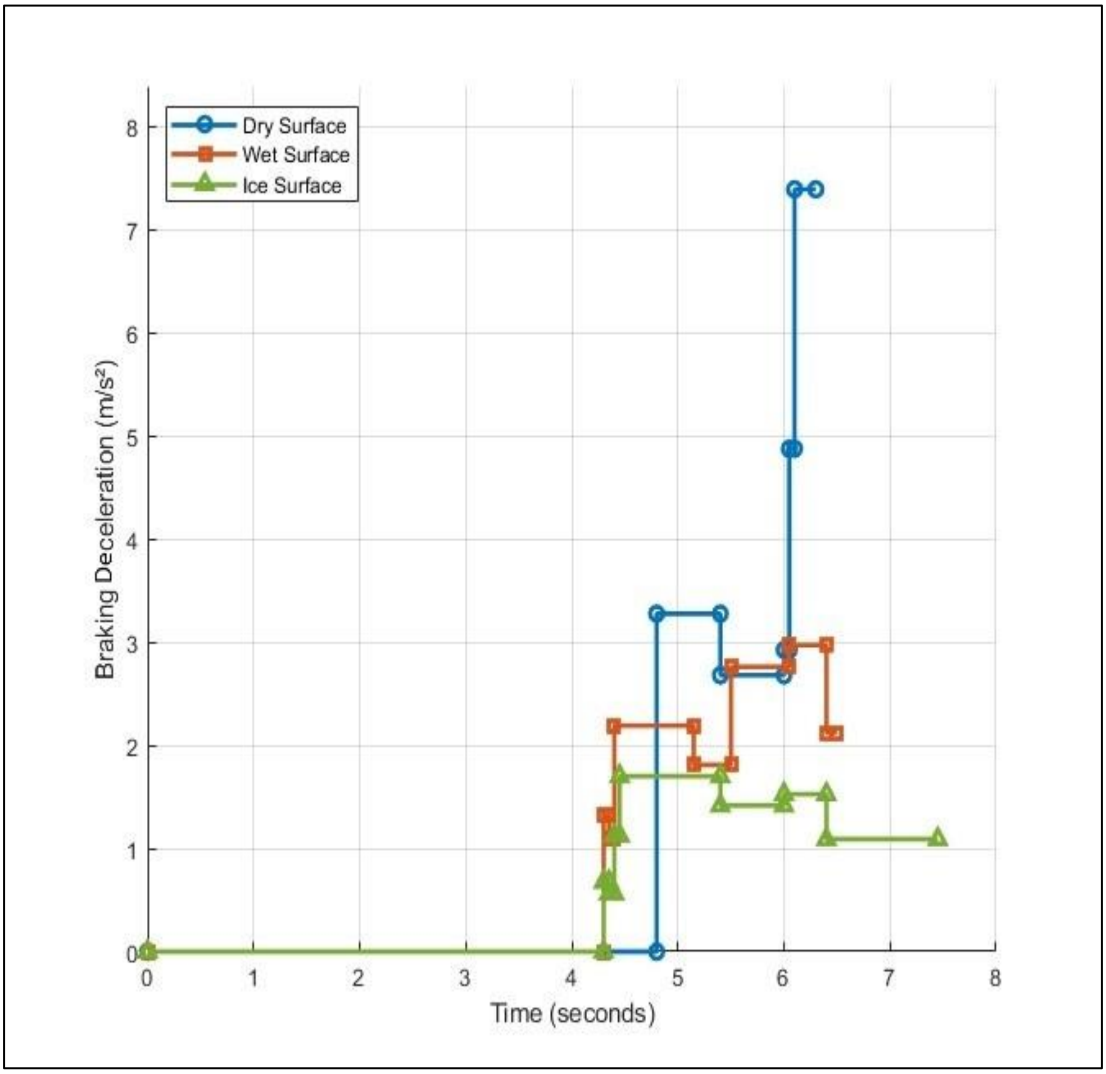


Figure 4.24: Comparative Deceleration Characteristics across Different Road Surfaces in CCFtap Scenario

4.2.2 Scenario CCRs Outputs

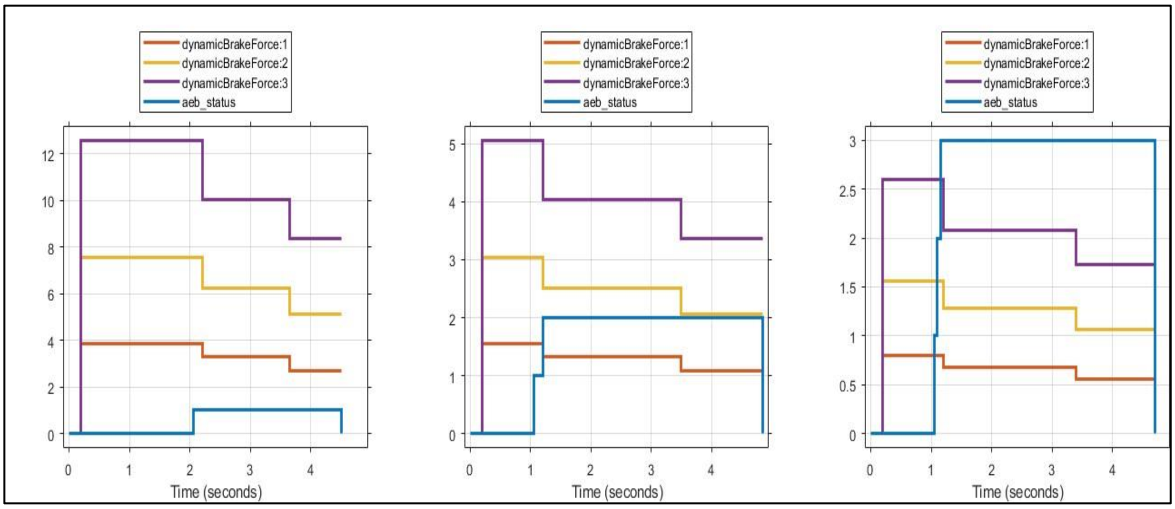
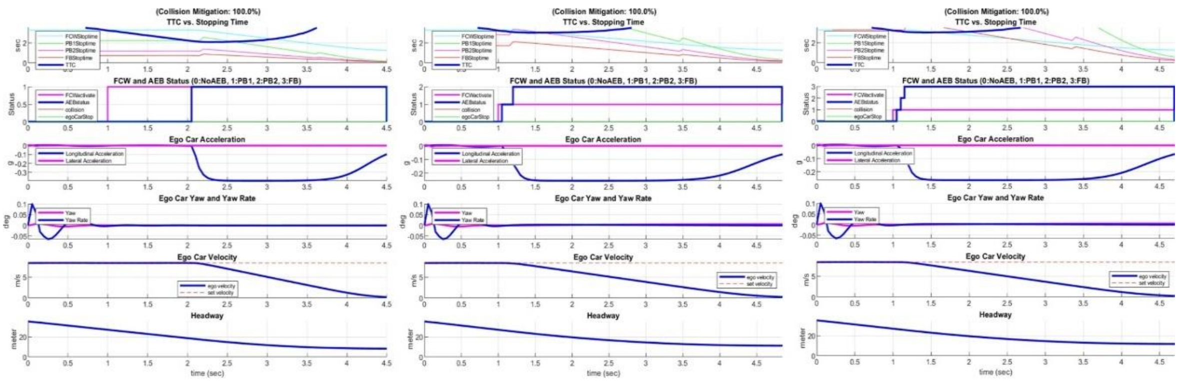


Figure 4.26: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the CCRs Scenario



Dry Road

Wet Road

Ice Road

Figure 4.25: Comparative AEB Response in the CCRs Scenario Using Varying Road Conditions

Table 4.9: Braking Behavior Data for CCRs Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	1.00	1.00	1.00
AEB 1 Activation Time	2.05	1.05	1.05
AEB 2 Activation Time	-	1.20	1.10
AEB 3 Activation Time	-	-	1.15
Ego Velocity Decrease Start Time	2.10	1.10	1.10
Ego Stop Time	4.50	4.85	4.70
Total Braking Time	2.45	3.80	3.65

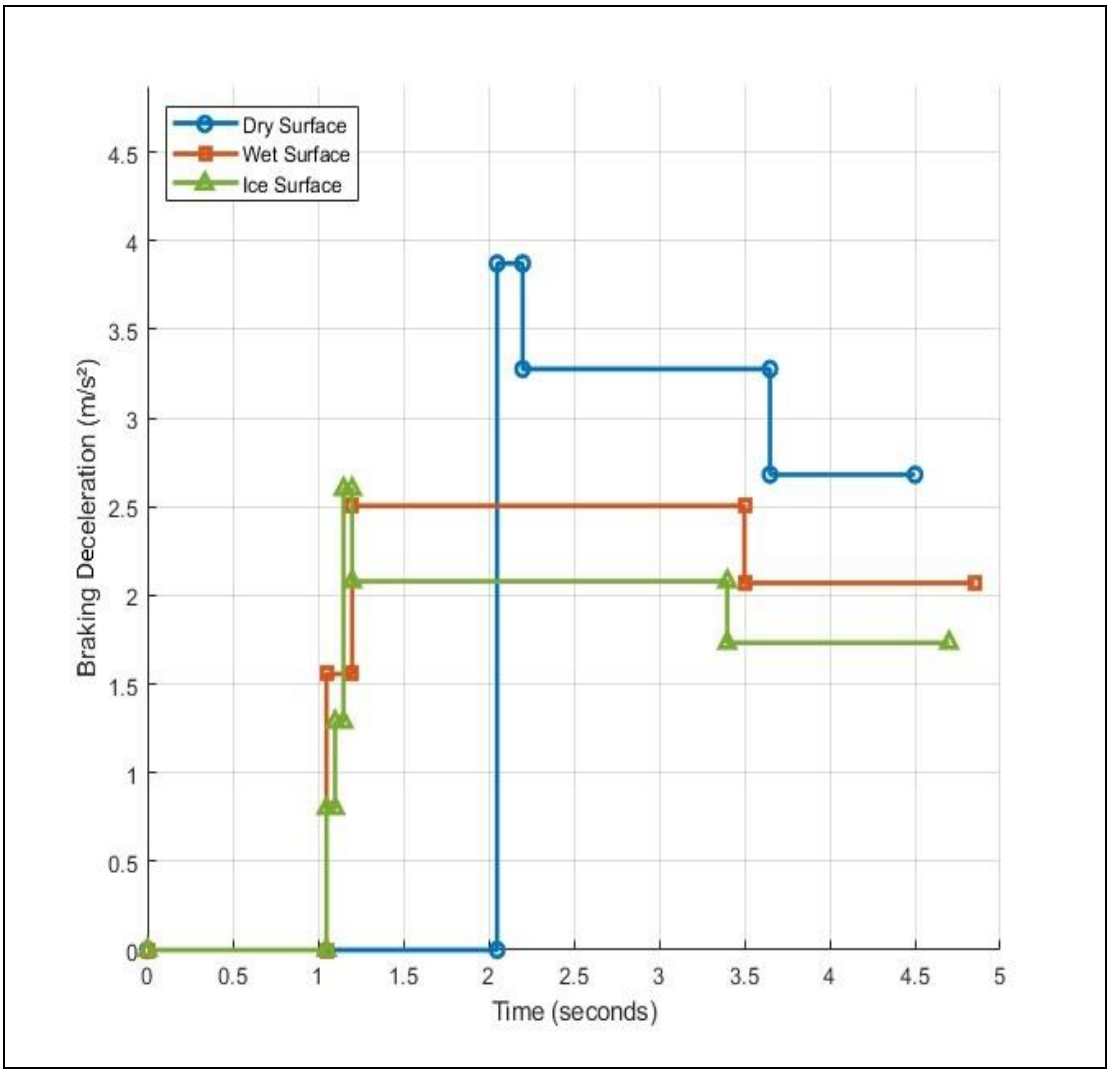


Figure 4.27: Comparative Deceleration Characteristics across Different Road Surfaces in CCRs Scenario

4.2.3 Scenario CCRm Outputs

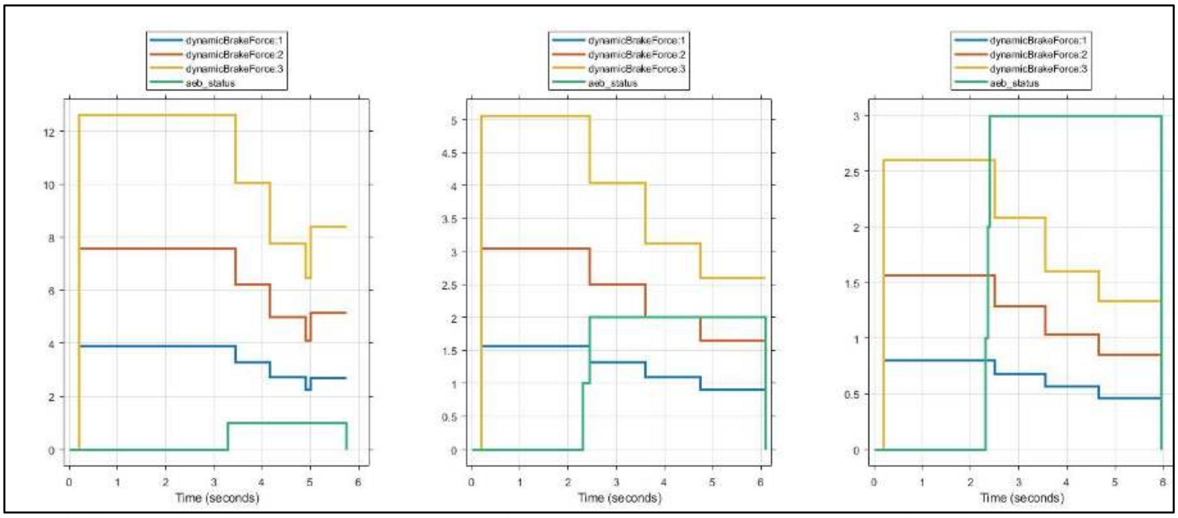


Figure 4.28: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the CCRm Scenario

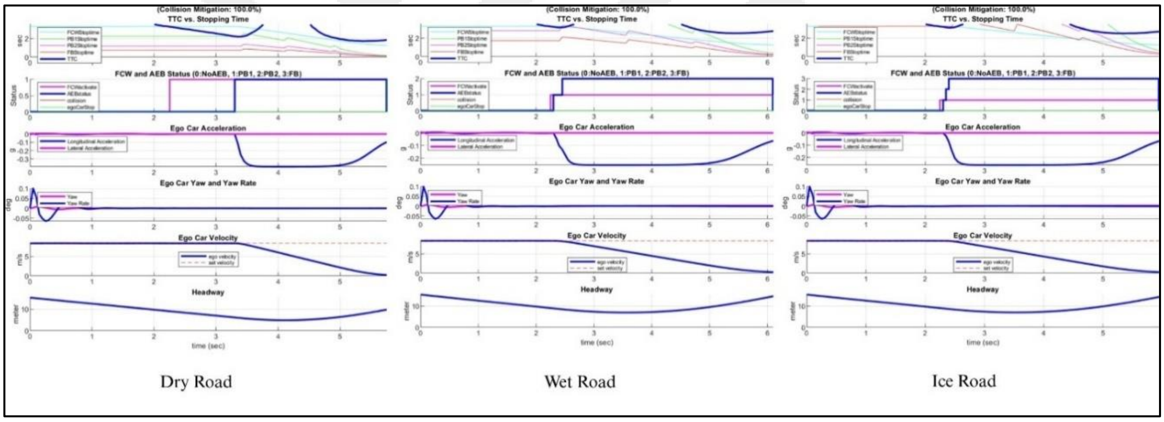


Figure 4.29: Comparative AEB Response in the CCRm Scenario Using Varying Road Conditions

Table 4.10: Braking Behavior Data for CCRm Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	2.25	2.25	2.25
AEB 1 Activation Time	3.30	2.30	2.30
AEB 2 Activation Time	-	2.45	2.35
AEB 3 Activation Time	-	-	2.40
Ego Velocity Decrease Start Time	3.35	2.35	2.35
Ego Stop Time	5.75	6.10	5.95
Total Braking Time	2.45	3.80	3.65

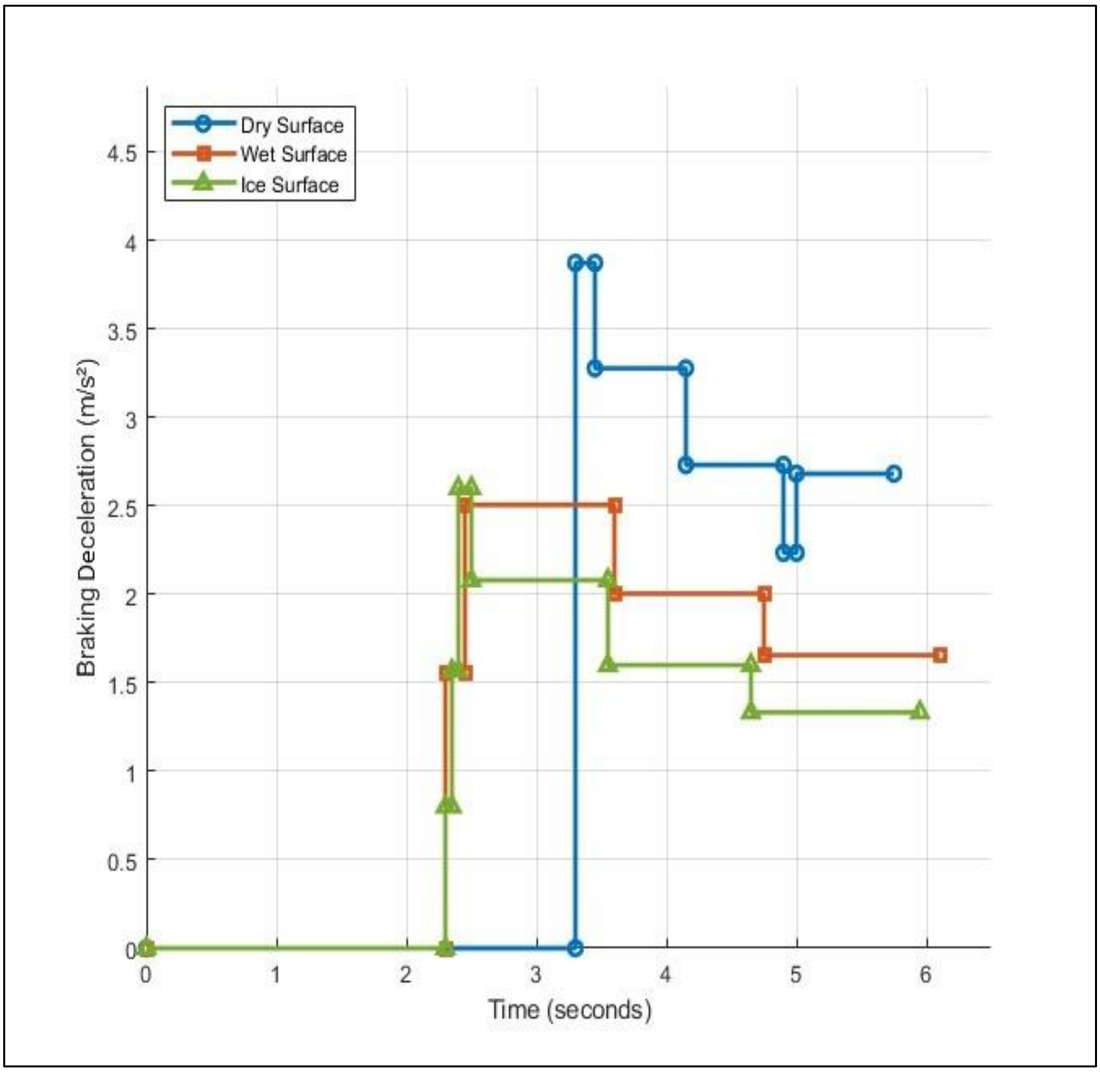


Figure 4.30: Comparative Deceleration Characteristics across Different Road Surfaces in CCRm Scenario

4.2.4 Scenario CCRb Outputs

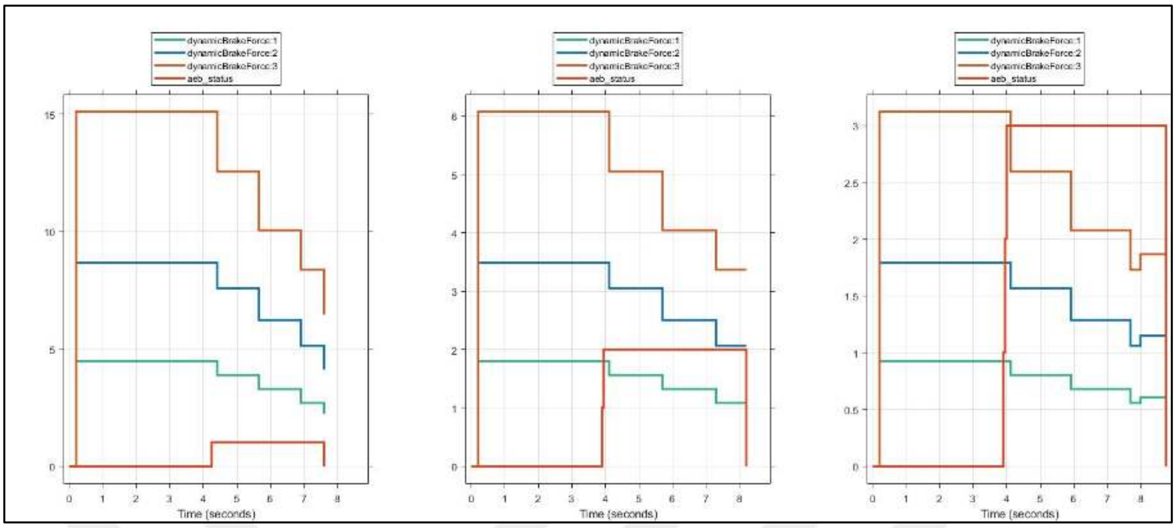


Figure 4.31: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the CCRb Scenario

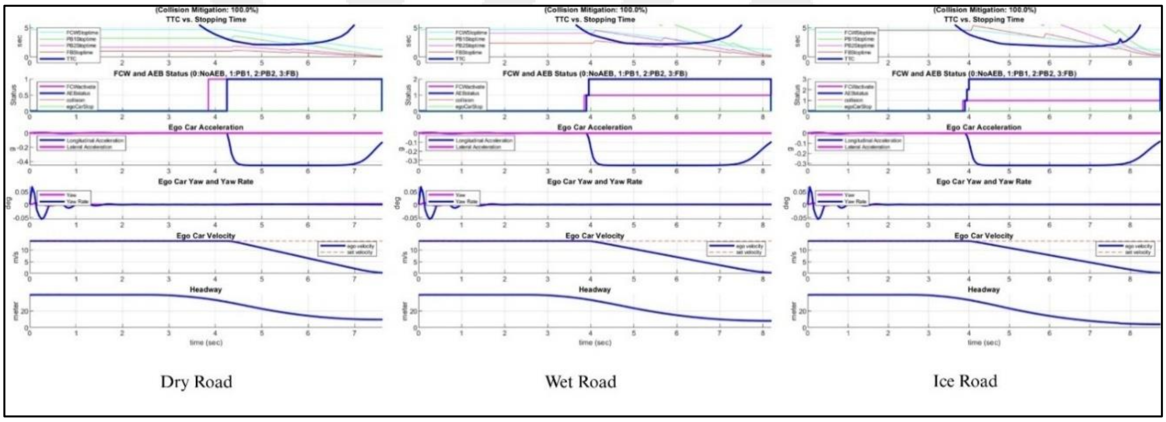


Figure 4.32: Comparative AEB Response in the CCRb Scenario Using Varying Road Conditions

Table 4.11: Braking Behavior Data for CCRb Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	3.85	3.85	3.85
AEB 1 Activation Time	4.25	3.90	3.90
AEB 2 Activation Time	-	3.95	3.95
AEB 3 Activation Time	-	-	4.00
Ego Velocity Decrease Start Time	4.30	3.95	3.95
Ego Stop Time	7.60	8.20	8.75
Total Braking Time	3.35	4.30	4.85

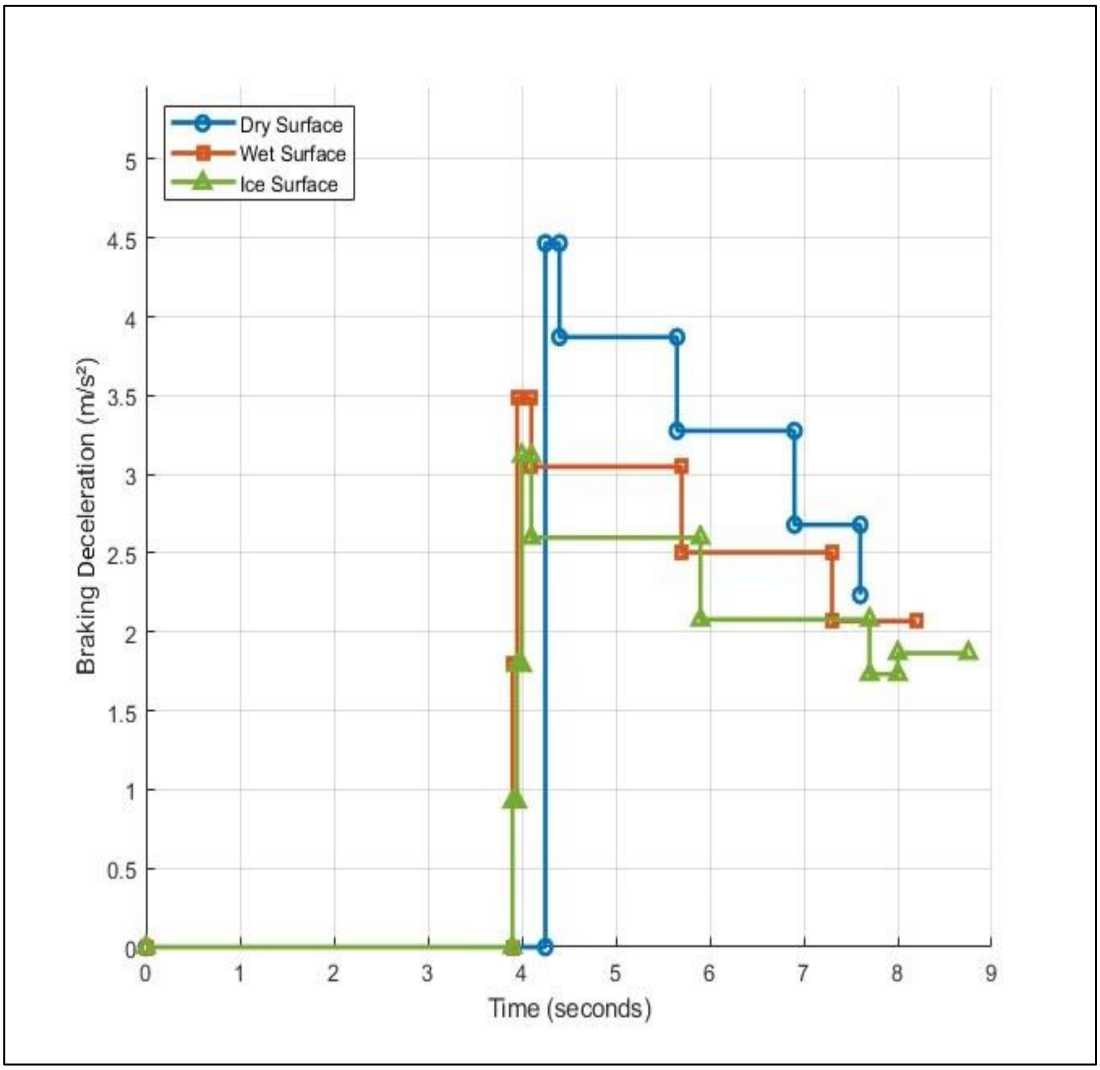


Figure 4.33: Comparative Deceleration Characteristics across Different Road Surfaces in CCRb Scenario

4.2.5 Scenario Pedestrian-Child Nearside Outputs

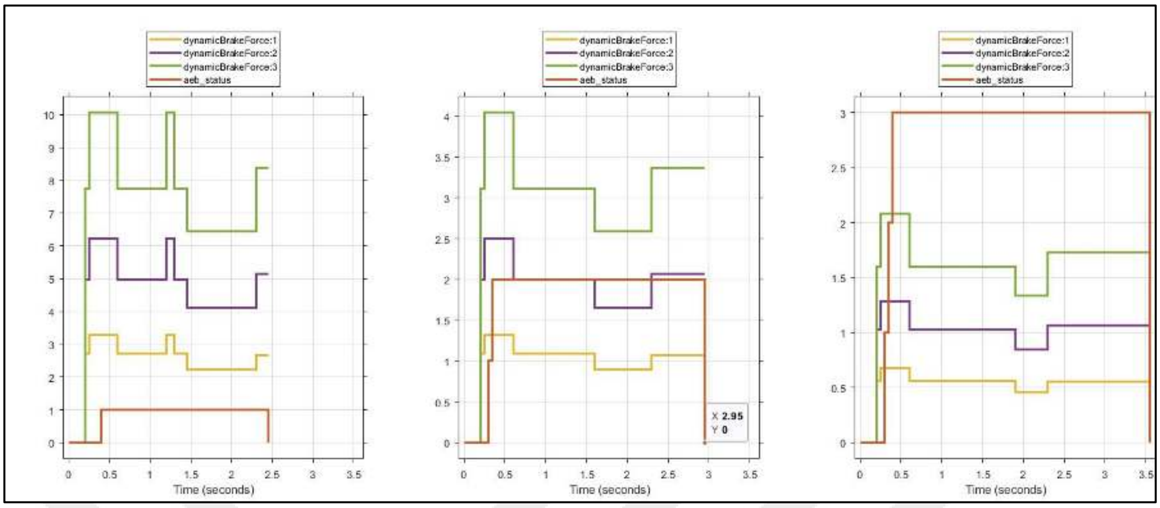
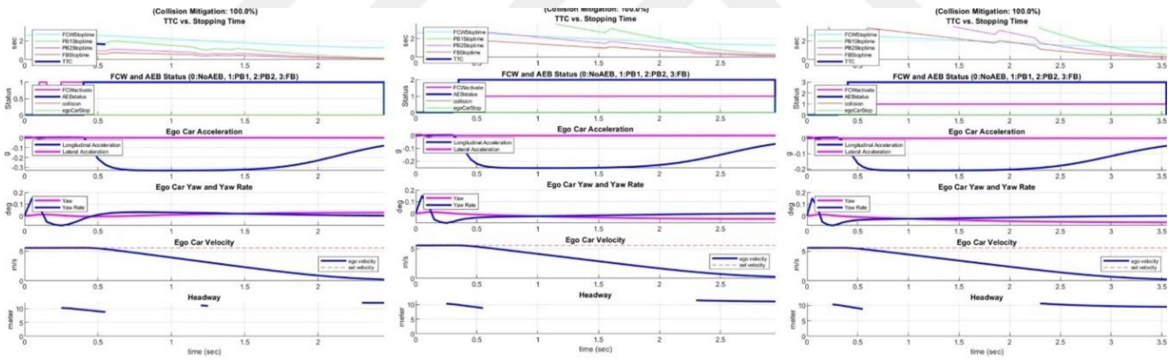


Figure 4.34: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the Pedestrian-Child Nearside Scenario



Dry Road Wet Road Ice Road

Figure 4.35: Comparative AEB Response in the Pedestrian-Child Nearside Scenario Using Varying Road Conditions

Table 4.12: Braking Behavior Data for Pedestrian-Child Nearside Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	0.30	0.30	0.30
AEB 1 Activation Time	0.40	0.30	0.30
AEB 2 Activation Time	-	0.35	0.35
AEB 3 Activation Time	-	-	0.40
Ego Velocity Decrease Start Time	0.45	0.35	0.35
Ego Stop Time	2.45	2.95	3.55
Total Braking Time	2.05	2.65	3.25

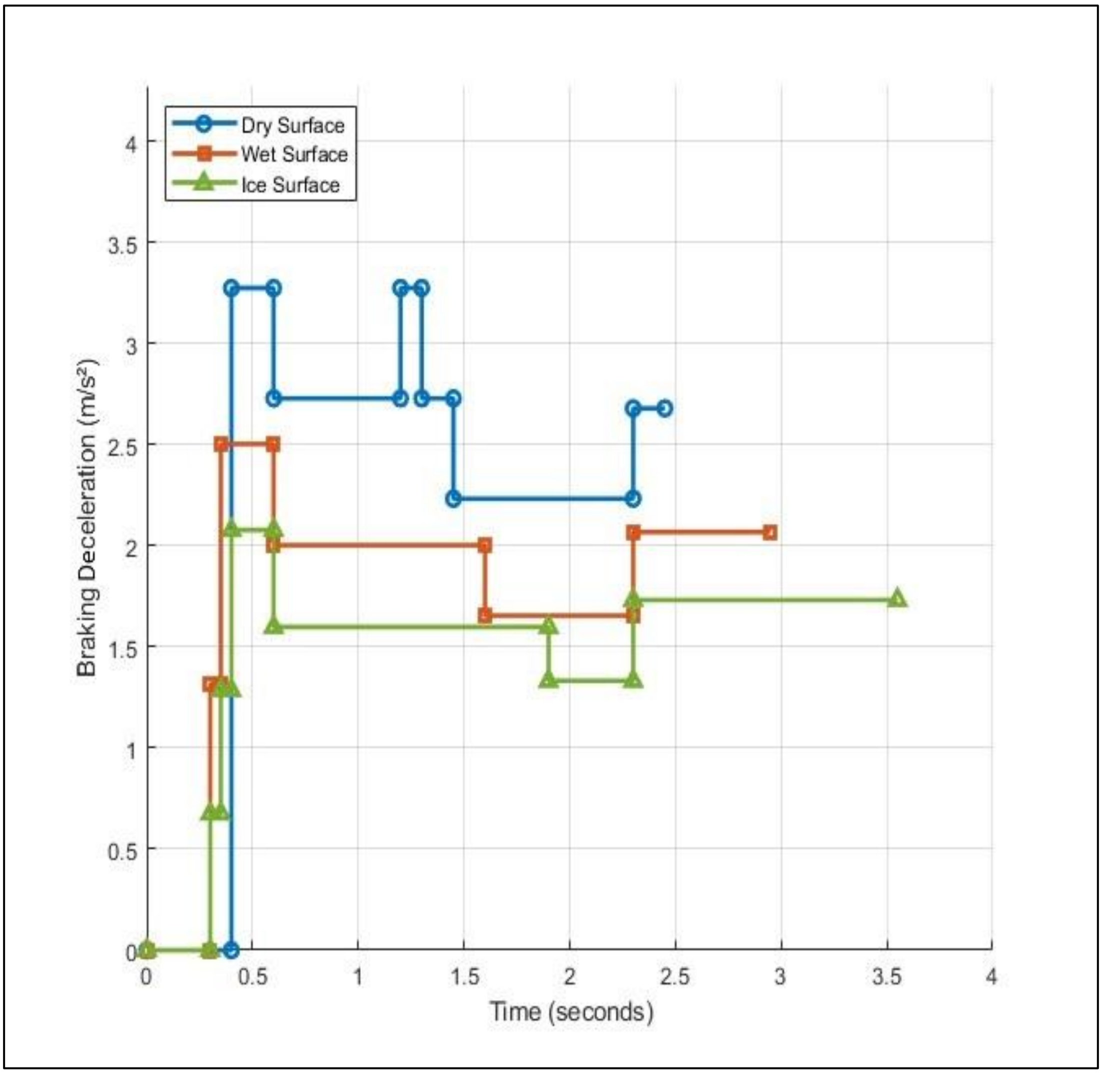


Figure 4.36: Comparative Deceleration Characteristics across Different Road Surfaces in Pedestrian-Child Nearside Scenario

4.2.6 Scenario Pedestrian Turning Farside Outputs

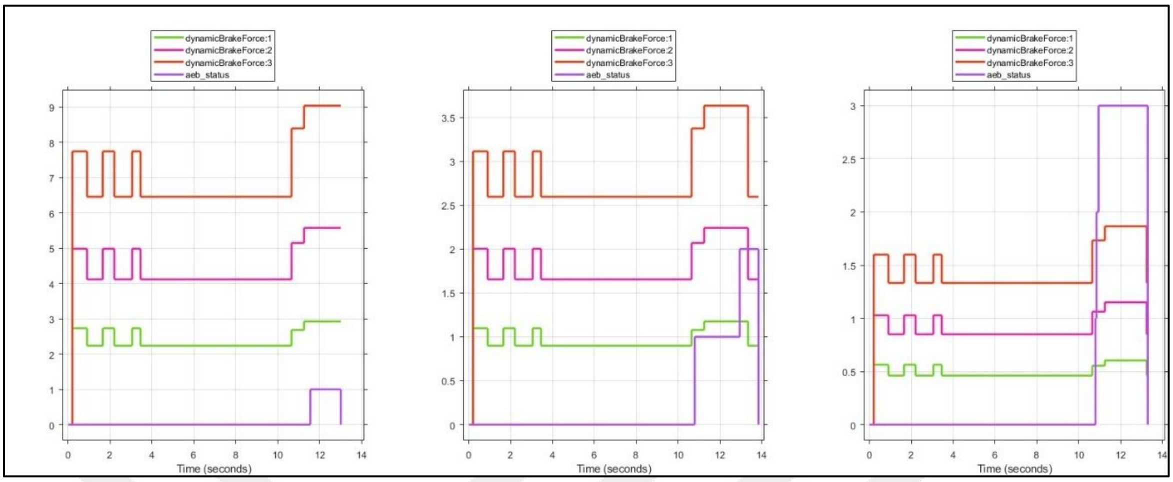


Figure 4.37: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the Pedestrian Turning Farside Scenario

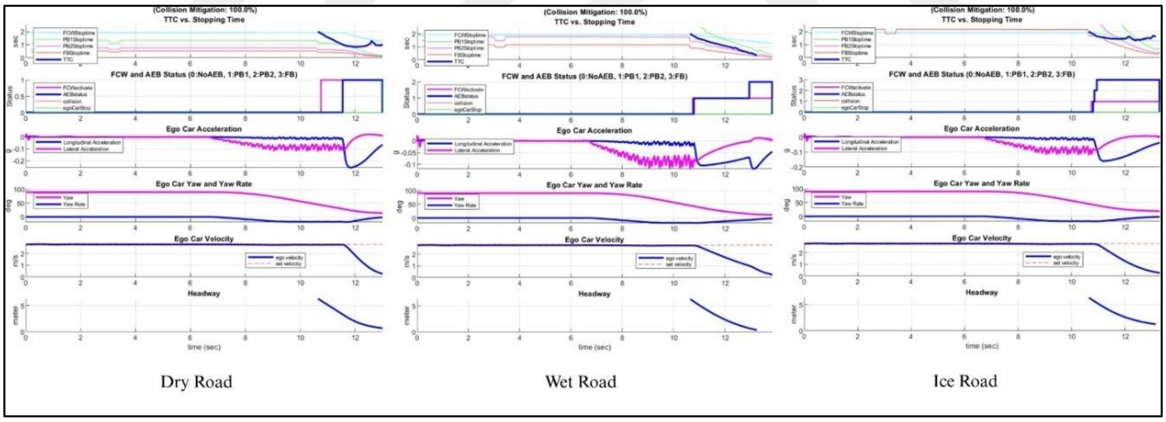


Figure 4.38: Comparative AEB Response in the Pedestrian Turning Farside Scenario Using Varying Road Conditions

Table 4.13: Braking Behavior Data for Pedestrian Turning Farside Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	11.0	11.0	11.0
AEB 1 Activation Time	11.55	10.80	10.80
AEB 2 Activation Time	-	12.95	10.85
AEB 3 Activation Time	-	-	10.95
Ego Velocity Decrease Start Time	11.60	10.85	10.85
Ego Stop Time	13.00	13.85	13.30
Total Braking Time	1.45	3.05	2.50

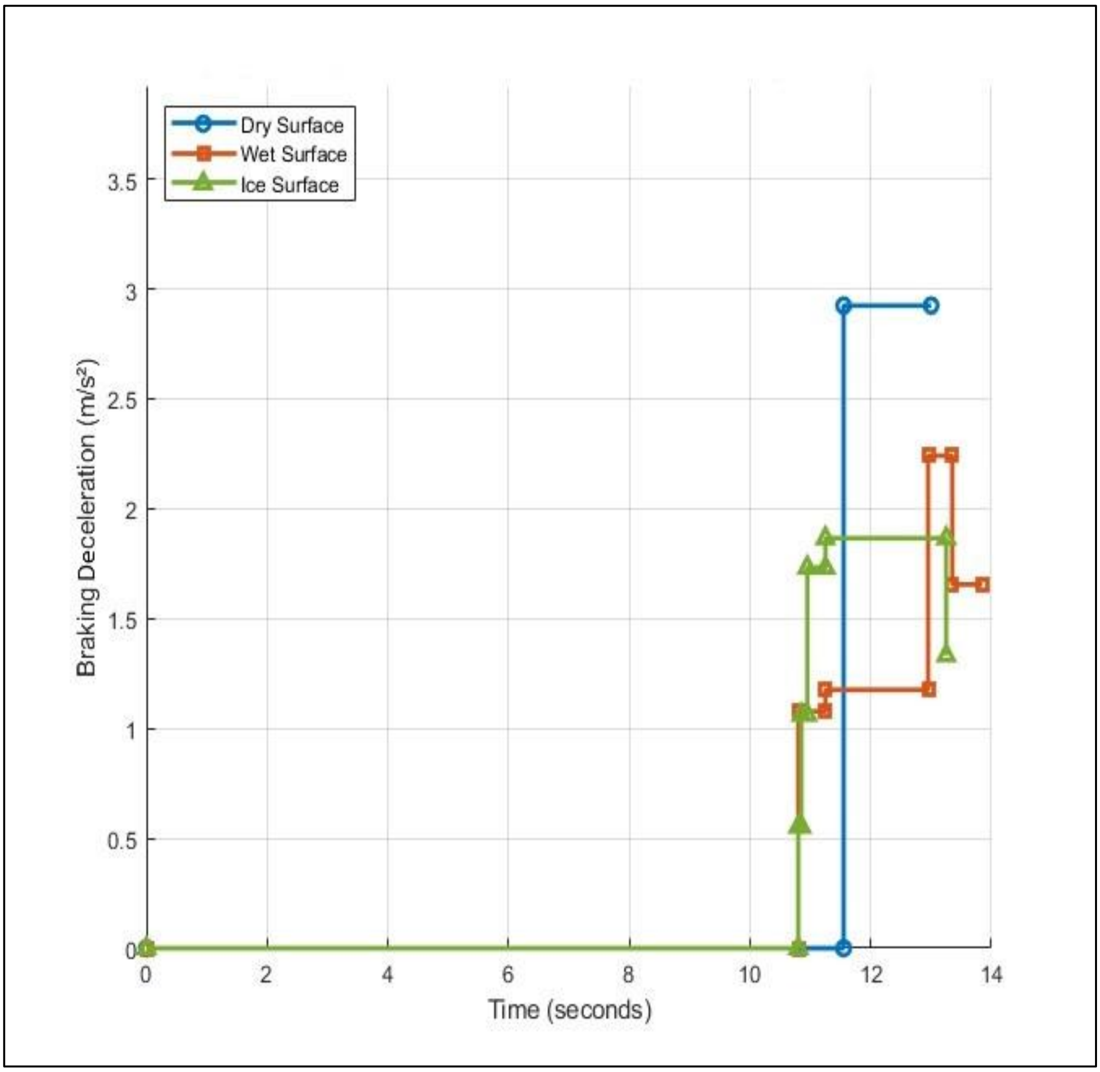


Figure 4.39: Comparative Deceleration Characteristics across Different Road Surfaces in Pedestrian Turning Farside Scenario

4.2.7 Scenario Bicyclist Longitudinal Outputs

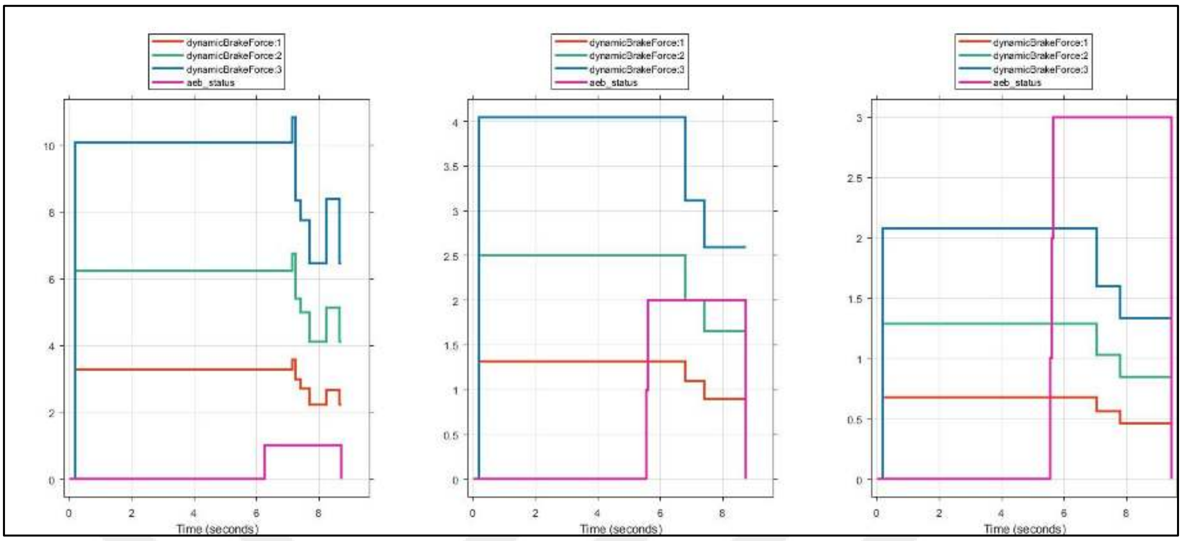


Figure 4.40: Adaptive Braking Force and AEB Activation under Varying Road Conditions in the Bicyclist Longitudinal Scenario

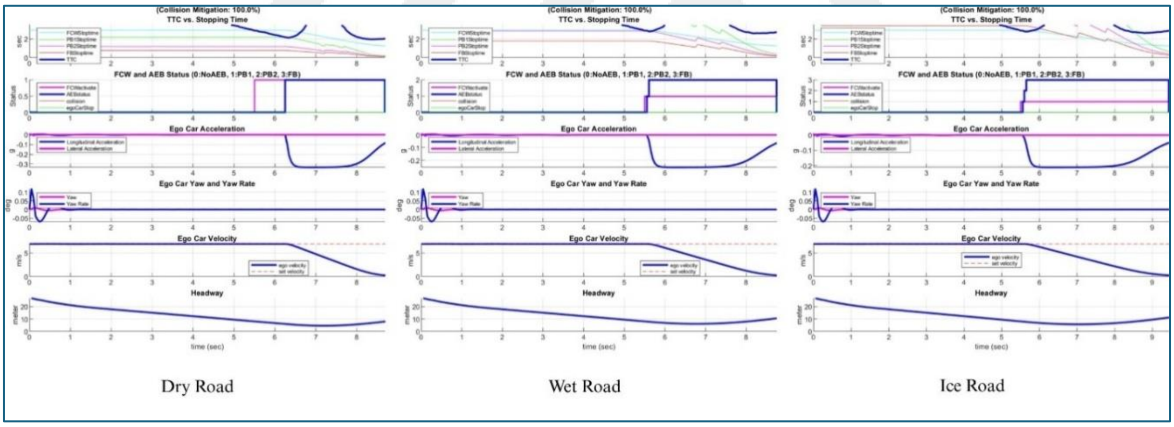


Figure 4.41: Comparative AEB Response in the Bicyclist Longitudinal Farside Scenario Using Varying Road Conditions

Table 4.14: Braking Behavior Data for Bicyclist Longitudinal Scenario in Variable Road Conditions

Variable	Dry Road (s)	Wet Road (s)	Ice Road(s)
FCW Activation Time	5.50	5.50	5.50
AEB 1 Activation Time	6.25	5.50	5.55
AEB 2 Activation Time	-	5.60	5.60
AEB 3 Activation Time	-	-	5.65
Ego Velocity Decrease Start Time	6.30	5.55	5.60
Ego Stop Time	8.70	8.75	9.45
Total Braking Time	2.45	3.25	3.90

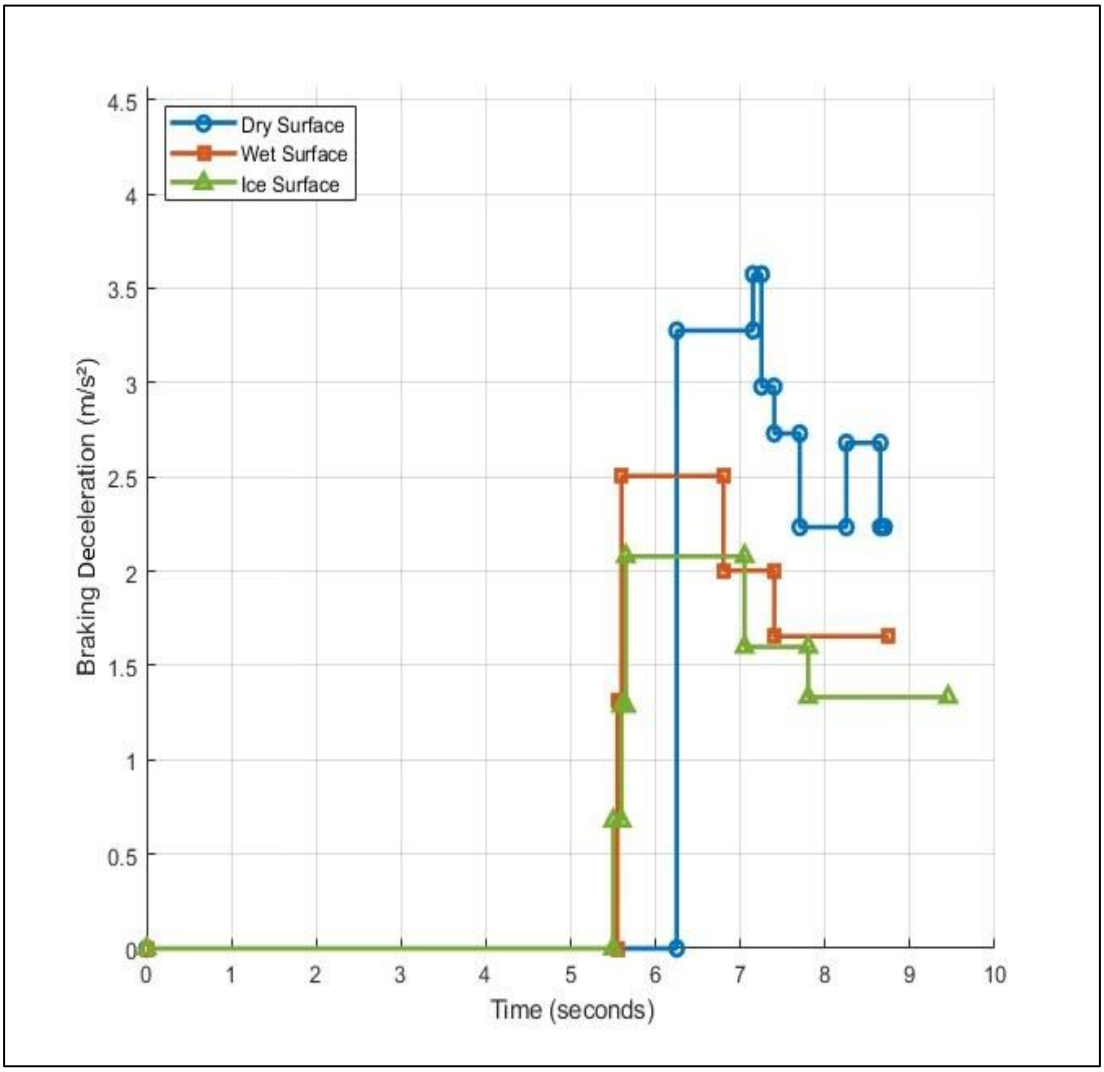


Figure 4.42: Comparative Deceleration Characteristics across Different Road Surfaces in Bicyclist Longitudinal Scenario.

5. EVALUATION AND DISCUSSION OF FINDINGS

5.1 GENERAL COMPARISON OF CONSTANT AND ADAPTIVE (DYNAMIC) BRAKING MODELS

In this section, the general performance comparison of the fixed braking model and the dynamic (adaptive) braking model is made based on simulation results obtained from different scenarios. The comparison is mainly about braking start times, AEB activation stages, total braking times and effectiveness in reducing the risk of collision and maintaining driving comfort.

The fixed braking strategy is based on the application of predefined fixed acceleration values at each AEB activation stage (PB1, PB2, FB). When a collision threat is detected, fixed braking forces are activated regardless of the environmental or vehicle dynamics. Although this method provides powerful braking, it can negatively affect driver and passenger comfort due to the constant and hard braking acceleration, puts unnecessary load on the vehicle's mechanical components (especially the brake pads) and can negatively affect driving safety in certain situations.

In contrast, the dynamic braking model adjusts the braking acceleration in real time depending on parameters such as time to collision (TTC), road surface condition (friction coefficient) and vehicle speeds. Simulation results show that dynamic braking starts braking earlier in some cases and later in others compared to fixed braking depending on the structure of the scenario and environmental conditions, but in both cases it prevents collisions by providing the necessary deceleration in a more balanced way and reduces unnecessary braking time. Adaptive (dynamic) braking also exhibits a more balanced and gradual acceleration profile, increasing both driving safety and significantly preserving in-car comfort.

Overall, the adaptive braking model provides a significant improvement by better balancing collision prevention effectiveness with driving dynamics compared to the fixed braking method. These results clearly demonstrate the necessity of using real-time data-driven braking strategies within modern Advanced Driver Assistance Systems.

5.2 EFFECT OF DIFFERENT ROAD CONDITIONS ON BRAKING PERFORMANCE

In this section, the effects of road surface conditions (dry, wet and icy) on dynamic braking performance are investigated. Simulation studies have revealed how the dynamic braking strategy responds on surfaces with different friction coefficients.

In dry surface conditions, when a collision risk is detected, the system calculates the optimum braking acceleration depending on the environmental parameters and applies an adaptive deceleration value. In this way, both effective deceleration is provided and driving comfort is preserved. Unnecessary early braking is avoided and acceleration changes in the vehicle are kept within controlled limits.

In wet surface conditions, the braking capacity is limited due to the low friction coefficient of the road; on the other hand, the system detects these surface conditions and adaptively adjusts the braking force to an appropriate deceleration level within the environmental limits. This situation provides a safe deceleration by maintaining the vehicle's balance during sudden braking moments.

In icy surface conditions, although the braking distance increases due to the very low friction coefficient, the system recognizes this limitation and reduces the acceleration level in a controlled manner and attempts are made to minimize the collision risk. AEB was activated earlier and was applied considering optimum deceleration and surface adhesion capacity.

In general, it was observed that the dynamic braking strategy was applied adaptively by calculating the optimum braking value sensitive to environmental variables in different road surface conditions, thus maintaining a high level of collision avoidance success.

5.3 ANALYSIS OF COLLISION AVOIDANCE PERFORMANCE

In this section, the collision avoidance performance of the developed dynamic braking algorithm on different road conditions and test scenarios is evaluated. The scenarios are modeled in MATLAB/Simulink environment and each of them is simulated with dynamic braking strategy under 3 different road surfaces (dry, wet, icy).

Evaluation Criteria:

i. AEB system activation timing (Status 1–3)
ii. Braking time and acceleration profile

iii. Stopping success of ego vehicle
iv. Whether a collision occurred

General Findings:

i. CCFtap Scenario (Turning vehicle): Timely stopping was achieved with early AEB-1 activation, especially on wet and icy surfaces; collision was avoided on all surfaces despite the risk of lateral collision due to the scenario type.
ii. CCRs Scenario (Stationary target vehicle): AEB-1 status was sufficient, collision was prevented, vehicle stopped without switching to AEB-2 and AEB-3.
iii. CCRm Scenario (Approaching the moving vehicle in front): In this scenario, which requires slow approach and continuous monitoring, braking stages were activated in time, and unnecessary sudden braking was avoided.
iv. CCRb Scenario (Situation where the vehicle in front brakes suddenly): Safe stopping was achieved, especially on low-adhesion surfaces, thanks to the responsive behavior of the dynamic system.
v. Pedestrian-Child Nearside: Due to the sudden passage of the small-sized target, the system responded quickly; collision was prevented by early deceleration without the need for AEB-2 or AEB-3 situations.
vi. Pedestrian Turning Farside: A brake profile was created according to the direction of the target's passage, no collision occurred even on wet/icy surfaces.
vii. Bicyclist Longitudinal (Approaching the cyclist in front): It is one of the scenarios where the earliest AEB activation occurs. In vehicle-bicycle interaction, the system provided early deceleration and comfortable stopping.

When all scenarios are considered, the dynamic braking system managed to avoid the collision in all seven scenarios. The system provided safe and comfortable deceleration with adaptive braking response regardless of road conditions and target type and produced successful results.

This situation shows that in collision prevention, not only strong braking is needed; but also a braking algorithm applied at the right time, at the right level and in accordance with the environment is needed.

5.4 SUMMARY OF OBSERVATIONS AND KEY FINDINGS

There are significant differences between the two models in terms of the activation of the AEB system. In the model with constant braking acceleration, once the system is triggered, it switches to the partial braking (PB1, PB2 and FB) stages with fixed values and these values do not change according to the external environmental conditions. This causes the system to make decisions only according to the time to collision (TTC) and follow a fixed scenario.

On the other hand, in the adaptive braking model, the AEB system continuously evaluates not only the TTC but also multiple parameters such as the distance to the GVT (target vehicle), the speed of the ego vehicle, the speed of the target vehicle and the friction coefficient of the road surface. In the light of these parameters, the model instantly recalculates the necessary braking acceleration and provides active control to keep it at the optimum level. Thus, both the probability of avoiding a collision increases and unnecessary braking and uncomfortable driving scenarios are prevented.

While the braking force is always applied with the same three stages in the fixed model, this value is constantly updated depending on real-time calculations in the dynamic model. Collision avoidance success was achieved in all dynamic scenarios; insufficient braking or excessive braking situations are prevented thanks to the system's environmental awareness. Driving comfort and system compatibility have provided a more consistent and user-friendly structure in the dynamic braking model.

6. CONCLUSION

In this thesis, an adaptive (dynamic) braking algorithm developed as an alternative to the traditional fixed braking strategy has been modeled and evaluated within the framework of the Autonomous Emergency Braking (AEB) system. The proposed system has been tested extensively in terms of collision avoidance success, contribution to driving comfort and ability to adapt to changing road and traffic conditions. Seven different scenarios determined in accordance with the Euro NCAP protocol were modeled in the MATLAB/Simulink environment, including vehicle-vehicle, pedestrian and cyclist interactions, and first the fixed and adaptive braking algorithms in the scenario we accepted as dry ground, and then the braking performance in dry, wet and icy road conditions with the adaptive braking model were analyzed.

Simulation results showed that although the fixed braking method provides a strong stopping effect, it cannot respond to environmental variables due to its fixed values and may cause unnecessary early or late braking in some cases. The application of fixed values in each stage of AEB (PB1, PB2, FB) led to early or late braking interventions in some cases; This has caused both reduced passenger comfort and unnecessary load on mechanical components such as the brake system. The developed dynamic braking algorithm can calculate and apply the optimum braking acceleration in real time by continuously monitoring critical parameters such as time to collision (TTC), distance between vehicles, ego vehicle speed, target vehicle speed and road surface friction coefficient. Thanks to this structure, the AEB system is not triggered only once and remains fixed, but can dynamically update the braking response with continuous calculations. This approach has provided smoother braking transitions, effective collision prevention in difficult conditions and significant improvements in driving comfort.

In tests conducted under seven different scenarios and three road conditions, the adaptive braking model managed to avoid collisions in all cases. The model not only increased safety but also presented a more balanced and sustainable solution in terms of passenger comfort and mechanical system compatibility. These findings clearly demonstrate that it is necessary to go beyond fixed rule-based models in safety-critical systems. While the study emphasizes the importance of real-time and context-aware braking strategies in Advanced Driver Assistance Systems (ADAS), it shows that these systems can be further improved in terms of flexibility, learning and long-term adaptation with the integration of artificial intelligence-based decision-making models.

7. FUTURE WORKS

The braking strategy developed in this study is based on a model-based approach that determines the braking acceleration in real time with a parameter-based decision mechanism. However, in order for the system to become more autonomous and to respond more flexibly to environmental factors, supporting it with artificial intelligence (AI)-based decision mechanisms stands out as a potential development area.

In future studies, a machine learning or deep learning-based model can be trained using the collected scenario data and this model can be provided with the ability to learn and make optimum braking decisions against the risk of collision. Such an approach can produce more successful results, especially in complex environmental conditions or in undefined scenarios.

In addition, the adaptation of the model to field conditions can be evaluated with hardware-based real system integration (Hardware-in-the-Loop, HiL) studies on a vehicle enriched and tested with real-time sensor data.

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