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Development and validation of a friction estimation model for collision avoidance manoeuvres in autonomous trucks

Master's thesis in Mobility Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover: SORA generated image of autonomous truck avoiding potential collision with a moose

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Abstract

Autonomous trucks are rapidly gaining interest in the commercial vehicle sector due to their potential to improve road safety, reduce operational costs, and optimize long-haul transport. However, one of the critical challenges in ensuring the safety of these vehicles lies in their ability to perform effective collision avoidance manoeuvres, especially under varying road surface conditions and near the tire-road friction limits. Accurate knowledge of the available friction is essential for making safe and optimal decisions regarding braking and steering during emergency situations. This thesis presents the development and validation of a real-time road-tire friction estimation model designed specifically for autonomous truck applications. The proposed estimator leverages a longitudinal vehicle dynamics-based approach, using the slip-slope method to estimate the tire-road friction coefficient. A recursive least squares (RLS) algorithm is employed to update the friction estimate in real time based on inputs such as wheel slip, normal load, and longitudinal acceleration extracted from truck test log data.The estimated peak friction coefficient is used by a collision avoidance controller that dynamically selects between braking-only and sequential brake-and-steer strategies. The controller incorporates constraints on maximum lateral acceleration and steering angle to ensure stability and safety. Simulation studies were performed using MATLAB to validate the integrated system, and physical tests were conducted with a Scania 4x2 tractor truck to compare the predicted trajectories with real-world behaviour.

Keywords: autonomous trucks, friction estimation, slip-slope method, vehicle dynamics, RLS algorithm, emergency manoeuvre.

Preface

This report presents the outcome of my master's thesis project carried out at the Department of Mechanics and Maritime Sciences at Chalmers University of Technology during the spring of 2025. The research was conducted at the steering functions team at Scania CV AB, in collaboration with the Division of Vehicle Engineering and Autonomous Systems at Chalmers university of Technology. The work presented here focuses on the development and validation of a friction estimation model for collision avoidance manoeuvres in autonomous trucks. The study combines theoretical modelling, simulation, and real-world testing to address one of the most safety-critical aspects of autonomous vehicle control—operation near the friction limits. The project has allowed me to deepen my understanding of vehicle dynamics, estimation algorithms, and safety-oriented control strategies in a highly practical and industry-relevant context. The experience has been both technically enriching and personally rewarding. It has strengthened my passion for the field of autonomous mobility and sharpened my interest in the interface between control systems and real-world implementation.

Acknowledgements

I would like to express my deepest gratitude to my academic supervisor and examiner, Bengt Jacobson, at Chalmers University of Technology, for his continuous guidance, technical insights, and thoughtful feedback throughout the project. His expertise in vehicle dynamics and control systems was instrumental in shaping the direction of this thesis. I am especially thankful to my supervisor at Scania, Oskar Nydahl, whose input and feedback during the early stages of this thesis were critical in shaping the problem formulation and validation strategy. My sincere thanks also go to my mentor, Masoud Pourasgharlafmejani, for his support, encouragement, and invaluable discussions during the course of this work. His practical perspectives and deep knowledge of truck systems significantly enhanced the quality and applicability of the thesis work. I would also like to thank the team members and employees at Scania for their cooperation during vehicle testing and for providing access to test facilities and data that made the real-world validation possible. Finally, I am grateful to my family and friends for their unwavering support and encouragement throughout my academic journey. Their patience and belief in me made this achievement possible.

Ganapati Girish Kamat, Gothenburg, June 2025

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Introduction

1.1 Background

Autonomous driving technology might revolutionize the transportation industry, and autonomous trucks offer numerous benefits, including increased efficiency, cost savings, and enhanced safety. However, the ability of these trucks to navigate complex traffic environments remains a critical challenge. One key aspect is the ability to perform collision avoidance manoeuvres, which are essential when dealing with hazards on the road. These manoeuvres often push the truck's tires to their friction limits, making the development of an accurate and reliable friction estimation model vital for ensuring safe and effective operation during such emergency scenarios. A proper friction estimator model would allow the truck to make real-time decisions regarding braking and steering, helping to optimize its trajectory and avoid collisions.

1.2 Problem motivating the project

Unpredictable hazards in traffic require autonomous trucks to make critical decisions in real-time, especially when nearing tire friction limits. Existing controllers, designed for nominal conditions, struggle under extreme friction conditions, leading to suboptimal performance during emergency manoeuvres. The problem is especially significant for trucks travelling at high speeds where the main actuators: steering and braking, must be actuated in the best possible way to avoid collisions, without exceeding tire friction limits.

1.3 Envisioned solution

The envisioned solution is to develop a road-tire friction estimator based on vehicle dynamics observations and validate it with truck test data. This estimator will be used by a control strategy to develop an optimized trajectory that performs collision avoidance while positioning the truck on the friction circle. The estimator and control strategy will be validated through simulations. The trajectories suggested by the control strategy will be validated by replicating the collision scenarios with real truck tests.

1.4 Objectives

The goal of this thesis is to enhance the safety performance of autonomous trucks by enabling friction-aware decision-making for collision avoidance manoeuvres. To achieve this, the work focuses on developing a simple and effective friction estimation model and integrating it into a control framework capable of selecting and executing optimal evasive actions. To ensure clarity and assessability, this goal is addressed through the following specific objectives:

- To formulate a friction estimator based on observations of the longitudinal dynamics of the moving truck.
- To validate the friction estimator using real truck test data under dry asphalt conditions. The validation aims to assess the model's convergence behaviour, accuracy in predicting deceleration, and reliability under realistic operational scenarios.
- To design a collision avoidance controller that utilizes the estimated friction coefficient to dynamically determine whether to apply full braking or initiate a combined brake-and-steer manoeuvre.
- To implement the integrated estimation and control system in a MATLAB simulation environment. This includes modelling vehicle response, control logic, and obstacle interactions across different initial conditions and available braking distances.
- To perform real-world validation of the proposed system using a Scania 4x2 tractor truck. The goal is to compare simulation results with actual vehicle behaviour thereby assessing the real-world feasibility and effectiveness of the friction-aware collision avoidance strategy.

By meeting these objectives, the thesis aims to contribute toward developing robust, real-time, and validated decision-making capabilities for future autonomous heavy vehicles operating under friction-limited conditions.

1.5 Limitations

While this thesis aims to develop and validate a robust friction estimation model for collision avoidance manoeuvres in autonomous trucks, certain constraints define the scope and applicability of the study. The key limitations are as follows:

- Focus on a specific truck configuration: The analysis and validation will be conducted on only one truck setup, specifically a 4×2 tractor unit. The findings may not be directly applicable to other configurations, such as multi-axle trucks or articulated combinations.
- Simplified collision scenarios: The thesis will focus on single vehicle and obstacle interactions, specifically involving the controlled autonomous truck and a single stationary, potential collision object. Complex multi-vehicle interactions, such as dense traffic environments or chain-reaction collisions, are

beyond the scope of this research.

- Exclusion of vision-based perception: The thesis will not incorporate vision-based sensors (e.g., cameras) for hazard detection. Instead, the study assumes that the only hazard information is available through a distance sensor, allowing the control strategy to focus on optimal braking and steering decisions based on estimated road-tire friction characteristics

These limitations ensure a well-defined research scope while maintaining the feasibility of model development, validation, and real-world applicability within the constraints of available resources and testing capabilities.

2

Theory

Collision avoidance systems that involve both steering and braking control have recently become a booming field in active safety systems [1][2][3]. The existing automatic emergency braking system (AEB) can to some extent prevent collisions in the case of trucks travelling at low to medium speeds [4]. Braking distance increases exponentially with speed, which also limits the effectiveness of braking-only collision avoidance systems such as automatic emergency brake (AEB). Thereby, there have been several studies conducted on steering-based collision avoidance. An important limitation of the steering-based method is the risk it poses at high speeds and low friction coefficients, where the vehicle's dynamic stability becomes highly sensitive. On surfaces with low friction (particularly lower than what is estimated or assumed), a sudden lateral avoidance manoeuvre can cause the tires to lose grip. If the loss of grip occurs predominantly at the rear axle, the vehicle may experience oversteer, leading to the build-up of side-slip angles. As the side-slip increases, lateral tire forces grow non-linearly, which can result in high lateral accelerations. These increased lateral accelerations, especially at high vehicle speeds and with a high centre of gravity like in trucks, significantly raise the risk of rollover. Even before reaching the rollover threshold, the vehicle may lose yaw stability or steering responsiveness, potentially causing accidents such as running off the road or colliding with other road users. These dynamics highlight the limitations of relying solely on steering for collision avoidance under low-friction conditions [6]. Thus to overcome these individual limitations, studies have proposed using a combined braking and steering method of collision avoidance [5]. Finally, the friction coefficient becomes the most important limiting factor not only for braking distance but also for determining the maximum achievable lateral force during steering. Knowing the available friction allows the vehicle to operate within the friction circle, balancing longitudinal and lateral forces to utilize the tires' capacity most effectively. More importantly, accurate estimation of the friction coefficient enables the collision avoidance controller to determine the latest possible safe intervention point. This helps ensure that avoidance manoeuvres are initiated early enough to handle low-friction conditions, but not unnecessarily early under high-friction conditions—avoiding false interventions. While such early interventions are less problematic in autonomous vehicles, they can disrupt the surrounding manually driven traffic, especially in mixed traffic scenarios. Therefore, precise friction estimation contributes both to safety and to cooperative traffic behaviour.

2.1 Friction estimation methods

Accurate real-time estimation of the tire-road friction coefficient is both challenging and essential for an effective collision avoidance system. Several approaches have been proposed for real-time friction estimation, each with varying levels of computational complexity. These methods also differ in several aspects, such as whether they estimate friction for each wheel individually or consider an average value across all wheels.

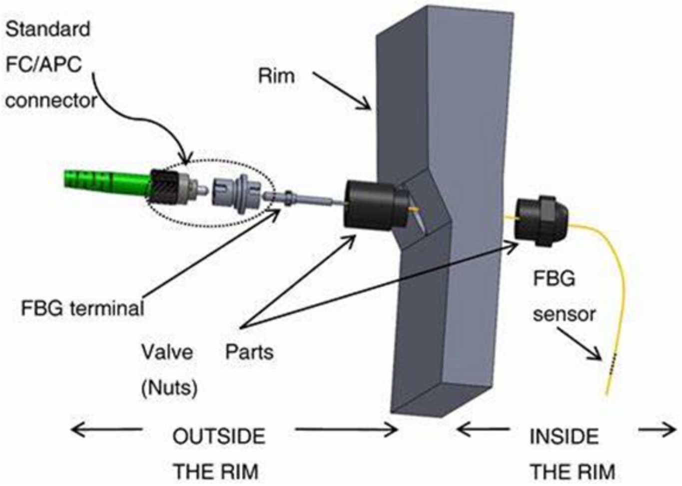

Figure 2.1: Intelligent tire monitoring system

2.1.1 Direct friction sensors

Direct friction sensors have gained attention in recent years due to their potential to provide real-time and accurate friction estimates [7]. These sensors are typically placed on the vehicle's tire or wheel and are designed to detect properties such as surface roughness, temperature, and wear, which all influence the friction coefficient [8]. One of the simplest and earliest methods involves measuring the temperature of the tire surface, as the frictional heat generated during contact with the road increases with the friction coefficient. When temperatures fall below $0°C$, the likelihood of icy conditions increases, significantly affecting friction. Another early method was to listen in on tire noise using a microphone to determine friction [16][17]. In recent times there have been several developments in hardware and led to complex sensor based implementations of friction sensors. These sensors can include strain gauges, accelerometers, and piezoelectric elements placed on the tire [18] or within the vehicle's suspension system. These sensors measure forces and deformations in the tire under different driving conditions, allowing for a direct estimate of the friction coefficient. For example, strain gauges can measure tire deformation under load, which is closely related to the frictional forces experienced by the tire. The readings from these sensors are typically fed into signal processing algorithms, such as Kalman filters or machine learning models, to produce real-time friction estimates. One such development is the use of piezoelectric sensors, which are sensitive to changes in stress and strain, and can detect subtle variations in tire contact pressure. The figure 2.1 shows one such example of an intelligent tire monitoring system where a FBG sensor embedded within the rim of the tire is able to monitor tire wear. These sensors are advantageous because they can provide high-resolution data and are relatively easy to integrate into existing vehicle systems [18]. Piezoelectric sensors have been successfully used in various applications, including the monitoring of tire wear and the detection of road surface conditions, both of which are critical for accurate friction estimation [8].

While direct friction sensors offer great promise, they also face several challenges. One of the primary difficulties is ensuring their durability and reliability under harsh driving conditions, as tires and sensor hardware are subjected to significant wear and environmental factors, including moisture, dust, and temperature fluctuations. Moreover, the integration of such sensors into production vehicles requires careful calibration and may involve significant costs in terms of both hardware and software development.

2.1.2 Cooperative methods

Connected road environments present an opportunity for friction estimation and to share this info among all concerned road users. Information obtained from multiple vehicles, such as simple temperature or humidity sensing can be collected, combined and analysed by the road infrastructure authorities. Various data-based methods such as machine learning models can be used for friction estimation and the results can be shared among the road users. An example of this is when there are slippery conditions and there ABS [9] and ESP being activated on vehicles, the road authorities collect this information from multiple vehicles and send out a warning to vehicles in that area [10]. This way the computational and sensor loads and costs are spread apart and there is more wide base for the estimation being performed. The cooperative method can combine environment sensing with vehicle dynamics observations.

2.1.3 Vehicle dynamics observation methods

These methods utilize vehicle dynamics based observations from sensors onboard the truck to estimate friction. They are of two types depending on the type of tire loading characteristics being observed.

2.1.3.1 Longitudinal dynamics based

Studies show that in the low-slip region, the the relationship between the longitudinal tire force F_{xt} and the longitudinal slip ratio s_x is approximately linear [11][12]. In this region, the basic idea of friction estimation is to measure F_{xt}(the force acting in the direction of motion at the tire-road interface) and s_x (the relative difference between wheel speed and vehicle speed) to identify points along the so-called slip curve. The Recursive Least Squares (RLS) algorithm is typically used to determine the slope of the linear approximation of these $F_{xt} - s_x$ points [13] which is referred to as the slip stiffness coefficient, denoted as CC_x. The Kalman filter, as used in [12], offers another option. The slip slope CC_x is then used to determine the value of friction coefficient. In [13], a direct linear relationship $\mu = A * CC_x + C$ is proposed, where A and C are constants determined through experimental correlation. In [12], artificial classification rules are developed based on multiple tests. According to these rules, the friction coefficient μ corresponds to a specific range of CC_x values. However, different tires can have varying properties, which may lead to inaccurate universal classification of μ. Currently, the only friction estimator available on the market was developed by NIRA Dynamics [19], based on this approach and partly inspired by the method in [12].

2.1.3.2 Lateral dynamics based

These methods use the relation between the lateral force F_{yt} and the self-aligning torque M_{zt}. They are both affected by the road-tire friction coefficient and are derived from the vehicle side slip angle α. The relation between F_{yt} and M_{zt} can be plotted in a Gough plot (as shown in figure 2.2 below) and using the actual values of F_{yt} and M_{zt}, α and μ can be determined. However to use this in a dynamic system, changes in longitudinal and vertical forces also need to be accounted for. Data-based algorithms such as neural networks have been suggested in the past for using data to generate Gough plots [14]. Another important discovery made in [15] was that the self-aligning torque is highly sensitive to variation in friction especially at low slip angles.

This method while theoretically sound, faces several practical challenges. One of the primary difficulties is obtaining accurate measurements of tire forces and self-aligning torque. While modern vehicles equipped with electric power steering (EPS) systems can estimate self-aligning torque on the steered axles. Variations in suspension geometry and steering kinematics introduce uncertainties in the measured or estimated longitudinal, lateral and vertical forces and thus a dynamic vehicle model should be used.

2.1.4 Conclusion to reviewed methods

From the review, it is evident that most friction estimation methods rely on observing tire behaviour using sensors mounted on the vehicle. These methods vary widely in their requirements for vehicle excitation, computational complexity, and the type and accuracy of sensor data they need. For instance, some methods can deliver accurate results under low excitation conditions, while others require higher dynamic input to extract meaningful friction estimates.

Each category of methods presents its own pros and cons. Direct friction sensors, while potentially very accurate, pose challenges in terms of durability, environmental sensitivity, and integration cost. Cooperative methods leverage shared vehicle data across a network but require connected infrastructure and timely communication. Vehicle dynamics-based methods offer a practical onboard solution but depend on accurate modelling of vehicle behaviour and high-quality sensor measurements. Ad-

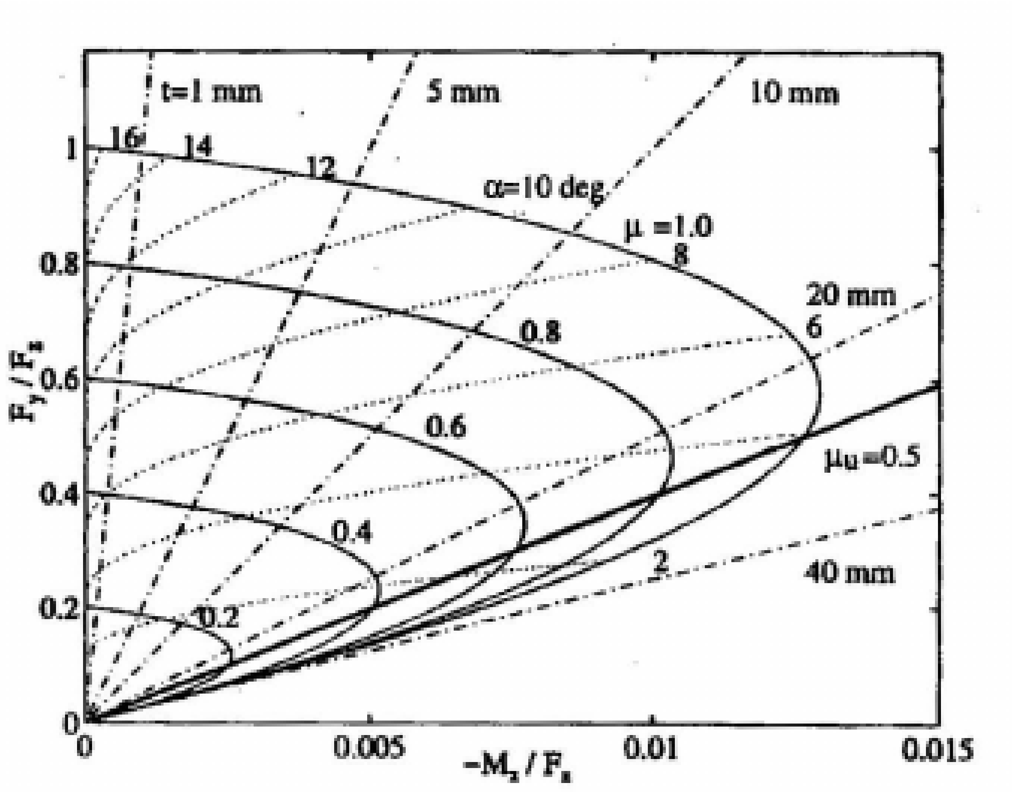

Figure 2.2: Gough plot - normalised lateral force against normalised aligning torque

ditionally, estimation accuracy can be affected by changes in tire properties or road surface conditions.

While several methods have been developed based on either pure longitudinal or pure lateral slip dynamics, relatively few studies have focused on friction estimation in combined slip situations—where both longitudinal and lateral slip occur simultaneously, such as during evasive braking and steering manoeuvres. Some advanced models exist that consider the full tire force surface (e.g., the Magic Formula or brush models), but explicit friction estimation in the combined slip domain remains less explored in the literature. The lack of widespread studies in this area is notable, especially since combined slip is a realistic and frequent condition during emergency manoeuvres. Therefore, further investigation in this direction could improve estimator robustness and relevance for real-world applications.

In the context of this thesis, the longitudinal dynamics-based approach has been selected for further study and implementation. This method strikes a good balance between feasibility and estimation performance, especially when operating in the low-slip region, which can be observed during normal driving conditions. Most importantly, all the sensors required for implementing this method—such as wheel speed sensors, vehicle speed estimation, and force estimation capabilities—are already available on the test trucks at Scania. This makes the method not only theoretically sound but also practically viable for integration and testing within the existing experimental framework.

As with any estimation task, predicting the road-tire friction coefficient inherently involves uncertainty. Most methods produce a single scalar estimate of μ, but it is often more informative and safer to provide a confidence interval—typically expressed as μ_{min} and μ_{max}—representing the possible range in which the true value lies. In the context of a collision avoidance controller, it is essential to choose which end of this range to rely on. Using μ_{max} (i.e., assuming higher friction) may allow for more aggressive manoeuvres, but introduces the risk of exceeding actual tire grip, especially if the true friction is lower. Conversely, basing decisions on μ_{min} ensures conservative behaviour, leading to safer, though possibly earlier or less efficient, interventions. For this thesis, the avoidance function prioritizes safety and therefore uses a conservative approach based on μ_{min} to ensure that braking and steering manoeuvres do not demand more friction than is confidently available. This choice reduces the risk of vehicle instability due to overestimation of friction, especially critical in emergency scenarios where maintaining control is paramount.

3

Methodology

3.1 Friction estimator design

A longitudinal dynamics-based approach [13] was used to estimate the available road friction using the slipslope method. This method relies on the estimation of the slipslope coefficient or more technically known as the longitudinal slip stiffness coefficient CC_x. It is defined as the proportional relationship between the normalized longitudinal force $F_x(t)/F_z(t)$ and the longitudinal slip ratio at the tires. The approach is particularly effective under low slip conditions and forms the basis for friction coefficient estimation during both acceleration and braking manoeuvres. The core of the estimation procedure utilizes a Recursive Least Squares (RLS) algorithm to dynamically estimate the slipslope CC_x in real time. The governing model for low slip conditions is given by equation 3.1:

$$F_x(t) = CC_x(t)(\alpha F_{zf}(t)s_{xf}(t) + F_{zr}(t)s_{xr}(t)) \tag{3.1}$$

Here, α is a weighting factor that equals 0 during acceleration (rear-wheel drive) and 1 during braking. The terms $s_{xf}(t)$ and $s_{xr}(t)$ represent the slip ratios of the front and rear wheels, respectively, while $F_{zf}(t)$, $F_{zr}(t)$ denote the corresponding normal loads on the front and rear axles.

Under high slip conditions, the relation between slip and friction coefficient is no longer linear and saturates. Thus, the force is modelled as shown in equation 3.2:

$$F_x(t) = \mu F_z(t) \tag{3.2}$$

where μ is the estimated friction coefficient and $F_z(t)$ is the total normal force.

Now, the general formula for the RLS algorithm is as shown below:

$$y(t) = \phi(t)\theta(t) + e(t) \tag{3.3}$$

To incorporate the physical model into the RLS estimation framework, Equations 3.1 and 3.2 are substituted into the general RLS formulation given by Equation 3.3. Under low slip conditions, Equation 3.1 becomes:

$$F_x(t) = CC_x(t) \cdot (\alpha F_{zf}(t)s_{xf}(t) + F_{zr}(t)s_{xr}(t)) \quad \Rightarrow \quad y(t) = \phi(t)\theta(t) + e(t) \tag{3.4}$$

where the output $y(t) = F_x(t)$, the regressor $\phi(t) = \alpha F_{zf}(t)s_{xf}(t) + F_{zr}(t)s_{xr}(t)$, and the parameter to be estimated $\theta(t) = CC_x(t)$.

Similarly, under high slip conditions, Equation 3.2 becomes:

$$F_x(t) = \mu(t) \cdot F_z(t) \quad \Rightarrow \quad y(t) = \phi(t)\theta(t) + e(t) \tag{3.5}$$

where, $y(t) = F_x(t)$, $\phi(t) = F_z(t)$, and $\theta(t) = \mu(t)$.

In both cases, the Recursive Least Squares algorithm recursively updates the parameter $\theta(t)$ based on the measured output $y(t)$, the regressor $\phi(t)$, and the prediction error $e(t)$. The update is governed by the forgetting factor λ, the gain vector $K(t)$, and the covariance matrix $P(t)$. The RLS algorithm is given by [20]:

1. Measure the system output $y(t)$ and compute the regression vector $\phi(t)$ as shown below in equation 3.6:

$$\phi(t) = \alpha F_{zf}(t)s_{xf}(t) + F_{zr}(t)s_{xr}(t) \tag{3.6}$$

2. Determine the prediction error $e(t)$ as the difference between the measured output and the model output predicted using the previous parameter estimate:

$$e(t) = y(t) - \phi^T(t)\theta(t-1) \tag{3.7}$$

3. Calculate the update gain vector $K(t)$ using:

$$K(t) = \frac{P(t-1)\phi(t)}{\lambda + \phi^T(t)P(t-1)\phi(t)} \tag{3.8}$$

   Update the covariance matrix $P(t)$ as:

$$P(t) = \frac{1}{\lambda}\left[P(t-1) - \frac{P(t-1)\phi(t)\phi^T(t)P(t-1)}{\lambda + \phi^T(t)P(t-1)\phi(t)}\right] \tag{3.9}$$

4. Update the parameter estimate vector $\theta(t)$ using the new gain and error values:

$$\theta(t) = \theta(t-1) + K(t)e(t) \tag{3.10}$$

Here, λ is the forgetting factor, typically slightly less than 1. It ensures that more recent data has a greater influence on the parameter estimates, allowing the algorithm to adapt to changes in system behaviour and helping to avoid covariance matrix wind-up.

3.2 Collision avoidance system design

The collision avoidance (CA) system is designed on top of the estimated peak friction coefficient given by the friction estimator. Once the collision alert is activated by the distance sensor onboard the truck, stopping distance is calculated.

3.2.1 Stopping distance calculation

The stopping distance is the total longitudinal distance a vehicle travels from the moment a braking manoeuvre is initiated until it comes to a complete stop. It typically consists of multiple components, including the system response delay, brake force build-up phase, and constant deceleration phase. Mathematically, it is influenced by the initial speed, braking delay time, maximum achievable deceleration, and brake ramping dynamics. To more accurately reflect real-world braking dynamics, the brake force is modelled to increase linearly over a ramp-up duration t_{ramp}, rather than being applied instantaneously. During this period, the deceleration increases from 0 to a_{max}. The total stopping distance is computed by considering three main phases: system delay, brake ramp-up, and constant full braking. The derivation proceeds as follows:

1. Maximum achievable deceleration

The maximum deceleration depends on the estimated peak friction coefficient and is calculated as:

$$a_{\text{max}} = \mu \cdot g \tag{3.11}$$

2. Average deceleration during ramp-up

Assuming a linear increase in braking force over a duration t_{ramp}, the average deceleration during this phase is:

$$a_{\text{avg}} = \frac{1}{2} a_{\text{max}} \tag{3.12}$$

3. Distance during ramp-up phase

The distance traveled during the ramp-up phase, starting from an initial velocity v_0, is derived using the equation of motion:

$$d_{\text{ramp}} = v_0 \cdot t_{\text{ramp}} - \frac{1}{2} a_{\text{avg}} \cdot t_{\text{ramp}}^2 \tag{3.13}$$

Substituting Equation 3.12 into the above, we get:

$$d_{\text{ramp}} = v_0 \cdot t_{\text{ramp}} - \frac{1}{4} a_{\text{max}} \cdot t_{\text{ramp}}^2 \tag{3.14}$$

4. Velocity at end of ramp-up phase

The vehicle velocity at the end of the ramp-up phase is:

$$v_{\text{ramp}} = v_0 - a_{\text{avg}} \cdot t_{\text{ramp}} = v_0 - \frac{1}{2} a_{\text{max}} \cdot t_{\text{ramp}} \tag{3.15}$$

5. Distance during full deceleration

After ramp-up, the vehicle continues to decelerate at a_{max} until it stops. The distance traveled during this phase is:

$$d_{\text{full}} = \frac{v_{\text{ramp}}^2}{2a_{\text{max}}} \tag{3.16}$$

6. Total stopping distance

Including system delay and a minimum safety buffer d_{min}, the total stopping distance is:

$$d_{\text{stop}} = d_{\text{min}} + v_0 \cdot t_d + d_{\text{ramp}} + d_{\text{full}} \tag{3.17}$$

3.2.2 Collision avoidance strategy

The proposed collision avoidance (CA) strategy aims to prevent frontal collisions by dynamically selecting either a braking-only or a combined braking-and-steering manoeuvre, depending on the vehicle's current velocity, distance to the obstacle, and dynamic feasibility constraints. The decision-making process is structured as a mode-based logic system, which is triggered when a potential collision is detected.

Mode Selection Logic

1. **Trigger:** Collision alert is activated by the onboard sensor system.
2. **Compute stopping distance:**

   $$d_{\text{stop}} \leftarrow \text{calculated using Equation 3.17}$$

3. **Compare available distance to stopping distance:**

   $$d_{\text{avail}} = d_o - d_s$$

   where,
   - d_o is the distance to the obstacle [m],
   - d_s is the minimum safe distance to be maintained at all times from the obstacle [m] (assumed as 3 metres for this thesis)
   - If $d_{\text{stop}} < d_{\text{avail}}$:
     - **Mode 1: Brake-Only Mode**
       - Apply full braking until complete stop.
       - End.
   - Else:
     - **Proceed to steering feasibility check**.
4. **Check feasibility of steering manoeuvre:**
   - Required steering radius R is determined (see Section 3.2.3).
   - Compute minimum feasible turning radius:

     $$R_{\text{min}} = \frac{L + K_u \cdot v^2}{\tan(\delta_{\text{max}})} \tag{3.18}$$

     Here, δ_{max} is the maximum steering angle limited by the ECU. This value is calculated using a separate system in the Scania software framework. Look-up tables developed based on rigorous testing are used to define the maximum possible steering angle based on the speed of the vehicle.
   - If $R \geq R_{\text{min}}$:
     - **Mode 2: Brake-and-Steer Mode**

    (a) Apply controlled braking to reduce speed to a safe steering threshold (typically 25 km/h), or until reaching the final steering initiation point.
    (b) Smoothly ramp down braking force.
    (c) Initiate steering manoeuvre with curvature commands. (refer to 3.2.3)
    (d) Once fully transitioned into adjacent lane and aligned:
        - Re-engage braking to bring vehicle to complete stop.

- Else:
  - **Fallback to Mode 1: Brake-Only Mode**
    - Steering not feasible — apply full braking until stop.
    - Results in an unavoidable head-on collision but at a much lower speed.
    - End.

This step-by-step logic ensures a safe and dynamically feasible avoidance manoeuvre, prioritising longitudinal deceleration when necessary, and using lateral avoidance only when it is both required and feasible. The next subsection details the lateral trajectory planning used in Mode 2.

3.2.3 Collision avoidance trajectory planning

For the vehicle to steer away from a potential colliding object, a geometrically optimized trajectory must be generated, keeping in mind the dynamics of the truck. The evasive steering to be performed must do so while making sure the truck always maintains a safe distance from the obstacle. The below figure 3.1 derived from a method described in [21] shows how the trajectory can be planned for optimized collision avoidance.

To start, a circle C_P is drawn with its centre located on the left edge of the obstacle and a radius equal to half the width of the truck along with some safe distance. Then, another circle C_R is constructed such that it fully encloses C_P, with their point of contact (point O) lying on a line parallel to the vehicle's direction of travel. This outer circle C_R represents the largest possible turning path that allows the ego-vehicle to safely avoid the obstacle. The point where C_R touches C_P is called the steering switching point, labelled as S.

Next, a second circle identical in size to C_R is drawn, but this time in a way that C_P fits inside it at the same contact point S. The finishing point F is defined such that the length of the arc from O to S matches the length of the arc from O to F. The resulting desired avoidance path follows a smooth curve connecting these three points: $O \rightarrow S \rightarrow F$. Under these conditions, a specific geometric relationship must be satisfied due to the way C_R is drawn to enclose C_P.

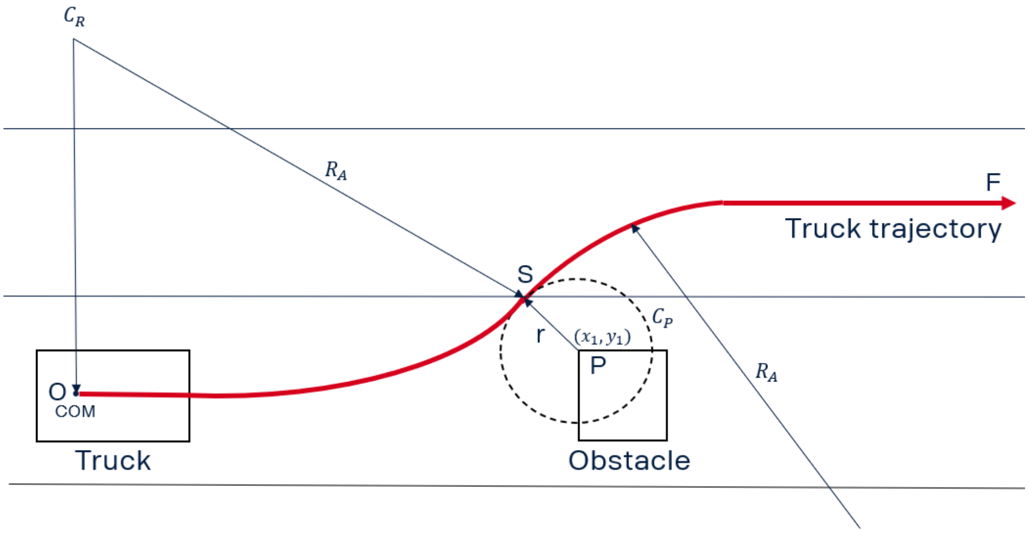

Figure 3.1: Geometric derivation of avoidance trajectory

3.2.4 Vehicle model

The vehicle model used in this thesis is a simplified single-track (bicycle) model implemented in MATLAB. It includes three dynamic states: longitudinal velocity (v_x), lateral velocity (v_y), and yaw rate (ω_z). Lateral tire forces are modelled using a linear tire approximation with a constant cornering stiffness (C_α), where $F_y = C_\alpha \cdot \alpha$ for each axle. The longitudinal forces are applied directly based on the braking demand and are distributed equally between the front and rear axles. No combined slip effects are modelled. The longitudinal and lateral dynamics are decoupled. The model assumes ideal actuation for both braking and steering, with no time delay or rate limitations in either. Static axle loads are used without accounting for dynamic longitudinal load transfer during acceleration or braking. Vehicle position and heading angle are updated at each time step using the calculated yaw rate and velocity.

3.2.5 Simulation setup

The simulation is setup using MATLAB with a controller model and a vehicle model as shown in figure 3.2. The controller model is setup as described above and sends out brake and curvature requests to the vehicle model. The vehicle model processes the requests from the controller and generates longitudinal force and front wheel angle according to the equation given below.

$$\delta = L \cdot \kappa + K_u \cdot \kappa_{req} \cdot v^2 \tag{3.19}$$

where,

- δ is the steering angle [rad],
- L is the wheelbase of the vehicle [m],
- κ_{req} is the curvature request [1/m],
- K_u is the understeering gradient [rad/(m/s^2)],

- v is the vehicle speed [m/s].

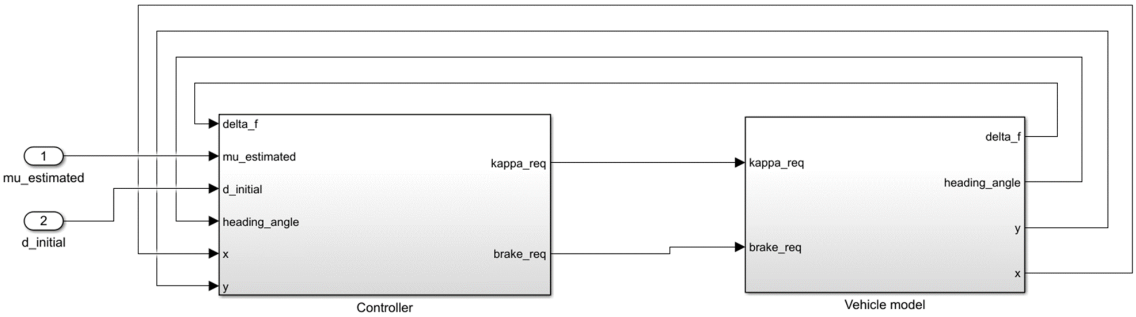

Figure 3.2: Simulation setup

Based on front wheel angle and longitudinal forces, heading angle and position of the truck w.r.t the obstacle are derived at each time step t. This is used in the end to generate full trajectory of the truck.

3.2.6 Real Truck Testing and Validation

Figure 3.3: Scania 4*2 tractor truck - similar vehicle is used for investigation and testing within this thesis

To validate the effectiveness of both the friction estimator and the collision avoidance system, a real-world test was conducted using a full-scale truck on a controlled test track. The objective was to replicate the brake-only and brake-and-steer trajectories predicted by the simulation. A professional test driver carried out the manoeuvres in a wide, obstacle-free section of the track.

For the brake-only test case, the driver began by accelerating the truck to a target speed of 72 km/h. Upon reaching this speed, maximum braking was applied until the truck came to a complete stop.

In the brake-and-steer test case, the procedure started similarly, with the driver accelerating the truck to 72 km/h. Once the target speed was reached, the driver applied maximum braking while monitoring the speedometer. As the vehicle decelerated and approached the predetermined safe steering speed of 25 km/h, the driver fully released the brakes and initiated a lane change manoeuvre. After completing the lane change and aligning the truck with the new lane, the driver re-applied full braking until the vehicle came to a complete stop.

Both test cases were logged for subsequent analysis. The tests were performed using a Scania 4x2 tractor truck (Figure 3.3) equipped with all the necessary sensors to record signals required for comparing the real-world performance with simulation results.

4
Results

This chapter presents the results obtained from the development, simulation, and testing of the proposed friction estimation model and its integration into the collision avoidance control strategy. The friction estimator, based on the slip-slope method and implemented via a recursive least squares (RLS) algorithm, is run using truck test data to estimate the peak road-tire friction coefficient under both low and high slip conditions. The estimated peak friction coefficient is then used by the collision avoidance system to determine whether braking alone or a combined braking and steering manoeuvre is required to avoid a collision. The results presented in this chapter include the performance of the friction estimator, collision avoidance system and the comparison between simulation outputs and real truck test data. Overall, this chapter aims to demonstrate the practical viability of the proposed friction estimation and control strategy in real-world autonomous truck applications.

4.1 Friction estimation

The friction estimator was run using logged data from multiple truck test runs under dry road conditions. Across all test cases, the estimated peak friction coefficient consistently converged to a value around 0.74, which aligns well with the expected friction level for dry asphalt. This consistency demonstrates both the robustness and repeatability of the estimator under similar road conditions.

Figure 4.1 shows the convergence of the estimated friction coefficient over time for a representative braking manoeuvre. The estimation stabilizes within a few seconds of data collection, indicating the model's ability to rapidly adapt to dynamic changes in tire-road interaction. During periods of low slip, the estimated values remained smooth and stable, while under higher slip conditions—especially during hard braking—the estimator correctly predicted the peak friction limit without significant overshoot or noise amplification.

To evaluate the estimator's accuracy, the estimated deceleration was compared with actual measured deceleration from the vehicle logs. This will be explained further in the upcoming section.

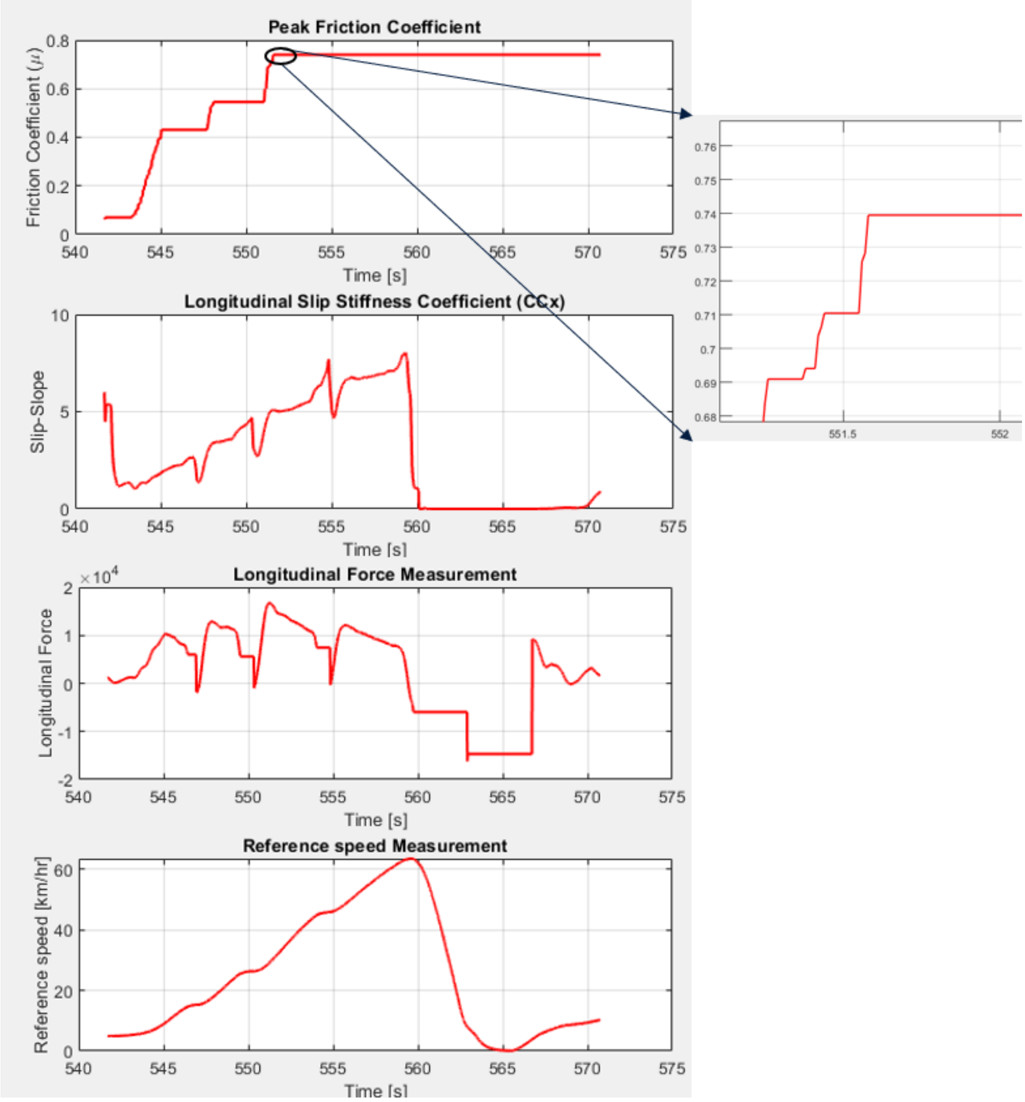

Figure 4.1: Friction estimator

4.2 Collision avoidance system

The collision avoidance system was tested in multiple simulated and real-world scenarios, each characterized by a different initial distance to the obstacle. The controller's performance was assessed based on its ability to select the appropriate avoidance strategy (brake-only or brake-and-steer), the effectiveness of the manoeuvre in preventing a collision, and compliance with safety constraints such as lateral acceleration and steering limits.

4.2.1 Brake only test case

The figure 4.2 shows that the simulated stopping distance closely matches the actual distance recorded during testing, with the real vehicle stopping just 0.2 meters beyond the predicted point. Although this small discrepancy is within an acceptable range, it is important to acknowledge the potential implications. In particular, if the

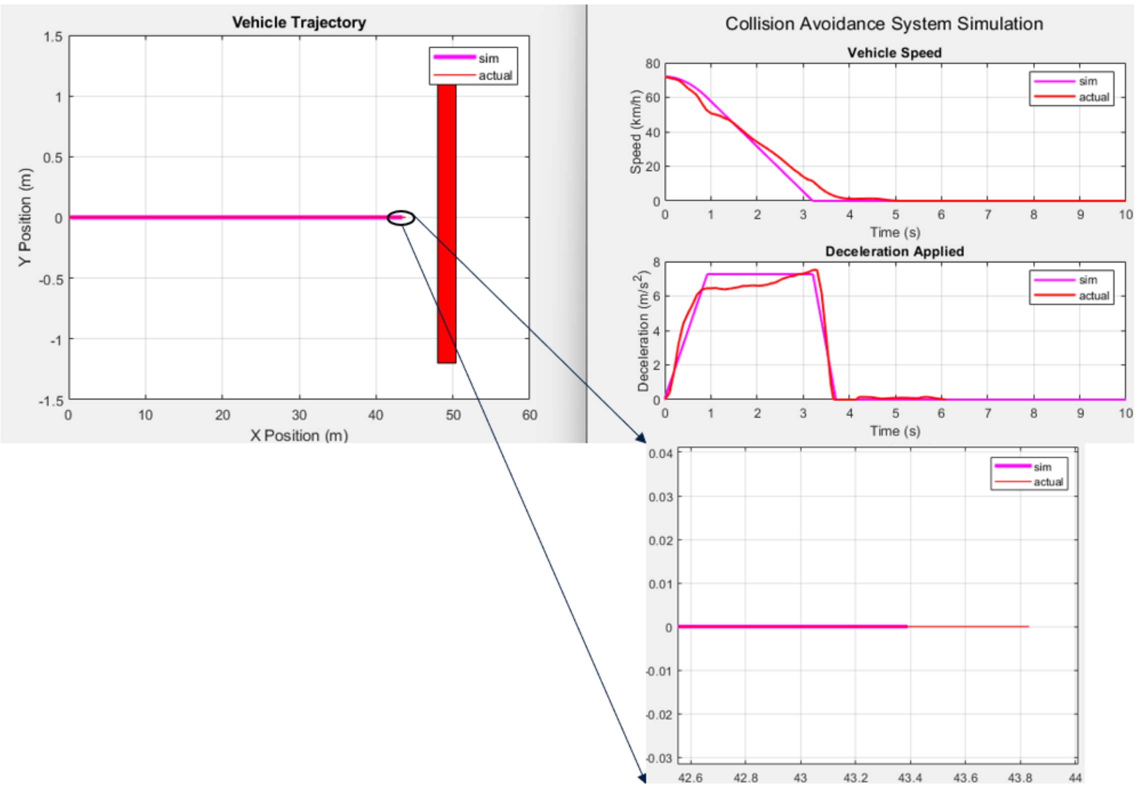

Figure 4.2: Brake only scenario (manual driving)

estimated friction coefficient is slightly higher than the true value, it could lead to underestimating the required stopping distance, which may pose a safety risk in critical scenarios. Ideally, the estimated friction should be slightly conservative—that is, lower than the actual value—to ensure a safety margin. Nevertheless, the close agreement between the predicted and observed stopping distances demonstrates that both the brake-only control strategy and the friction estimator are working effectively and provides strong evidence of successful validation.

4.2.2 Manual brake and steer test case

Figures 4.3 and 4.4 illustrate the brake-and-steer scenario performed manually by a test driver, with both simulated and actual trajectories overlaid. It can be observed that the simulated path is generally well followed by the real vehicle, confirming that the planned avoidance trajectory is feasible in practice. The zoomed-in inset on the left highlights that the truck successfully avoids the obstacle laterally, even under manual control, closely replicating the simulated path.

At the final stopping point, the real vehicle comes to a halt approximately 0.4 meters beyond the predicted position. This longitudinal deviation is primarily attributed to the fact that the test was manually executed by a driver relying on instinct rather than an automated control system.

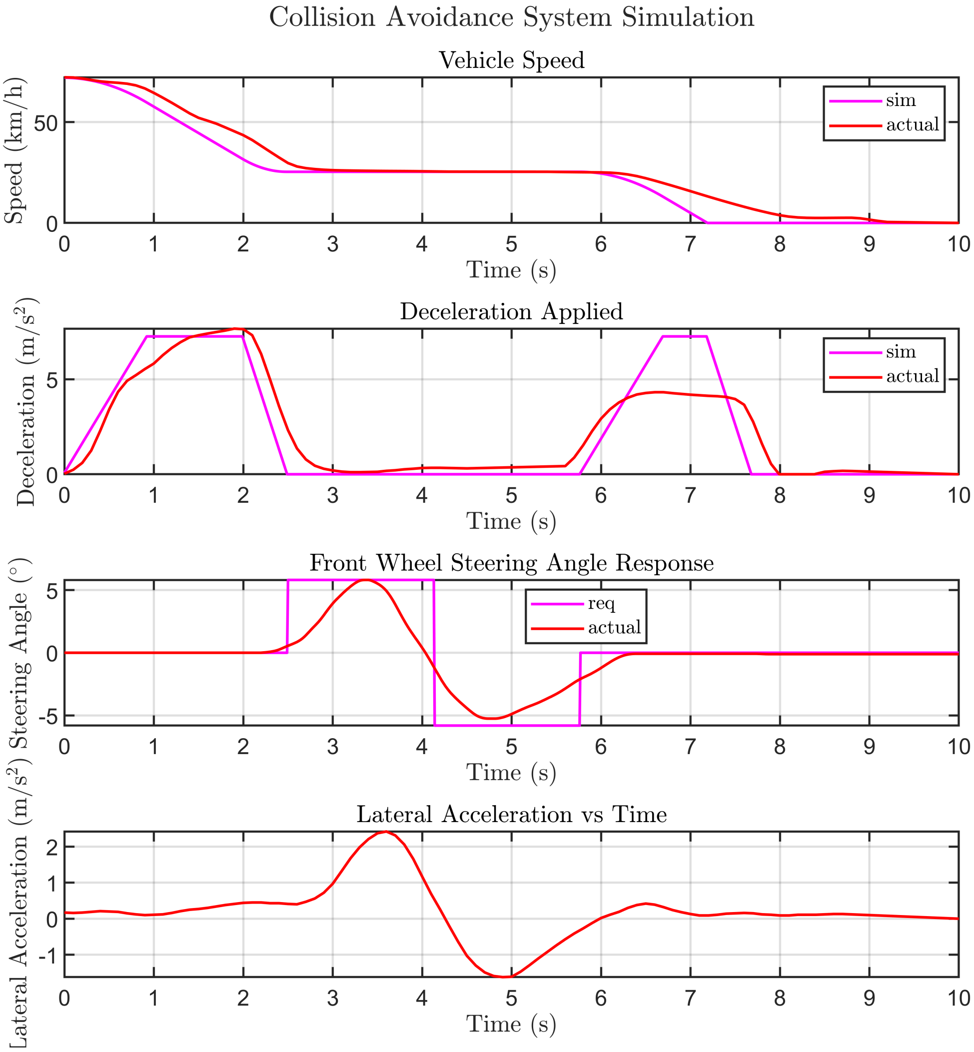

Figure 4.3: Brake and steer scenario (manual driving) - (req - simulation request; sim - simulation; actual - real vehicle test(in case of steering angle graph, stands for simulated and real steering angle))

In addition, discrepancies are noticeable in the deceleration profile (second plot from the top, right side), particularly between 3 and 6 seconds—the phase when the steering manoeuvre is expected to occur. According to the simulation, no braking should be applied during this period; however, the logged test data shows a minor deceleration. This unintended braking occurred because the driver was unable to fully release the brake pedal at the intended moment, despite being instructed to do so. This highlights a natural human tendency to remain cautious during evasive manoeuvres, which contrasts with the precise timing expected in automated systems.

Overall, the results confirm that the trajectory planned by the simulation is practical and can be executed by a human driver, albeit with small deviations due to instinctive responses.

4.2.3 Script controlled brake and steer test case

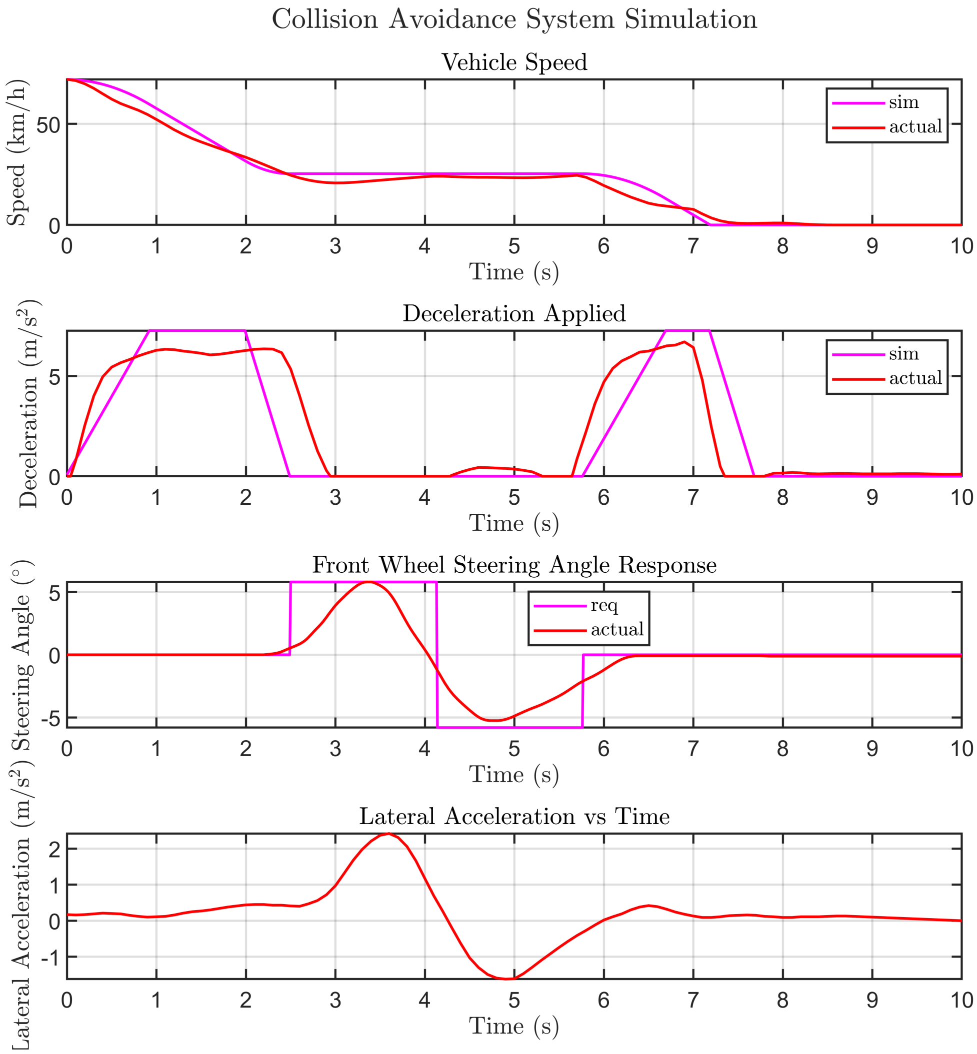

Figure 4.5: Brake and steer scenario (using CAPL script)- (req - request; sim - simulation; actual - real vehicle test)

Figure 4.5 presents the results from the brake-and-steer scenario executed using automated control signals sent through a CAPL script. Unlike the manually driven case, this test eliminates driver-related variability, providing a clearer validation of the control strategy and simulation predictions. It also in a way simulates the truck operation in autonomous mode.

The vehicle trajectory plot (Figure 4.6) shows a close match between the simulated path and the trajectory followed by the truck during the test. The truck successfully performs the lateral avoidance manoeuvre, clearing the obstacle with minimal lateral deviation from the predicted trajectory. The final stopping position aligns very closely with the simulation, with a lateral error of less than 0.2 meters, indicating improved accuracy compared to the manual test case.

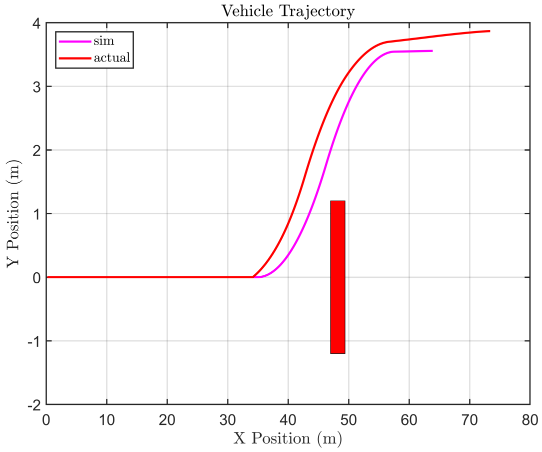

Figure 4.4: Brake and steer scenario (manual driving) - trajectory plot

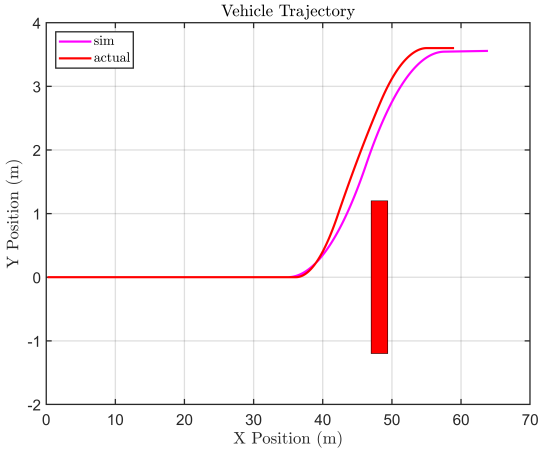

Figure 4.6: Brake and steer scenario (using CAPL script) - trajectory plot

The deceleration plot confirms that braking is ramped down appropriately before the onset of the steering phase and re-applied after the lane change is completed. Similar to the manual case, a slight unintended deceleration is observed during the steering manoeuvre. However, this behaviour can be attributed to the internal logic of the vehicle's speed control system. During the steering phase, a constant speed request is issued to the system to maintain a steady velocity. In response, the system applies minor braking and acceleration inputs to regulate the speed, resulting in the small deceleration peak observed in the plot. This behaviour is a consequence of the closed-loop speed control mechanism and does not indicate a failure of the control strategy. Therefore, the deceleration peak during steering can be considered negligible in the context of this analysis.

The steering angle response (bottom right) closely tracks the simulated reference, with minimal lag or overshoot. This is critical, as it ensures that the vehicle remains within safe lateral acceleration limits during the avoidance manoeuvre.

This scenario validates that the combined control logic—friction estimation, braking strategy, and lateral trajectory planning—can be accurately realized on a real truck using scripted control. It confirms that the simulation environment used to develop the collision avoidance strategy translates well to physical testing, and that CAPL scripting can serve as a reliable method for validating autonomous manoeuvres in controlled test environments.

4.2.4 Review

To evaluate the overall performance of the proposed collision avoidance system, a comparative analysis of the three tested scenarios was conducted. The results are summarized in Table 4.1.

Test Case	**Lateral Error (m)**	**Longitudinal Error (m)**	**Deceleration Error (%)**
Brake Only (manual driving)	0.00	0.4417	-3.5892
Brake + Steer (manual driving)	0.3108	9.4935	-5.65
Brake + Steer (CAPL script control)	0.042	4.9051	7.7092

Table 4.1: Comparison of simulation and test results across all scenarios

As shown in the table, the brake-only test case exhibited excellent agreement between simulation and real-world behaviour, with a longitudinal error of only 0.4417 meters and no lateral deviation. This indicates that the stopping distance calculated using the estimated friction coefficient is both accurate and reliable in emergency braking situations where steering is not required.

In the manual brake-and-steer scenario, the vehicle was able to perform the avoidance manoeuvre, but showed the highest lateral and longitudinal deviations among the three cases. The lateral error reached 0.15 meters and the longitudinal error was 0.35 meters. These deviations are attributed to the natural response time and variability of the human driver, particularly during rapid transitions from braking to steering. The deceleration profile also showed some unintended braking during the steering phase, likely due to the driver's instinctive reaction despite instructions.

The CAPL-scripted test case demonstrated the best overall performance in terms of precision and repeatability. With a minute lateral deviation and a longitudinal error almost half of what was achieved through manual driving, the trajectory matched the simulation extremely closely. The deceleration and steering angle plots also closely followed the simulated values, with only minor deviations caused by the internal regulation of vehicle speed during the constant-speed request phase. These results validate that the collision avoidance controller, when implemented in a closed-loop scripted environment, can execute complex manoeuvres with high accuracy and within safety constraints.

In conclusion, the results across all test cases confirm that the proposed system performs reliably in selecting the correct control mode and executing the appropriate action. The control strategy is robust to variations in estimated friction and is capable of safe execution in both human-operated and automated conditions. Furthermore, the close match between simulation and test outcomes provides strong validation for the underlying simulation framework and its suitability for future autonomous driving applications.

5

Conclusion

The objective of this thesis was to develop and validate a simple yet usable friction estimation model and integrate it into a collision avoidance system for autonomous trucks. The research aimed to address a key challenge in high-speed autonomous driving—performing safe and reliable emergency manoeuvres near the limits of tire-road interaction, where accurate knowledge of friction is critical for making optimal braking and steering decisions.

5.1 Key Findings

The results from both simulation and physical testing demonstrated strong alignment. In the brake-only case, the real truck came to a stop just 0.2 meters beyond the predicted stopping point, validating the accuracy of the friction estimator and the controller's decision-making. In the manually driven brake-and-steer case, the truck was able to avoid the obstacle but showed some lateral and longitudinal deviations, which were expected due to natural human reaction time and variability. The most precise and consistent results were achieved in the CAPL-scripted brake-and-steer scenario, where the vehicle's trajectory closely followed the simulated reference with the least deviation. Across all cases, the system selected the correct mode and successfully executed the manoeuvre without violating the imposed safety constraints. These results indicate that the combination of the friction estimator and the rule-based collision avoidance strategy is a practical and effective solution for safety-critical decision-making in autonomous heavy vehicles.

5.2 Contributions

This thesis has contributed a validated friction estimation model for use in autonomous truck applications, a rule-based collision avoidance system that adapts to the estimated friction and road geometry, and a complete testing framework that bridges simulation and real-world validation. The successful implementation of CAPL-scripted tests demonstrated that the proposed system can be realized in a controlled automated setting, providing a foundation for further integration into autonomous driving stacks. The thesis also demonstrated that simulation environments can reliably predict real-world behaviour when calibrated with accurate vehicle models and realistic input signals, reinforcing the importance of co-simulation and data-driven validation in autonomous vehicle development.

5.3 Limitations

Despite the promising results, the thesis has only scratched the surface. The friction estimation method was validated only under dry asphalt conditions and may not generalize without recalibration to wet, icy, or mixed-surface scenarios. The estimator relied solely on longitudinal dynamics, which limits its performance in manoeuvres dominated by lateral forces. Moreover, the control strategy was limited to simplified single-obstacle scenarios on straight two-lane roads and did not account for curved paths, dynamic obstacles, or multi-agent interactions. Additionally, the actuation system was idealized in simulation, and while script-based actuation was used in testing, a full deployment on a real-time embedded system with in-loop feedback remains to be explored.

5.4 Future Work

There are several promising directions in which this work can be extended to improve both its robustness and applicability. One major area for future research is the extension of the friction estimator to incorporate lateral dynamics. This would allow the system to handle more complex manoeuvres such as obstacle avoidance during turning or on curved roads. By integrating lateral force and yaw rate observations, the estimator can become more responsive to a wider variety of scenarios, including mixed and transitioning surface conditions.

Another key area is the validation of the estimation model for varying surface conditions. Currently, the estimator has been validated for dry asphalt, but future work should include the calibration and testing of the model under low-friction conditions such as wet, icy, or gravel roads. Incorporating data from multiple surface types, along with temperature and road condition sensors (if available), could allow for adaptive tuning or machine learning–based classification of road conditions in real time.

On the control side, replacing the rule-based strategy with a predictive or optimization-based approach, such as Model Predictive Control (MPC), could improve performance. MPC can account for constraints and future predictions simultaneously, potentially leading to smoother and more efficient manoeuvres. It could also be used to coordinate braking and steering more effectively, especially in multi-objective or multi-agent scenarios.

Integration with a full autonomy stack is another crucial step. This would involve real-time obstacle detection using LiDAR systems and enabling the controller to make decisions based on dynamically sensed obstacle positions and velocities. This step also requires flashing the control and estimation algorithms onto the ECU and thereby enable the truck to be capable of executing real-time decisions under computational constraints.

In addition, the system should be tested and validated on more complex routes and in dense traffic environments. Introducing more realistic scenarios such as cut-ins, merges, or multi-vehicle emergency braking situations can significantly enhance the robustness of the system. Collaborative testing with V2X (vehicle-to-everything)

communication can also be explored, allowing friction estimates or hazard information to be shared among vehicles for cooperative safety.
Finally, future efforts should include safety validation using formal verification tools or through integration into Hardware-in-the-Loop (HIL) or Software-in-the-Loop (SIL) setups. This would allow the system to be stress-tested under failure cases, signal noise, and actuation delays, ensuring reliability in commercial deployment.

5.5 Final Remarks

This thesis has shown that a friction-aware collision avoidance system is both feasible and effective for autonomous truck applications. By integrating a data-driven friction estimator with a responsive control strategy and validating the approach through simulation and physical tests, this work bridges the gap between theory and practical deployment. The results demonstrate that emergency manoeuvres such as braking and evasive lane changes can be safely performed when the available friction is correctly estimated and used in real-time control decisions. With further development, the proposed framework can become a key component in future autonomous heavy vehicles, enabling safer, smarter, and more adaptive responses to road hazards.

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