

Neuro-Fuzzy Control of Commercial Vehicles Braking

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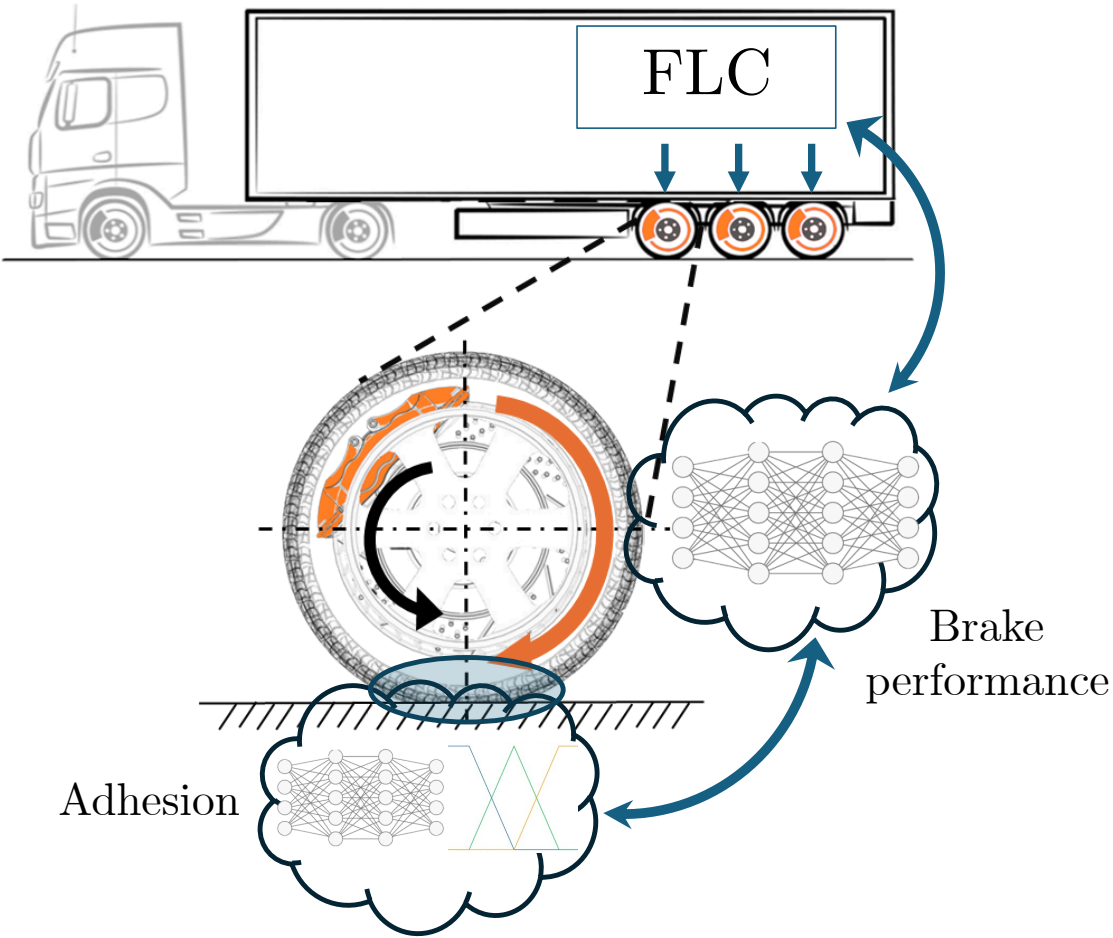
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Abstract

Increasing dynamic performance and the general level of automation of commercial vehicles emphasize the issue of safety. Modern braking systems focus on sustaining vehicle stability, often degrading the brake performance. The major downgrades of the braking performance are nearly impossible to model using a classical mathematical approach, making them not feasible to use in real braking system controllers. In this paper, the use of combined Neural Networks and Fuzzy logic for the control of the braking system of a commercial vehicle while maximizing performance and sustaining stability is proposed. The control system comprises adhesion estimation, an inverse brake model, and a fuzzy logic controller to keep the system giving optimal control signals in various brake conditions while sustaining vehicle stability and steerability. The results based on a semi-trailer system reveal the success of the proposed AI-based braking system algorithm while braking under varying conditions.

Keywords: braking system, fuzzy logic, artificial neural networks, vehicle safety, active safety

Graphical abstract



Abbreviations

ABS Anti-lock Braking System.
AI Artificial Intelligence.
ANFIS Adaptive Neuro Fuzzy Inference System.
ANN Artificial Neural Networks.
EBS Electronic Braking System.
FL Fuzzy Logic.
FLC Fuzzy Logic Controller.
MIMO Multiple Input Multiple Output.
NN Neural Networks.
RL Reinforcement Learning.
RMSE Root Mean Squared Error.
SI Swarm intelligence.
TEBS Trailer Electronic Braking System.

List of Variables

F_z Vertical force at the tyre-road contact point.
 F_φ Longitudinal tyre-road contact force.
 M_b Braking torque.
 T_b Brake temperature.
 $\Delta\varphi$ Predicted and minimal adhesion difference.
 Δp Brake actuation pressure correction.
 ω_r Current angular wheel speed.
 ε_a Difference in demanded and current deceleration (deceleration error).
 φ Adhesion coefficient.
 φ_{est} Estimated adhesion coefficient.
 φ_{min} Minimal adhesion coefficient needed to achieve demanded deceleration.
 a_r Current longitudinal vehicle deceleration.
 m Vehicle mass.
 p_b Brake actuation pressure.
 p_p Predicted brake actuation pressure.
 p_r Current brake actuation pressure.
 p_{sug} Suggested brake actuation pressure.
 r_d Dynamic wheel radius.
 v Longitudinal speed of the vehicle centre of mass.

1 Introduction

The automotive industry is constantly evolving at a rapid pace with advanced technologies supported by artificial intelligence. It leads to new breakthroughs and innovations in the field. The focus of this industry is always set on improving safety, efficiency, and performance. In order

to enable this, the automotive control system must cope with environmental complexities coupled with structured and unstructured uncertainties (Taghavifar and Shojaei, 2023). The new and changed requirements can be expected at the mobility level, vehicle level, system level, and component level (Vey, 2019). Since motor vehicles and trailers are becoming more advanced, automated, and autonomous, there is a growing need to prioritize their safety. To address these concerns, new control strategies for braking systems need to be developed. It is especially related to active safety. A significant portion of incidents that endanger a vehicle's safety arises when the operator attempts to decelerate without considering the vehicle's performance in environmental circumstances. Due to their size and mass, commercial vehicles are more prone to serious crash consequences and can be exposed to a greater risk of collision (Grinerud, 2022). Active safety of this type of vehicle is always given a high priority since the accidents involving these vehicles are often fatal. Ensuring a high performance level and stability of commercial vehicles is crucial for their safe operation under all driving conditions. That is why modern active safety systems, which rely on braking system performance, such as Anti-lock Braking System (ABS), Electronic Braking System (EBS), and Trailer Electronic Braking System (TEBS), emphasize performance, traffic safety, and roadworthiness. Such control systems base their algorithms mainly on wheel slip control, which indeed showed great results in terms of sustaining stability and steerability of a vehicle (Gaurkar et al, 2022). The major disadvantage of the wheel slip control is that the wheel slip cannot be measured directly, it must be estimated. Moreover, a braking system can be considered as a complex Multiple Input Multiple Output (MIMO) system that exhibits highly nonlinear dynamics. As a consequence, the braking process is hard to precisely model using a classical mathematical approach (Amirkhani and Molaie, 2023).

The computerization of vehicles has significantly impacted their functionality, resulting in a dynamic development of vehicle control systems in response to customer and societal needs and requirements (Kiencke and Nielsen, 2000). This progress has led to a shift towards more advanced Artificial Intelligence (AI)-based control techniques, which have shown great potential in

enhancing the performance, safety, and efficiency of vehicle control systems (Mohamed et al, 2023). AI control systems, powered by advanced algorithms and machine learning techniques, enable vehicles to make intelligent decisions and adapt their behavior based on real-time data and environmental conditions. Integration of AI into vehicle braking control systems, proposed in this paper, aims to optimize various aspects of vehicle operation, including performance, stability, and safety during the braking process.

The advantages of AI-based features utilized in this research are found in the power of precise input-output mapping of the braking model and its influencers using Artificial Neural Networks (ANN) and Fuzzy Logic (FL). ANNs proved themselves to be a powerful tool for creating valid models based on data from real systems. They can capture complex and nonlinear relationships that are often difficult to express using conventional mathematical models. On the other hand, recent advances in fuzzy methods have emerged as effective for addressing various modern challenges (Baranidharan et al, 2024). FL facilitates the development of complex systems by enabling the creation of heuristic control strategies through natural-language rules rather than mathematical models (Mehraban et al, 2024). Therefore, the implementation of human intuition and experience in vehicle system control strategy can be enabled by applying FL in systems (Srivastava and Kumar, 2024).

That is why a new strategy for braking system control has been introduced in this paper by developing a new control strategy for commercial braking system control using artificial intelligence. The control is based on a developed new model of the brakes' performance in synergy with the new model of tyre-road adhesion conditions estimation during a braking cycle. These models were integrated into the new control strategy for the brake actuation pressure control, providing braking performance adjusted to the desired performance, changes in adhesion conditions, and vehicle stability requirements.

The paper is structured on following way: Section 2 summarizes the relevant state of the art in the field of intelligent braking system control, providing new possibilities for further improvements; Section 3 provides traditional brake dynamic fundamentals with the emphasis on

the problems related to the use of such mathematical models in the braking system control; Section 4 is related to explanation of a new proposed neuro-fuzzy control strategy; Section 5 explains details about the implementation of such control strategy; Section 6 shows evaluation of developed models and introduced neuro-fuzzy control strategy; Section 7 provides the results of complete neuro-fuzzy in various braking cycles with discussion; Section 8 is related to conclusions and future work.

2 State of the art

Contrary to the classical mathematical approach, there is a constant tendency to use cutting-edge tools and techniques to create and design systems and subsystems of motor vehicles and trailers that are more reliable, safe, and sustainable. AI, as one of those techniques, is not a novelty to the automotive industry (Zhang and Lu, 2021). AI applications in braking system control are summarized in Table 1. Some of the applications were introduced through the optimization of wheel slip control using AI for further enhancing the controller's anti-lock capabilities (Ćirović et al, 2013b; Gounis et al, 2022; Ćirović et al, 2013a). Good results in the field of use of AI for the purpose of intelligent control of braking systems are related to machine learning techniques using Neural Networks (NN) often in synergy with FL. These techniques have been widely used regarding braking system control. A substitution for a standard ABS is proposed in research by Lin and Le (2017), with a self-organizing fuzzy neural network controller supported with a compensation controller for removing approximation error. Another enhancement of ABS is proposed by Sharma et al (2023) with the use of an Adaptive Neuro Fuzzy Inference System (ANFIS) together with a PID controller. A braking control strategy that showed good results is the use of ANN for modeling and the prediction of the brake performance (Aleksendric et al, 2008; Aleksendrić et al, 2012). Furthermore, use of Reinforcement Learning (RL) was proposed in (Vodovozov et al, 2023; Abreu et al, 2023), and Swarm intelligence (SI) (Zhang et al, 2022) for a braking process control.

In the case of commercial vehicles, the load state of the vehicles should be taken into consideration. Examples of the research that tried to

Table 1: Summarized use of AI for the braking control in the literature.

Work	Braking control strategy	Adhesion considered	Vehicle type	Brake performance considered	Different laden states
Ćirović et al (2013b)	NN wheel slip control	Indirectly	Commercial	✓	✓
Gounis et al (2022)	NN wheel slip control	Yes, Pacejka	Car	x	x
Ćirović et al (2013a)	NN wheel slip control	Indirectly	Commercial	✓	✓
Lin and Le (2017)	Fuzzy-neuro ABS	Indirectly	Car	x	x
Aleksendric et al (2008)	NN controller	No	Car	✓	x
Aleksendrić et al (2012)	NN controller	No	Car	✓	x
Mei et al (2022)	FL sliding-mode control	Indirectly	Car	x	x
Ming (2023)	FL control	No	Car	x	x
Vodovozov et al (2023)	RL control	Yes, Pacejka	Car	x	x
Abreu et al (2023)	RL control	Yes, FTire	Car	x	x
Ivanova et al (2024)	Fuzzy PID controller	Indirectly	Car	x	x
Sharma et al (2023)	ANFIS ABS	Indirectly	Car	x	x
Zhang et al (2022)	Swarm intel. control	Yes, Pacejka	Commercial	x	x
Our paper	Fuzzy-neuro control	Yes, novel fuzzy-neuro model	Commercial	✓	✓

take this in a braking control algorithm design are shown in ([Šarkan et al, 2020](#); [Tamaddoni and Taheri, 2008](#); [Nieto et al, 2018](#)). The Importance of tyre-road interaction modeling has been recognized as a significant parameter for introducing any control of the braking system. According to the Table 1, the majority of studies indicate that the road-tyre adhesion condition is not taken directly into account when designing the control strategy. Research works that utilize wheel slip in the control consider adhesion indirectly, through

the estimation of the wheel slip. Published work that uses adhesion directly in control uses Pacejka’s model or FTire model ([Gounis et al, 2022](#); [Zhang et al, 2022](#); [Vodovozov et al, 2023](#); [Abreu et al, 2023](#)). The lack of these investigations is using Pacejka’s model. That model is complex and practically unusable for application in real control strategies. On the other hand, the FTire model gives good results only on rough terrain. The current state-of-the-art in braking control of

commercial vehicles needs improvement to optimize braking performance, taking into account the tyre-road interactions (Tung, 2021; Tung et al, 2020).

The analysis presented in Table 1 reveals a significant gap in the current state of the art. The main problem is that there is no model of the brakes' performance nor an applicable model of tyre-road adhesion conditions, which are incorporated into the braking system control strategy. This represents a notable limitation in many existing studies, as knowing braking performance together with tyre-road adhesion condition is a crucial factor in the overall braking system dynamics, as evidenced by Equations 3 and 4. This led to suboptimal control strategies and potentially compromised braking performance. Furthermore, Table 1 illustrates that the majority of related studies did not assess their proposed solutions under different laden states. While this omission may not significantly impact AI-based braking control applications in passenger vehicles, it introduces substantial limitations for commercial vehicle applications. The relevance of vehicle laden state is expressed in Section 3, more specifically through Equations 4 and 5.

On one hand, as evident from the related work mentioned so far, the use of neural networks, fuzzy logic, or a combination has proven to be successful and is not a novelty. On the other hand, how the complete control architecture is designed has a big impact on the stability, performance, safety, and applicability of the research. The key novelty in the paper is related to the development of a Neuro-Fuzzy controller that directly takes into consideration the estimation of adhesion conditions in order to maximize braking performance while maintaining vehicle stability. The relevance of adhesion conditions for the braking cycle is depicted in Equations 1 and 2. The aim is to create a control algorithm that adjusts the brake activation pressure in real time based on the desired deceleration by the driver, the vehicle load state, the estimated level of tyre-road adhesion, and an inverse model of the brakes' performance.

The summarized primary contributions of the current paper are delineated in terms of the following:

- Novel concept of Neuro-Fuzzy control, including neural network inverse brake model, fuzzy-neuro adhesion model, and fuzzy logic controller to maximize braking performance is proposed, and evaluated.
- The proposed Neuro-Fuzzy brake control strategy considers the commercial vehicle load state.
- The proposed Neuro-Fuzzy brake control strategy directly considers tyre-road adhesion conditions estimation using the fuzzy-neuro adhesion model.
- The proposed Neuro-Fuzzy brake control is based on the developed inverse model of brake performance, able to predict the control pressure signal versus the desired deceleration, current speed, and the brake temperature.

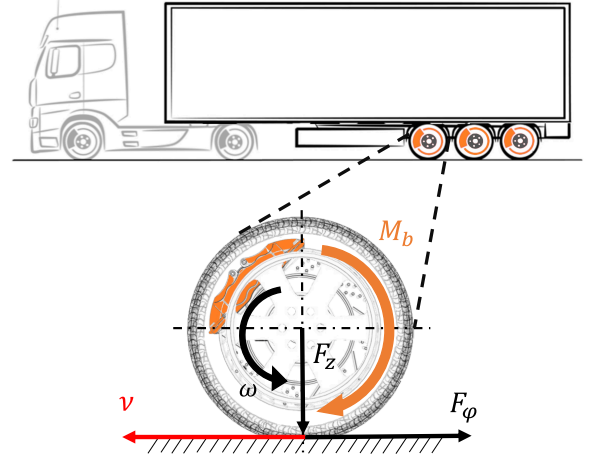


Fig. 1: Three-axle semi-trailer with wheel dynamics during the braking process.

3 Commercial vehicle braking

The proposed braking strategy will be implemented in the case of a three-axle semi-trailer, Figure 1. This kind of vehicle is a typical representation of a vehicle whose braking system should be better controlled regarding possible traffic fatalities. The importance of this lies in the complex working conditions that need to be taken into consideration to provide the desired braking performance and traffic safety. The braking performance of these vehicles has been based on one-wheel dynamics for a long period of time. Using

the single-corner mathematical model (Sousa and Ayala, 2020), the motion equations can be defined as described by Equations 1 and 2.

$$J\dot{\omega} = r_d F_\varphi - M_b, \quad (1)$$

$$m\dot{v} = -F_\varphi. \quad (2)$$

In order to be able to create a good control algorithm for decelerating a vehicle based on the set of motion equations, see Equations 1 and 2, longitudinal tyre–road contact force F_φ and braking torque M_b have to be well defined. It should be kept in mind that there is not a linear relation between the angular speed of the wheel ω and the longitudinal speed of the vehicle centre of mass v due to the wheel slip phenomenon.

Deceleration of a wheel, and therefore a whole vehicle, during the braking process, depends directly on the braking torque M_b . Braking torque generated by the brake actuation pressure is a complex variable. The analysis and experience showed that the braking actuation pressure, brake temperature, and the wheel translation speed strongly affect the braking torque, see functional relation 3.

$$M_b = f(p_b, T_b, v). \quad (3)$$

In order to transfer a torque generated by the brake, a road–tyre adhesion level is required. It is known that the force generated by the tyre–road interaction F_φ is considered very stochastic and nonlinear (Kaliske et al, 2021). The braking force depends on an adhesion coefficient φ that could be determined or estimated under some conditions. Despite the complexity of the existing physical and numerical models of tyre–road interaction, their prediction accuracy of parameter influences remains too inaccurate to be relied upon. As a result, most braking controller applications have neglected the direct influence of this variable. Neglecting the effect can lead to a decrease in braking performance, especially in adverse weather and road conditions. The proposed research developed AI methods driven by real data to estimate the current influences on adhesion conditions during a braking cycle, instead of relying on improved physical models for calculations.

The vehicle’s laden state is another parameter that should be taken into consideration. It is

important because in this case, the semi-trailer’s axle group load can vary from an unladen state of 11550kg to a laden state of 36000kg. A simple transformation of Equations 1 and 2 can demonstrate the relevance of vehicle mass and its effect on the wheel dynamics during the braking process, see Equations 4 and 5.

$$J\dot{\omega} = r_d F_z \varphi - M_b, \quad (4)$$

$$m\dot{v} = -F_z \varphi. \quad (5)$$

In order to solve these equations and have a state-based mathematical model prone to control purposes, the use of limiting simplifications is mandatory (Savaresi and Tanelli, 2010). As a result, classical approaches have been limited in developing a suitable control algorithm. Efforts have been made in order to precisely model the trailer’s braking system (Tung, 2021; Tung et al, 2020), but so far only partial success has been made. The authors have highlighted the difficulties related to the use of classical mathematical models for the modeling of the braking systems of semi-trailers. Accordingly, many feedback control systems were introduced to improve the semi-trailer’s stability and handling comfort, such as the work done by Tamaddoni and Taheri (2008).

4 Neuro-fuzzy control strategy

This paper proposes a novel approach of Neuro-Fuzzy control of the braking system, addressing the problems and limitations of conventional controllers discussed in the previous section. The Neuro-Fuzzy controller’s objective is to determine the optimal brake actuation pressure at each discrete time during a braking cycle. This control signal aims to meet the driver’s deceleration request, taking into consideration the current brake capabilities and available tyre–road adhesion conditions. The control strategy proposed in this paper is depicted in Figure 2. Green-coloured blocks represent FL, and the blue ones represent the ANN-based models. The adhesion model utilizes both AI-based techniques therefore it is represented in such a way.

The input of the proposed neuro-fuzzy braking system control is the demanded brake actuation pressure that originates from the driver. The

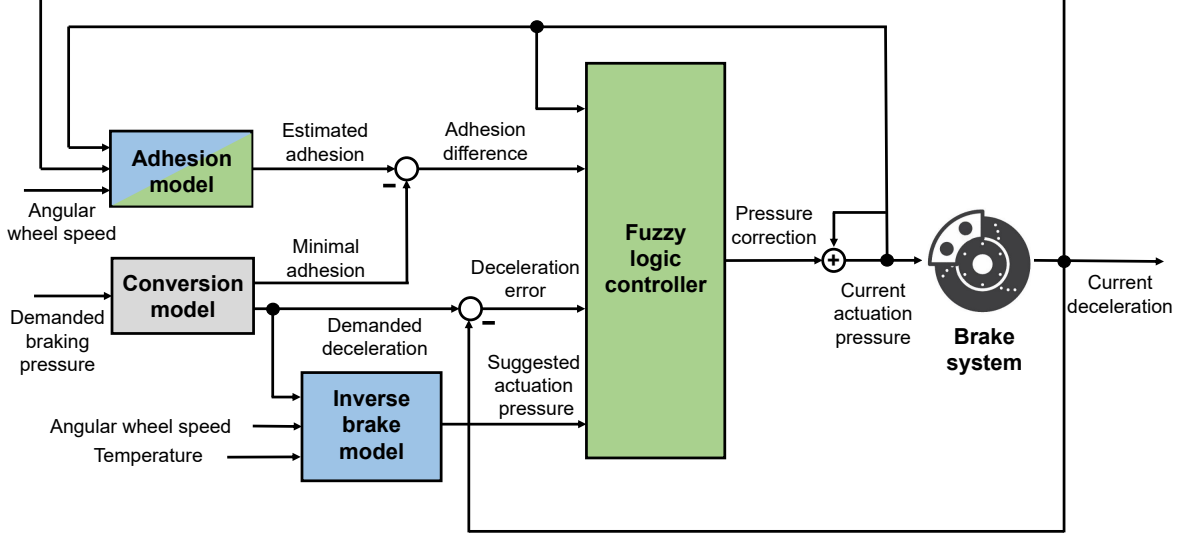


Fig. 2: The modular architecture of neuro-fuzzy braking control system (modules for: conversion of driver demands, tyre-road adhesion estimation, inverse brake performance prediction, and fuzzy logic controller).

variations in the vehicle's load state, brake temperature, vehicle speed, and tyre-road adhesion, for the same braking pressure, can invoke different decelerations. Apparently, in cases of low tyre-road adhesion, the desired deceleration can not be achieved. Further pressure increase can cause wheels to lock and loss of vehicle stability, affecting traffic safety and roadworthiness. Therefore, the main requirement of the braking system is to maximize the vehicle brake performance without compromising vehicle stability, depending on current tyre-road adhesion conditions in a longitudinal direction. The first block that shapes the input from the driver is the conversion model. The output of this block is the demanded deceleration. This deceleration requires a minimal tyre-road adhesion coefficient. The brake demand converter transfers driver demands into the brake actuation pressure that should provide the desired vehicle deceleration using a developed inverse model of brake performance.

The inverse model of brake performance is ANN-based, and it is used as an advisory part of the controller to suggest the needed brake actuation pressure. The ANN can provide an effective way to model the braking system performance by learning the relationships between the input and output variables from real data. The model takes

the demanded deceleration as an input and predicts the brake actuation pressure that is needed to achieve the desired deceleration. Moreover, the model also takes the brake's current temperature and wheel angular speed as additional inputs. The brake temperature is an important factor that should be taken into account during designing the brake system controller (Irawan et al, 2022), as shown in the functional relation 3. A high temperature of the brakes can cause a significant drop in braking performance. This enables a more comprehensive and accurate control strategy that is able to adjust the brake performance versus variations in these influencing factors. The signal output of the inverse brake model is represented in the form of suggested brake actuation pressure, which is later fed to the Fuzzy Logic Controller (FLC).

Selecting the appropriate brake actuation pressure for the specific braking situation requires knowledge of tyre-road adhesion conditions. The adhesion estimation model has been developed to support the decision related to the selected brake actuation pressure. The model works in parallel with the inverse brake model. Estimation of the current tyre-road adhesion conditions φ is the key factor that affects the final braking performance, i.e. vehicle deceleration. This is shown in the Equations 4 and 5. The fuzzy logic approach to modeling tyre-road adhesion has already been

used by [Jayachandran et al \(2013\)](#). The model developed in this paper provided that changes of the wheel deceleration, angular speed, and the brake actuation pressure versus time were taken into account during a braking cycle. It provides tyre-road estimation versus braking time and adjustment of the brake actuation pressure during braking. This was done by combining fuzzy logic and artificial neural networks (neuro-fuzzy model) to construct the tyre-road adhesion estimation block. A combination of expert knowledge through fuzzy modeling and extending the model with neural networks provided greater flexibility and fast response. This hybrid neuro-fuzzy approach allows the model to benefit from the interpretability and transparency of the FL while having the pattern recognition capabilities of neural networks to enhance the overall predictive performance. The expert knowledge was used in modeling the correlation between the angular deceleration of the wheel, current deceleration of the trailer, and brake actuation pressure in the estimation of the adhesion coefficient, see Figure 2.

It was important to develop a block that takes into account the effect of tyre-road interaction together with the current brake capabilities (inverse brake model). The heart of the proposed neuro-fuzzy braking system controller is the FLC). The main purpose of the FLC is to avoid the limitations caused by the use of conventional control strategies, see Equations 4 and 5. FLC-based systems are the one control strategy preferred with their adjustable, adaptable features, flexibility, and robust structure against uncertainty ([Beşkardeş et al, 2024](#)). It combines the information from the inverse brake model, adhesion estimation model, current control signal, and deceleration (output) error. Therefore, the FLC model takes four input variables: suggested actuation pressure from the inverse brake model, deceleration error represented as the difference between demanded and real vehicle deceleration, the difference between estimated and minimal required adhesion coefficient, and current actuation pressure. Combining all these data relevant to the braking system operation, the fuzzy controller adjusts the brake's actuation pressure. Pressure correction outputted from the fuzzy controller adds to the current braking actuation pressure and generates the final brake control signal, see Figure 2.

5 Neuro-fuzzy brake controller implementation

Upon careful analysis of the proposed strategy from a theoretical standpoint, it becomes evident that it offers a wide range of significant benefits. The implementation of models and subsystems shows the real overall advantages and boundaries of the proposed controller.

5.1 Implementation of inverse brake model

The inverse brake model was trained based on data obtained during testing of the brakes using the full-scale inertial dynamometer. For the purposes of this research, data were acquired from the brake test bench with a frequency of 50Hz, the setup of the test bench was explained by [Aleksendrić \(2010\)](#). The following data were available during the brake testing: brake actuation pressure, brake temperature, angular wheel speed, and calculated vehicle speed (for known tyre radius), braking force based on the calculated deceleration. The brake testing methodology was chosen to provide data about the cold brake performance (temperature below 100°C), performance during the brake fading test (hot performance), and the brake recovery performance, after the fading test. Based on that, the data related to the brakes' performance covered the whole range of pressure, speed, and temperature change. Later in the paper, just a few characteristic braking cycles (cold and hot brakes) will be shown to illustrate the inverse model capabilities to predict the brake actuation pressure versus temperature-speed change in a braking cycle. The first scenario will be with the cold brake ($\sim 100^\circ\text{C}$) with initial vehicle speed between 30 km/h and 80 km/h and braking pressures ranging from 1 to 6.5 bar. The second one is with the hot brakes ($\sim 260^\circ\text{C}$). This approach ensured a reliable mapping of the brakes' performance in different braking situations. Recorded data of the brake performance was used for ANN model training. The inputs of the ANN inverse brake model were deceleration, the brake temperature, and wheel angular speed. The output was the brake actuation pressure. The data were split into training data and test data sets. The model was trained iteratively until the most

precise model was obtained. The ANN architecture of the model that showed the best prediction performance was 3 [3, 4] 1, meaning 3 input neurons, the three neurons in the first hidden layer, 4 neurons in the second hidden layer, with 1 neuron at the output layer. The training process was done with the Bayesian method.

5.2 Implementation of fuzzy-neuro adhesion model

The model for estimation of the tyre-road-adhesion coefficient was developed using FL. The output of the FL adhesion model serves as a basis for further actions of the fuzzy controller. The inputs and output of the model are shown in Figure 3. The fuzzy process was initiated by defining the fuzzy membership function of all input/output variables. The input variables are assigned with three linguistic values: small (S), medium (M), and large (L). The adhesion coefficient as the output was extended with two more linguistic values, medium-small (MS) and medium-large (ML), for a more precise result. Linguistic variables used for defining the fuzzy model of tyre-road adhesion, with their ranges are shown in Figure 3. The most important step is related to defining the knowledge base fuzzy rules. These rules define dependencies between inputs and output. The number of rules that were used in this research is 27. The fuzzy rules incorporated in the model are shown in Table 2. Mamdani's fuzzy method is picked for the mathematical implementation of the adhesion model, where a minimum function was used for the intersection operator, and the maximum function was used for the union operator.

Data for training the ANN model, able to learn and generalize adopted fuzzy rules, was generated using cross-combined input/output data. The ranges of input/output variables are shown in Figure 3. After the process of ANN model training and testing, the best performance was obtained with the Bayesian algorithm and with ANN architecture 3 [3, 5] 1, with 3 neurons in the first, and 5 neurons in the second hidden layer.

5.3 Implementation of fuzzy logic controller

The key objective of the FLC is to harmonize the tyre-road adhesion with the current brake performance, represented by the inverse brake model. Based on that, FLC adjusts the optimal brake activation pressure in every braking cycle. The use of proposed FLC enables the implementation of expert knowledge and experiential insights into the control strategy, eliminating the need for using mathematical models that have severe limitations for real application.

The input values of current (p_r) and suggested actuation pressure (p_{sug}) are represented by three linguistic variables each, similar to the input variables of fuzzy adhesion model [S-small, M-medium, L-large], see Figure 4. Deceleration error (ε_a), adhesion difference ($\Delta\varphi$), and fuzzy controller output variable of pressure correction (Δp) can have both positive and negative values, these variables are represented with linguistic variables such as: negative large (NL), negative medium (NM), negative small (NS), null (N), positive small (PS), positive medium (PM) and positive large (PL). The input signals are normalized before entering the controller. The values of p_r and p_{sug} are set in the range [0, 1], and inputs ε_a and $\Delta\varphi$ are normalized to the range [-1, 1], before entering the fuzzy controller. The triangular membership functions are chosen for all linguistic variables due to their simplicity of calculation. The membership functions are equally distributed to the variable's range, see Figure 4.

The FLC was based on the rules that define the adopted control strategy. The total number of fuzzy rules is 441, which were implemented with the Mamdani fuzzy method of conclusion (Iancu, 2012). AND logical connector is used in all cases, through the union operator. Relevant fuzzy rules are shown in Table 3. The rules are designed in such a way that the highest influence on the output decision had the inputs ε_a and $\Delta\varphi$ for successful convergence to the demanded or possible deceleration versus adhesion conditions. This will ensure that the braking performance and the vehicle safety are provided, keeping the vehicle stable during braking. The input variables p_r and p_{sug} were used for intelligent support of the FL decision-making. It ensures current brake activation pressure corrections based on the current

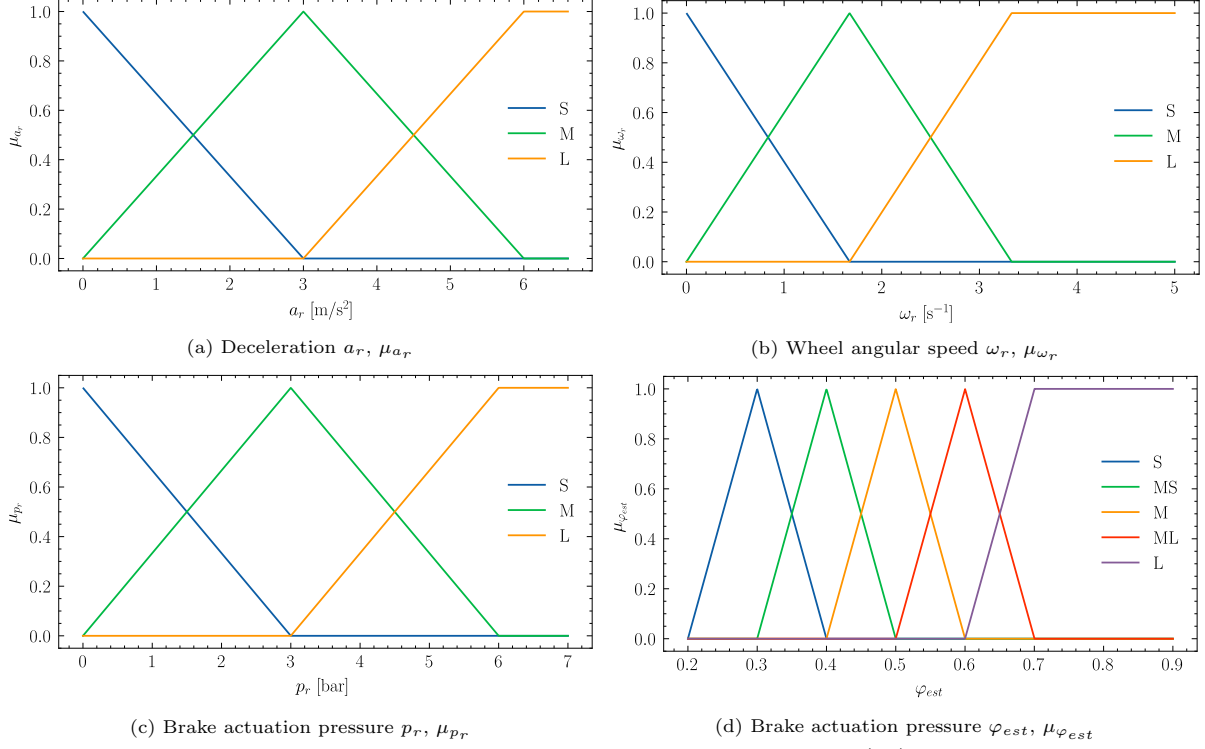


Fig. 3: Membership functions of the fuzzy adhesion model: deceleration (a_r) 3a, wheel angular speed (ω_r) 3b, brake actuation pressure (p_r) 3c, estimated adhesion coefficient (φ_{est}) 3d.

Table 2: The tyre-road adhesion model fuzzy rules for input (a_r , p_r , ω_r) and output (φ_{est}) linguistic variables mapping.

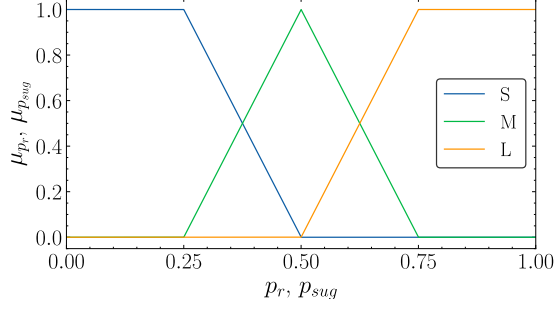
No.	a_r	p_r	ω_r	φ_{est}	No.	a_r	p_r	ω_r	φ_{est}	No.	a_r	p_r	ω_r	φ_{est}
1	S	S	S	M	10	M	S	S	ML	19	L	S	S	L
2	S	S	M	MS	11	M	S	M	M	20	L	S	M	ML
3	S	S	L	S	12	M	S	L	MS	21	L	S	L	ML
4	S	M	S	S	13	M	M	S	L	22	L	M	S	L
5	S	M	M	MS	14	M	M	M	ML	23	L	M	M	ML
6	S	M	L	MS	15	M	M	L	M	24	L	M	L	M
7	S	L	S	S	16	M	L	S	ML	25	L	L	S	L
8	S	L	M	S	17	M	L	M	M	26	L	L	M	L
9	S	L	L	S	18	M	L	L	MS	27	L	L	L	ML

brake performance (inverse brake model) and the current control signal.

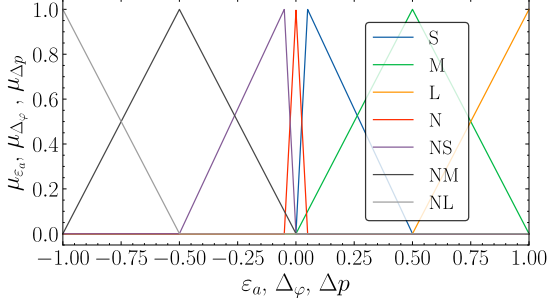
6 Verification of Neuro-Fuzzy brake controller

The verification of the models used for the control strategy was done to represent the quality and

transparency of the results from the braking cycles results shown in Chapter 7. Each of the models is represented with an appropriate evaluation technique that best represents the AI technique used to create a model.



(a) Real and suggested brake activation pressure p_r, p_{sug}



(b) Deceleration error ε_a , adhesion difference $\Delta\varphi$, activation pressure correction Δp

Fig. 4: FLC model membership functions, 4a the input: brake activation pressure real p_r and suggested p_{sug} ; 4b the input: deceleration error ε_a , road-tyre adhesion difference $\Delta\varphi$, and output: correction of brake activation pressure Δp .

6.1 Verification of the inverse brake model

For the evaluation of the inverse brake model, two criteria were used: Root Mean Squared Error (RMSE) and coefficient of determination (R-squared). The trained model showed a satisfyingly low error that is represented in values of RMSE = 0.281 and R-squared = 0.978. A low value of RMSE and a high value of R-squared have practical implications that the trained model shows performance close to the real braking system. The performance of the trained inverse brake model is presented in Figures 5 and 6. Two characteristic braking cycles were taken to test the model for the worst-case scenario at the limit of the ranges used for the model training. Figure 5 shows verification of the neural network model performance regarding brake actuation pressure change versus the real one obtained on the test bench. The model in this

Table 3: FLC fuzzy rules - relevant examples. The total number of fuzzy rules engaged is 441, therefore only the relevant part is illustrated.

No.	p_r	p_{sug}	ε_a	$\Delta\varphi$	Δp
1	S	S	NL	NL	N
2	S	S	NL	NM	N
3	S	S	NL	NS	N
142	S	L	PL	NM	PS
143	S	L	PL	NS	PS
144	S	L	PL	N	PM
145	S	L	PL	PS	PM
146	S	L	PL	PM	PM
248	M	L	NL	NS	NM
249	M	L	NL	N	NM
250	M	L	NL	PS	NM
255	M	L	NM	NS	NS
256	M	L	NM	N	NS
257	M	L	NM	PS	NS
262	M	L	NS	NS	NS
263	M	L	NS	N	NS
264	M	L	NS	PS	NS
276	M	L	PS	NS	PS
277	M	L	PS	N	PS
278	M	L	PS	PS	PS
283	M	L	PM	NS	PS
284	M	L	PM	N	PM
285	M	L	PM	PS	PM
416	L	L	N	NS	N
417	L	L	N	N	N
418	L	L	N	PS	N

case predicted the actuation pressure successfully, with the largest offsets at the beginning of the braking cycle. The model successfully mapped the braking actuation pressure and the influence of speed and brake temperature T_b , as depicted in the functional relation 3. During the dynamic change of real actuation pressure in the later stages of the braking cycle, the model achieved high precision. It should be noted that the trained model highly resembles a real correlation between input/output quantities. It is expected that mapped brake pressure-temperature-speed sensitivity could be changed during vehicle use, and therefore increase the RMSE of the trained model. This will be overcome by appropriate brake pressure correction done by FLC or by introducing the online ANN model recalibration using the data from every new braking cycle.

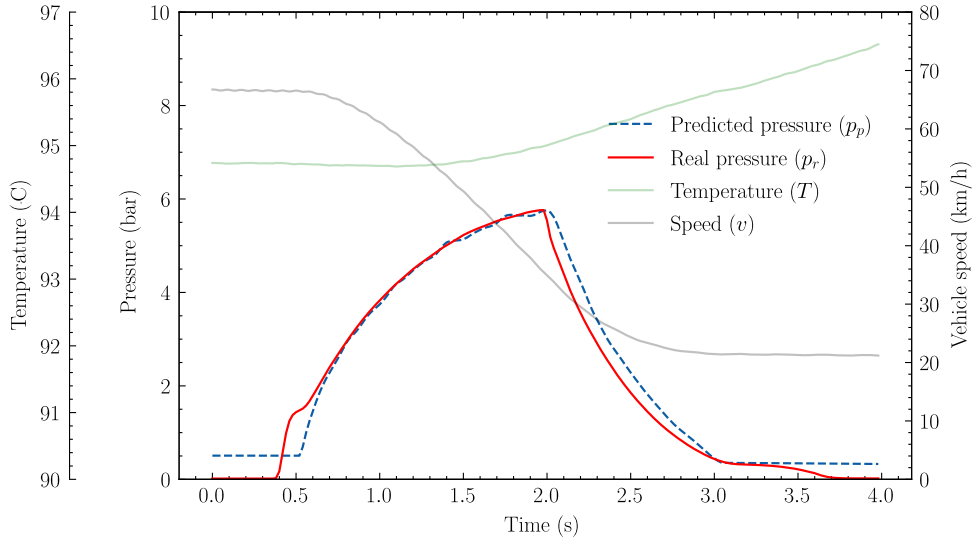


Fig. 5: The inverse brake model performance verification. A comparison of predicted and measured values of the brake actuation pressure during a braking cycle - cold brake performance ($< 100\text{ }^{\circ}\text{C}$).

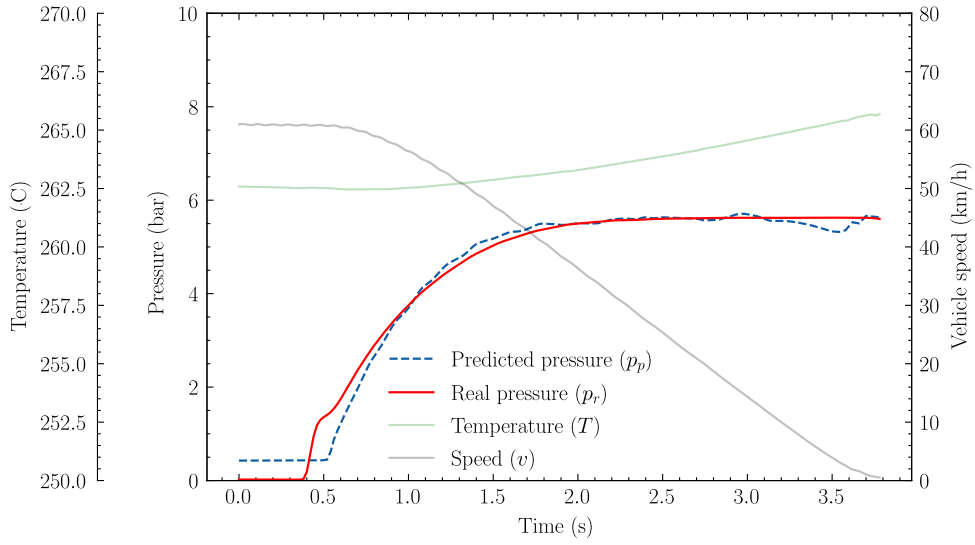


Fig. 6: The inverse brake model performance verification. A comparison of predicted and measured values of the brake actuation pressure during a braking cycle - hot brake performance ($> 250\text{ }^{\circ}\text{C}$).

Since the brake performance has been strongly influenced by the brake temperature, Figure 6 shows model verification in the case of high temperatures of the brake. This verification was done

in the case of a hot brake when the brake temperature had been first increased by 20 consecutive braking cycles. The inverse braking model, in this case, has also shown acceptable prediction performance regarding the brake actuation pressure

needed for selected deceleration, see Figure 6. The beginning of the braking cycles shows the same limitations as with the cold brake, in terms of the first milliseconds of the braking cycle.

6.2 Verification of adhesion model

Verification of the tyre-road adhesion model is shown in Figure 7. The Figure contains three mesh 3-D surfaces and represents the output of the neuro-fuzzy model. The colored surface represents estimated values of the adhesion coefficient for ranges of input values. Since three input variables together with output create a 4-dimensional surface, three specific cases are shown in each subplot to evaluate the fuzzy-neuro model. The mesh plot from Figure 7a represents the values output of the trained model for the constant value of $\omega_r = 3s^{-1}$, for the range of values from a_r and p_r . More specifically, it represents the evaluation of fuzzy rules No. {3, 6, 9, 12, 15, 18, 21, 24, 27} from the Table 2. On the subplots 7b and 7c, the constant values of $p_r = 5\text{bar}$ and $a_r = 3\text{m/s}^2$, respectively. They are the result of fuzzy rules No. {7, 8, 9, 16, 17, 18, 25, 26, 27} and {10, 11, 12, 13, 14, 15, 16, 17, 18} from the Table 2.

6.3 Verification of fuzzy logic controller

A partial evaluation of the implemented FLC model is presented in Figure 8. Two mesh 3-D surfaces, each containing two input values, with the output from the fuzzy logic controller represented in the z-axis. Figure 8a represents the output of the FLC for the case of constant values of $p_r = 3.5\text{bar}$ and $p_{sug} = 6\text{bar}$, which in a fuzzified sense mean a value of M (medium) for p_r and L (large) for p_{sug} . It shows the work of 147 fuzzy rules, among which are the rules No. {248-250, 255-257, 262-264, 276-278, 283-285} from Table 3. On the other hand, Figure 8b depicts the fuzzy logic controller output for the constant values of the other two input variables, $\varepsilon_a = 5\text{m/s}^2$ and $\Delta\varphi = -0.28$. Again, a total of 147 rules are the cause for this behavior, among rules No. {3, 142-146, 249, 256, 264, 277, 284, 417} from Table 3. The total evaluation of the FLC, together with the synthesis of depicted models is shown in Chapter 7.

7 Results and discussion

The verification of the proposed neuro-fuzzy brake control system has been conducted through validation using MATLAB's Simulink platform to simulate real operating conditions. The simulation sample time was set to 0.05 s. The validation process is done under two different braking scenarios, encompassing various braking situations. Both braking cycles were chosen to represent different everyday scenarios of commercial vehicle braking. Two different initial conditions were examined, involving the temperature of the disc brakes during the braking process, the initial speed of the trailer, and the laden state of the trailer. It was done aiming to assess the overall controller performance and its adaptability. The braking cycles were carried out until the full stop of the three-axle semi-trailer. The first scenario focused on a high-speed scenario with an initial speed of 70 km/h, a cold brake temperature of 100 °C, an unladen vehicle state, and the demanded braking actuation pressure was 4.5 bar. This braking cycle is graphically represented in Figures 9 and 10. Figure 9 visualizes the change of the brake actuation pressures and decelerations during the braking process. Figure 10 shows the adhesion conditions and the vehicle speed. This case of the braking cycle shows the success of the overall controller. Estimated adhesion was above the minimal required for the demanded deceleration, which led the controller to successfully fulfill the demanded deceleration by proper brake pressure selection and ensure the convergence of the deceleration error. The values of the suggested pressure in this case were around the 4.5 bar. The inverse brake model confirmed the cold brake capabilities to generate the wanted deceleration. The full stop of the unladen semi-trailer was made possible after 5 s and 54.36 m of braking travel.

The significance of the results from the first braking case lies in the controller's ability to accurately estimate and utilize available adhesion, ensuring optimal braking performance. The controller's success in maintaining the suggested pressure close to the driver's demand demonstrates its effectiveness in translating driver input into appropriate brake actuation. This performance is crucial for maintaining consistent braking behavior, which is essential for overall road safety.

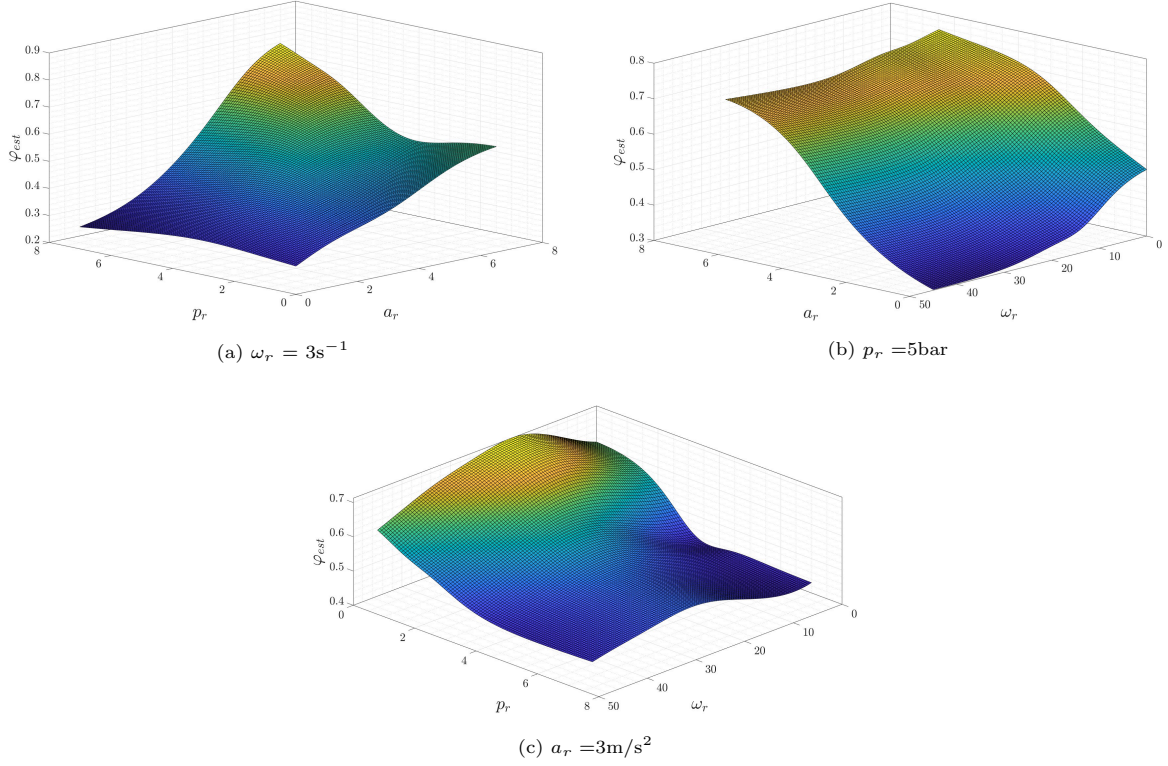


Fig. 7: Verification of the trained neuro-fuzzy adhesion model with constant angular wheel speed 7a, brake actuation pressure 7b, and vehicle deceleration 7c.

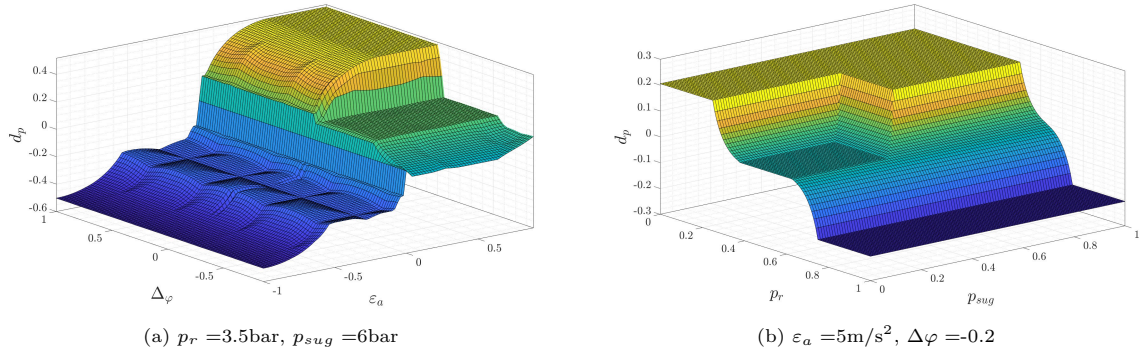


Fig. 8: Verification of the fuzzy logic controller with constant real and suggested brake actuation pressure 8a, deceleration error and adhesion difference 8b.

The FLC performance was evaluated in a second braking scenario characterized by a vehicle initial speed of 70 km/h, a hot brake temperature of 264°C, and a fully laden vehicle. The demanded braking actuation pressure from the driver was 6.5 bar. This case is a typical emergency braking situation when the brake actuation

pressure needs to be controlled in the best way to provide the desired braking performance and enable traffic safety at the same time. Figures 11 and 12 represent this braking cycle scenario. This braking cycle can be broken down into three phases. The first phase was from the start until the 4.7 s, and it represents the braking while the

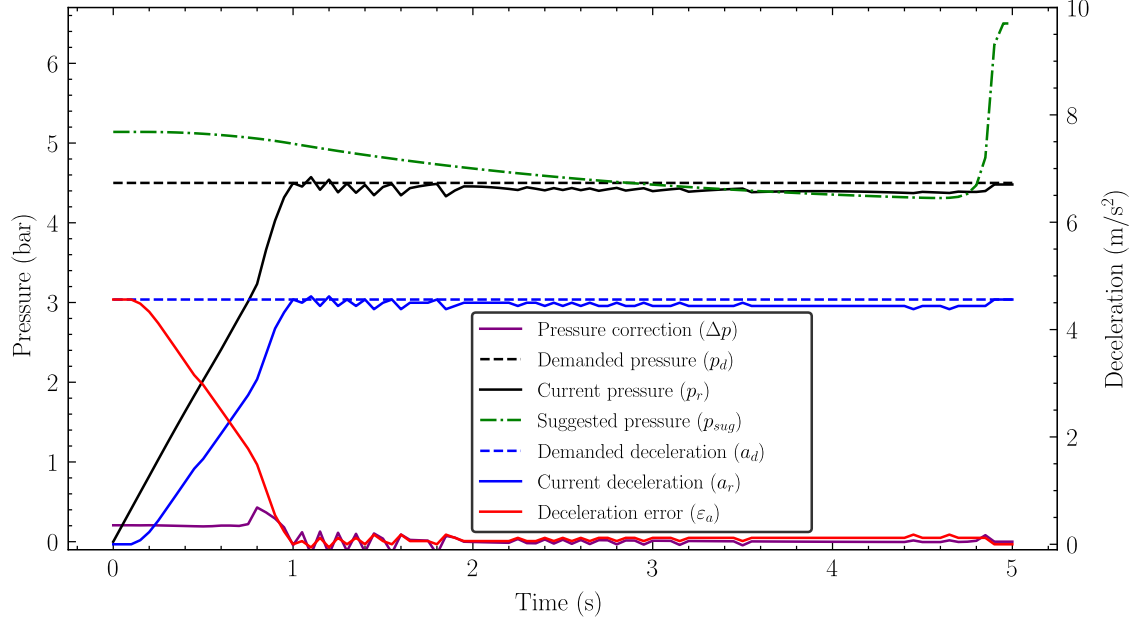


Fig. 9: Braking scenario 1 (unladen vehicle, cold brakes) - Change of pressure and deceleration.

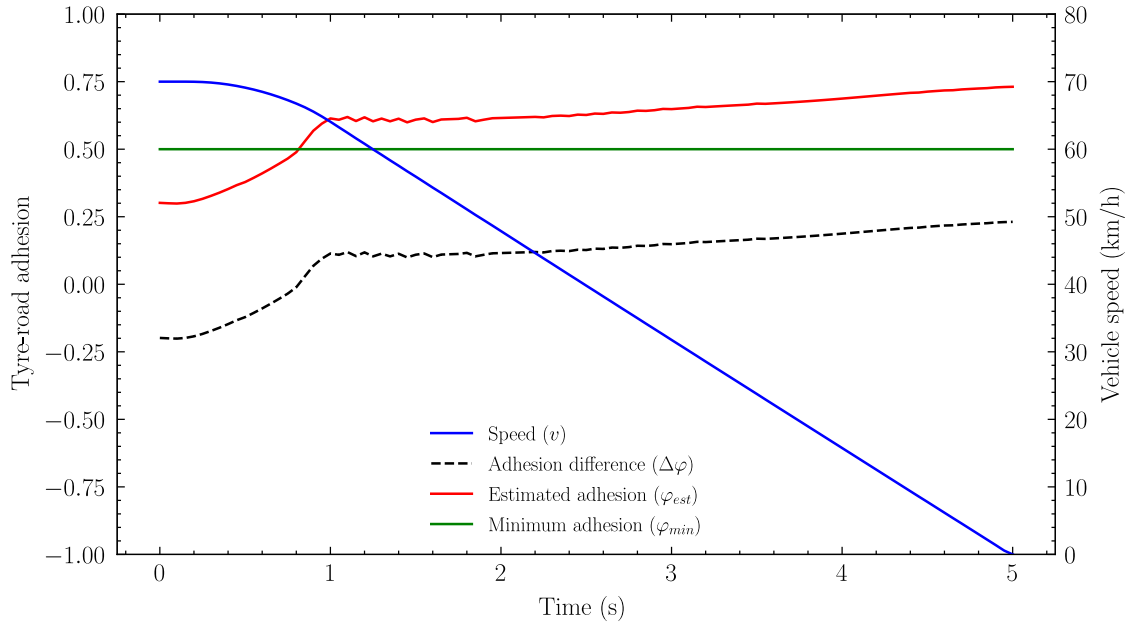


Fig. 10: Braking scenario 1 (unladen vehicle, cold brakes) - Change of adhesion conditions and vehicle speed.

estimated adhesion was lower than the required minimum level for achieving the demanded deceleration of around 5 m/s^2 . During this phase, the pressure was increasing until it reached the value

of 4 bar, which led to the maximum deceleration of this phase, 2.5 m/s^2 . Further increase of the pressure during this phase would lead to the loss of stability, due to the negative adhesion difference. Therefore, the pressure was limited here

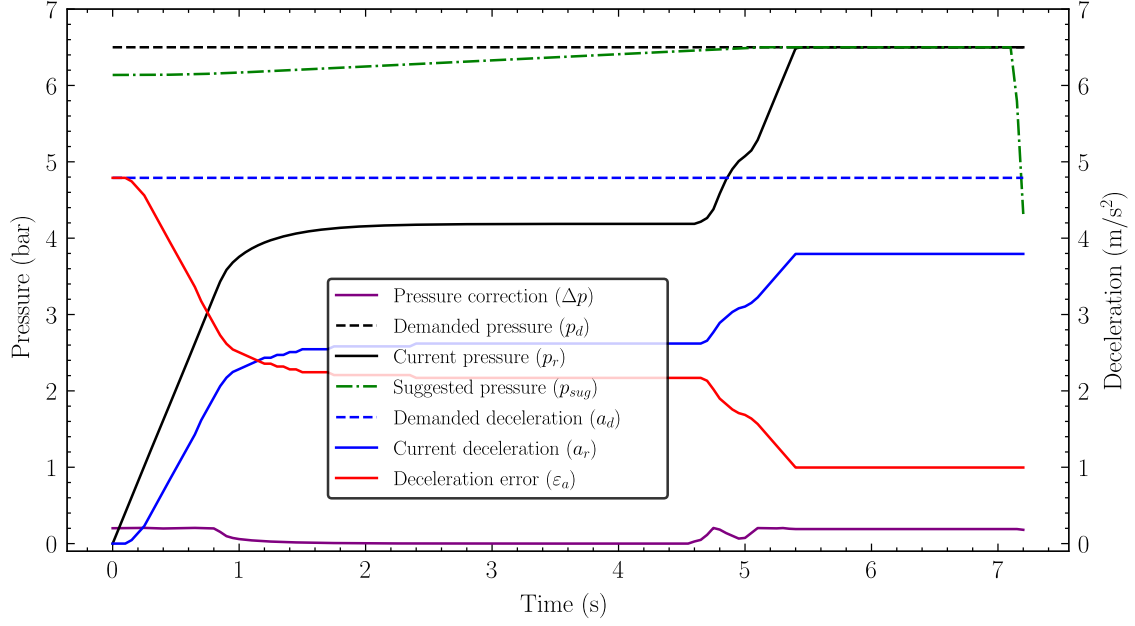


Fig. 11: Braking scenario 2 (laden vehicle, hot brakes) Change of pressure and deceleration.

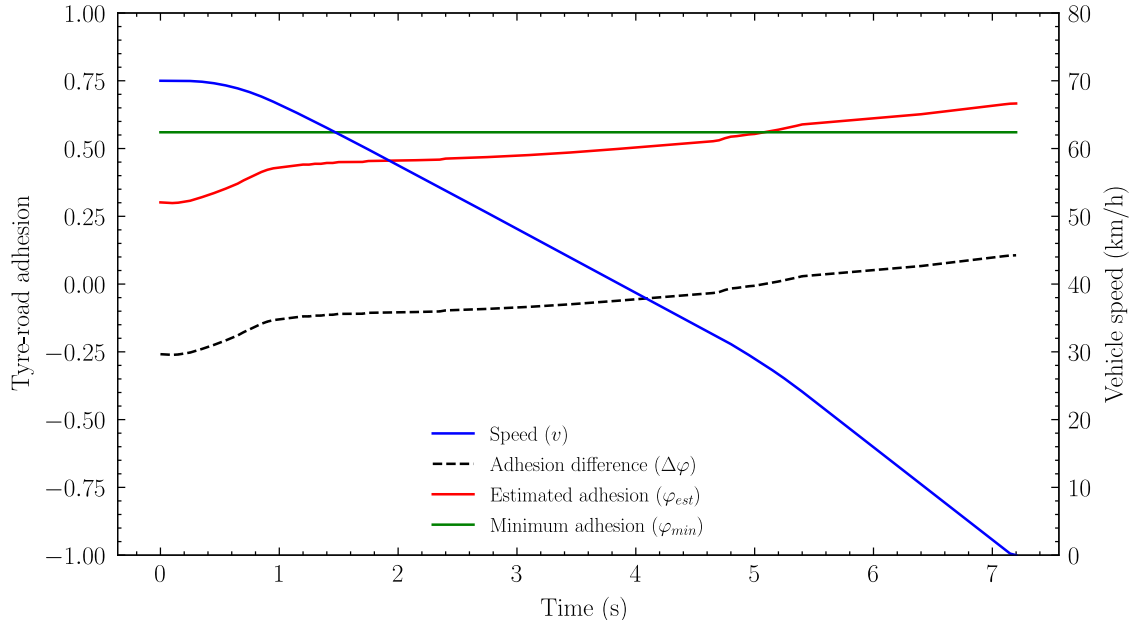


Fig. 12: Braking scenario 2 (laden vehicle, hot brakes) - Change of adhesion conditions and vehicle speed.

due to the lower achieved adhesion. The second phase occurred from 4.7 to 5.4 s, and during it, the tyre grip was increased. Therefore, the estimated adhesion coefficient reached a value of minimal adhesion for this demand, which allowed the controller to further increase the actuation

pressure to its maximum value of 6.5 bar. Fuzzy rules that were engaged during this phase were No. {276, 277, 278, 283, 284, 285} from the Table 3, therefore the shape of the signal Δp was as represented in Figure 11. In the third phase of the

cycle, the controller kept constant output until the vehicle finally stopped after 7.2 s and 81.50 m of braking travel. It should be noted that the maximal deceleration achieved for the actuation pressure of 6.5 bar in this case was below 4 m/s^2 , while the first case generated a deceleration of around 4.5 m/s^2 for the pressure of 4.5 bar. This drop in braking performance is affected by the high brake temperature, together with the higher vehicle load.

The significance of the results from the second scenario should be further elaborated. Firstly, it demonstrates the controller's ability to adapt to challenging conditions, including high brake temperatures and a fully laden vehicle. The proposed controller's approach highlights its successful decision-making process, prioritizing vehicle stability and traffic safety over immediate fulfillment of the driver's demand. Secondly, the controller's response to the change in adhesion conditions shows its dynamic adaptability. Finally, the observed fluctuation in braking performance shows the controller's ability to take into account influencing factors, providing a more realistic and safe braking response. This adaptive behavior is particularly significant for commercial vehicles, where load and brake temperature can vary in a wide range, affecting braking performance substantially.

8 Conclusion

The utilization of AI in control systems holds the promise of revolutionizing the automotive industry by unlocking new possibilities for safer and more efficient vehicles. The proposed neuro-fuzzy control of the braking system offers several significant advantages for enhancing the overall braking performance of commercial vehicles. The introduction of fuzzy logic and artificial neural networks has enabled the fuzzy logic controller to effectively combine data from the inverse brake model and adhesion estimation model with efforts to create optimal pressure control signals. It is shown that the FLC model was able to recognize influencing factors on the braking performance and provide vehicle active safety.

The results showed that the proposed semi-trailer controller can handle and adapt to the stochastic and nonlinear nature of the tyre-road interaction, the brake condition, and the vehicle

load state. The proposed FLC model was able to adjust the braking pressure to optimize the braking performance and vehicle stability. The results obtained provide valuable insights into the performance and effectiveness of the proposed controller in diverse operational scenarios.

While demonstrating promising results, the proposed solution is subject to certain limitations that require further investigation. Firstly, the current research assumes the same performance across all wheel brakes, neglecting potential variations in individual brake performance. To address this, the development of a separate inverse model trained on data from each specific brake is required. Secondly, brake wear during exploitation or material change will lead to further brake performance changes over time. In order to overcome this, the inverse model for each brake needs to be online retrained in real-time. Thirdly, braking scenarios depicted in the results consider only longitudinal cases of braking. The Neuro-Fuzzy controller should be improved to be able to control and optimize the brake actuation pressure during braking in a curve, when optimization between longitudinal and lateral deceleration should be found. All of the mentioned limitations are aimed to be addressed in future work.

Compliance with Ethical Standards

Conflict of interest. The authors declare that they have no conflict of interest.

Ethical approval. All authors consciously assure that this manuscript has not been previously published or is currently being considered for publication elsewhere. The paper reflects the authors' research and analysis truthfully and completely. The results are appropriately placed in the context of prior and existing research.

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Data availability. The data and models that were the output of this research are available upon reasonable request.

Author contributions. All authors contributed equally to this research.

Human Participants and/or Animals. This article does not contain any studies with human participants or animals performed by any of the authors.

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