Model-free Intelligent Control for Antilock Braking Systems on Rough Roads

Abstract

Advances made in Advanced Driver Assistance Systems such as Antilock Braking Systems (ABS), have significantly improved the safety of road vehicles. ABS enhances the braking and steerability of a vehicle under severe braking conditions. However, ABS performance degrades on rough roads. This is largely due to noisy measurements, the type of ABS control algorithm used, and the excitation of complex dynamics such as higher-order tire mode shapes that are neglected in the control strategy. This study proposes a model-free intelligent control technique with no modelling constraints that can overcome these un-modelled dynamics and parametric uncertainties. The Double Deep Q-learning Network algorithm with the Temporal Convolutional Network is presented as the intelligent control algorithm. The model is initially trained with a simplified single-wheel model. The initial training data is transferred to and then enhanced using a validated full-vehicle model including a physics-based tire model, and a 3D rough road profile with added stochasticity. The performance of the newly developed ABS controller is compared to a baseline algorithm tuned for rough road use. Simulation results show a generalizable and robust control algorithm that can prevent wheel lockup over rough roads without significantly deteriorating the vehicle's stopping distance on smooth roads.

Keywords: Anti-lock Braking System, Rough terrain, Reinforcement learning, Model-free control, off-road vehicle dynamics

1 Introduction

Vehicle safety has a significant impact on the health of humans globally. According to the World Health Organization (WHO) report on road accidents [1]:

- More than 3700 people die on the world's roads every day and tens of millions of people are injured or disabled every year.
- Road traffic injuries are the eighth leading cause of death for all age groups. More people die as a result of road traffic injuries than from HIV/AIDS, tuberculosis, or diarrheal diseases.
- The risk of a road traffic death is more than three times higher in low-income countries than in high-income countries.
- There has been no reduction in the number of road traffic deaths in any low-income country since 2013.
- Road infrastructure is strongly linked to fatal and serious injury causation in road traffic collisions.
- Vehicle safety is increasingly critical to the prevention of crashes and has been shown to contribute to substantial reductions in the number of deaths and serious injuries resulting from road traffic crashes. Features such as electronic stability control and advance braking are examples of vehicle safety standards that can prevent a crash from occurring or reduce the severity of injuries.

Significant advances towards vehicle safety have been made over the last few decades; one such advance is the development of the Antilock Braking System (ABS). ABS is becoming more and more prevalent, driven largely by legislation in the European Union (EU) and the United States requiring ABS on almost all vehicles [2]. These modern vehicles are also being sold in developing, low-income countries, often without adapting them to the challenging environmental conditions typical of roads in these countries.

ABS is a feedback control system that attempts to maintain controlled braking under all operating conditions by limiting the slip at each wheel. By sensing imminent wheel lockup and modulating the hydraulic brake pressure accordingly, an ABS not only prevents wheel lockup but allows for the development of lateral force between the tires and the road that help to maintain directional control of the vehicle during severe braking [3]. This contributes to the stability of the vehicle too, and is one of the fundamental contributions to vehicle safety of ABS [4]. Pretagostini*, et al.* [5] provide a detailed survey of the state-of-the-art of modern ABS. They specifically note the challenge of changing road conditions and the need for ABS to adapt to the prevailing road conditions quickly and effectively. The interested reader is encouraged to consult the work by Pretagostini*, et al.* [5] for a comprehensive overview of existing ABS architectures.

Despite notable decreases in multi-vehicle crashes and fatal pedestrian crashes with the inclusion of ABS [6], the performance of an ABS on rough roads has a lot of room for improvement. Poor road surface conditions, as typically encountered in developing countries, contribute to increased wheel lockup, bad stopping distances, and poor lateral control [7-9]. Braking over rough roads challenge the performance of an ABS by introducing effects that interfere with its normal operation. These effects include noisy measurements [10], road excitations and corresponding vehicle body motions inducing load transfer, tire carcass oscillations, and undulations in the surface that change the effective rolling radius of the tire [11] and the vertical and torsional dynamics of the wheel causing loss of contact between the tire and terrain [12].

Two aspects are often addressed to improve off-road braking. The first is to reduce the effect of the road excitation by controlling the suspension system [8, 13-15]. The second explores improving the ABS control algorithm to compensate for the vertical excitations and rotational tire dynamics. Limited literature addressing control algorithm development is found in the public domain, as this development is usually funded by international OEMs and thus not published [7, 16, 17].

1.1 Conventional, rule-based ABS algorithms

ABS control is a non-linear problem and several conventional, model-based control strategies exist such as: linear and non-linear control, sliding mode control, gain scheduling control, and fuzzy logic control [18].

The best-documented ABS algorithm was published in 1999 and is referred to as the Baseline algorithm in this study [4]. This algorithm is a bang-bang type, rule-based control strategy that takes the wheel angular acceleration and longitudinal slip as inputs, and makes use of three different pressure control modes to control the brake pressure at each wheel: *pump* (increase pressure), *dump* (reduce pressure), and *hold* (maintain pressure). Dictated by two upper and one lower threshold for the angular acceleration, and an upper longitudinal slip threshold, the Baseline algorithm combines these three pressure control modes in various configurations resulting in a repetitive ABS control cycle that consists of eight phases. Studies show that fine tuning the parameters of the Baseline algorithm lead to reasonable results when braking over rough terrain, highlighting its suitability as a Baseline algorithm [7, 9].

Owing to the difficulty involved in developing a mathematical model capable of describing all the dynamics of an ABS control problem, researchers have turned towards the development of intelligent control methods such as Neural Networks (NN) that can adapt to and mitigate the effects of an inaccurate model.

1.2 Modern ABS algorithms

Keshmiri & Shahri [19] implemented an intelligent ABS fuzzy controller capable of adjusting its slip and brake thresholds according to the different friction surfaces (dry, wet, and icy asphalt road), yielding robust results for the respective friction surfaces. John & Pedro [20] proposed a multi-layered NN-based Feedback Linearization ABS control scheme on dry asphalt road. This approach tracked a pre-determined slip ratio with results proving that slip regulation using a NN-based control scheme is feasible and robust to external disturbances. Poursamad [21] proposed an adaptive NN-based hybrid controller, which combined two NNs to learn the nonlinearities of an ABS; results indicate desirable performances during the transition between various flat friction surfaces (dry, and icy asphalt road). Pretagostini*, et al.* [5] indicates that NN-based approaches require a large set of training data that is time consuming and onerous to achieve the required level of robustness. However, the NN-based studies considered in their survey did not include Temporal Convolutional Networks (TCNs) and only briefly mentioned reinforcement learning. This is discussed in Section 2.1.

Model-based control approaches are often undesirable over rough terrain, where mismatches tend to occur between the control design model and the real process, leading to performance degradation due to un-modelled dynamics and parametric uncertainty [22]. This leads to an interest in model-free control techniques, such as Reinforcement Learning (RL).

The field of RL is a relatively new concept, however its application to non-linear control problems such as ABS control have been explored with promising results. Zhao*, et al.* [23] applied a supervised actor-critic approach to adaptive cruise control with success. This approach approximates its optimal control policy and can be modified to the control of an ABS. Sardarmehni & Heydari [24] proposed the use of RL for the optimal control of an ABS over smooth terrain by penalizing the braking distance of the vehicle; results outperform many existing solutions in the literature. Drechsler*, et al.* [25] investigated an actor-critic algorithm as a form of traction control. This method tracks the position of the accelerator pedal and wheel slippage, and results show the ability of the controller to maintain the slip ratio under adequate levels on different surfaces (dry, and icy asphalt road). The design and implementation of a model-free ABS slip control through Q-learning was implemented over smooth terrain by Radac & Precup [22], with the performance of the algorithm proving its capability over a wide operating range.

1.3 Research question

The majority of ABS controllers are simulated on smooth terrain (dry/wet/icy) with a focus on improving the vehicle's stopping distance. However, excessive wheel lockup also results in loss of directional control and yaw stability of the vehicle, which is of great importance in preventing serious accidents. The main contribution of this study is the development of a model-free ABS controller that:

- Improves braking performance on rough terrain by preventing wheel lock-up, thus maintaining directional stability without reducing stopping distance.
- Does not negatively influence braking performance on smooth roads.

These goals were achieved by using RL to train several NN-based ABS algorithms and comparing their performance with the Baseline algorithm [4] and a conventional, no-ABS braking system. The methodology followed presents a more data efficient approach to train NN-based ABS algorithms and quantifies the performance of the newly developed controllers.

2 Methodology

The methodology followed in this study consists of three steps:

- Developing a RL-based ABS controller architecture.
- Training and evaluating several RL training methods with a highly simplified, single wheel model.
- Extending the selected controller to a full vehicle model that includes a high-fidelity, physics-based tire model that brakes on an experimentally measured, 3D road profile of a Belgian paving.

2.1 Reinforcement-learning ABS controller development

RL is a method that is driven by the Markov Decision Process and involves the interaction between an autonomous active decision-making agent and its dynamic environment, with the objective of the agent to maximize a reward signal despite uncertainty about its environment [26]. Adadi [27] states that RL is more data efficient compared to supervised learning and therefore reduced the large dataset required as stated by Pretagostini*, et al.* [5]. Beyond the agent and environment, RL consists of three subsystems [26]:

1. A policy - a strategy the agent follows to discern its next action based on the current state and/or value function - expected reward by an agent for being in a state *s*. Also known as state-value function. Some RL use either just a policy (PPO) or value function (Q-learning) or both (A3C)
2. A reward function - an instant return awarded when the agent executes a particular action; influenced by the current state, the action just performed, and the next state.
3. A model of the environment - which simulates the behaviour of the environment.

Model-free RL methods make use of empirical evidence from past experiences, enabling the agent to learn from its environment through trial and error despite no prior knowledge of the environment. Basic model-free approaches update according to the Temporal Difference (TD) learning rule and can be separated into two types: Q-Learning, and Policy Optimization [26].

Q-Learning is an action-value method that makes use of Q-values (action-value functions) to choose an optimal policy based on the actions of the agent. This off-policy method is easy to implement and has a high sample efficiency. Examples include the Deep Q-learning (DQN) and Double Deep Q-learning (DDQN) algorithms. Policy optimization methods learn a parameterized policy that can select actions without consulting a value function and are referred to as policy gradient methods. Actor-critic methods are methods that learn approximations to both policy and value functions, where the policy structure is known as the *actor* that selects the actions, and the estimated value function (the *critic*) which criticizes the actions taken. Examples of policy gradient methods include the Asynchronous Advantage Actor-Critic (A3C), Advantage Actor-Critic (A2C), as well as the Soft Actor-Critic (SAC) algorithm [26].

Examples of both Q-learning and policy optimization have been used in vehicle control, specifically during braking maneuvers [22-25], with the Q-learning methods proving to be advantageous for their simplicity and speed [22] while the policy optimization methods advantageous in continuous action spaces with stochastic policies [28]. Despite the different pros and cons, each RL method has shown that its performance is largely problem dependent, and as a result, the DQN, DDQN, A3C, A2C, and SAC approaches are compared as alternative ABS control algorithms to identify the most suitable method for this problem. Due to the availability of baseline implementations for RL algorithms, the GitHub repository of Deep-Reinforcement-Learning-Algorithms-with-PyTorch [29] is used as the main source of implementation and comparison of the RL algorithms.

Real-life applications normally involve time-series data consisting of sequence dependency amongst the input variables. This data provides beneficial information over an extended period of time to the controller, adding an aspect of predictive modelling to the control problem. Function approximation is a technique for estimating the underlying function involved in mapping the inputs (historical or recent) to the outputs, and is achieved in RL by standard feed forward NNs (FFNN). Alternatively, two types of NNs capable of handling sequence dependency and time-series data modelling are Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). The TCN is a variation of the CNN, and makes use of dilated causal convolutions as seen in Figure 1(A), where an output at time t is convolved with elements from time t and earlier in the previous layer, ensuring no leakage of information over time. Figure 1(B) plots the residual block found at each dilation layer; this block stabilizes the TCN and allows the layers to learn modifications to the identity mapping rather than the entire transformation [30].

Bai*, et al.* [30] underlines the ability of the TCN to exhibit longer effective memory and consistently outperform general RNNs such as the Long Short-Term Memory (LSTM) on a vast range of tasks. This is confirmed by simulation results using the single wheel model, in which the TCN function approximator with an architecture of two dilation levels with 128 filters that have a kernel size of 5 applied to each layer, outperformed a two layered LSTM with a size of 128 in each layer. The benefit of the TCN function approximator compared to the FFNN is investigated in the initial stages of this study (see Section 2.2).

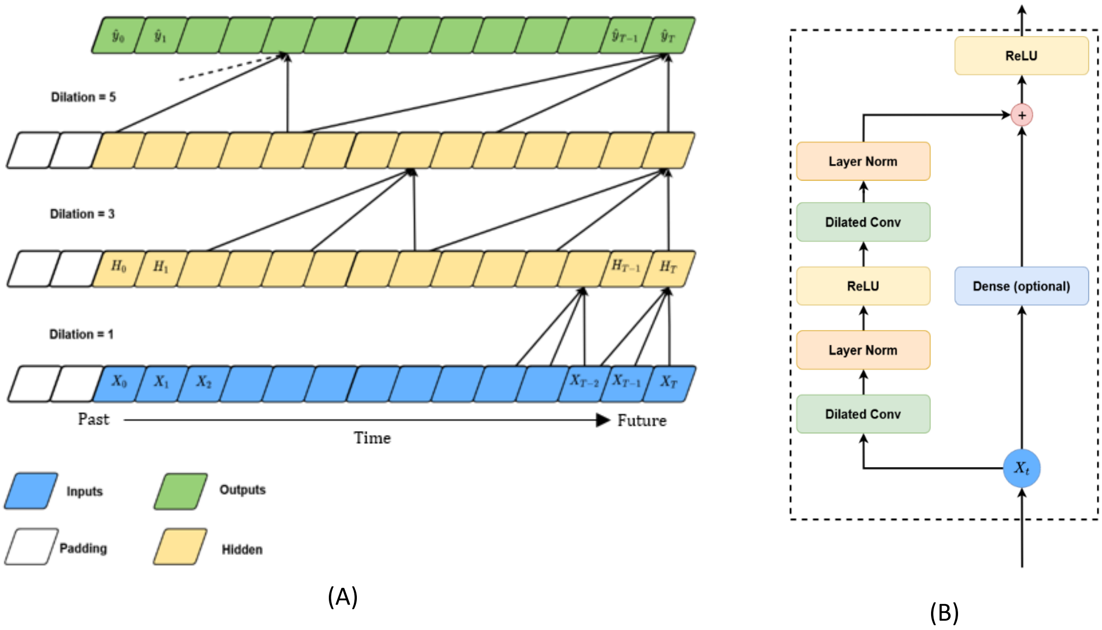


FIGURE 1. TEMPORAL CONVOLUTIONAL NETWORK (TCN) ARCHITECTURE (A) DILATION LAYERS ARCHITECTURE (B) RESIDUAL BLOCK USED AT EACH DILATION LAYER

To model the controller, a state space and action space are defined. Several combinations of states can be used as input such as brake pressure, vehicle speed, wheel angular velocity, bristle deflection (from the friction model), and/or longitudinal slip. These inputs, however, need to be easily accessible/measurable in a physical system and should avoid redundancy. A state space consisting of the vehicle and wheel speed $[\frac{v}{r}; \omega]$ is therefore proposed. Both parameters can sufficiently detail when wheel lockup is imminent as well as determine the longitudinal slip of the wheel. The vehicle velocity is normalized by the wheel rolling radius for two reasons: firstly, to normalize it with respect to the angular velocity, and secondly, to ensure that both inputs are independent of wheel radius. A discrete action setting of [pump, dump, hold] is obtained as output from the NN. A schematic of the relationship between the controller and the simulation model is seen in Figure 2.

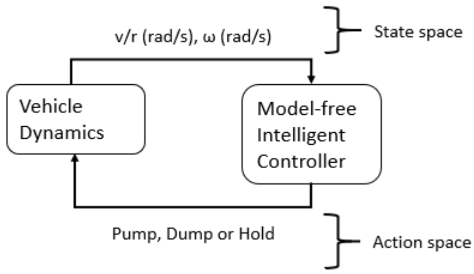


FIGURE 2. MODEL BREAKDOWN OF THE PROPOSED CONTROLLER

The reward function determines the behavior of the ABS controller; therefore, it is crucial to use a properly defined reward function to ensure its reliability. Several aspects in determining the ideal reward/penalty function exist, such as 1) regulating the longitudinal slip by means of predetermined slip thresholds, and/or 2) monitoring the stopping distance of the vehicle. The first approach is the most commonly used ABS penalty system. However, it restricts the model, thus no longer representing a model-free approach, and is limited by the type of terrain the vehicle travels over, requiring it to be adjusted accordingly. The second approach neglects the importance of the lateral control of the vehicle and generates rewards that are sparse, rendering it undesirable.

When considering the reward function for the ABS algorithm, there is conflict between two intuitive objectives of an ABS: 1) the vehicle is encouraged to brake hard to achieve the shortest possible stopping distance, and 2) the wheels may not lock/slide, which is common during hard braking. If unbalanced, the agent becomes either too conservative or reckless, leading to low deceleration or wheels locked at 100%. Taking this into consideration, the following reward function is proposed:

$$R = P - P_{max} - j(\lambda), \qquad j(\lambda) = \begin{cases} k_{pen}\lambda & if \ \lambda > 20\% \\ 0 & if \ \lambda \leq 20\% \end{cases} \tag{1}$$

This function serves as a penalty function which always returns a negative reward (R), resulting in the agent attempting to minimize the total penalties received. The penalty function also penalizes the duration of the braking process; the longer the vehicle brakes, the greater the number of penalties received. This encourages the agent to slow down the vehicle as quickly as possible. To further reduce the stopping time, the braking force can be considered via either pressure or longitudinal acceleration. Equation 1 includes brake line pressure (P), and knowing that the maximum pressure (P_{max}) pumped from the brake valve is 10 MPa, the negative rewards are achieved by vertically shifting the rewards to below 0 with the constant value $P_{max} = -10$. To satisfy objective (2), the function $j(\lambda)$ is introduced. This function is dependent on the longitudinal slip and penalizes the model as the wheels begin to slip. Depending on the tire, maximum braking forces tend to occur between the region of 10-30% slip [18]. Assuming nothing of the environment except that the peak friction is below 20% slip. The peak force is likely closer to the 10% region with lockup occurring almost instantly past 20% slip. Thus, an internal investigation into the penalty gain yielded that a factor of $k_{pen} = 15$ was adequate in penalising slip greater than 20%, and should prevent lockup occurring and keep the friction oscillating around the peak. Due to the inherent system response delay (due to valve dynamics, hydraulic transportation delays, etc.), perfect control of the slip will not be achieved, thus retaining some margin for the generation of lateral forces in the contact patch.

2.2 Initial training and results with simplified, single wheel model

2.2.1 Model Development

The simplified dynamics of a single wheel model is used in the initial stages of this study. This model is demonstrated in Figure 3.

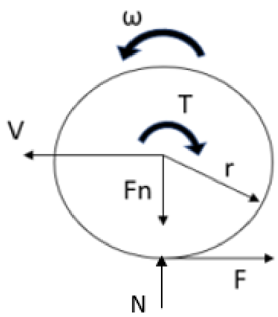


FIGURE 3. SINGLE WHEEL FREE-BODY DIAGRAM WITH LUMPED FRICTION

This model only considers longitudinal and rotational degrees of freedom, and accounts for normal and frictional forces acting on the tire, brake torque, and angular velocity of the wheel. For the sake of simplicity, the vertical force is assumed to act in line with the center of the wheel, thus neglecting the effects of pneumatic trail. Suspension dynamics and effects such as the torsional deflection of the sidewall and rolling resistance are neglected. The single wheel model provides a link between tire braking dynamics and brake hydraulic dynamics, and although simple, retains the essential characteristics of the actual system. From Figure 3 the dynamics of the wheel can be obtained as:

$$m\dot{v} = -F, \tag{2}$$

$$I\dot{\omega} = rF - T_b, \tag{3}$$

where *m* is a quarter of the vehicle mass, *I* the mass moment of inertia of the wheel about is center, and *r* is the radius of the wheel. The vehicle velocity, angular velocity, brake torque, and tire road friction force are represented by *v*, ω, T_b, and *F* respectively. The brake torque is the force applied at the brake disc to stop its motion and is defined, for the sake of simplicity at this point, as a linear relationship with the brake pressure *P* multiplied by a constant K that was experimentally obtained [7]:

$$T_b = KP, \tag{4}$$

$$\dot{P} = \frac{P_{set} - P}{\tau}. \tag{5}$$

The pressure in the hydraulic brakes is modelled as a first order model with time constant ($\tau = 0.5$s, [7]) and backpressure (P_{set}) according to the specifications used in [7]. The delay captures the total delay of the ABS system which includes, switching delay/bandwidth and pressure build up, The friction force (*F*) is described by a lumped, LuGre model defined below [31]:

$$\dot{z} = v_r - \frac{\sigma_0 |v_r|}{g(v_r)} z, \tag{6}$$

$$F = (\sigma_0 z + \sigma_1 \dot{z} + \sigma_2 v_r) F_n, \tag{7}$$

with

$$g(v_r) = \mu_c + (\mu_s - \mu_c) e^{-|v_r/v_s|^{\alpha}}. \tag{8}$$

This model describes the state of friction between the tire and terrain through the friction state (deflection) parameter *z*(*t*) and is characterized by Coulomb friction and static friction coefficients (μ_c, μ_s), normalised lumped stiffness and damping, viscous damping coefficients ($\sigma_0, \sigma_1, \sigma_2$), and relative velocity v_r. A lumped LuGre friction model was used, because it captures the transients of bristle deflection, is a physics-based, yet simple approach [31]. It is anticipated that the LuGre model will perform adequately for training purposes at this stage of the investigation. In the next stage, when the full vehicle model is used, an FTire model will be used, adding further complexity to the tire-terrain interaction.

The final single wheel model consists of four non-linear differential equations $[\dot{P}, \dot{z}, \dot{v}, \dot{\omega}]$, solved using a variable step integrator in Python.

The complex interaction between the tire and the undulating terrain must be retained even when investigating a simplified off-road braking scenario. The single wheel model does not directly account for the vertical tire excitation and suspension dynamics as these aspects are by far the most complex to model. The computational time needed to simulate a high-fidelity, physics-based tire model on a 3D road model is impractical for fast algorithm training purposes. Instead, the vertical excitation is modelled as a stochastic process where the experienced tire vertical force input to the LuGre model is sampled.

The sampled model consists of a quarter car model including a physics-based FTire tire model braking over a experimentally measured 3D Belgian paving road profile [32]. The FTire model is used as the tire model because of its high accuracy over rough terrain [33, 34]. The Belgian paving represents a rough, almost randomly excited class D road according to ISO8608 [35]. Becker & Els [36] physically measured the vertical road profile of the Belgian paving at Gerotek Test Facilities – the 3D road profile was available to this study.

Different samples are simulated at varying braking speeds (54 km/h to 68.5 km/h) and locations along the terrain, and averaged according to each speed. From this, an FFT of the vertical tire force is obtained that captures the speed dependent vertical excitation as the vehicle begins to slow down. This process represents a reasonable approximation of the vertical force over a rough terrain provided the vehicle slows down at a similar rate. During initial training this may not be the case, but better approximations are obtained as the model improves. From the FFT model an artificial excitation profile is randomly generated every fifth episode during training to ensure that the agent learns the general phenomena of braking over rough terrain instead of memorizing a specific tire over a specific terrain.

To further improve the generalization of the model, additional stochasticity is introduced at the beginning of every episode which include:

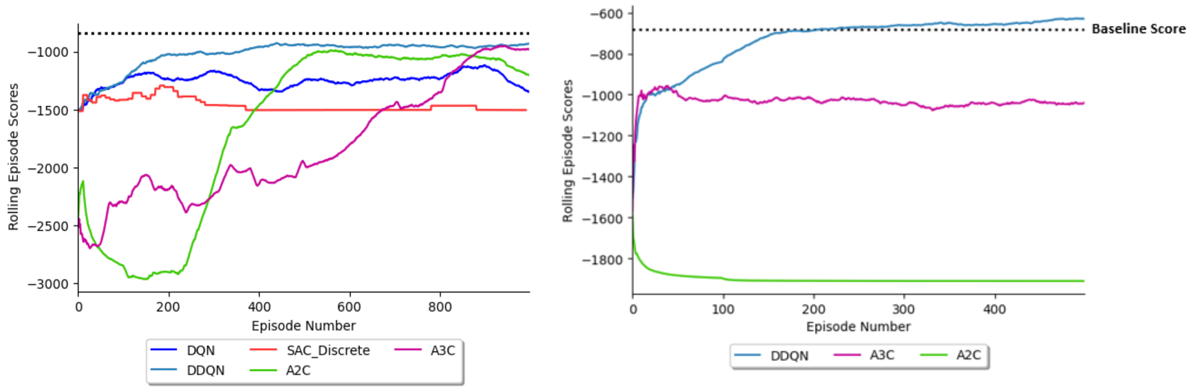
(1) Randomly sampling the initial vehicle speed between 54 km/h and 68.5 km/h.
(2) Randomly sampling uniformly distributed values between 0 and 0.5, and 0 and 5 which are added to the moment of inertia *I*, the LuGre friction properties μ_s and μ_c, and mass of the body respectively.

Initial training of the RL algorithms over rough terrain is achieved using the single wheel model to identify the best performing algorithm. Training is performed on a FFNN network taking in only the current state, and a TCN network which takes in an array of the past 100 states sampled at 100Hz. The aim of the initial training is to identify the best approach (DQN, DDQN, SAC, A2C, etc.) to carry forward to the full vehicle model and to demonstrate the advantages of a TCN over a vanilla FFNN. The simplified model is used to expedite the process, as the simulation time associated with the full vehicle model renders it impractical for all the aforementioned approaches.

The single tire model is trained doing straight-line braking using the different Q-learning (DQN and DDQN) and policy gradient methods (A2C, A3C, and SAC). Using the original algorithm hyperparameters and FFNN as the function approximator [29], the ABS controller is set to make decisions at 100Hz and is trained for 1000 episodes.

2.2.2 Results

Figure 4(A) plots the mean rolling episode scores against the episode number for the five different RL algorithms. An average score of -680 was achieved for the Baseline algorithm and is used as a benchmark for the intelligent algorithms. None of the algorithms are capable of matching or exceeding the performance of the Baseline algorithm. This is partly due to the simplicity of the FFNN function predictor and the absence of the dynamics that cause the Baseline algorithm to fail (unmodelled wheel torsional dynamics and noisy wheel speed signals leading to problems in slip calculation and angular acceleration [10]). These dynamics will be introduced during the full vehicle simulations and their effect on braking performance will be investigated when evaluating controller performance on the full vehicle model. As an alternative to the FFNN, the effect of a TCN function approximator is investigated by training the three best-performing RL algorithms from the first simulation (DDQN, A2C, and A3C) over 500 episodes. The benefit of using time-series data is immediately seen in Figure 4(B), where despite the A3C and A2C models failing to learn, the DDQN algorithm was able to achieve fewer braking penalties, exceeding the Baseline algorithm over time.



(A)

(B)

FIGURE 4. COMPARISON OF RL ALGORITHMS OVER ROUGH TERRAIN. (A) FFNN FUNCTION APPROXIMATOR, (B) TCN FUNCTION APPROXIMATOR

This enhanced performance is further confirmed by the summary in Table 1 and speed profile analysis in Figure 5. Table 1 emphasizes the ability of the DDQN models (with and without TCN) to prevent wheel lockup over rough terrain. These models average lower wheel slippage during the braking maneuver and produce a lower percentage of slip values greater than 20%. The stopping distances of the DDQN-TCN algorithm are within 1m of the average distance achieved by the Baseline algorithm, and thus acceptable.

TABLE 1. SUMMARY OF PERFORMANCE MEASURES OF BASELINE, DDQN-NN, DDQN-TCN, AND NO ABS

Stopping Distance (m)	Baseline	DDQN-FFNN	DDQN-TCN	No ABS
Mean	24.37	26.14	23.65	22.17
Std. dev	1.69	2.10	1.98	2.13

Longitudinal Slip (%)				
Mean	9.53	3.84	5.56	64.61
Std. dev	19.64	10.87	15.97	42.42
λ < 10%	66.47	77.91	75.94	18.81
10% < λ < 20%	16.76	15.73	17.19	8.90
λ > 20%	16.77	6.36	6.88	72.29

Figure 5 demonstrates the ability of the DDQN-TCN algorithm to cycle the wheel speed, achieving lower wheel slippage within the same amount of step intervals (observations) as the Baseline algorithm, qualitatively demonstrating that better wheel slip control is achieved within the same stopping distance. Therefore, due to the consistency and ability of the DDQN-TCN model to prevent wheel lockup over rough terrain without deteriorating the stopping distance, it is proposed that the DDQN-TCN algorithm be used as the ABS control algorithm. This algorithm is trained and evaluated further in the full vehicle model.

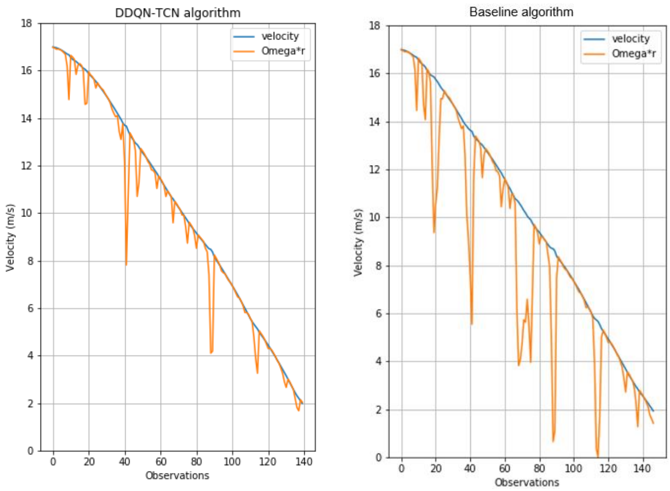


FIGURE 5. VEHICLE AND WHEEL SPEED COMPARISON OVER THE BELGIAN PAVING

The full vehicle model significantly increases the complexity of the environment in which the controller is applied.

2.3 Full vehicle model investigation

2.3.1 Model setup and training

A 15 degree of freedom full vehicle model of a 1997 Land Rover Defender, developed in ADAMS by [37] and used in co-simulation with MATLAB/Simulink, is used to investigate the performance of the ABS controller and forms the basis of this study. The vehicle model includes body torsional stiffness, modelled by separating the sprung mass into a front and rear body coupled with a revolute joint about the roll axis with an experimentally determined torsional stiffness, suspension kinematics and bushings, and experimentally determined center of gravity position (x, y, and z) and mass moments of inertia about the x, y, and z axes [38]. A high-fidelity, physics-based FTire model of the Michelin LTX A/T^2 235/85R16 tire is used [39, 40]. The vehicle has a semi-active suspension system with independently variable spring and damper settings. Figure 6 shows a graphical topology of the front and rear vehicle suspension.

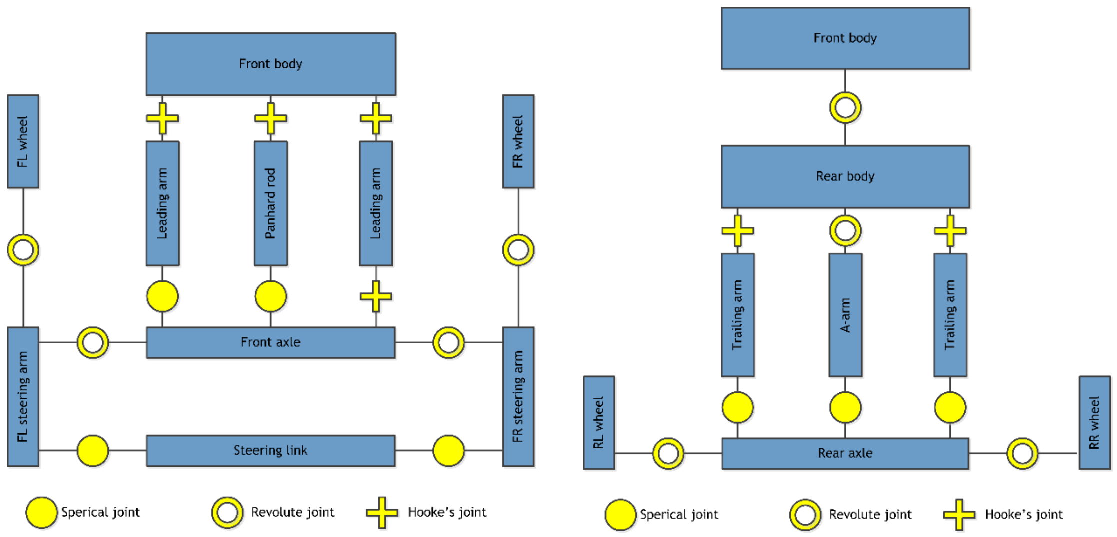


FIGURE 6. TEST VEHICLE SUSPENSION MODEL FOR FRONT (LEFT IMAGE) AND REAR (RIGHT IMAGE) SUSPENSION [37, 41]

TABLE 2. FULL VEHICLE MODEL PARAMETERS

Parameter	**Front body value**	**Rear body value**
Sprung mass [kg]	798.5	783.5
Unsprung mass [kg]	166	166
Roll moment of inertia [kg m^2]	387.5	387.5
Pitch moment of inertia [kg m^2]	1660	1660
Yaw moment of inertia [kg m^2]	950	950

The vehicle model has been experimentally validated for vertical dynamics [42], lateral dynamics [43], and longitudinal dynamics [8]. While the tire model provides high accuracy over rough terrain the developed tire model does exhibit a very flat saturation curve in that the longitudinal force does not reduce once peaked. This is expected to affect the result of stopping distance as a locked tire's braking distance will not be negatively affected at higher slip.

During training the front and rear spring and damper suspension settings are randomly sampled every episode (high or low stiffness, high or low damping). Multiple combinations of suspension settings are possible and directly impact the ABS braking performance over rough terrain [8], thus randomizing these settings forces the agent to generalize braking over rough terrain regardless of the suspension settings. Additional stochasticity is introduced every episode by:

(1) Randomly sampling the initial vehicle speed between 50km/h and 80km/h.
(2) Altering the acceleration of the vehicle to bring it up to speed.

Randomizing the braking speed and acceleration of the vehicle not only causes the vehicle to brake at different speeds, but also at various locations along the Belgian paving, preventing the model from learning the exact terrain profile. In the full vehicle model, variations on the tire model and inertia properties are more difficult to perform compared to the single tire model therefore these properties are kept constant.

After training, the following test procedures are simulated to evaluate the performance of the ABS as recommended by SAE International [44]:

1. Straight line braking:
    a) High friction surface
    b) Low friction surface
2. Braking in a turn:
    a) High friction surface
    b) Low friction surface

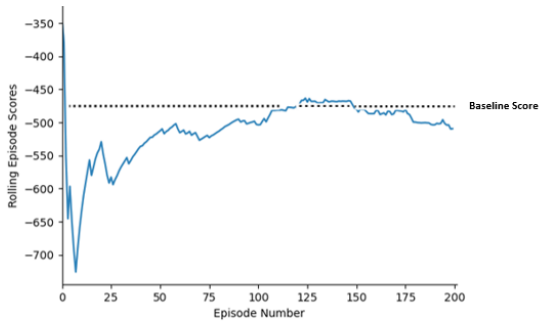
3. Split friction coefficient braking

To measure the performance of the ABS over rough terrain additional braking tests are conducted over the Belgian paving and class D road, respectively. Simulations over the class D road, generated according to the ISO 8608 standard [35], provide a measure of the robustness of the controller to rough terrain previously not trained on. Five iterations of each scenario are repeated for three different vehicle configurations: 1) DDQN-TCN algorithm, 2) Baseline algorithm, and 3) conventional braking system (no ABS). A conventional, no ABS, model was included, because an experimental investigation revealed that the stopping distance on a Belgian Paving is sometimes shorter for the no ABS case than for an ABS-equipped vehicle [14]. An initial braking speed of 55km/h is simulated, and the following suspension configuration is used: hard spring and damper settings in the front and soft spring and damper settings in the rear, as recommended by [8]. The high and low friction surface have a friction coefficient of 1 and 0.4 respectively. The high friction surface and class D road braking-in-turn simulations have a constant radius of 70m, and the low friction surface has a constant radius of 120m. The split-mu surface has a friction coefficient of 1 under the left side, and 0.4 under the right side of the vehicle. All the simulations are terminated when the vehicle speed is below 15km/h.

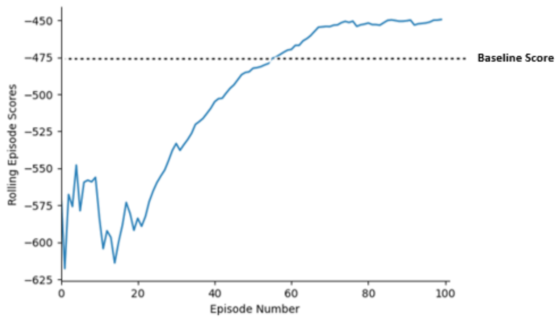
Training on the full vehicle simulation model is achieved by means of transfer learning, which involves the passage of knowledge from one task to another [45]. The best performing model trained in the single wheel simulations is saved and trained further on the full vehicle model. Thus, the model starts off with knowledge of how to brake on the simple model which significantly speeds up training on the full vehicle model.

2.3.2 Results

To prevent the common occurrence of catastrophic forgetting with deep NNs [46], which occurred during training as indicated in Figure 7(A), a combination of a reduced learning rate of 0.005 (from 0.01) and early stopping (100 episodes) was used [46, 47]. The best DDQN-TCN model was achieved after 600 episodes (500 transferred) and is plotted in Figure 6(B).



(A)



(B)

FIGURE 7. TRAINING RESULTS ACHIEVED WITH TRANSFER LEARNING, USING DDQN-TCN ALGORITHM

The wheel speed profiles of the different braking configurations are plotted in Figure 8. This straight-line braking test provides insight into the ability of the DDQN-TCN algorithm to prevent wheel lockup and maintain directional control and yaw stability (brake in a straight line). As summarized in Table 3, the DDQN-TCN algorithm achieves an average wheel slippage of 8% with a std. deviation of 10%, compared to 15% mean slippage with 20% std. deviation of the Baseline Algorithm. This illustrates the ability of the DDQN-TCN algorithm to prevent wheel lockup over rough terrain, accomplishing lower slippage than both the Baseline algorithm and no ABS, without significantly worsening the stopping distance of the vehicle.

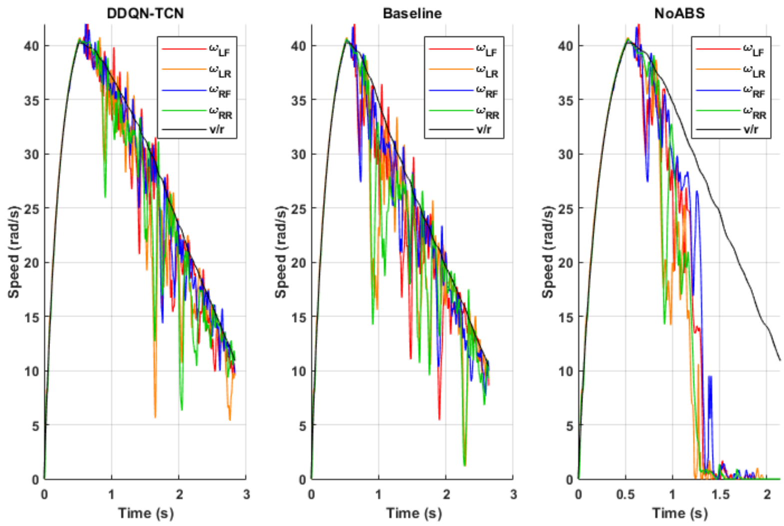


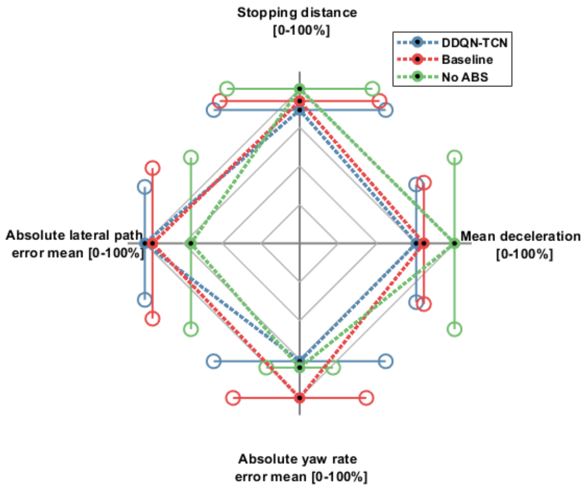
FIGURE 8. WHEEL SPEED COMPARISON OF THE DIFFERENT BRAKING CONFIGURATIONS STRAIGHT-LINE BRAKING OVER THE BELGIAN PAVING

3 Analysis

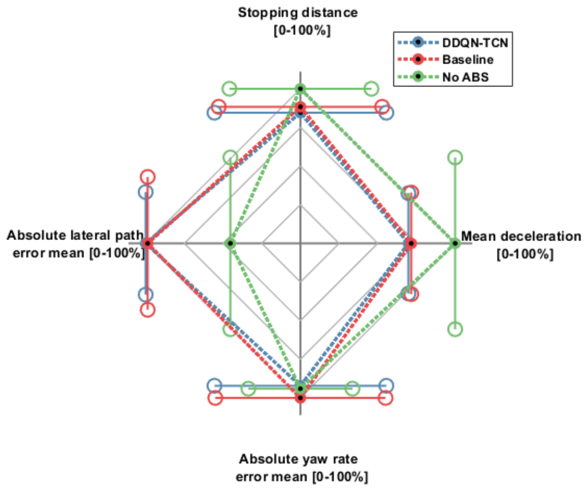
While no single metric capable of comparing one ABS controller to another exists, the ABS performance evaluation technique proposed by [17] is used for evaluation. This technique considers the mean and standard deviation of four metrics that can be used to better evaluate the performance of a vehicle under braking: vehicle stopping distance vehicle deceleration, absolute vehicle yaw rate error, and absolute lateral path following error. These metrics are presented on a radar plot. Although the radar plot does not give a quantifiable indication of each metric, it gives an indication of the performance and repeatability of each braking configuration regarding each metric respectively, while allowing for an easy comparison between different controllers. The best performing algorithm occupies the outermost corners of the plot.

Figure 9(a) compares the performance of the different braking configurations over the Belgian paving using the proposed evaluation technique. The conventional braking system results in the best stopping distance and highest mean deceleration, however both ABS algorithms generate better directional stability of the vehicle as expected. The DDQN-TCN algorithm results in the best lateral control of the vehicle and prevents wheel lockup over rough terrain without significantly compromising the stopping distance (4% further than the Baseline Algorithm, and 15% further than no ABS as summarized in Table 3). Both ABS algorithms fail to achieve the best stopping distance and mean deceleration due to the flat response of the FTire models longitudinal slip relationship at higher wheel slippage as highlighted by Hamersma [48]. As a result, there is almost no difference in the friction coefficient experienced between the peak friction (20%) and 100% lockup causing no loss of braking between 20-100% slip, consequently wheel lockup does not penalize stopping distance.

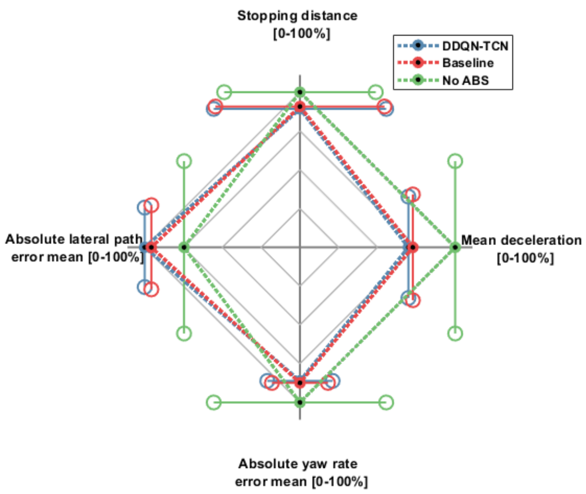
To investigate the robustness of the performance of DDQN-TCN algorithm over rough terrain, an alternative rough terrain, not trained on, is required. Figures 8(b) and 8(c), and Table 3, compare the braking configurations during straight-line braking and braking-in-turn with a radius of 70m over the class D road introduced in Section 2.1.1. The DDQN-TCN algorithm prevents wheel lockup in both scenarios, ensuring the best lateral stability of the vehicle, without significantly compromising the stopping distance (2% further than the Baseline Algorithm, and 13% further than braking without ABS). Further robustness of the DDQN-TCN algorithm is demonstrated in Figure 9(d), which plots the braking configurations over the split mu surface. Braking in split-mu conditions causes the vehicle to rotate and can lead to total loss of control. The advantage of braking with ABS under such conditions is that it ensures stability of the vehicle. This is seen by the DDQN-TCN algorithm, which is the best performing braking configuration in 3 out of the 4 metrics and achieves the best yaw rate mean error, reducing the chance of any unwanted yaw torque acting on the vehicle.



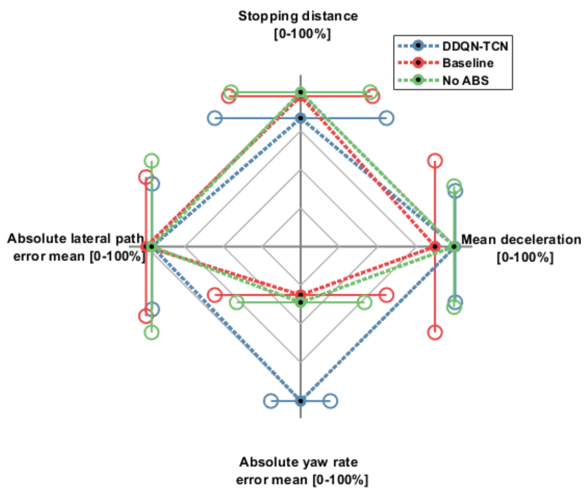
(a) Straight-line braking: Belgian Paving



(b) Straight-line braking: Class D Road



(c) Braking-in-turn: r = 70m, Class D Road



(d) Braking on split-mu

FIGURE 9. COMPARISON OF DIFFERENT BRAKING CONFIGURATIONS OVER MULTIPLE SIMULATION TYPES

TABLE 3. STOPPING DISTANCES AND LONGITUDINAL SLIP OF DIFFERENT BRAKING CONFIGURATIONS OVER MULTIPLE SIMULATION TYPES

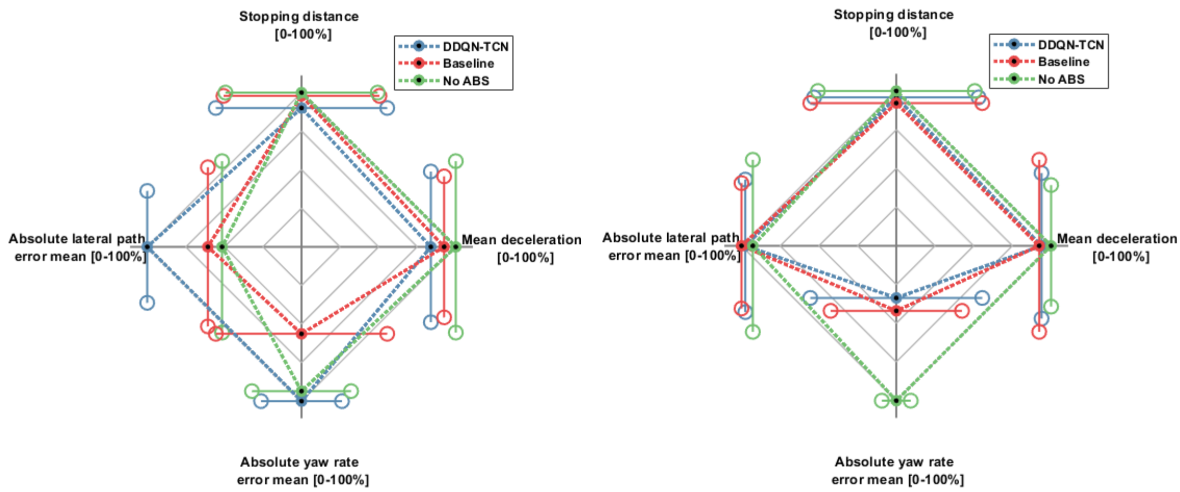
	Straight-line: Belgian Paving			Straight-line: Class D Road		
Stopping Distance (m)	**Baseline**	**DDQN-TCN**	**No ABS**	**Baseline**	**DDQN-TCN**	**No ABS**
Mean	20.4	21.4	18.2	22.0	22.5	19.5
std. dev	1.8	1.9	1.6	2.1	2.0	1.8
Longitudinal Slip (%)						
Mean	14.7	8.1	43.9	12.2	10.5	46.9
std. dev	20.0	10.1	36.8	10.6	10.5	43.4
$\lambda < 10\%$	56.5	65.5	36.7	51.0	54.3	38.1
$10\% < \lambda < 20\%$	25.1	25.2	3.2	27.4	34.1	6.0
$\lambda > 20\%$	18.4	9.4	60.1	21.6	11.6	55.9
	Braking-in-turn: Class D Road			**Split-mu Surface**		
Stopping Distance (m)	**Baseline**	**DDQN-TCN**	**No ABS**	**Baseline**	**DDQN-TCN**	**No ABS**

Mean	48.9	49.0	43.7	20.5	22.7	18.8
std. dev	1.7	1.7	1.6	1.8	2.1	1.6
Longitudinal Slip (%)						
Mean	9.1	7.9	30.1	40.6	29.5	51.4
std. dev	10.7	10.0	41.9	32.7	31.9	43.1
$\lambda < 10\%$	63.2	62.9	61.8	35.1	45.5	36.5
$10\% < \lambda < 20\%$	20.1	25.9	2.0	2.5	7.1	2.6
$\lambda > 20\%$	16.7	11.1	36.2	62.4	47.4	60.9

A limitation of the DDQN-TCN and Baseline algorithm is identified when braking over a low friction flat surface, where wheel lockup occurs. This is illustrated in Figure 10 and Table 4, which compare braking over a smooth high friction road versus a smooth low friction road. Subsequently, the best braking configuration for low friction terrain is the conventional braking system (braking without ABS). Despite no numeric indication, lack of directional control of the vehicle is shown by the scaling of all three configurations in the lateral path error and absolute yaw rate error. To overcome this limitation two possible solutions are presented:

1. Train the DDQN-TCN algorithm over low friction smooth terrain.
2. Train using a modern ABS modulator with decreased brake delays.

The first solution recommends incorporating low friction smooth terrain in the training of the algorithm and presents many future opportunities such as training over multiple terrains, as well as with a road classifier. For the second solution, Penny & Els [7] found that at least a half-second delay on the ABS modulator was needed to accommodate for the delay in the measurement, solenoid response, mechanical relay and pressure build-up in the brake line for the ABS algorithm. This leads to a slow response time, resulting in the ABS modulator being unable to cycle the wheel speed fast enough on a low friction surface where wheel lockup occurs almost immediately. Additionally, a general argument can be made that the Baseline and DDQN-TCN algorithms have related results due to these modulator limitations. Therefore, the performance of the ABS controller is largely limited by the modulator. A faster, modern modulator that can mitigate these delays and result in better braking efficiency is recommended, after which re-training of the algorithm can be completed and simulations re-run.



(a) Straight-line braking: Flat Road, μ = 1 (b) Straight-line braking: Flat Road, μ = 0.4

FIGURE 10. STRAIGHT-LINE BRAKING OVER A HIGH FRICTION SURFACE VERSUS A LOW FRICTION SURFACE

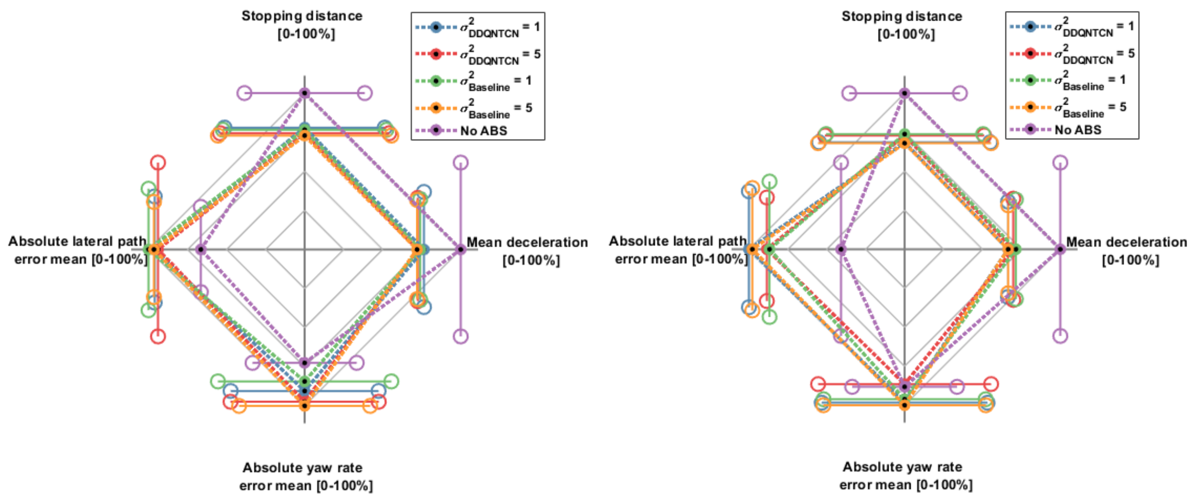
TABLE 4. STOPPING DISTANCES AND LONGITUDINAL SLIP OF STRAIGHT-LINE BRAKING OVER A HIGH FRICTION SURFACE VERSUS A LOW FRICTION SURFACE

	High Friction flat road			Smooth Friction flat road		
Stopping Distance (m)	**Baseline**	**DDQN-TCN**	**No ABS**	**Baseline**	**DDQN-TCN**	**No ABS**
Mean	17.2	18.3	16.3	32.2	30.8	29.4
std. dev	1.2	1.4	1.2	2.1	1.8	1.7
Longitudinal Slip (%)						
Mean	6.9	5.2	26.3	49.3	46.9	75.1
std. dev	9.9	8.9	32.1	41.9	39.6	41.6
λ < 10%	81.7	79.5	54.8	33.7	28.4	21.7
10% < λ < 20%	7.8	17.2	5.8	5.8	9.3	1.3
λ > 20%	10.5	3.3	39.4	60.6	62.3	77.0

All previous simulations illustrate the robustness of the DDQN-TCN algorithm across different braking scenarios and terrains using a realistic simulation model, however a key aspect to the physical world, noisy measurement, is not considered. Terrain effects and vibration of the wheel speed sensors are sufficient to hamper the performance of an ABS over rough terrain. The effect of introducing a zero-mean White Gaussian Noise (WGN) with some variance σ^2 at the wheel speed measurements in the full vehicle model is explored. This variance at any sample time reflects the intensity of the underlying white-noise process, and an increasing noise variance (σ^2 = 0, σ^2 = 1, and σ^2 = 5) is investigated. Using the same braking conditions as previously, two straight-line braking simulations are performed over the Belgian paving and Class D Road, and comparisons are drawn to the Baseline algorithm and conventional braking system, as seen in Figure 10 and Table 5.

Attempts to evaluate the ability of the Baseline algorithm to handle noisy wheel speed data without a filter proved unsuccessful - the ADAMS solver fails to converge. Thus, a first order filter with a time constant T_f = 0.095s is used to filter the data used by the Baseline algorithm. This highlights an advantage of the DDQN-TCN algorithm: testing the Baseline algorithm in the physical world would require filtering noise delays in conjunction with the modulator and actuator delays, whereas the DDQN-TCN algorithm would only experience the latter, resulting in fewer delays and better braking efficiency.

Figure 11 and Table 5 further emphasize the robustness of the DDQN-TCN algorithm as it is able to prevent wheel lockup, matching the performance of the filtered Baseline algorithm while achieving better directional stability of the vehicle than the conventional braking system, without considerably compromising the stopping distance in both simulation types and at different noise variances.



(a) Straight-line braking: Belgian Paving (b) Straight-line braking: Class D Road

FIGURE 11. RESPONSE OF DDQN-TCN TO NOISY WHEEL SPEED MEASUREMENTS

TABLE 5. STOPPING DISTANCES AND LONGITUDINAL SLIP OF DIFFERENT BRAKING CONFIGURATIONS TO NOISY WHEEL SPEED MEASUREMENTS

	Straight-line: Belgian Paving			**Straight-line: Class D Road**		
Stopping Distance (m)	**Baseline**	**DDQN-TCN**	**No ABS**	**Baseline**	**DDQN-TCN**	**No ABS**
Mean	22.8	22.3	18.4	24.8	24.1	19.9
std. dev	2.2	2.1	1.6	2.2	2.0	1.7
Longitudinal Slip (%)						
Mean	9.5	9.3	47.9	9.8	9.5	46.9
std. dev	10.7	10.5	43.9	10.2	9.5	43.4
$\lambda < 10\%$	65.7	66.0	36.8	55.9	60.1	38.1
$10\% < \lambda < 20\%$	20.1	23.2	3.2	27.4	32.5	6.0
$\lambda > 20\%$	15.2	10.7	60.1	16.6	7.4	55.9

The objective of the proposed DDQN-TCN algorithm is to prevent wheel lockup on rough terrain without significantly deteriorating the stopping distance. This objective is met in all simulations performed over rough terrain: straight-line braking over the Belgian paving and class D road, and braking-in-turn over a class D road. The DDQN-TCN algorithm ensures the best directional stability of the vehicle. Its robustness is further highlighted by being the best braking configuration for straight-line braking and braking-in-turn on a high friction flat surface, as well as achieving the best directional stability and yaw rate mean error over the split-mu surface. An insight to the robustness and adaptability of the algorithm to noisy data over rough terrain is underlined by its ability to prevent wheel lockup over rough terrain and achieve similar braking performances to a filtered Baseline algorithm, without the use of a filter. An implication of this study is that it provides further encouragement for the use of model-free algorithms in complex environments with unmodelled non-linear dynamics.

A limitation of the DDQN-TCN algorithm is identified when braking over the low friction flat surface, where wheel lockup occurs. Under these conditions, the best braking configuration is to brake without ABS. Two solutions are recommended to overcome this limitation. The first solution is training the model over a low friction surface. This presents many future opportunities for an ABS controller, such as training over multiple surfaces and/or in conjunction with a road classifier, which could have a broader impact on the safety of vehicles under emergency braking. The second solution is to improve the braking efficiency of the controller by making use of a more modern ABS modulator. This would result in decreased brake delays that exist between the ABS modulator and the actuators.

4 Conclusion and recommendations

This study set out to develop a model-free intelligent ABS control method capable of detecting and reducing high slip conditions on rough terrain. The Double Deep Q-Learning Network (DDQN) algorithm with the Temporal Convolutional Network (TCN) is proposed as the intelligent control algorithm. A validated full-vehicle simulation model, based on a Land Rover Defender, is used with an FTire tire model in ADAMS. This model was trained over the measured Belgian paving, with stochasticity used in the measurements to ensure the generality and robustness of the controller. Applying the performance evaluation technique introduced by [17] and an initial braking speed of 55km/h, eight braking scenarios were simulated according to the [44] requirements.

The DDQN-TCN algorithm is able to prevent wheel lockup without significantly diminishing the vehicle's stopping distance in all simulations over rough terrain. This includes straight-line braking over the Belgian paving and class D road, and braking-in-turn over a class D road. The robustness of the algorithm to noisy data over rough terrain is underlined by its ability to prevent wheel lockup and achieve similar braking performances to that of a modified Baseline algorithm, without the use of a filter. A limitation of the algorithm is identified on the low friction flat surface, where wheel lockup occurs following the inability of the algorithm to cycle the wheel at the required speed. Three workable solutions are proposed that should be investigated in further studies: 1) training the model over a low friction surface and/or multiple surfaces, 2) including a road classifier in the model, and 3) decreasing the brake delays present in the simulation model through a more modern ABS modulator.

Four parameters that affect the performance of an ABS are considered in this study: terrain, type of controller, tire model, and suspension setup. Additional parameters can also be explored including tire carcass oscillation and tire force run-in-effect. Further studies should include:

- evaluating the algorithm experimentally over the Belgian paving and expanding the training and evaluation to other rough road types.
- further training the algorithm with additional parameter changes, such as:
    - vehicle mass, center of gravity position and inertia
    - tire inflation pressure
    - including brake hysteresis [49]
- including other parameters in the reward function. For this initial study, the number of parameters were limited by the parameters available from the simplified single wheel model. Increasing the complexity to the full vehicle simulation model results in additional parameters being accessible; these include the yaw rate and/or path following error which can be used to improve the performance of the algorithm. However, it is important to avoid redundancy.
- following a risk-based design approach, such as described in [50], to ensure that the ABS limits the risk, even though a non-deterministic approach was used to design the algorithm.

The proposed DDQN-TCN algorithm can be included as a low-level slip controller that is activated by a supervisory controller when it detects that the vehicle is performing an emergency braking maneuver on a rough road. Although experimental validation of the proposed controller is still needed, it is anticipated that the proposed DDQN-TCN algorithm may contribute to improved performance of vehicle safety systems on rural roads.

Disclosure statement

The authors confirm that there are no relevant financial or non-financial competing interests to report.

References

[1] World Health Organisation. (2020, 29 March 2020). *Road traffic injuries*. Available: https://www.who.int/violence_injury_prevention/road_traffic/en/
[2] National Highway Traffic Safety Administration, "Federal motor vehicle safety standards; electronic stability control systems; controls and displays," *Federal Rule, FMVSS,* vol. 126, 2007.
[3] Breuer, B. & Bill, K. H., *Brake technology handbook*, First English Edition ed. Warrendale, PA: SAE International, 2008.
[4] Bosch Gmbh, R. & Girling, P., *Driving-Safety Systems (2nd Edition)*. Society Of Automotive Engineers, 1999.
[5] Pretagostini, F., Ferranti, L., Berardo, G., Ivanov, V. & Shyrokau, B., "Survey on Wheel Slip Control Design Strategies, Evaluation and Application to Antilock Braking Systems," *IEEE Access,* vol. 8, pp. 10951-10970, 2020.
[6] Garrott, W. R. & Mazzae, E. N., "An overview of the national highway traffic safety administration’s light vehicle antilock brake systems research program," 1999.
[7] Penny, W. C. W. & Els, P. S., "The test and simulation of ABS on rough, non-deformable terrains," *Journal of Terramechanics,* vol. 67, pp. 1-10, 10// 2016.
[8] Hamersma, H. A. & Els, P. S., "Improving the braking performance of a vehicle with ABS and a semi-active suspension system on a rough road," (in English), *Journal of Terramechanics,* vol. 56, pp. 91-101, Dec 2014.
[9] van der Merwe, N. A., Els, P. S. & Žuraulis, V., "ABS braking on rough terrain," *Journal of Terramechanics,* vol. 80, pp. 49-57, 2018.

[10] Vivekanandan, N. & Fulambarkar, A., "A study on performance parameters associated with the effectiveness of antilock braking system on rough roads," in *Industrial Safety Management*: Springer, 2018, pp. 37-49.
[11] Hamersma, H. A., Botha, T. R. & Els, P. S., "The dynamic rolling radius of a pneumatic tyre on hard terrains," *Int. J. Vehicle Systems Modelling and Testing,* vol. Vol 11, No 3, pp. pp. 234-251, 2016.
[12] Hamersma, H. A., Botha, T. R. & Els, P. S., "Wheel hop estimation on rough roads," presented at the The Dynamics of Vehicles on Roads and Tracks: Proceedings of the 25th International Symposium on Dynamics of Vehicles on Roads and Tracks (IAVSD 2017), 14-18 August 2017, Rockhampton, Australia, 2017.
[13] Reul, M. & Winner, H.**,** "Enhanced braking performance by integrated ABS and semi-active damping control," in *Proceedings of the 21st International Technical Conference on Enhanced safety of vehicles, Stuttgart, Germany*, 2009, pp. 09-0204, 2009.
[14] Els, P. S., Botha, T., Hamersma, H., Becker, C., Savitski, D., Heidrich, L. & Höpping, K.**,** "The effect of controllable suspension settings on the ABS braking performance of an off-road vehicle on rough terrain," in *Proc. of the 7th ISTVS Regional Americas Conference at Tampa, Florida*, 2013.
[15] Shao, J., Zheng, L., Li, Y., Wei, J. & Luo, M.**,** "The integrated control of anti-lock braking system and active suspension in vehicle," in *Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007)*, 2007, vol. 4, pp. 519-523: IEEE.
[16] Adcox, J., Ayalew, B., Rhyne, T., Cron, S. & Knauff, M., "Interaction of anti-lock braking systems with tire torsional dynamics," *Tire Science and Technology,* vol. 40, pp. 171–185, 2012.
[17] Hamersma, H. A. & Els, P. S., "ABS performance evaluation taking braking, stability and steerability into account," *International Journal of Vehicle Systems Modelling and Testing,* vol. 12(3/4), 2017.
[18] Aly, A. A., Zeidan, E.-S., Hamed, A. & Salem, F., "An antilock-braking systems (ABS) control: A technical review," *Intelligent control and Automation,* vol. 2, p. 186, 2011.
[19] Keshmiri, R. & Shahri, A. M., "Intelligent abs fuzzy controller for diverse road surfaces," *World Academy of Science, Engineering and Technology,* vol. 2, pp. 62–67, 2007.
[20] John, S. & Pedro, J. O., "Neural network-based adaptive feedback linearization control of antilock braking system," *International Journal of Artificial Intelligence,* vol. 10, pp. 21–40, 2013.
[21] Poursamad, A., "Adaptive feedback linearization control of antilock braking systems using neural networks," *Mechatronics,* vol. 19, pp. 767–773, 2009.
[22] Radac, M.-B. & Precup, R.-E., "Data-driven model-free slip control of anti-lock braking systems using reinforcement Q-learning," *Neurocomputing,* vol. 275, pp. 317-329, 2018.
[23] Zhao, D., Wang, B. & Liu, D., "A Supervised Actor—Critic Approach for Adaptive Cruise Control," *Soft Computing,* vol. 17, pp. 2089–2099, 2013.
[24] Sardarmehni, T. & Heydari, A.**,** "Optimal switching in anti-lock brake systems of ground vehicles based on approximate dynamic programming," in *Dynamic Systems and Control Conference*, 2015, vol. 57267.
[25] Drechsler, M. F., Fiorentin, T. A. & Göllinger, H., "Actor-Critic Traction Control Based on Reinforcement Learning with Open-Loop Training," *Modelling and Simulation in Engineering,* vol. 2021, 2021.
[26] Sutton, R. S. & Barto, A. G., *Reinforcement learning: An introduction, second edition*. MIT press, 2018.
[27] Adadi, A., "A survey on data-efficient algorithms in big data era," *Journal of Big Data,* vol. 8, no. 1, pp. 1-54, 2021.
[28] Haarnoja, T., Zhou, A., Abbeel, P. & Levine, S.**,** "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor," in *International conference on machine learning*, 2018, pp. 1861-1870: PMLR.
[29] Christodoulou, P., "Deep Reinforcement Learning Algorithms with PyTorch," in *Deep Reinforcement Learning Algorithms with PyTorch*, ed: GitHub, 2017.
[30] Bai, S., Kolter, J. Z. & Koltun, V., "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling," in *An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling*, ed, 2018.
[31] de-Wit, C. C., Tsiotras, P., Velenis, E., Basset, M. & Gissinger, G., "Dynamic Friction Models for Road/Tire Longitudinal Interaction," *Vehicle System Dynamics,* vol. 39, pp. 189-226, 2003.
[32] Hamersma, H. A. & Els, S.**,** "A comparison of quarter, half and full vehicle models with experimental ride comfort data," in *International design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2015, vol. 57106, p. V003T001A011: American Society of Mechanical Engineers.

[33] Stallmann, M. J. & Els, P. S., "Parameterization and modelling of large off-road tyres for ride analyses: Part 2 – Parameterization and validation of tyre models," *Journal of Terramechanics,* vol. 55, pp. 85-94, 2014.

[34] Bosch, H.-R. B., Hamersma, H. A. & Els, P. S., "Parameterisation, validation and implementation of an all-terrain SUV FTire tyre model," *Journal of Terramechanics,* vol. 67, pp. 11–23, 2016.

[35] ISO, *ISO 8608 Mechanical Vibration–Road Surface Profiles–Reporting of Measured Data*. Geneva, Switzerland: International Organization for Standardization, 2016.

[36] Becker, C. M. & Els, P. S., "Profiling of rough terrain," *International Journal of Vehicle Design,* vol. 64, pp. 240–261, 2014.

[37] Thoresson, M. J., Uys, P. E., Els, P. S. & Snyman, J. A., "Efficient optimisation of a vehicle suspension system, using a gradient-based approximation method, Part 1: Mathematical modelling," *Mathematical and Computer Modelling,* vol. 50, pp. 1421-1436, 2009.

[38] Uys, P., Els, P., Thoresson, M., Voigt, K. & Combrinck, W., "Experimental determination of moments of inertia for an off-road vehicle in a regular engineering laboratory," *International Journal of Mechanical Engineering Education,* vol. 34, no. 4, p. 291, 2006.

[39] Bosch, H.-R. B., Hamersma, H. A. & Els, P. S., "Parameterisation, validation and implementation of an all-terrain SUV FTire tyre model," *Journal of Terramechanics,* vol. 67, pp. 11-23, 2016.

[40] cosin scientific software. (2022, 11 May 2022). *FTire - Flexible Structure Tire Model Modelization and Parameter Specification*. Available: https://www.cosin.eu/support/documentation/

[41] Thoresson, M. J., Uys, P. E., Els, P. S. & Snyman, J. A., "Efficient optimisation of a vehicle suspension system, using a gradient-based approximation method, Part 1: Mathematical modelling," (in English), *Mathematical and Computer Modelling,* vol. 50, no. 9-10, pp. 1421-1436, Nov 2009.

[42] Els, P. S., Theron, N. J., Uys, P. E. & Thoresson, M. J., "The ride comfort vs. handling compromise for off-road vehicles," *Journal of Terramechanics,* vol. 44, pp. 303–317, 2007.

[43] Botha, T. R.**,** "High Speed Autonomous Off-Road Vehicle Steering," University of Pretoria, Master's thesis 2011.

[44] SAE International**,** "Antilock Brake System Review," SAE Standard J22462014, Available: https://www.sae.org/standards/content/j2246_201404/.

[45] Pan, S. J. & Yang, Q., "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering,* vol. 22, pp. 1345-1359, 2010.

[46] Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A. A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A. & others, "Overcoming catastrophic forgetting in neural networks," *Proceedings of the national academy of sciences,* vol. 114, pp. 3521–3526, 2017.

[47] Parisi, G. I., Kemker, R., Part, J. L., Kanan, C. & Wermter, S., "Continual lifelong learning with neural networks: A review," *Neural Networks,* vol. 113, pp. 54–71, 2019.

[48] Hamersma, H. A.**,** "ABS braking on rough terrain," Ph.D. dissertation, University of Pretoria, 2017.

[49] Shyrokau, B., Wang, D., Augsburg, K. & Ivanov, V., "Vehicle dynamics with brake hysteresis," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering,* vol. 227, no. 2, pp. 139-150, 2013.

[50] *ISO/PAS 21448 Road vehicles - Safety of the inteded functionality*, 2019.