

Enhanced Anti-Lock Braking System Performance: A Comparative Study of Adaptive Terminal Sliding Mode Control Approaches

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Abstract: Sliding Mode Control (SMC) has gained significant attention due to its simplicity, robustness, and rapid response in ensuring system stability, particularly with the Lyapunov approach. Despite its advantages, SMC faces challenges such as chattering near equilibrium, sensitivity to parameter variations, and delayed convergence. To address these issues, advanced techniques like Terminal Sliding Mode Control (TSMC) and Integral Terminal Sliding Mode Control (ITSMC) have been proposed. TSMC ensures finite-time convergence while mitigating chattering, while ITSMC further handles singularities and disturbances. Additionally, Adaptive Switching Control (ASC) based on Particle Swarm Optimization (PSO) is applied to achieve faster convergence, suppress chattering, and enhance system robustness. The adaptive control law, utilizing a Lyapunov-based approach, is employed to estimate and compensate for external disturbances, further improving system performance under uncertainties. Gain tuning, essential for optimizing system performance and reducing tracking errors, is achieved using the efficient Teaching–Learning-Based Optimization (TLBO) algorithm. This study applies TSMC, ITSMC, and ASC-based PSO to an Anti-Lock Braking System (ABS), aiming to enhance robustness, stability, and finite-time convergence while reducing chattering. Stability is analyzed through the Lyapunov theory, ensuring rigorous validation. MATLAB simulations demonstrate the effectiveness of the proposed methods in improving ABS performance, offering a valuable contribution to robust control techniques for systems operating under dynamic and uncertain conditions.

Keywords: terminal sliding mode control; integral TSMC; adaptive control law; anti-lock braking system; gain-tuning; particle swarm optimization algorithm; finite-time convergence; chattering reduction; Lyapunov



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1. Introduction

Over the years, control systems have seen continuous growth and development, attracting increasing attention from researchers and scientists. Sliding Mode Control (SMC) was first introduced in the 1960s and has demonstrated effective results across various industrial applications, including robotics [1,2], power electronics [3], aerospace [4–6] and automotive systems [7,8]. SMC provides a simple structure and robust performance for nonlinear systems, particularly in the presence of uncertainties and external disturbances. However, system dynamics can exhibit a slow convergence rate near the equilibrium point, making it difficult for the system state to reach the desired position [9]. To address the issue of delayed convergence time and ensure a finite-time convergence, Terminal Sliding

Mode Control (TSMC) was developed. It has been applied to both linear and nonlinear systems in Single-Input Single-Output (SISO) systems [10,11] and Multiple-Input Multiple-Output (MIMO) systems [12–14]. Despite the robustness of the controller, one of its main challenges is chattering, which can arise from singularities introduced by the sliding surface term. To address this issue, a new concept called Integral Terminal Sliding Mode Control was introduced. In ITSMC, an integral term is added to the sliding surface, making the switching phase smoother and the system more robust against external disturbances. These control strategies have been enhanced by various adaptive control methods in recent years to achieve optimal system performance.

In contrast, the performance of control systems without Terminal Sliding Mode Control has also been extensively studied. Classical SMC approaches, while robust and relatively simple, may not guarantee finite-time convergence or effectively mitigate slow convergence issues near the equilibrium point. These limitations have motivated the development of terminal sliding mode-based strategies. By comparing systems with and without TSMC, a clearer understanding of their respective strengths and weaknesses can be achieved, enabling better optimization for real-world applications.

To better reflect real-world nonlinear system environments, the presence of external disturbances and uncertainties is unavoidable and cannot be neglected. Recent studies have highlighted this challenge and proposed various methods to design adaptive and robust control strategies that counteract external disturbances while maintaining system stability. For instance, in [15,16], an adaptive nonsingular Sliding Mode Control approach was integrated with a barrier function to estimate the upper bound of external disturbances. In [17,18], several observer-based methods, such as disturbance observers and lumped perturbation observers, were introduced to approximate unknown disturbances, ensuring fast and finite-time convergence of the system. Furthermore, in [19], an adaptive nonsingular fast TSMC was designed using Lyapunov-based parameter estimation to reject external disturbances without requiring prior knowledge of their upper bounds.

On the other hand, the Anti-Lock Braking System is now considered an essential functionality in modern vehicles due to its crucial role in enhancing human safety. ABS research focuses on the integration of various components such as wheel speed sensors, hydraulic modulators, and electronic control units (ECUs) [20]. Numerous studies have demonstrated the effectiveness of ABS in reducing the number and severity of collisions. ABS has shown significant improvements in vehicle stability and control during braking, especially on wet or slippery roads [7,21]. Thus, studies have delved into several algorithms and control strategies employed by ABS to optimize braking performance under different driving conditions. Several robust control strategies have been introduced in the literature to maintain the wheel slip ratio at a desired value despite the presence of unknown dynamics and external disturbances, including SMC [22–25], a fuzzy logic controller [26–29], or even fuzzy logic combined with a PID controller for gain tuning [30].

However, the control gains play a crucial role in determining both the convergence time and tracking performance of a system. As a result, numerous studies have focused on gain tuning to achieve optimal performance [31–33]. One widely recognized algorithm is the Teaching–Learning-Based Optimization algorithm. Inspired by the behavior of students in classrooms, TLBO operates by iteratively updating the best student solution, converging towards optimal parameter configuration. A key advantage of TLBO is that it requires only a few hyperparameters. This algorithm has been particularly useful in enhancing Sliding Mode Control by providing an efficient means for selecting gains that improve system performance, especially in response to variations in the controlled system output.

This article addresses the following key points:

- Enhancements to TSMC and ITSMC, as reported in the literature, are discussed with a focus on improving sliding surfaces and the reaching law for nonlinear systems under external disturbances. These enhancements aim to improve convergence speed and tracking performance, and reduce chattering;
- The Teaching–Learning-Based Optimization algorithm is introduced for gain and parameter tuning, further enhancing system performance;
- Novel control strategies, including an adaptive switching control law based on Particle Swarm Optimization, are applied to an Anti-Lock Braking System. Simulations are conducted to compare the performance of these strategies on the system;
- External disturbances are compensated using a Lyapunov-based approach by adapting the control law.

The remainder of this paper is organized as follows: Section 2 provides an overview of TSMC and ITSMC, highlighting their advantages, limitations, and improvements for nonlinear systems. Section 3 introduces the TLBO algorithm, characterizing its working principles and its role in gain tuning to achieve optimal system performance. Section 4 presents the application of the discussed controllers on an ABS system, followed by simulation results using Matlab code in Section 5. The final section concludes the study with an analysis of the control strategies applied to the ABS system.

2. Terminal Sliding Mode Control Approaches

In this work, we consider the following second-order nonlinear system model [13,34]:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(\underline{x}, t) + g(\underline{x}, t) \times u(t) + D(t) \\ y = x_1 \end{cases} \quad (1)$$

where $\underline{x} = [x_1, x_2]$ is the state vector of the system and $f(\cdot)$ and $g(\cdot)$ represent the nonlinear dynamical system function and the control gain function, respectively. $u(t)$ is the control input, while $D(t)$ accounts for uncertainties and external disturbances. To achieve the controller's objective, a control law must be designed so that the system output y accurately tracks the desired reference signal. Consequently, the tracking error is defined (2) where x_{1d} is the desired output system as follows:

$$e = x_1 - x_{1d} \quad (2)$$

2.1. Terminal Sliding Mode Control

In traditional Sliding Mode Control, the sliding surface is typically defined as a linear function of the error and its derivatives (3) with positive control gain γ . The convergence is generally exponential, meaning that the error decreases over time but does not necessarily reach zero in a finite time [9]. This limitation arises because when the error is small (i.e., near the sliding surface), the gain γ governs the SMC behavior, which can result in slower convergence in these regions. Furthermore, in the presence of uncertainties and disturbances, SMC may experience reduced robustness and induce chattering due to its intrinsic switching mechanism, as follows:

$$S = \dot{e} + \gamma e \quad \gamma > 0 \quad (3)$$

On the other hand, Terminal Sliding Mode Control introduces a nonlinear sliding surface that achieves finite-time convergence (4) [13,34,35]. By incorporating fractional powers of the error, TSMC ensures faster convergence as the error decreases due to its high sensitivity near zero. When a nonlinear term is added to a linear sliding surface, resulting

in a Terminal Sliding Mode, finite-time convergence of the system's states is achieved by appropriately designing the nonlinear terms and control gains to satisfy stability conditions based on the Lyapunov approach. This results in more responsive control as the system approaches the desired state. TSMC delivers smoother control, enhanced performance near the origin, and a significant reduction in chattering. Additionally, the nonlinear terms improve convergence dynamics, especially in the presence of small errors, as follows:

$$\dot{S} = \dot{e} + \alpha e^{p/q} \quad \alpha > 0 \quad (4)$$

$$\dot{S} = \dot{e} + \alpha |e|^{p/q} \text{sign}(e) \quad \alpha > 0 \quad (5)$$

where p and q are positive odd integers with $q > p$ and $0 < p/q < 1$ ensuring smooth convergence and avoiding singularities as the error approaches zero, and α is a positive control gain. An enhanced sliding surface for TSMC, introduced in [9], provides additional refinements (5). By incorporating the absolute value in the second term of Equation (4), this method guarantees real-valued outputs for both positive and negative errors. This is crucial because, when the error is negative, fractional powers can yield complex numbers, as fractional powers of negative numbers are only real if the exponents are integers [36]. The conditions on p and q ensure that this issue does not arise. The sign function is then applied to restore the original sign of the error, improving the stability and smoothness of the sliding surface for practical control applications. This second sliding surface (5) is preferred due to its robustness when errors cross zero, ensuring continuous behavior without discontinuities or undefined conditions when handling negative errors.

To further accelerate the convergence speed, a novel reaching law is adopted for TSMC [35]. As the system states change, the system may not achieve optimal performance. Therefore, the proposed novel reaching law is given in Equation (7):

$$\dot{S} = -K_1 \text{sign}(S) - K_2 S \quad K_1, K_2 > 0 \quad (6)$$

$$\dot{S} = -\frac{K_1}{N(S)} \text{sign}(S) - K_2 S \quad K_1, K_2 > 0 \quad (7)$$

where K_1 and K_2 are the control gains, and $N(S)$ is the additional term to Equation (6), designed as follows:

$$N(S) = \delta + (1 - \delta)e^{-\sigma|S|} \quad 0 < \delta < 1, \sigma > 0 \quad (8)$$

The purpose of the term $N(S)$ is to dynamically adjust the control gain, ensuring fast convergence when $|S|$ is large and smoother control when $|S|$ is small. This is achieved by using δ to shape both the reaching dynamics and the control effort. However, both SMC and TSMC still face challenges such as singularities and chattering. To improve convergence speed based on the reaching law (6), the gains need to be increased; however, excessively high values introduce chattering into the controller [36]. To address this, several studies have proposed adaptations to the reaching law. In [36], an adaptive switching power term was introduced that integrated the sliding surface with its absolute value. In [34], an adaptive switching control law based on a Particle Swarm Optimization (PSO) algorithm was developed, where inertia weights were adjusted to accelerate convergence and eliminate chattering, even in the presence of disturbances. The effectiveness of this adaptive control law was demonstrated through simulation results.

In [37], an Adaptive Terminal Sliding Mode Control (ATSMC) was designed using a Recurrent Neural Network (RNN). A terminal function was incorporated into the terminal sliding surface to ensure that the system's tracking error converged to zero in finite time, eliminating the need for a separate reaching phase and providing a faster, more precise

response. Additionally, to reduce the impact of unknown disturbances and further minimize chattering, a fuzzy logic approach was integrated with the RNN to approximate the equivalent control law. In [38], a dynamic Terminal Sliding Mode Control law was proposed for Single-Input Single-Output (SISO) uncertain nonlinear systems, ensuring a balance between chattering suppression and tracking accuracy. A dynamic terminal sliding mode surface, based on a terminal function, eliminates the reaching phase, and, consequently, reduces chattering. Using the Lyapunov approach, the control law was shown to provide robust tracking performance, finite-time convergence, and strong resistance to external disturbances.

2.2. Integral Terminal Sliding Mode Control

The main purpose of Integral Terminal Sliding Mode Control is not only to ensure finite-time convergence with enhanced robustness but also to eliminate steady-state errors in the presence of significant external disturbances. By adding an integral term to the sliding surface of TSMC, the system can immediately enter the sliding manifold, avoiding the effects of the reaching phase during the initial time period [39]. This approach allows for the error to accumulate over time, effectively eliminating steady-state error and reducing chattering. In [40], two novel integral terminal sliding surfaces were introduced for robust nonlinear systems: the sign integral (9) and the fractional integral (10) terms, each with a positive constant gain $\beta > 0$, as follows:

$$S = e(t) + \beta \int_0^t \text{sign}(e(\tau)) d\tau \quad (9)$$

$$S = e(t) + \beta \int_0^t e^{p/q}(\tau) d\tau \quad (10)$$

where $0 < \frac{p}{q} < 1$ with p and q being positive odd integers. Combining the sign integral and the fractional integral into a single integral terminal sliding surface offers several advantages. The sign integral enhances robustness by effectively handling discontinuities, while the fractional integral adds smoothness and stability to the control action. In [9,41], an adaptive integral terminal sliding surface was presented (11) to avoid singularities, ensure finite-time convergence, and dynamically adapt to changes in system conditions or external disturbances. However, the sign function can introduce discontinuities in the sliding surface around zero. To address this, a tanh function can be employed as an alternative to achieve smoother performance, as follows:

$$S = e(t) + \beta \int_0^t |e(\tau)|^{p/q} \text{sign}(e(\tau)) d\tau \quad (11)$$

Many studies across various fields have proposed novel Integral Terminal Sliding Mode Control (NITSMC) strategies, demonstrating their effectiveness compared to traditional approaches or existing methods. In [41], an NITSMC-based adaptive integral backstepping control was introduced and applied to a piezoelectric ultrasonic motor to handle external disturbances and model uncertainties while maintaining high tracking precision. The study first employed an integral terminal sliding surface (11) and used an integral backstepping methodology based on the first and second derivatives of the sliding surface. The switching gain of the designed control was then estimated using the Lyapunov approach, as it must be determined in advance based on the upper bound of disturbances, which is often difficult to obtain. In [42], a Global Integral Terminal Sliding Mode Control (GITSMC) with an adaptive reaching law was applied to proton exchange membrane fuel cells and compared with a traditional Integral Terminal Sliding Mode Control. A global integral terminal sliding surface (12) was defined, from which the equivalent control law

was derived. The switching control gain was then adapted to be variable, depending on the sliding surface and the upper bounds of uncertainties and disturbances. Experimental results demonstrated the superior performance of the proposed approach in terms of robustness, tracking accuracy, and the reduction in chattering effects when compared to other methods. The equation is given as:

$$S = e(t) + \beta \int_0^t e(t)dt + \eta \left(\int_0^t e(t)dt \right)^{p/q} \beta, \eta > 0 \quad (12)$$

An Adaptive Gain Integral Terminal Sliding Mode Control (AGITSMC) with Time-Delay Estimation (TDE) was proposed in [43] for a pneumatic artificial muscle system to ensure finite-time convergence of tracking errors in the presence of unknown dynamics and disturbances. The ITSMC was designed to reject uncertainties and disturbances, with TDE used to approximate system nonlinearities and an adaptive gain-based Lyapunov approach used to estimate the ideal robust control gain. Similarly, in [44], a novel ITSMC was introduced for MIMO discrete systems, where the switching gain was adaptively estimated to suppress chattering without sacrificing tracking accuracy.

3. Teaching–Learning-Based Optimization (TLBO) Algorithm

When developing a system, finding the best and optimal solutions is the primary concern of scientists and researchers. Nature has long been a source of inspiration for countless breakthroughs in industry and human progress. Humans possess the unique ability to observe, learn from nature, and apply these insights to innovate and achieve their goals. Several algorithms have been introduced and developed based on social swarm behaviors in nature, including: Ant Colony Optimization (ACO) [45]; Bee Colony Optimization (BCO) [46]; and Particle Swarm Optimization [47,48]. These techniques belong to the family of Swarm Intelligence (SI) algorithms. Frequently, comparative studies and enhancements of these methods are conducted across various fields to validate and improve their performance [49–51].

On the other hand, inspired by human interactions in a classroom, the Teaching–Learning-Based Optimization algorithm has gained substantial attention and has found broad applications across various fields in recent years [52–54]. Developed by Rao et al. in 2011, the TLBO algorithm operates in two primary phases. The first phase, known as the Teaching Phase, involves the teacher (the current best solution) guiding the students (the population) toward improved solutions (13) based on their fitness (objective function) values (14). The teacher aims to elevate the students' understanding, effectively pushing them toward higher-quality solutions. In the second phase, the Learning Phase, students interact with one other, sharing and learning through a peer-to-peer process. They collaboratively discover new, potentially better solutions, enhancing the overall quality of the population's solutions, as follows:

$$X_{new} = X_{old} + rand \times (X_{teacher} - TF \times Mean_Solution) \quad (13)$$

$$fitness = \int_0^t |e| \quad (14)$$

where X represents the solution and TF is the teaching factor. The algorithm starts by defining parameters, such as population size and maximum iterations, initializing the population within the solution space. At each iteration, the fitness of all solutions is evaluated, with the best (teacher) solution selected. In the Teaching Phase, learners update their solutions relative to the teacher's knowledge level. In the Learning Phase, pairs of learners interact, moving toward each other based on their fitness values. The process

continues until the maximum number of iterations is reached, yielding optimal gains based on the lowest fitness value achieved. The TLBO algorithm is shown in Figure 1, where *best_idx* is the best index of the control gains given the best objective function.

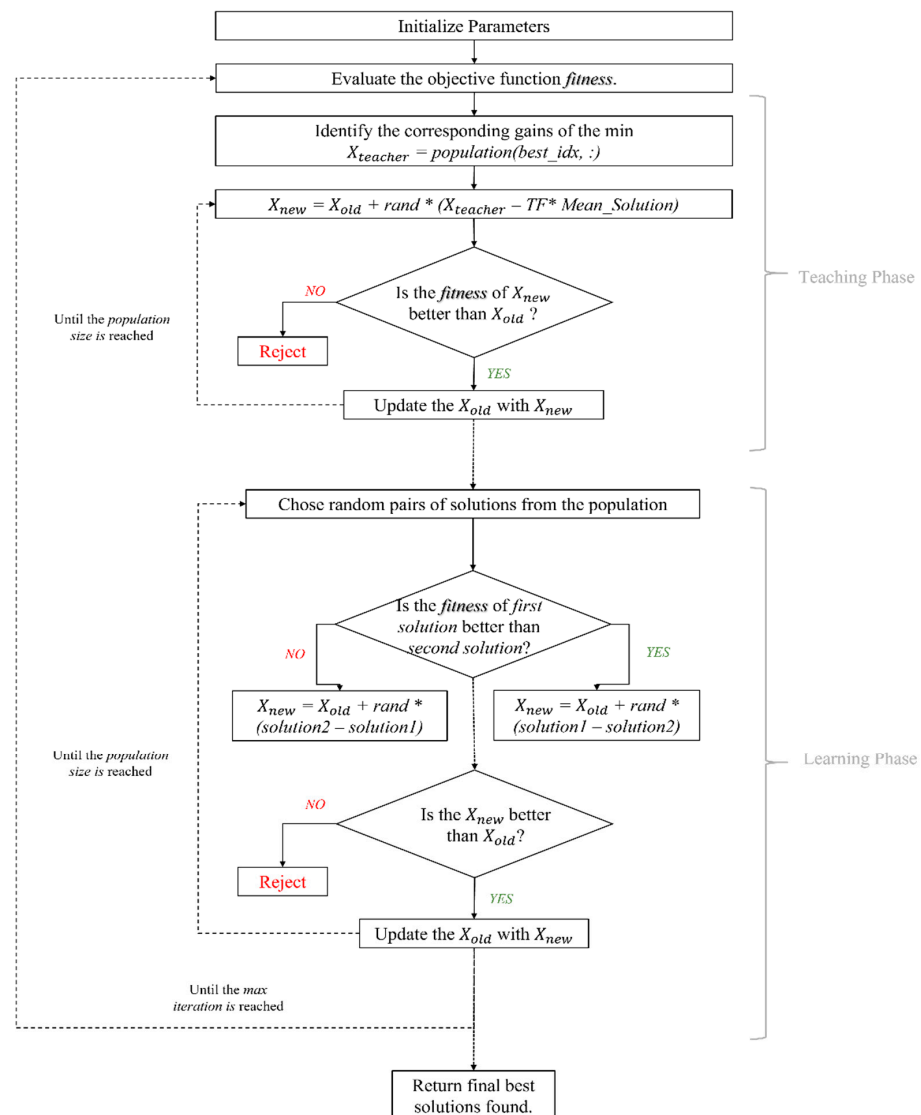


Figure 1. TLBO algorithm structure.

4. Anti-Lock Braking System (ABS)

In this paper, we consider the following nonlinear dynamical system of the Anti-Lock Braking System (ABS) presented in Figure 2 [7]:

$$\dot{\omega} = \frac{(F_t - F_f)}{J} R + \frac{(T_e - T_b)}{J} \quad (15)$$

$$\dot{v} = \frac{-F_t}{M} - \frac{F_a}{M} \quad (16)$$

where ω and v represent the wheel angular velocity and vehicle velocity, respectively. T_e and T_b are the engine and braking torques, F_a is the air resistance, F_t is the longitudinal tire force of the wheel, F_f is the rolling resistance of the wheel during braking operations, R is the radius of the wheel, and J is the moment of inertia of the wheel.

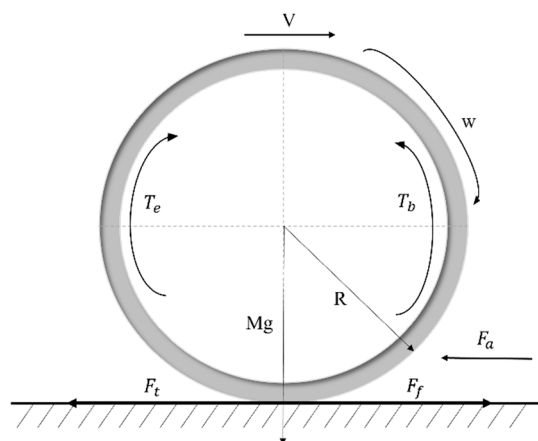


Figure 2. ABS system for quarter-car model.

The state-space representation of Equations (17) and (18) are as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{(F_t - F_f)}{J} R - \frac{1}{J} u + \Delta \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = \frac{-F_t}{M} - \frac{F_a}{M} \end{cases} \quad (17)$$

where x_1 , x_2 , x_3 and x_4 represent the state-space variables, Δ represents the external disturbances bounded by $\eta > 0$, and u is the control input, which corresponds to the braking torque during the deceleration phase [22].

The tractive force F_t is generated by the longitudinal tire displacement of the wheel in contact with the ground. It depends on the vehicle mass M and the magnitude of the acceleration due to gravity g . F_t is then defined as follows:

$$F_t = \mu(\lambda) \frac{Mg}{4} \quad (18)$$

where $\mu(\lambda)$ denotes the road–tire friction coefficient (19), depending on both road–tire conditions and the wheel slip ratio λ . The Magic Formula (Pacejka) describes the tire longitudinal force F_x , lateral force F_y , and aligning torque M_z as functions depending on the wheel slip and various parameters, including the stiffness factor B , shape factor C , peak value D , and curvature factor E [55].

In this study, the lateral force coefficient $\mu(\lambda)$ is used as the output parameter, considering the parameters for dry concrete road conditions described in Table 1, as follows:

$$\mu(\lambda) = D \times \sin\{C \times \arctan[B \times \lambda - E(B \times \lambda - \arctan(B \times \lambda))]\} \quad (19)$$

Table 1. Parameters of the lateral force coefficient for dry concrete road conditions.

Parameter	Value
D	0.9
C	2.2
B	6
E	0.98

The wheel slip ratio is defined as the output of the Anti-Lock Braking System. The objective of the proposed Terminal Sliding Mode Control is to track the desired output despite dynamic uncertainties and external disturbances and to converge the error towards

zero in a finite time. The tracking error is defined as follows, where λ_d represents the desired wheel slip ratio and λ is the actual wheel slip ratio:

$$e = \lambda_d - \lambda \quad (20)$$

During the braking phase, the wheel slip ratio is defined as follows:

$$\lambda = \frac{V - \omega R}{V} \quad (21)$$

By taking the time derivative of the wheel slip ratio (21) and substituting the wheel's angular velocity $\dot{x}_2 = \dot{\omega}$ and the vehicle's velocity $\dot{x}_4 = \dot{V}$ from the system dynamics, assuming no disturbances, we obtain, as follows:

$$\dot{\lambda} = \frac{1}{V} \left(\frac{R^2}{J} F_f - \frac{(1-\lambda)}{M} F_a \right) - \frac{1}{V} \left(\frac{R^2}{J} + \frac{(1-\lambda)}{M} \right) F_t + \frac{R}{JV} u \quad (22)$$

- *Application of TSMC approaches:*

To derive the equivalent control law, the terminal sliding surface S defined in Equation (5) is selected, and its first-time derivative is set to zero. By substituting Equation (22) into this condition, the equivalent control law is obtained as expressed in Equation (23):

$$u_{eq_TSMC} = \frac{J}{R} \left[\frac{R^2}{J} (F_t - F_f) + \frac{(1-\lambda)}{M} (F_t + F_a) + \dot{x}_4 \alpha |e|^{p/q} \text{sign}(e) \right] \quad (23)$$

The reaching control law is defined initially using the traditional reaching law in Equation (6) and subsequently refined using the novel reaching law in Equation (7), which includes an additional term $N(S)$. Consequently, the corresponding switching control laws are defined as follows:

For the traditional reaching law (TRL):

$$u_{sw_TRL} = \frac{Jx_4}{R} [K_1 \text{sign}(S) + K_2 S] \quad (24)$$

For the novel reaching law (NRL):

$$u_{sw_NRL} = \frac{Jx_4}{R} \left[\frac{K_1}{N(S)} \text{sign}(S) + K_2 S \right] \quad (25)$$

To ensure system stability, the Lyapunov approach is employed. The Lyapunov function is chosen as:

$$V(t) = \frac{1}{2} S^2 > 0 \quad (26)$$

and its derivative is defined as follows:

$$\dot{V}(t) = S\dot{S} \quad (27)$$

By substituting the global control laws (u_{eq_TSMC} and u_{sw_TRL}) and (u_{eq_TSMC} and u_{sw_NRL}) into the derivative of the sliding surface and then into the Lyapunov function derivative, the following results are obtained:

For TRL:

$$\dot{V}_{TRL}(t) = S(-K_1 \text{sign}(S) - K_2 S) \rightarrow \dot{V}_{TRL}(t) = -K_1 |S| - K_2 S^2 < 0 \quad (28)$$

For NRL:

$$\dot{V}_{NRL}(t) = S(-\frac{K_1}{N(S)}\text{sign}(S) - K_2 S) \rightarrow \dot{V}_{NRL}(t) = -\frac{K_1}{N(S)}|S| - K_2 S^2 < 0 \quad (29)$$

The negative definiteness of the Lyapunov function derivatives confirms the stability of the system [56]. Here, K_1 , K_2 , and $N(S)$ are all defined as positive constants to guarantee convergence and stability.

- *Application of Integral TSMC approach:*

In this section, an enhanced integral terminal sliding mode surface is applied, as defined in Equation (30) [41]:

$$S = \rho e(t) + \theta \int_0^t |e(\tau)|^\kappa \text{sign}(e(\tau)) d\tau \quad (30)$$

where $0 < \kappa < 1$, ρ and θ are positive control gains. The first derivative of the sliding surface is expressed as follows:

$$\dot{S} = \rho \dot{e}(t) + \theta |e(t)|^\kappa \text{sign}(e(t)) \quad (31)$$

By substituting Equation (22) into the tracking error's derivative and incorporating these results into Equation (31), the equivalent control law is derived as follows:

$$u_{eq_ITSMC} = \frac{J}{R} \left[\frac{R^2}{J} (F_t - F_f) + \frac{(1-\lambda)}{M} (F_t + F_a) + \frac{x_4}{\rho} \theta |e|^\kappa \text{sign}(e) \right] \quad (32)$$

The switching control law, based on the tradition reaching law, is defined as follows:

$$u_{sw_ITSMC} = \frac{J}{R} \frac{x_4}{\rho} [K_1 \text{sign}(S) + K_2 S] \quad (33)$$

Using the Lyapunov function $V(t)$ and its derivative $\dot{V}(t)$, as defined in Equations (26) and (27), the derivative of the Lyapunov function for the ITSMC case becomes:

$$\dot{V}_{ITSMC}(t) = S \left(-K_1 \text{sign}(S) - K_2 S + \frac{\rho R}{x_4} \Delta \right) \quad (34)$$

$$\dot{V}_{ITSMC}(t) \leq |S| (-K_1 - K_2 |S| + \frac{\rho R}{x_4} \eta) < 0 \quad (35)$$

To guarantee system stability, given that $\frac{\rho R}{x_4} > 0$, the condition $K_1 > \frac{\rho R}{x_4} \eta$ must hold for $\dot{V}(t) < 0$. Since the upper bound of the disturbances η is unknown, K_1 is adaptively estimated without requiring prior knowledge of η using Lyapunov approach. The adaptive switching control law is expressed as:

$$u_{sw_ITSMC}^{adap} = \frac{J}{R} \frac{x_4}{\rho} [\hat{K}_1 \text{sign}(S) + K_2 S] \quad (36)$$

A new Lyapunov function is introduced in Equation (37) to account for the adaptive estimation, where $\tilde{K}_1 = \hat{K}_1 - K_1$. By setting $\dot{\tilde{K}}_1 = -\left| \dot{S} \right|$, system stability is ensured, as follows:

$$V_{ITSMC}(t) = \frac{1}{2} S^2 + \frac{1}{2} \tilde{K}_1^2 \quad (37)$$

$$\begin{aligned}\dot{V}_{ITSMC}(t) &\leq |S|(-\hat{K}_1 - K_2|S| + \frac{\rho^R}{x_4}\eta) + (\hat{K}_1 - K_1)\dot{\hat{K}}_1 \\ \dot{V}_{ITSMC} &\leq |S|(K_2|S| - K_1 + \frac{\rho^R}{x_4}\eta) < 0.\end{aligned}\quad (38)$$

This ensures the stability of the system, as the Lyapunov function remains negative definite, validating the effectiveness of the adaptive ITSMC approach.

5. Simulation and Results

In the simulation section, a comparative study was carried out to evaluate the performance of Terminal Sliding Mode Control, its enhancements, and Integral TSMC in the presence of significant external disturbances. The following four simulation scenarios were considered:

- TSMC with Basic Reaching Law: In the first simulation, TSMC was applied to an Anti-Lock Braking System. The combined control law u_{eq_TSMC} and u_{sw_TRL} were implemented to evaluate fundamental convergence dynamics;
- TSMC with Novel Reaching Law: The second simulation introduced an improved reaching law, employing the control laws u_{eq_TSMC} and u_{sw_NRL} . This approach aimed to accelerate convergence rates and reduce chattering effects;
- Adaptive TSMC using PSO: The third simulation integrated an adaptive switching control law based on a Particle Swarm Optimization algorithm. This approach dynamically adjusted the inertia weight to enhance robustness and minimize chattering. The PSO-based switching law is defined as follows:

$$u_{sw} = w \times u_{sw} + c_1 \times rand \times (x_p - u_{sw}) + c_2 \times rand \times (x_g - u_{sw}) \quad (39)$$

where c_1 and c_2 represent the cognitive and social parameters of PSO algorithm, respectively; x_p and x_g denote the personal best and global best solutions; and w is the adaptive inertia weight, defined as follows:

$$w = a + \frac{b \times \exp(S^2)}{1 + \exp(S^2)} \quad a > 0, b > 0; \quad (40)$$

- ITSMC simulation: The fourth simulation focused on ITSMC, employing the control law u_{eq_ITSMC} and $u_{sw_ITSMC}^{adap}$ to address the steady-state error, singularity problem, and further mitigate disturbances.

The parameters of the system dynamics and controller are presented in Table 2 [7].

Table 2. System dynamics and controller parameters.

Parameters	Value	Parameters	Value
M	415 Kg	p/q	5/7
R	0.3 m	δ	0.5
J	100 Kgm ²	σ	10
g	9.81 m/s ²	θ	0.5
λ_d	2	κ	0.8

The convergence speed, tracking performance, sliding surface behavior, and control input were compared across the four simulations based on their overall performance and robustness. To optimize the control gains (α , ρ , K_1 , K_2), the Teaching–Learning-Based Optimization algorithm was employed in each simulation to identify the optimal parameter

values. Additionally, the selected parameters for the PSO algorithm and the resulting optimal values obtained through the TLBO algorithm are summarized in Table 3:

Table 3. PSO and TLBO parameters.

Parameters	Value	Parameters	Value
c_1	1.5	α	[0 8]
c_2	2.5	K_1	[0.02 10]
a	0.1	K_2	[0.01 5]
b	0.8	ρ	[0 10]

The control and optimization parameters were chosen based on several simulations. The chosen values were optimized to ensure effective system performance.

The results of the first simulation, illustrated in Figure 3, demonstrate the tracking performance of the wheel slip ratio under the influence of external disturbances, as depicted in Figure 4. Both the Terminal Sliding Mode Control with traditional and novel reaching laws exhibit effective tracking capabilities. However, the novel reaching law achieves a slightly faster convergence rate compared to the traditional approach. On the other hand, the Adaptive TSMC optimized using Particle Swarm Optimization showed remarkable performance. It achieved faster convergence while maintaining precise tracking performance and ensuring system stability, ultimately approaching the performance of the Integral Terminal Sliding Mode Control.

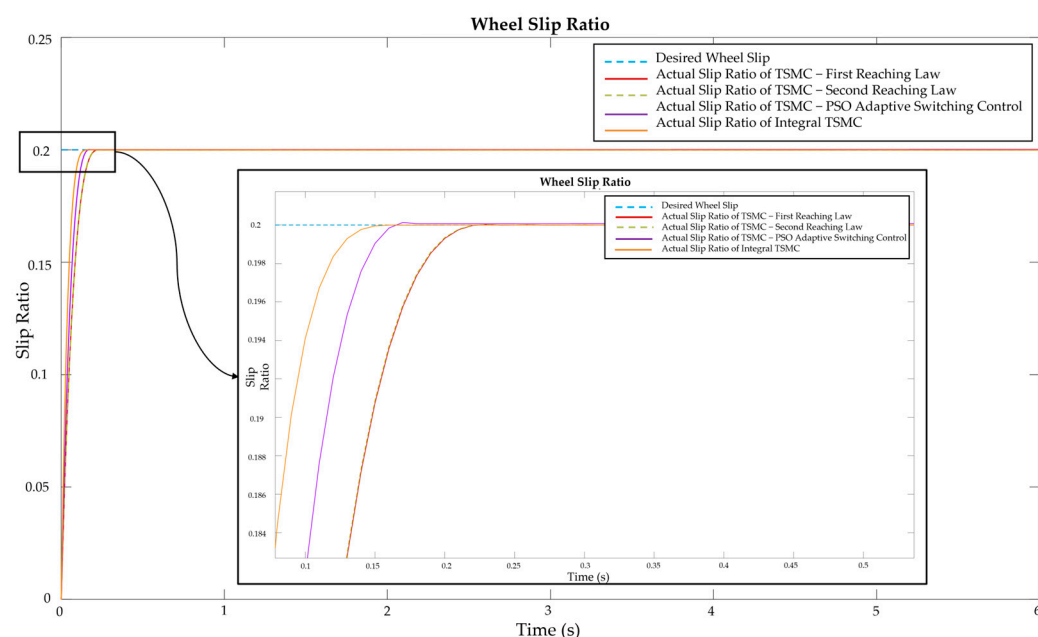


Figure 3. Wheel slip ratio tracking for different TSMC and ITSMC control strategies.

Figure 5 presents the control input behavior of the system. The Adaptive TSMC-based PSO effectively suppresses chattering and compensates for the impact of external disturbances. The control input remains stable and significantly smoother than that of the ITSMC. Furthermore, the control input using the novel reaching law exhibits minor chattering and smoother behavior compared to the traditional reaching law, highlighting its superior performance.

The third simulation, depicted in Figure 6, illustrates the evolution of the sliding surface. The Adaptive TSMC-based PSO rapidly converges to zero, with a slight overshoot dur-

ing the initial phase. Despite this, it achieves a smoother overall behavior and outperforms the other TSMC methods in terms of reducing chattering. This underscores the effectiveness of the Adaptive TSMC-based PSO in ensuring robust and precise control performance.

The ITSMC showed, throughout all the simulations, better compensation of the disturbances using the estimated Lyapunov-based approach. This approach enabled it to adaptively account for the nonlinear dynamics and external uncertainties of the system, ensuring superior robustness and stability while maintaining precise control under varying conditions.

The control gains for these simulations were optimized using the Teaching–Learning–Based Optimization algorithm, with the resulting optimal values summarized in Table 4.

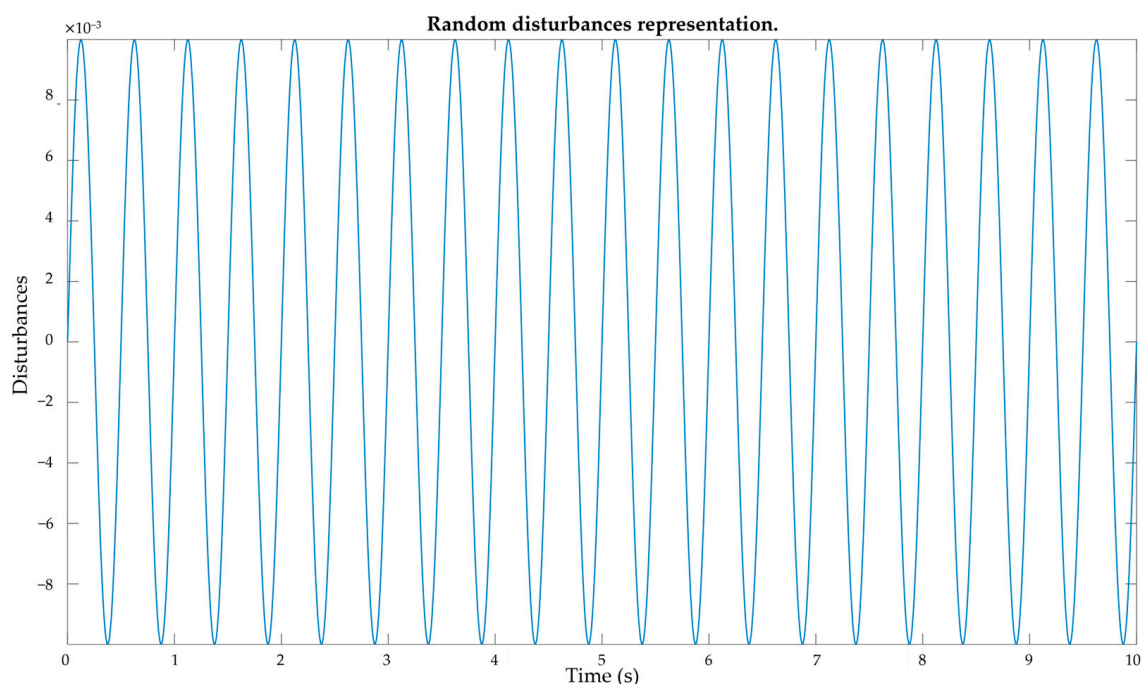


Figure 4. External disturbances.

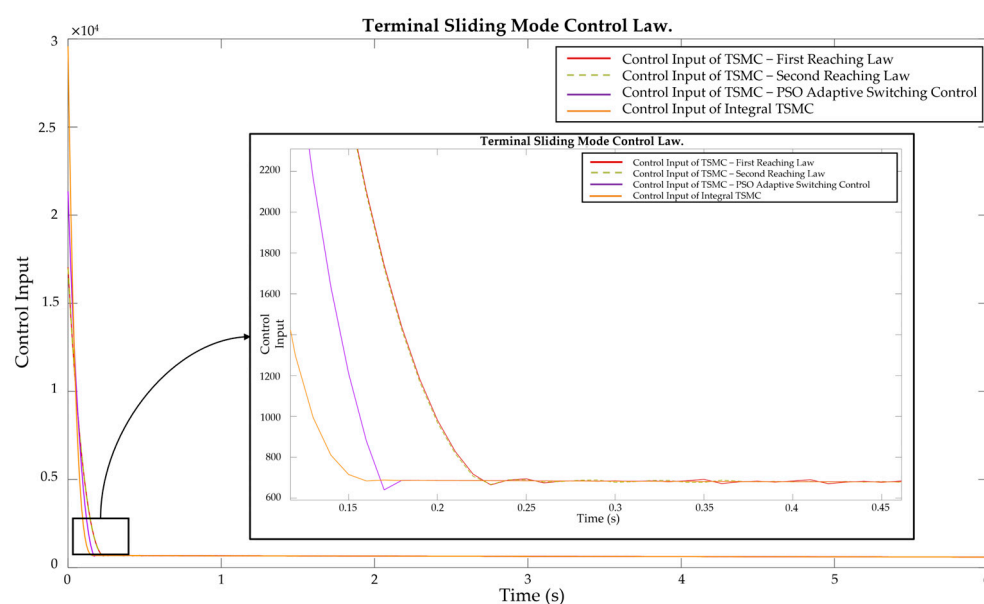


Figure 5. Control law input for TSMC and ITSMC.

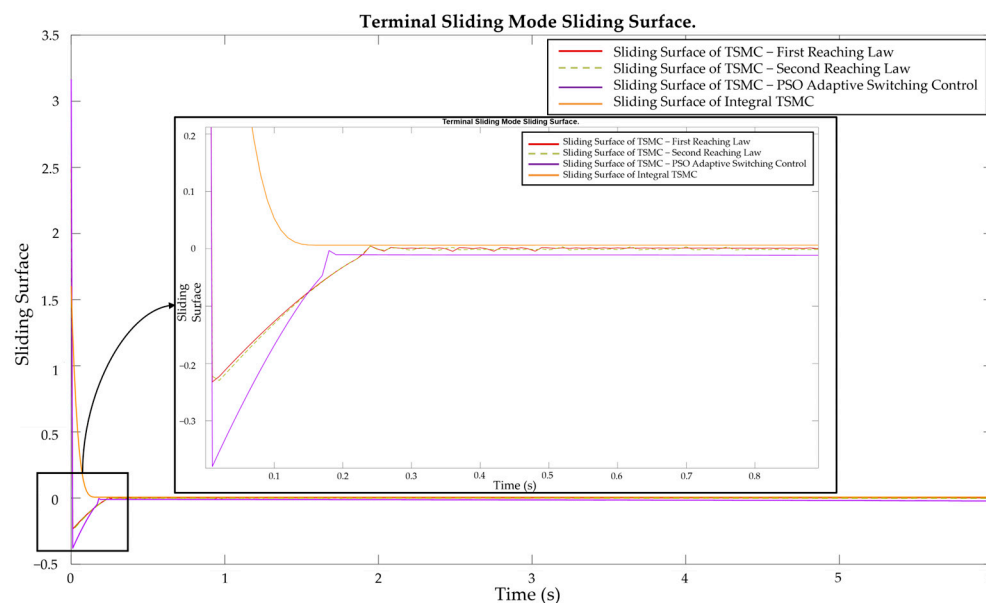


Figure 6. Sliding surface for TSMC and ITSMC.

Table 4. Control parameter tuning using TLBO.

Designed Control	Tuned Parameters
First Reaching Law for TSMC	$\alpha = 7.95, K_1 = 0.02, K_2 = 0.0129$
Second Reaching Law for TSMC	$\alpha = 8, K_1 = 0.02, K_2 = 0.01$
Adaptive switching control law for TSMC	$\alpha = 10$
Integral Terminal Sliding Mode control	$\rho = 10, K_1 = 0.02, K_2 = 0.01$

Real-time experiments would greatly enhance the validation of the simulation results by providing a more accurate assessment of the control system's performance under practical conditions, including external disturbances and real-world uncertainties. While these experiments offer significant benefits, such as verifying the system's robustness and reliability, they also present challenges, including the complexity of setup, managing external factors, and ensuring a controlled environment that closely replicates ideal simulation conditions.

6. Conclusions

This study provides a comprehensive review of Terminal Sliding Mode Control, with a particular focus on the various enhancements introduced over the years to improve controller performance. Advancements in sliding mode surfaces and reaching laws were thoroughly examined, emphasizing their roles in achieving fast and finite-time convergence, minimizing chattering, smoothing control responses, and avoiding singularities. The implementation of the Teaching–Learning–Based Optimization algorithm ensured the precise tuning of control parameters, leading to optimized performance. A comparative simulation was conducted to evaluate different TSMC approaches alongside Integral TSMC. The results demonstrated that each control method performed as expected, with the proposed enhancements delivering substantial improvements in convergence speed, tracking accuracy, and robustness. These findings underscore the effectiveness of the refined approaches in addressing key challenges associated with traditional sliding mode techniques. For further research, it is essential to explore the integration of adaptive control techniques, such as fuzzy logic and neural networks, with TSMC and ITSMC, to enhance the system's performance under dynamically changing conditions. Additionally, real-time experiments and real-world testing will be conducted to validate the simulation results,

as they offer a deeper understanding of how these methods perform under practical, real-world disturbances and uncertainties. Future studies could also focus on addressing the singularity issues in Terminal Sliding Mode and optimizing the disturbance rejection capabilities for a broader range of applications.

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