INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue X October 2025

Overview of Use of PID, Fuzzy Logic, and Model Predictive Control in Autonomous Vehicle Systems

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DOI: https://dx.doi.org/10.51244/IJRSI.2025.1210000318

Received: 02 October 2025; Accepted: 08 October 2025; Published: 21 November 2025

ABSTRACT

This review article provides a brief overview of the applications of Proportional – Integral – Derivative (PID), Fuzzy Logic, and Model Predictive Control (MPC) technologies in the autonomous vehicles industry. PID is a popular control method used in various industries because of its simplicity and tuning methods. PID control serves as a fundamental building block for many control systems due to its simplicity. Fuzzy Logic control offers flexibility and robustness to handle uncertainties. MPC provides advanced predictive control while working as a cutting-edge control strategy. This paper tried to develop an overview of the use of the above-mentioned technologies in autonomous vehicle speed control, steering control, path following, stability control, and energy management in the recent past, while providing a brief introduction to the controlling mechanisms along with their history.

Keywords: Autonomous, Fuzzy logic, MPC, PID, Process control, Robot control

INTRODUCTION

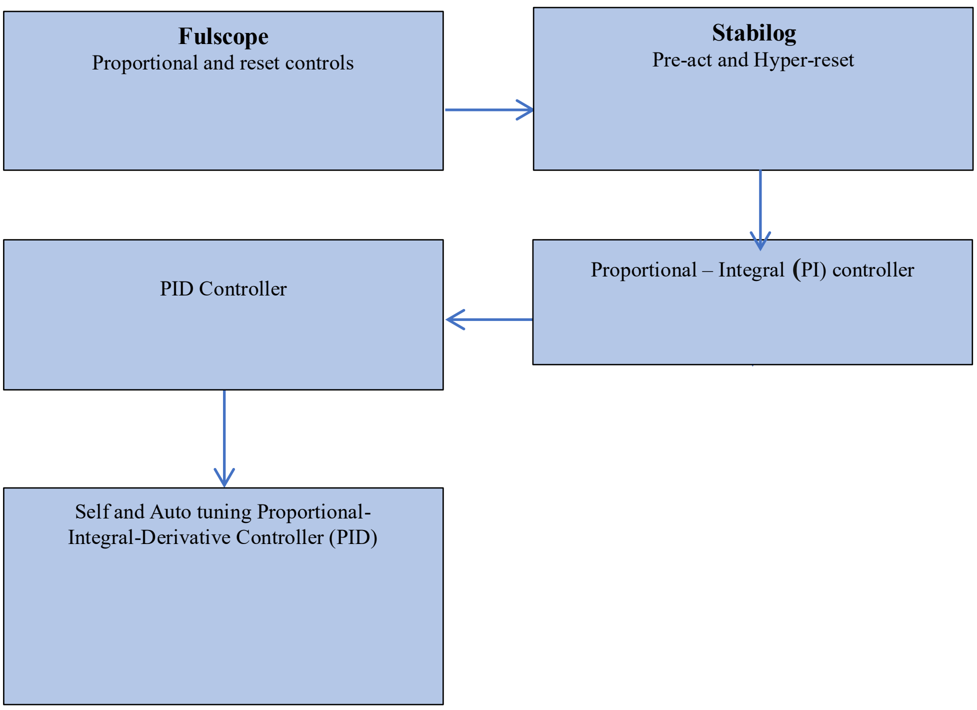

Figure 1: The development of PID controlling technology in the past decades

A brief history of PID technology

PID technology has a very long history. N. Minorsky first introduced the concept of PID controlling technology by analyzing the ship steering problem and proposing a mathematical model for automatic control [1]. Taylor layered a great foundation on PID technology with their "Fulscope" pneumatic controller in 1939 [2]. In the next decades, this controller developed its function according to the following Figure 1.

Introduction to PID technology

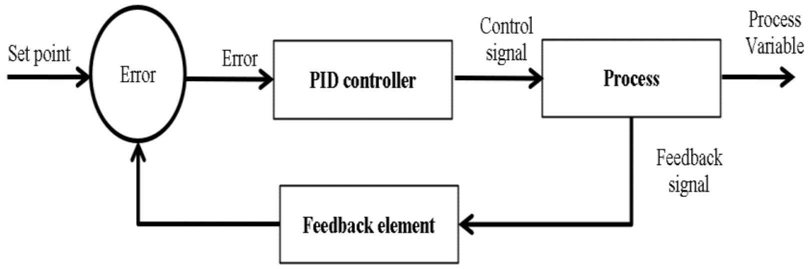

Figure 2：Closed loop control system with an PID controller

A PID controller operates in a closed-loop control system, as given in Figure 2.

According to Figure 2, the PID controller observes the error between the process variable and the set point. Then, it generates the controlling signal and provides it to the process to minimize the error. The controller's output is derived from the sum of three distinct components called proportional, integral, and derivative modes [3], [4]. The controlling signal can be expressed as "Equation (1)".

$$u(t) = K_p\, e(t) + K_i \int_0^t e(t)\ dt + K_d \frac{de(t)}{dt} \qquad (1)$$

Where Kp is the proportional gain. Ki is the integral gain. K_d is the derivative gain, where e(t) and u(t) are errors. The proportional term is directly proportional to the present error of the system. It takes necessary actions to correct the real-time error. However, the only use of proportional terms can't remove the steady state error that can occur in the process.

The integral controller has the ability to correct the error that occurred past by integrating. This eliminates the steady-state error and reduces the system's error by considering its average error over the past time. However, the use of integral mode along with proportional mode can lead to overshoots and oscillations. A derivative controller can be employed to reduce overshoots and unnecessary oscillations. The derivative mode is responsive to the rate of change of the error, which predicts future errors and corrects them.

Fuzzy logic controlling

1). A brief history of fuzzy technology:

Fuzzy logic was first introduced in 1965 by Prof. Lotti Zadeh, who is a mathematician, computer scientist, and electrical engineer [5]. Later, he published works such as 'A Rationale for Fuzzy Control' in 1972 and 'Linguistic Approach' in 1973, which layered a strong foundation for other researchers in this field [6]. In the next decades, this topic improved very well, and hardware was also developed as fuzzy logic controllers beyond the mathematical concept developments [7].

2). Introduction to Fuzzy Logic:

Fuzzy logic is a popular controlling mechanism used in different fields, such as automotive systems, robotics, and industrial process systems. Fuzzy logic can be identified as an extended version of Boolean logic. In the Boolean systems, it only represents two states called 0 and 1, or OFF and ON, or LOW and HIGH. However, the main drawback of the Boolean system is that it cannot be used to represent states such as VERY LOW,

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PARTIALLY LOW, MEDIUM, PARTIALLY HIGH, and VERY HIGH states that are between the LOW to HIGH (0 to 1) states. As a solution, these system variables are presented as a value between 0 and 1 [8], [9].

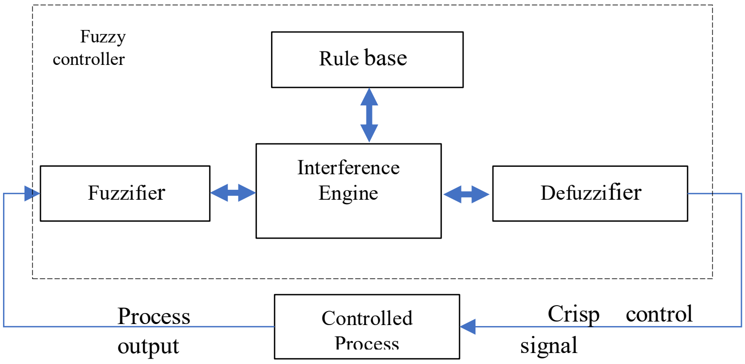

Figure 3 : Fuzzy logic system architecture

In fuzzy logic control, there are four major components to follow, as given below.

i) Fuzzification: The system variable is converted into a fuzzy variable.

ii) Rule-based: This component involves the rule setting. The rule settings are mostly followed by the IF-THEN function.

iii) Inference engine: This component applies the fuzzy rules to the fuzzy input values to produce fuzzy outputs.

iv) Defuzzification: The fuzzified values are converted again to the system variable values.

Technical considerations in Fuzzy logic control

When applying fuzzy logic to autonomous vehicle control, the design of membership functions, rule base, inference mechanism, and defuzzification method critically affects performance.

i) Membership function design: It defines how continuous inputs, such as steering error, lateral deviation, or speed error, map to fuzzy sets [10].

ii) Rule-based construction: The rule base dictates how the controller responds to different conditions using linguistic IF-THEN statements. Increasing the number of rules generally improves control precision but also increases computational burden [11].

iii) Inference mechanism: The Mamdani inference method is commonly used in automotive fuzzy control due to its intuitive reasoning and continuous implementation. It combines rules using fuzzy AND/OR operations and aggregates the outputs.

iv) Defuzzification strategy: After inference, fuzzy outputs must be converted to crisp actuator signals. There are different methods, including Centroid and Mean of Maximum Bisector.

In centroid, it provides smooth output but is computationally heavier. The mean of the maximum method is simpler but potentially less precise. In many vehicle control applications, the centroid method is used because of its accuracy, even at the cost of some computation [12].

Model predictive control (MPC)

1). A brief history of MPC:

The controlling methods, such as PID and Fuzzy logic, are not self-tuning; instead of incorporating them are incorporated with some developments for self-tuning. The foundation for MPC was first laid in the 1970s and

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue X October 2025

1980s by several research studies. The survey conducted by Garica et al. analyzed several MPC techniques available in the 1980s. This study has analyzed the MPC relation to linear quadratic control as well [13]. Keyser et al. also conducted similar research by comparing the available long-range MPC techniques by comparing them with each other [14].

In the next decades, several researchers introduced and developed the MPC to the present level by introducing features such as Constrained receding-horizon predictive control [15]and the use of long-range (LR), long-range quadratic programming (LRQP), and quadratic programming (QP) methods along with MPC to handle input and output constraint controlling [16].

2). Introduction to MPC

MPC is the complex and precise control method used in feedback control systems. The main advantage of this method is that it can be used with multi-input output systems while maintaining constraints. MPC is different from PID and Fuzzy logic in future predictive behavior.

MPC uses a mathematical model to make several predictions to reach the reference value. These predictions are made to predict the future behavior of the system over a time horizon in a systematic way. During these predictions, the MPC model satisfies the given constraints for both inputs and outputs. This model optimizes the mathematical model in order to reduce the cost function of the system.

MPC functions in accordance with mainly two parameters called the prediction horizon and the control horizon.

Prediction horizon: The future window that predicts the behavior of the system. A longer prediction horizon allows the system to better long-term planning, but it requires higher computational power.

Control horizon: The control horizon is smaller than the prediction horizon. The control variables are optimized within this window to follow a pre-defined path.

Control function: The cost function represents the amount of errors produced by the system with weighted values. In order to improve the performance of the system, MPC always tries to minimize the cost function [17].

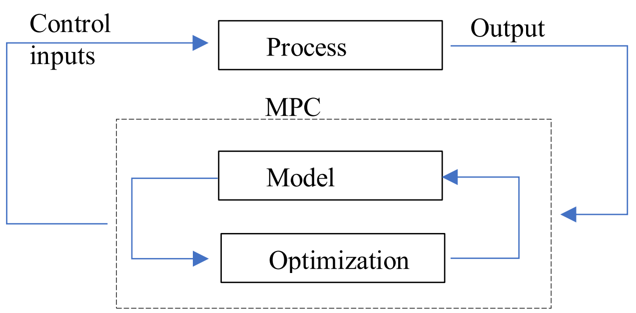

Figure 4: MPC system architecture

A brief history of autonomous technology

With the developments of electrical and electronic engineering, computing technology, and network systems, vehicles have been developed into very advanced systems over the past few decades. The first implication of the concept of autonomous technology was introduced in the 1920s with radio-controlled vehicles by the Houdini Radio Control Company, which was called the “American Wonder” [18]. This vehicle was operated by radio signals from another pilot vehicle. After several attempts and research, the 21st century marked the evaluation of autonomous vehicles with many commercially available products. Most of the major vehicle manufacturing companies started to spend a considerable amount of money on the R&D activities of autonomous car development. The development of autonomous cars was highly contributed to by the development of electrical

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and electronic engineering, computing technology, sensing technology, image processing, and artificial intelligence, along with its subfields such as machine learning and deep learning. The Google company took a good initiative by developing the Google car, which achieved a significant number of miles in 2010 in urban areas. After that, there were commercial productions such as Mercedes-Benz S-Class S500 and Tesla Model S. Along with these commercial products, Uber and General Motors have developed AV taxi services [19], [20].

The development of autonomous vehicle technology helps to reduce accidents since there is no possibility of conditions such as drunk driving or distractions. However, this reduction can only be successful if this vehicle fulfills all the safety requirements along with the advanced controlling techniques with minimum or zero errors [21].

As mentioned in the previous paragraphs, PID is a popular and well-established control method in control systems. It has been well developed in autonomous vehicle technology as well, with the integration of techniques such as fuzzy logic and artificial intelligence [22]. In the 21st century, these controlling mechanisms have been well developed with the introduction of mechanisms such as MPC, Artificial Neural Networks, and Genetic Algorithms in autonomous vehicle controlling [23].

Comparative Evaluation of PID, Fuzzy Logic, and MPC in Autonomous Vehicle Control

Autonomous vehicle control requires robust, efficient, and adaptive algorithms to handle dynamic environments, nonlinear vehicle dynamics, and real-time constraints. PID, Fuzzy Logic, and MPC method offers distinct strengths and limitations. The comparative table provides an analysis of each of the methods in comparing of complexity, real-time feasibility, nonlinear handling, and predictive ability.

Table 1: Comparative summary table

Feature	PID	Fuzzy Logic	MPC
Complexity	Low	Medium	High
Real-time feasibility	High	Medium	Limited
Nonlinear handling	Weak	Strong	Strong
Predictive ability	None	None	Strong
Best for	Basic control, Speed	Uncertain environments	Steering, stability, optimization

Hybrid and AI Augmented Control for Autonomous Vehicles

Recent research increasingly focuses on hybrid and AI-enhanced control strategies that combine the strength of classical control methods, such as PID and MPC, with intelligent methods. Hybrid and AI-enhanced methods are:

Fuzzy-PID hybrid controllers: Fuzzy logic can dynamically adjust the gains K_p, K_i, and K_d of a PID controller based on driving conditions, improving adaptability and performance under varying vehicle conditions and uncertainties. Studies have shown that fuzzy-PID controllers achieve reliable, superior response time and stability in lane-keeping tasks [11].

Fuzzy-MPC for adaptive cruise control: In adaptive cruise control systems, a fuzzy-MPC framework has been proposed that adapts weighting factors in the MPC objectives based on driving conditions. This enables real-time interchange between safety, comfort, and energy efficiency [24].

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Neural- Fuzzy and Learning based controllers: These types of controllers have been designed for steering control in vision-based unmanned vehicles, improving robustness under parametric uncertainty and external disturbances [25].

PID for Speed Control of Autonomous Vehicles

PID controllers play a crucial role in maintaining precise speed control for autonomous vehicles. Research by Tagor Hossain et al. [26]demonstrates their application in adjusting the throttle pedal position based on the calculated velocity error. This ensures the vehicle adheres to the desired speed profile, contributing to overall trajectory tracking performance, especially when navigating sharp curves.

The design of a speed controller within the path-tracking system highlights how the controller utilizes vehicle dynamics and trajectory data to regulate the vehicle's speed while following a predefined path. Another study [27] explores optimizing PID controller performance for speed control. This research investigates the use of metaheuristics like genetic algorithms to achieve this. Optimizing PID parameters minimizes factors like overshoot, settling time, and steady-state error, leading to a high level of control accuracy and stability for autonomous vehicles.

The speed control is based on the integration of vehicle dynamics into the control system, where the dynamic model of the vehicle influences the speed adjustments to ensure accurate path tracking. Lu et al. [28] discuss the development of a Personalized Behavior Learning System (PBLS) for Human-Like longitudinal speed control in autonomous vehicles, focusing on improving motion planning in complex traffic environments. The study highlights the importance of personalized adaptation in motion planning to enhance driving smoothness, comfort, and human-like behavior in autonomous vehicles, aiming to increase their acceptance by considering human personalities. The process of reproducing observed real driving scenes in PreScan using collected real driving data emphasizes the integration of real-world driving behaviors into the simulation environment for training purposes.

The PID controller is utilized to generate control commands for throttle and brake systems based on the output of the controller. The PID controller output is converted into throttle and brake control commands through a conversion block embedded in PreScan, known as the 'Path follower' module. Real driving data is collected and used to train the PBLS in PreScan for speed control applications. The PID controller is tested in a simulation platform built by PreScan and MATLAB /Simulink for evaluating the performance of the proposed learning system in speed control applications.

The paper proposes a novel coupled lateral and longitudinal controller based on MPC for autonomous vehicles. An 8-degree-of-freedom (DOF) vehicle model is used as the prediction model, while a 14-DOF vehicle model is employed as the plant model. The MPC controller determines the optimal road-wheel steering angle for lateral control, and a PID controller is embedded in the solution to regulate the total driving or braking wheel torque for longitudinal control. The PID controller is utilized for longitudinal dynamics control in the proposed system. In the suggested system, longitudinal dynamics are controlled using a PID controller. It regulates the overall driving or braking wheel torque based on the difference between the target and the actual speed of the vehicle. The PID controller assists in keeping the vehicle's speed near to the intended speed by changing the acceleration and braking input signals as needed. The research accomplishes effective speed control by incorporating the PID controller within the MPC framework and considering time-varying speed profiles in the path-tracking process [29].

Tiwari et al. [30] implement a PID controller for both lateral and longitudinal control of the autonomous vehicle. The longitudinal control module focuses on maintaining the speed profile of the vehicle, integrating both lateral and longitudinal controllers for improved performance in various terrains and speeds. The PID controller in the longitudinal control system generates acceleration commands for the upper-level controller, which then translates these commands into throttle and brake inputs for precise vehicle tracking and utilizes feedback control mechanisms to adjust the vehicle's acceleration based on deviations from the desired speed profile, thus aiding in achieving accurate speed tracking.

PID For Steering and Stability Control of Autonomous Vehicles

PID control is a valuable tool for steering control in autonomous vehicles. One study [31] emphasizes its role in maintaining stability and smoothness during maneuvers, ensuring the vehicle stays centered within the lane boundaries. This control mechanism is crucial for both software simulations and hardware testing of autonomous vehicles.

Beyond basic steering control, advanced techniques utilizing PID controllers have also been explored. Furthermore, research by Chunjiang Bao et al. [32] discusses the use of adaptive PID control algorithms for path tracking in unknown environments. This approach demonstrates the adaptability of PID control for various steering control scenarios in autonomous driving.

A PID controller that enables track maneuvering for self-driving cars is proposed by Farag et al. [33]. Three distinct design approaches are employed to identify and optimize the controller hyperparameters. One of these is "WAF- Tune," an ad hoc trial-and-error technique proposed in this research for this particular application. The suggested controller accepts only the cross-track error as an input and outputs the steering command. Extensive simulation studies on complex tracks with many sharp curves were conducted to assess the performance of the proposed controller at various speeds. The analysis demonstrates that the proposed strategy outperforms the others. The utility and limitations of the suggested tuning mechanism are also examined in detail.

The PID controller in one of the research [34] showed varying performance compared to other controllers like PD and MPC. In the closed-loop steering performance evaluation with jacked front wheels, the PID controller had a steady state error exceeding 2%. This indicated that the PID controller struggled more with maintaining the setpoint accurately. During on-road testing at 1 km/h, the PID controller performed with an error below 2%, showing a relatively higher error compared to the PD controller. At higher speeds, such as 2 km/h, the PID controller outperformed the PD controller, which initially experienced instability but eventually recovered. However, the PID controller still exhibited some unstable responses. The PID controller's power consumption was noted to be the lowest in a specific scenario compared to the PD and MPC controllers. As the sampling time of the controller decreased to -0.002 seconds, the PID controller's performance degraded compared to PD and MPC controllers, indicating that lower sampling times impacted its performance significantly. It is important to note that while the PID controller showed lower power consumption in certain scenarios, it struggled with achieving precise setpoint control in comparison to the other controllers tested in the research.

PID control contributes significantly to stability control in autonomous vehicles. A study conducted by Lin et al. [35] explores the application of PID controllers in maintaining roll stability using a fuzzy PID algorithm.

The PID controller is integrated into the fuzzy PID control framework to regulate the lateral transfer ratio (LTR) and ensure vehicle roll stability by controlling the braking cylinder pressure of each tire. This approach combines the strengths of fuzzy control and PID control to provide robustness, fast response, and the ability to handle nonlinearities, all crucial for maintaining vehicle stability. This application emphasizes the role of PID controllers in enhancing safety for autonomous vehicles. The study by Tingting Wang et al. [36] investigates the use of PID controllers within an adaptive fuzzy control algorithm to ensure the stable operation of AGVs. This approach utilizes dynamic modeling and parameter analysis to design the steering control system for AGVs, achieving stable operation after optimization. This demonstrates the effectiveness of PID control in enhancing in-situ steering stability for specific types of autonomous vehicles. The PID controller is embedded into the system to analyze and enhance the stability of the AGV during steering operations by regulating the steering dynamics and minimizing deviations in the rotation center.

Motion sickness (MS) is caused by inappropriate wheel turning, causing significant lateral acceleration and increased head movement. Passengers tilt their heads toward the direction of lateral acceleration, causing an increment in MS. The study proposes a fuzzy-proportional integral derivative (PID) controller for an MS minimization control structure, focusing on lateral acceleration and head tilt to reduce lateral acceleration. The control uses head movement as a controlled variable for corrective wheel angle computation. An experiment using a driving simulator confirmed the system's performance, reducing motion sickness incidence by 3.95% for single laps and 11.49% for ten laps [37].

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The paper employs a multi-objective digital PID controller design method using the parameter space approach of robust control. It starts by focusing on absolute stability, ensuring that the closed-loop poles remain inside the unit circle in the digital PID controller parameter space. Additionally, the design considers phase margin, gain margin, and a mixed sensitivity bound as frequency domain constraints to enhance controller performance and robustness. An example illustrating the application of this method in path following controller design for an automated driving vehicle is provided, showcasing the practical utility of the proposed approach [38].

The paper proposed a novel method for steering control in autonomous vehicles, utilizing type-2 fuzzy logic control combined with PI control. This primary control system had inputs of distance, navigation, and speed, with the output being the steering angle value. This output was then used as input for the secondary control, PI control, which adjusted the motor's position based on the steering angle. The study results demonstrated that type-2 fuzzy logic control and PI control provided better and smoother control compared to type-1 fuzzy logic control and PI. Type-2 fuzzy logic control showed more robustness to disturbances, resulting in smoother turning angle control and shorter response times. The secondary control, PI control, played a crucial role in adjusting the motor's position to manifest the steering angle. It ensured that the motor response closely followed the output of the fuzzy logic control system, leading to fast and precise control responses. Additionally, the paper explored the use of PD and PID controls in conjunction with type-2 fuzzy logic control. The results showed that while PID control responded faster initially, PD control was better at maintaining the expected values over time [39].

The research uses a Proportional-Integral-Derivative (PID) controller paradigm to provide longitudinal trajectory tracking in autonomous electric vehicles using the CARLA simulation environment. A three-level iterative testing approach is used to assess the performance of the developed controller. This method involves modifying the controller's error definition and proportional gain to determine its stability and accuracy. To assess the controller's performance, a sequence of ten increasingly oscillating trajectories is employed to disturb the control process. This testing method aids in determining how well the controller can handle various tough conditions. The study undertakes an investigation of several error ratio definitions to examine their impact on the controller's effectiveness [40].

PID for Path Following of Autonomous Vehicles

PID controllers are instrumental in achieving accurate path following for autonomous vehicles. A core study [41] investigates the use of a PID controller with three different tuning approaches for steering an autonomous car along a pre-defined track. The controller utilizes Cross-Track Error (CTE) as input and generates steering commands as output, enabling the car to navigate complex tracks with sharp turns. The Path Tracking Controller (PTC) of autonomous vehicles also utilizes PID control. As highlighted in another research [42], the PTC acts as an interface between the vehicle's dynamic behavior and the path planner, using sensory feedback to implement accurate path tracking. Additionally, research by Chunjiang Bao et al.[32] discusses the use of a nested PID steering control algorithm for path-tracking experiments on roads with uncertain curvature. This showcases the effectiveness of PID control in various path-following scenarios for autonomous vehicles. PID controllers are extensively applied in autonomous vehicles, particularly in Automated Guided Vehicles (AGVs) [43]. The study utilized Particle Swarm Optimization (PSO) to optimize the PID controller parameters for each motor of the AGV, enhancing route-tracking performance. By adjusting 12 parameters based on the error between reference and actual motions, the PSO algorithm determined optimal PID coefficients for each motor, ensuring efficient control input generation. This optimization process facilitated the adjustment of AGV motion by correlating wheel angular velocities with motor control input voltages, resulting in successful route tracking with fast response and strong stability.

Holovatenko et al. [44] implemented PID controllers for each wheel of a two-wheel AGV, with parameters such as an overshoot of 0% and fast settling time. The PID controllers were constructed with specific P, I, and D constants for both the left and right wheels. By utilizing PID controllers in AGVs, the system can effectively regulate the movement of the vehicle, ensuring precise trajectory tracking with minimal energy consumption.

The PID controller is used for comparison with the SDC-NMPC controller to evaluate performance, showing that the SDC-MPC outperforms the PID controller in handling complex tracks with sharp turns. The PID controller is employed in the SDC system for offline training of the neural network before adaptive nonlinear MPC approach testing, where data is collected from the system running under PID control.

The PID control strategy is applied to calculate the lateral deviation between the expected and actual path, enabling the vehicle to track the desired trajectory effectively [45]. By simplifying the vehicle's structure into a two-degree-of-freedom kinematic and dynamic model, the PID feedback control law is utilized to enhance path-tracking performance, ensuring safety and stability during operation. This approach improves the speed and accuracy of path tracking control, making it suitable for intelligent vehicles operating under safe conditions. The simulation results demonstrate that the designed PID control system offers excellent tracking accuracy, real-time performance, and driving stability across different speeds, validating its effectiveness in autonomous vehicle path-tracking applications.

Yao et al. [46] propose a trajectory optimization method for autonomous vehicles, focusing on driving efficiency, safety, comfort, and handling stability. It addresses issues like vehicle handling stability, model simplification, and lack of objective evaluation of comfort. The paper also presents a hierarchical control framework based on SMC for enhancing control strategies for autonomous vehicle path tracking. Additionally, the Hamilton algorithm-based vehicle yaw rate follow control method is discussed for improving path tracking. In this approach, the model parameters are identified through the forgetting factor least squares algorithm, and PID control parameters are adjusted using a BP neural network.

A novel path-tracking approach for autonomous driving addresses the limitations of traditional methods like PID controllers and pure pursuit (PP) in another research conducted by Shan et al. [44]. It uses a reinforcement learning (RL) model to integrate PID with PP, improving tracking performance and ride quality. The RL model includes an actor model trained for smoothness and accuracy in path-tracking tasks. PID directly adjusts to tracking errors, reducing lateral errors in path tracking. By adjusting the weight of PID, tracking accuracy can be significantly enhanced while maintaining system stability. However, improper weights may amplify jerks and oscillate, highlighting the challenge of finding a balance between tracking error and ride quality. The RL model effectively addresses the weight-adjustment problem of PID and PP, surpassing traditional manual adjustments for optimal performance in path tracking.

The research paper proposes a comprehensive control method that combines MPC and Fuzzy PID control. MPC is utilized to ensure the vehicle's yaw stability during path tracking by considering various factors such as front wheel angle, sideslip angle, tire slip angles, and yaw rate. The PID control aspect, specifically the Fuzzy PID algorithm, contributes to maintaining the vehicle's roll stability by regulating the braking force applied to each tire. The combination of MPC for yaw stability and Fuzzy PID control for roll stability creates a robust and effective control system that significantly improves the autonomous vehicle's path-tracking performance [35].

Two-layer controllers also can be used for accurate lateral path tracking control of autonomous vehicles [47]. The upper-layer controller consists of a Linear Time-Varying MPC (LTV-MPC) optimized offline with PSO, implementing front wheel steering angle control. A constraint on the slip angle is imposed to maintain vehicle stability by preventing lateral forces from saturating. The lower layer employs a radial basis function neural network proportion-integral-derivative (RBFNN-PID) controller to generate electric current control signals for steering motor operation. The nonlinear characteristics of the steering system are modeled and adapted online using RBFNN (Radial Basis Function) to adjust PID control parameters. The PID controller outputs the steering angle while ensuring accurate lateral path tracking control in autonomous vehicles. By using an RBFNN-PID setup, the system can rapidly track the target steering angle by adjusting the electric current signals sent to the steering motor.

The RBFNN helps in identifying the nonlinear characteristics of the steering system so that the PID controller can effectively adapt and maintain stability during the path tracking process.

The paper simplifies the vehicle structure into a two-degree-of-freedom kinematic and dynamic vehicle model to design the path-tracking controller based on PID control. This controller calculates the lateral deviation between expected and actual paths and outputs the front wheel rotation angle for the vehicle to travel along the expected path. The developed PID path tracking controller is used to follow a circular reference path at a speed of 30 km/h. The results reveal that the front wheel angle changes smoothly, allowing for regular vehicle operation and stability during the tracking procedure [48].

PID For Energy Management of Autonomous Vehicles

Autonomous vehicles use PID control to optimize energy. Another research article on energy management in autonomous vehicles discusses the application of a PID controller in reducing fuel consumption [49]. The PID controller is utilized to control the air/fuel ratio by adjusting the throttle angle based on the road power demand model, which considers environmental conditions, driver behavior, and vehicle specifications. The intelligent energy management system, incorporating a Fuzzy Logic System and the PID controller, aims to optimize engine torque generation and air/fuel ratio control to enhance energy efficiency in conventional autonomous vehicles. Through simulations, it was demonstrated that implementing this intelligent energy management system led to a 6.8% improvement in energy efficiency, showcasing the effectiveness of PID controllers in optimizing energy consumption in autonomous vehicles. Phan et al. [50] discuss the application of a PID controller in energy management systems for conventional autonomous vehicles, aiming to enhance powertrain efficiency. The PID controller is utilized to regulate the throttle of the engine, adjusting the air-to-fuel ratio to produce the desired torque based on the optimal torque generated by a neuro-fuzzy system. This system dynamically considers the road power demand of the vehicle, leading to improved fuel efficiency. Another great application of the PID controller can be identified as being utilized specifically for managing the state of charge (SoC) of the battery in the hybrid electric vehicle, ensuring efficient energy utilization and optimal performance [51]. The PID controller in this application helps regulate the charging and discharging of the battery to maintain the SoC within desired levels, contributing to improved fuel economy and overall system efficiency. By effectively controlling the SoC of the battery, the PID application ensures that the energy management system operates optimally, leading to enhanced performance and reduced energy consumption in the vehicle.

Ye et al. introduce a new PID energy management structure optimized using the Particle Swarm Optimization (PSO) algorithm, resulting in the PSO-PID energy management strategy [52]. The PID controller is utilized to optimize the battery working mode by controlling the power system, aiming to reduce energy consumption while maintaining battery operation. Results show that the PSO-PID strategy effectively optimizes battery output current, compensates for high-frequency power output with a supercapacitor, and minimizes the total energy consumption of the HESS (hybrid energy storage system).

The PID control strategy optimized by the PSO algorithm effectively reduces the peak current of the battery by 17.9350 A and 2.1906 A under different simulation conditions, showcasing improved energy efficiency and battery protection.

CONCLUSION AND FUTURE DIRECTIONS

In this review, the principal control strategies were discussed including PID, Fuzzy logic, and MPC. Each method has unique advantages. PID for simplicity and real time implementation, Fuzzy logic for handling uncertainty and nonlinearity and MPC for prediction, optimization and constraint management.

However, no single control methodology enough for all autonomous driving tasks. Hybrid controllers such as Fuzzy-PID and Fuzzy-MPC give reliable performance by leveraging the strengths of each underlying controller.

Based on the studies the future research should focus on developing real time computationally efficient MPC solvers for embedded automotive platforms, integrating reinforcement learning with MPC to enable online adaption and applying these control strategies to energy efficient autonomous vehicle, where control decisions directly impact energy consumption.

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