

An Investigation of Model Predictive Control in Self-driving Vehicles

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Abstract

Autonomous vehicles, which are often known as self-driving automobiles or driverless cars, are vehicles that can navigate and operate without human intervention. They require efficient controllers capable of handling complexities, with reduced computational costs, and should handle multiple inputs and outputs simultaneously. Model predictive control (MPC) possesses all these characteristics which means it can be utilized effectively for the same purpose. MPC for autonomous vehicles proposes various ways of achieving efficient strategies for major path-tracking problems of autonomous vehicles (AV) focusing on their design, implementation, and performance across various scenarios. The experimental simulation results, the inferences, and the future scope of the work are also specified. This review paper encapsulates the various MPCs used in various control problems related to AV. Model Predictive Control (MPC) is an algorithm that has proven to be an effective tool for managing the dynamic and complex situations encountered by self-driving cars. This article explores the fundamentals of MPC, its applications in autonomous driving, and the challenges and potential advancements in this field of technology.

Keywords: Model predictive control (MPC), autonomous vehicles (AV), path tracking, optimization function, neural network (NN)

INTRODUCTION

Autonomous vehicles represent the mode of transportation in the future, where an effectively working vehicle would be able to increase the comfort of the user, optimize fuel consumption, and reduce the time taken for travel. The major functionality of autonomously driven vehicles lies in their ability to traverse the designed path. This is known as the path tracking of the vehicle. Path tracking requires the controller to be robust, free of error, and capable of making instantaneous decisions. It should also be able to return to the same path even after being affected by any disturbance or hindrance. Model predictive control (MPC) is one such type of controller that utilizes current information to produce an optimal control signal given the possible future state. Each step of the MPC signal is formulated after

solving an optimal control problem. The computational complexity of this method is high. The path-tracking problem using different strategies has a major emphasis on the improvement of optimization and simplification of real-time implementations. For this purpose, MPC is coupled with other algorithms to obtain a better optimization function, thereby reducing the computational load of the MPC.

Enhanced MPC [1] was used to overcome the problem of autonomous vehicles during path tracking. This improvement was achieved by combining MPC with fuzzy adaptive weight control. The controller ensures tracking accuracy

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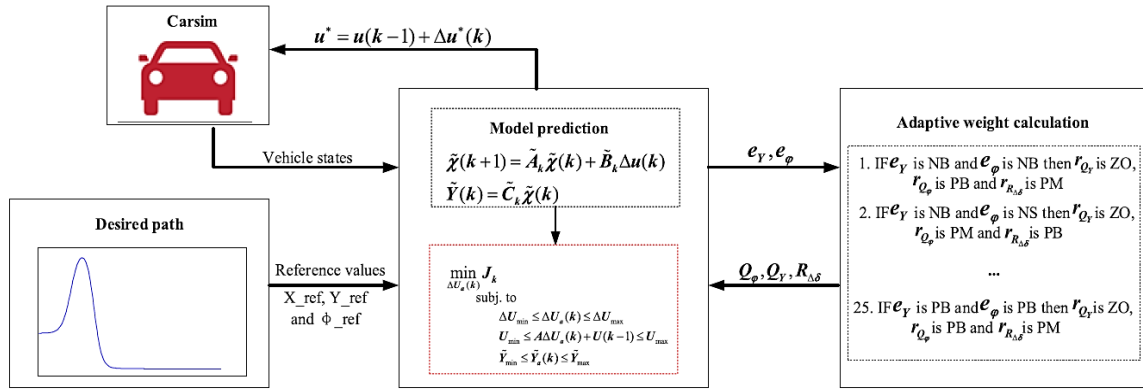


Figure 1. Path-tracking MPC architecture proposed [1].

and considers the vehicle's dynamic stability. The classical MPC controller steering wheels are drastically revised in a short period in pursuit of tracking efficiency. The driver's comfort problem owing to the fixed weight assumed in the cost function is far away from the desired path. The weight updating is done with the help of a fuzzy adaptive control algorithm. The controller effectiveness is simulated in MATLAB-CarSim/Simulink by considering two scenarios: one where the initial point of starting the autonomous vehicle coincides with the path of the pre-determined trajectory, and the next scenario is when the vehicle is far away from the target trajectory. The simulations verified that high tracking accuracy was achieved, the improved MPC ensured steering smoothness and ride comfort, and lateral dynamic stability was also obtained. The improved MPC controller compared to the pure-pursuit controller for autonomous vehicle path tracking experimentally shows that it excels in accuracy and smooth steering, in contrast to the jerky maneuvers of the pure-pursuit method. It dynamically adjusts weights and effectively balances path convergence and high-precision tracking, particularly in scenarios involving GPS errors as shown in Figure 1.

A Homothetic Tube-based MPC (HTMPC) framework is used to optimize the system's future trajectory and tube geometry simultaneously, which dynamically resizes tubes according to the uncertainty and the system's current state. This algorithm also provides both a feasible formulation of the tube and a homothetic factor with low computational complexity. This algorithm can be coupled with MPC to form a framework for a linear path-tracking system [2]. The robustness of the algorithm was evaluated by simulations of different scenarios in which the system parameters and measurement noises were varied. Tube-based MPC (TMPC) decomposes robust MPC into a robust local controller and an online open-loop nominal MPC controller. The proposed HTMPC framework dynamically adjusts the tube size based on the system states to enhance the robustness. Simulations evaluated the algorithm's performance, showing improved tracking capabilities compared to other control methods under various scenarios. The proposed strategy aims to compensate for model mismatches and improve the robust performance of the tracking system. It is evident from the table that the proposed HTMPC has the least measurement noise and is better than the MPC and TMPC for low road friction and parametric uncertainties. An experimental comparison was performed with three other controllers under different conditions, and the results are presented in Table 1.

Table 1. Result of tests for controller comparison [2].

S.N.	Controller	Low road friction	Measurement noise	Parametric uncertainties
1	MPC	1.39	1.53	1.2
2	TMPC	1.11	1.37	1.25
3	HTMPC	1.15	1	1.12
4	I&I	1	2.56	1

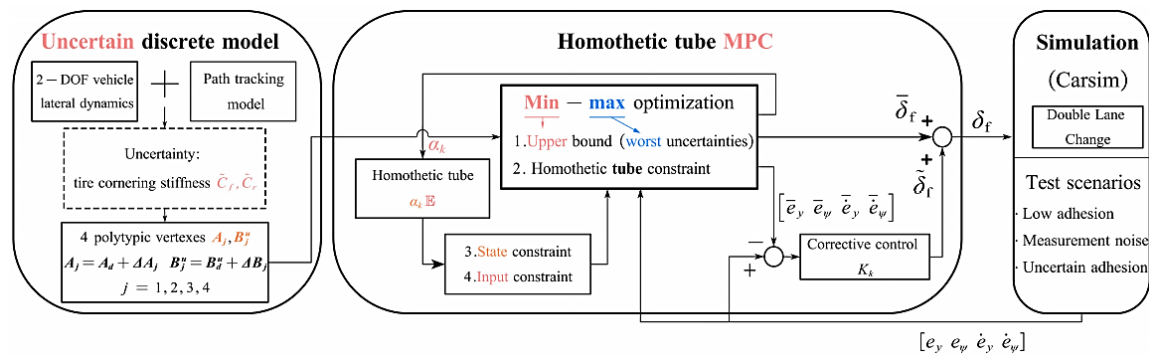


Figure 2. The architecture of formulating robust MPC for autonomous vehicles [2].

The disadvantage of MPC is that it requires the solution of an optimization problem at each control step. This increases the computing overhead, thereby affecting the real-time implementation. A tracking control strategy has been suggested to reduce this burden by using the MPC to handle problems of road curvature and cascading it with the proportional integral derivative (PID) feedback monitoring the yaw rate to reject uncertainties and modeling errors, and a vehicle sideslip angle compensator for adjusting the above forecasting procedures. This was the major work performed [3]. The controller design should be based on the objective of path-tracking control at the desired speed such that the vehicle must be as close as possible to the desired path. The challenge of path tracking is divided into two parts: the lateral and longitudinal control designs. The emphasis is only on lateral control, assuming that the supplied path and required speed are achieved. The proposed controller has only one output: the steering angle of the front wheels. A novel lateral control scheme was proposed and tested with other controllers. The proposed control system is illustrated in Figure 2. A hybrid MPC-PID control cascade loop is created. The results of using various control strategies to emphasize the advantages of the proposed system. Kinematic MPC works well at slow speeds, whereas dynamic MPC works well at faster speeds. The cascaded PID reduces the yaw rate error. The tracking error of the proposed system was limited to 0.4m. The highest lateral inaccuracies under sideslip compensation were less than 0.1 meters. The controller was tested in real-life scenarios by implementing an autonomous electric vehicle, the Dongfeng A60EV. Experimental validation was performed using a circular route with a radius of 14 m. The vehicle speed varied from 10 km/h to 32 km/h, and the lateral acceleration was 5.84 m/s^2 . The proposed controller [3] limits the lateral tracking error to a range of 0.08 m, indicating excellent tracking accuracy [4] discussed substituting the classical mechanism framework for a recurrent neural network (RNN) for vehicle dynamical state forecasting within the context of MPC to gain higher control effects during high-speed steering processes. In the past, longitudinal and lateral control of the vehicle was accomplished by two independent controllers without considering the coupling influence, which led to a significant controller error and affected the control accuracy. The data is generated during driving to establish a learning-based vehicle dynamics model and based on this a longitudinal/lateral coupled MPC is designed. The advantage of using recurrent neural networks lies in the fact that they update the algorithm based on the error from the previous step, which further optimizes the MPC functionality. This model was trained using the “Honda Research Institute Driving Dataset (HDD),” which consisted of 104 hours of real vehicle driving data collected. The MPC’s optimization problem is formulated using the output of the RNN; thus, it cannot be solved normally. Hence, used differential evolution (DE) algorithm is used. Comparison of the different models to predict the change rate of the lateral velocity and the change rate of yaw rate. Between the linear mechanism model, nonlinear mechanism model, and the RNN model, the prediction accuracy was significantly better than linear and nonlinear models for both lateral dynamics and yaw control. The suggestion to replace the traditional state prediction model in MPC with an RNN model, to improve the accuracy of dynamic state prediction was supported experimentally. The maximum lateral error for the proposed model was only 0.452 m/sec and yaw error 0.398 rad/s. The RNN-modeled data are used to formulate the coupled controller for the lateral and longitudinal dynamics parameters, which are highly effective in this case, as shown in Figure 3.

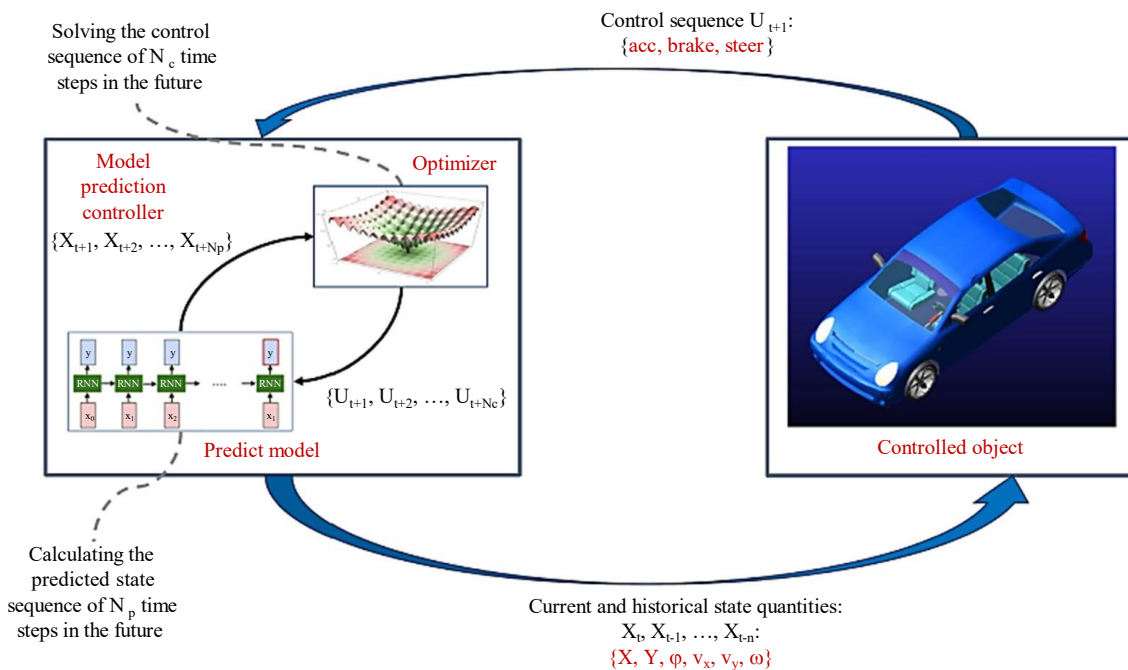


Figure 3. RNN-based coupled lateral and longitudinal MPC proposed [4].

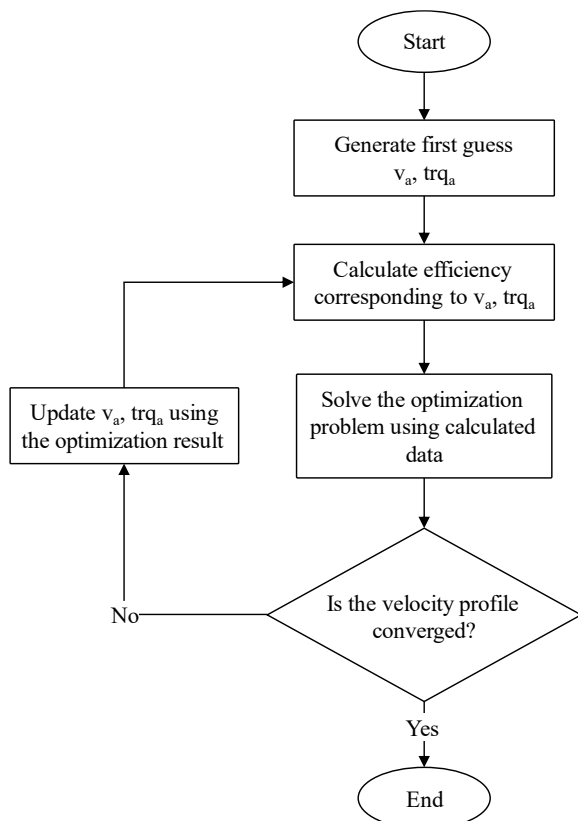


Figure 4. A convex optimization algorithm was used [5].

Further improvement can be achieved by developing a two-level MPC platform that considers detailed internal and external losses of an autonomous electric vehicle, as described [5]. An iterative method using the successive convex approach, as shown in Figure 4, was used to solve the optimization problem. The optimization problem formulation requires the formation of an optimization function,

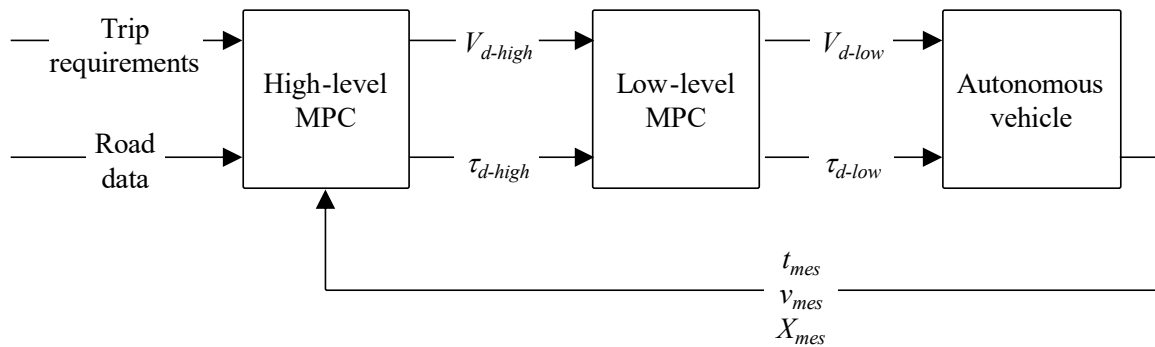


Figure 5. Two-level MPC using convex optimization for autonomous vehicles [5].

which is a convex function with convex constraints. The issue formulation is divided into four parts: (1) vehicle dynamics, (2) losses, (3) physical restrictions and critical constraints, and (4) optimization targets. The goal of this study is to propose a new convex formulation of the energy-optimal speed issue on a two-level MPC platform that considers detailed internal and external losses of an electric vehicle (EV) to produce a highly accurate answer. The algorithm uses the successive convex technique to provide a real-time method for addressing the optimization issue with a combined objective of time and energy. The internal losses that could not be formulated were calculated using the successive approach used in convex programming. The high-level MPC generates the overall speed trajectory and provides input to the low-level MPC. The low-level MPC has two settings: the length of the opening ahead and the number of pieces. According to various case studies, the optimal speed is not always the maximum or minimum allowed speed, because it varies over the duration of travel. The proposed two-level MPC trajectory planning framework shown in Figure 5 was designed to optimize energy-efficient driving speeds using detailed efficiency maps and a clever convex formulation. The approach tested on the Tesla Model S against real-world data shows promising energy savings of up to 4.63% over certain distances. Notably, the importance of considering accessory losses in autonomous vehicles to achieve truly optimal driving trajectories is considered. The balance between execution time and optimization accuracy, shedding light on important considerations for implementing such systems in real-world scenarios is also observed.

The idea of integrating a neural network-based model rather than a conventional model for the required prediction horizon into MPC for improved tracking performance [6]. Rigidly defined vehicle models may not be suitable for different vehicles under various operating conditions. Some aspects are bound to change in the vehicle model owing to working conditions. An adaptive data-driven approach is required to identify and design a dynamic vehicle model. A properly trained NN with sufficient data can identify the internal representation of the time-varying dynamics. Neural network-based model designs have been used in various fields. Owing to the abundant operational data available owing to the modern vehicle data acquisition system, the learning method can be used for reliable modeling of the system. A new data driven MPC with two sets of states and an input measurement history was maintained for a few previous steps for NN prediction. The First set contains the controlled vehicle's state and input measurements, and the second set is used for the predicted states and corresponding inputs during the MPC optimization. These histories with current measurements were used to estimate future states. This approach allows a more accurate prediction in the presence of uncertainties in the vehicle parameters, such as the surface friction coefficient and load variation. The use of the state and input measurement history allows for more accurate predictions up to a specific prediction horizon. The performance of the proposed controller is compared with that of the existing Linear Model predictive control (LMPC), which uses a linear tire model, and NMPC (Nonlinear Model Predictive Control), which uses a nonlinear tire model. It is found that the newly proposed NN-MPC outperforms NMPC and LMPC in controlling autonomous vehicles. The NN-based vehicle transition model provides a more comprehensive approximation of vehicle dynamics. The controller also demonstrates robustness to

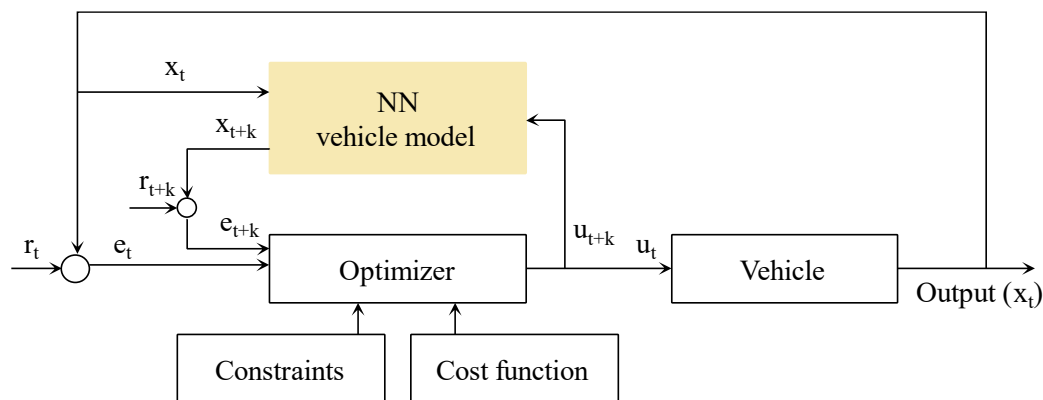


Figure 6. NN-based MPC model for autonomous vehicles [6].

changes in road friction parameters. The NN-based approach efficiently handles variations in vehicle shapes, sizes, and characteristics. It can also be noted that the NN-based approach does not significantly increase the computation costs. The RMS (Root Mean Square) error using this method is significantly less (about range 40–70%) than the other two MPC methods used for comparison [6]. Thus, MPC optimization techniques can be modified to obtain better tracking results and minimize errors. The NN-based MPC model for autonomous vehicles is illustrated in Figure 6.

MPC-BASED AUTONOMOUS VEHICLES IN DIFFERENT SCENARIOS

MPC-based Vehicle for Collision Avoidance

An MPC is based on a non-uniformly separated horizon technique that uses tiny time gaps for the near future and large time intervals for the distant future to increase the length of the entire prediction horizon with a preset number of prediction stages. This idea was described [7] to ensure collision avoidance of an autonomous vehicle. The method of using a time-varying spaced horizon is to discretize the prediction horizon with nodes densely placed near the current time to capture immediate dynamics properly and with nodes sparsely placed for the rest of the horizon to approximate the future steps. First, two types of prediction models were constructed, defining the near future as a dense model and the distant future as a sparse model. Varying the prediction models over the entire prediction horizon of MPC may lead to large control input changes. Subsequently, the variation was only observed in the sparse model. The sampling time of the sparse model is reduced if the path-following performance degrades to improve the control performance of the entire prediction horizon. Similarly, when the performance increases, the sampling time of the sparse model is increased to extend the entire prediction length. Second, the sampling time of the prediction model was set to change by the same time or less as the control period. Third, both the optimal control costs and the magnitude of the curvature of the desired path were also considered. The algorithm is designed for sparse sampling such that if the target path curvature is large due to path-following degradation, it needs to be supplemented by reducing the sampling time of the prediction model. Similarly, when the path-following error is reduced significantly compared with the previous control period, and if the target path curvature is less than a threshold, the sampling time of the prediction model must be increased to obtain information about obstacles from a distant future. Four types of MPC-based controllers were used to perform path-following and obstacle avoidance tests. STD-MPC with nine steps, DUAL-MPC, proposed MPC, and STD-MPC with 30 steps. The proposed method was able to reduce the maximum and average distance errors by 18% and 61%, respectively, compared with the DUAL-MPC method, which simply increased the prediction length. The MPC architecture of autonomous vehicles for collision avoidance is shown in Figure 7. The proposed method avoids obstacles by reducing the number of MPC prediction steps. Compared with the standard MPC, the computational time can be reduced by 72% while avoiding obstacles. Table 2 is presenting the simulation results of comparative analysis between MPC using 6-step and 30 step. The path-following and collision prevention effectiveness were examined by employing both the CARLA (Car Learning to Act) simulator and an actual automobile.

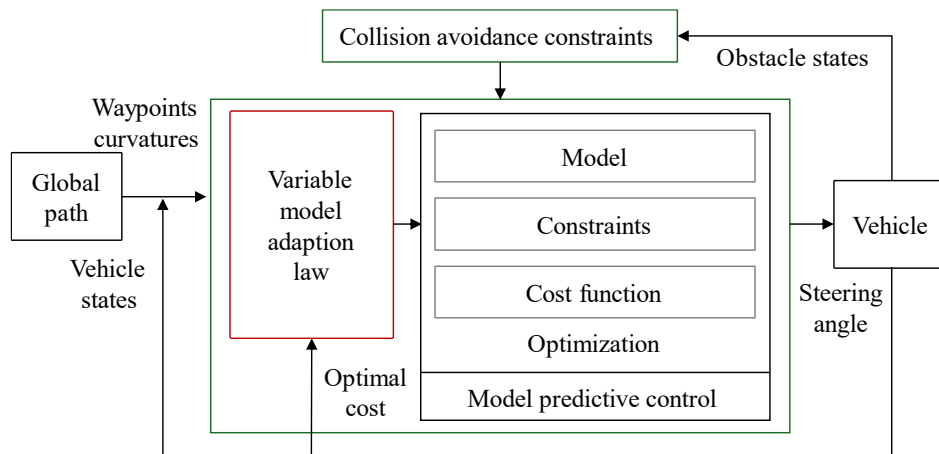


Figure 7. MPC architecture for autonomous vehicles for collision avoidance [7].

Table 2. Simulation result of comparison between MPC using six-step and 30-step and other controllers [7]

S.N.	Methods (# of horizons)	Max. distance error (m)	Avg. distance error (m)	Collision avoidance
1	STD-MPC (9)	0.53	0.06	X
2.	DUAL MPC (9) [8]	0.64	0.18	O
3.	Proposed MPC (9)	0.52	0.07	O
4.	STD-MPC (30)	0.49	0.07	O

Model-based Predictive Control for Autonomous Vehicles: Major Lane Change

The improvement of the lane-changing capability of autonomous vehicles using soft constraint modeled MPC [9]. Lane-changing strategies were analyzed at different velocities for autonomous vehicles. The MPC controller design requires discretization of the system, which is performed using the zero-order hold method. An autonomous vehicle is assumed to change lanes on a two-lane road. The modeling of the plant requires the formulation of error and motion dynamics equation models.

The lateral and longitudinal control logics are formulated separately. Lane changing is considered under the maximum acceleration strategy and the minimum acceleration strategy. The proposed MPC empowers autonomous vehicles to ensure precise navigation in dynamic environments. The implementation of indirect control over front-wheel steering significantly enhances the control accuracy and improves the overall effectiveness of autonomous driving systems. The causes of lag in lane changing are analyzed from the perspective that the tire's longitudinal and lateral forces are constrained by the tire friction circle. The experiment was also tested for overshoot oscillation, underdamping, hysteresis, and unsuccessful lane changing. The experiments were performed at speeds of 30 km/hr, 60 km/hr, and 120 km/hr, and it was found that the controller was effective in producing the results.

Model Predictive Control Method for High-speed Autonomous Driving

The high-speed application of autonomous vehicles can be achieved using a two-layer MPC with curvature adaptation aimed specifically at the path tracking of high-speed autonomous vehicles, as described [10]. The primary goal of the new MPC is to efficiently limit cross-track error and analyze various driving circumstances to provide safe and steady driving speeds, thereby mitigating the hazards associated with rollover and speed overshoot. Insufficient lateral support may cause the vehicle to become imbalanced. The critical constraints to be considered when designing the MPC for autonomous vehicle driving are as follows.

1. The path curvature should be considered during the MPC design.
2. Traditional MPC methods have fixed prediction-time domains. A small prediction-time domain can lead to significant control deviations because the road information cannot be considered beforehand.

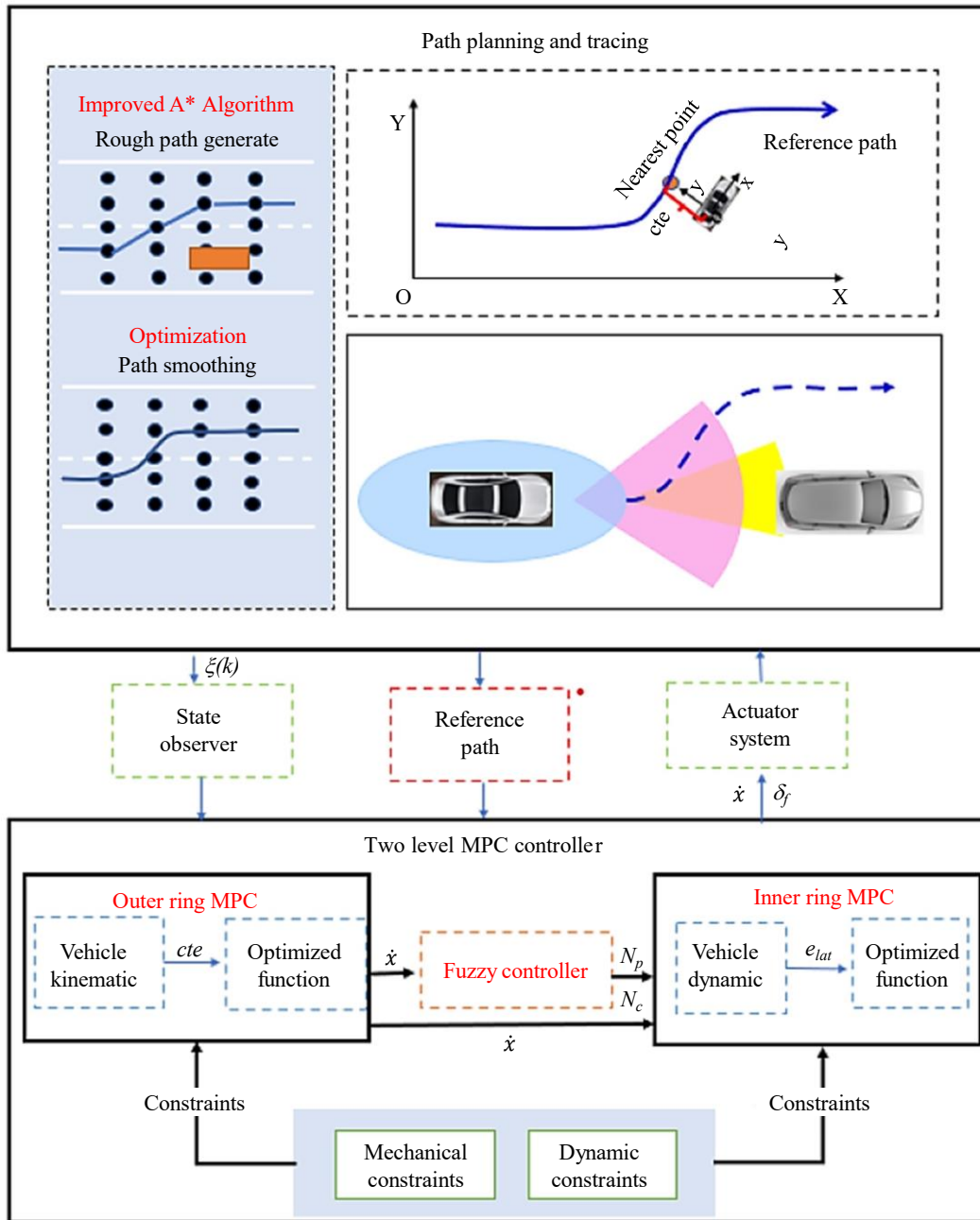


Figure 8. Proposed two-layer MPC control strategy [10].

The development of a path model is critical for the controller design. The two scenarios in which the path planner optimizes the path are rough and smooth paths. The controller was tested under various conditions for adaptive curvature capability and continuous obstacle avoidance capability. In experimental trials, even with the added predictive feature, the system could react faster to changes on the road. It keeps the car on course, whether it is moving quickly or slowly. The system worked at lower speeds, such as 30 km/h, ensuring that the car followed the path perfectly. And even when speeds pick up to 108 km/h, it maintains a maximum cross-track error of just 0.21 m. The proposed two-layer MPC control strategy is shown in Figure 8.

Model Predictive Control-based Merging Strategies for Connected Autonomous Vehicle Platoons

The merger involves setting control constraints such that the maximum acceleration and deceleration of each vehicle is a fixed value. The controller design model can be obtained [8]. The DMPC (Decentralized

Model Predictive Control) controller has two main categories according to their function to create the space for the merging platoon and to control the merging platoon to fill the gap. Before merging, the Distributed MPC DMPC controller controls the target platoon splitting to make free space for the merge platoon, and then the controller will control the merge platoon to fill in the free space to the way one platoon merges into another platoon reduces communication and processing strain, and the platoon merge procedure is more accurate and faster than typical single vehicle merge approaches. The vehicles exchange information with each other, and a control decision is made based on the state of the other vehicle. Simulation runs show that the proposed DMPC algorithm provides a stable solution. This helps in improving space enforcement on highways. The average calculation time and the maximum calculation time of each time step in the DMPC2 controller were less than those of the LQR (Linear–quadratic Regulator) and DMPC controllers. Moreover, in the two scenarios, the average calculation time and maximum calculation time of each time step in the platoon.

Advantages and Limitations

There are numerous advantages with their respective limitations for few developed studies in this area as discussed in Table 3.

Table 3. Limitations and advantages of developed studies.

	Advantages	Limitations
Improved MPC for Path planning [1]	<ul style="list-style-type: none"> Improved MPC controller ensures tracking accuracy and dynamic stability. Fuzzy adaptive control algorithm enhances steering smoothness and tracking performance. Proposed controllers outperform pure-pursuit and classical MPC controllers. Adaptive weight control balances tracking accuracy and ride comfort effectively. 	<ul style="list-style-type: none"> Simplifications in vehicle models include neglecting suspension movements and aerodynamics.
Robust tube based MPC [2]	<ul style="list-style-type: none"> HTMPC outperforms controller II in measurement noise and parametric uncertainty. HTMPC provides better robustness compared to MPC and TMPC. HTMPC dynamically resizes tubes to reduce the conservative performance of TMPC. 	<ul style="list-style-type: none"> TMPC cannot handle state-dependent uncertainty due to fixed tubes. Uncertainty in system parameters and measurement noises affect robustness.
Kinematic MPC for high-speed tracking [3]	<ul style="list-style-type: none"> Improved path-tracking accuracy with cascaded MPC-PID controller. Proposed vehicle sideslip compensator enhances model accuracy at high speeds. Superior steady-state response and robustness in field experiments. 	<ul style="list-style-type: none"> Classic kinematic and dynamic MPC have poor tracking accuracy. Measurement error affects tracking performance but within certain limits.
Coupled NN-based MPC [4]	<ul style="list-style-type: none"> RNN model improves dynamic state prediction accuracy in high-speed steering. Differential evolution algorithm enhances optimization in the controller. Higher control accuracy and stability are achieved with RNN-based MPC. Longitudinal/lateral coupled control realized with RNN vehicle dynamic model. 	<ul style="list-style-type: none"> The proposed method only considers battery faults, not communication errors. Further studies involve the special case analysis of the multi-agent system: partially observable scenario.
Two-level MPC considering internal and external losses [5]	<ul style="list-style-type: none"> Energy savings potential of 1% to 20% for different driving conditions. Detailed internal and external losses considered for optimal speed profile planning. 	<ul style="list-style-type: none"> Maximum torque output depends on the motor’s rotational speed. Driver comfort requires a smooth velocity trajectory without hard acceleration.
MPC with learned vehicle dynamics [6]	<ul style="list-style-type: none"> MPC accommodates multiple variables and constraints with inherent robustness. NN-based vehicle model balances accuracy and complexity for efficient performance. MPC with learned vehicle dynamics enhances tracking performance in various conditions. 	<ul style="list-style-type: none"> Linearized vehicle models are only applicable to specific operating regions. Highly complex vehicle models may not be suitable for real-time operation. Uncertainties in vehicle dynamics can affect controller performance significantly.

CONCLUSION

This review provides valuable insights into MPC-based control strategies for autonomous vehicles. The robust nature of MPC aids in dealing with the nonlinearities associated with autonomous vehicle control. The various improvements in the optimization function generated for the MPC help to reduce the computational burden and thus achieve better and faster decisions for autonomous vehicle control. The addition of a neural-network-based architecture to MPC, cascading it with other forms of control strategies to improve the reliability and computational capability of the controller, has been widely discussed. The application of similar ideology-based controllers in different scenarios, such as achieving high-speed travel, lane changing, collision aversion, and interconnected movement of vehicles, was also observed. The experimental comparison of the modified controllers with the traditional controllers used on the same problem was conducted to find that the modified MPC controllers were better. The advantages and limitations of the modified controllers were also observed. The future scope of the controllers can be achieved using real-world testing and collection of data and improving the strategies to achieve feasible, economical, and robust controllers to solve any problems faced by autonomous vehicles.

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