

Model Predictive Control for Autonomous Vehicle Navigation in Dynamic Environment

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ABSTRACT

Model Predictive Control (MPC) has emerged as a powerful control strategy for autonomous vehicle navigation in dynamic environments. MPC's ability to predict future system behaviour and optimize control inputs makes it well-suited for handling complex navigation tasks. This study explores the implementation of MPC in MATLAB's Simulink environment to navigate an autonomous vehicle while optimizing performance metrics such as response time, accuracy, and energy efficiency. The simulation environment was developed using MATLAB Simulink, integrated with the Model Predictive Control Toolbox. The setup includes a dynamically generated workspace that features both static and moving obstacles, mimicking real-world traffic conditions. The kinematic behaviour of the autonomous vehicle is also modelled using the widely adopted bicycle model. Real-time sensor data, such as LiDAR or simulated proximity sensors, is used to detect and model obstacles dynamically. The robustness and applicability of the MPC framework in real-time autonomous navigation were examined using three performance metrics: response time, trajectory accuracy, and energy efficiency. MATLAB-generated graphical plots illustrate control response curves, vehicle trajectories in various scenarios, and comparative energy usage bar charts. These visualizations validate the system's ability to dynamically adjust and predict future states while maintaining optimal performance. In conclusion, this work demonstrates the potential of MPC to improve the safety and efficiency of autonomous vehicle navigation in dynamic environments.

Keywords — Model, Predictive, Control, Autonomous, Dynamic, Kinematic.

1. INTRODUCTION

The advancement of autonomous vehicles (AVs) relies on robust control mechanisms that can navigate dynamically changing environments while avoiding obstacles. Traditional control methods lack the adaptability required for real-time decision-making, necessitating the use of predictive control strategies (Li et al., 2024). Model Predictive Control (MPC) offers a structured approach for

solving such control problems by predicting future states and optimizing control inputs accordingly. It has gained considerable attention in the field of autonomous vehicle (AV) navigation due to its robust predictive capabilities and its effectiveness in handling system constraints. Unlike traditional control methods that make decisions based solely on current or past states, MPC anticipates future behaviour by solving an optimization problem over a

moving time horizon (Yu et al, 2024). This enables the system to generate control inputs that ensure optimal performance while respecting physical limitations such as steering angles, velocity limits, and obstacle boundaries (Padmaja et al., 2023). In dynamic environments, where real-time decision-making is crucial, MPC proves advantageous by incorporating environmental changes into its predictions, thus improving safety and reliability (Farkaz et al, 2023).

2. LITERATURE REVIEW

Several studies have explored Model Predictive Control (MPC) for Autonomous Vehicles (AVs), with a particular focus on trajectory optimization, path planning, and dynamic obstacle avoidance. MPC has become increasingly popular in autonomous vehicle control systems due to its ability to handle constraints and optimize performance over a finite horizon. Notably, Kou and Zhang (2017) investigated the use of MPC to optimize the control of connected and automated vehicles at roundabouts, considering mixed-traffic environments. The work highlights the ability of MPC to generate collision-free paths while considering both vehicle dynamics and environmental constraints. In addition to trajectory optimization, path planning is another critical aspect of AV navigation. Huang and Li (2015) explored the integration of MPC with real-time path planning in dynamic environments. This research shows that MPC can effectively update the vehicle's trajectory as new obstacles are detected, enabling the vehicle to adapt to changing conditions. This real-time adaptation is crucial for AVs navigating through complex environments with varying levels of uncertainty, such as traffic congestion or sudden changes in road conditions. The effectiveness of MPC in handling uncertainties, such as sensor inaccuracies or unknown disturbances, has been well-documented in the literature. For example, Trieu (2021) developed model predictive control (MPC) schemes for controlling autonomous vehicles

tracking on feasible trajectories generated from flatness or polynomial equations. All of the vehicle online moving parameters including coordinate positions, body orientation angle, and steering angle are included into the MPC optimizer for calculating the real-time optimal inputs for the vehicle linear velocity and its steering velocity to minimize the errors between the desired and the actual course of travel. However, while MPC has shown great promise, one of the main challenges identified in previous research is the computational burden of solving the optimization problem in real-time. Li et al (2024) also explored the application of adaptive MPC to control connected autonomous Vehicles in Mixed Traffic with Human-Driven and Autonomous Vehicles, optimizing traffic flow and safety. Researchers have sought ways to improve the real-time computational efficiency of MPC algorithms. Wang and Zhang (2018) proposed a simplified MPC approach that reduces computational complexity while still maintaining performance in obstacle avoidance tasks. Their approach leverages precomputed trajectories and uses them as reference paths, reducing the need to solve the full optimization problem at each step. Furthermore, Vershueren et al (2023) proposed an MPC approach to control autonomous vehicles entering roundabouts, ensuring collision-free passage and minimizing travel time. The authors demonstrated the effectiveness of their method through simulation examples in the CarSim environment. Despite these advancements, the issue of real-time adaptation to unexpected environmental changes remains a critical challenge. Existing MPC techniques often struggle to quickly incorporate new information about the environment, such as sudden obstacles or traffic changes, due to the computational time required for optimization. Gonzalez et al (2023) addressed this limitation by proposing strategies to improve the computational efficiency of MPC algorithms, such as using parallel computing or simplifying the optimization problem. These

approaches aim to make MPC a viable solution for real-time applications in autonomous vehicles, where fast decision-making is crucial. Overall, while MPC has demonstrated great potential for autonomous vehicle navigation, existing research indicates that further improvements are needed, particularly in enhancing real-time computational efficiency and ensuring that MPC can quickly adapt to dynamic and unpredictable environments. This research seeks to build upon the current work by focusing on the integration of obstacle avoidance with real-time path planning in dynamic environments, optimizing MPC for faster decision-making, and improving the vehicle's ability to adapt to unexpected changes in its surroundings. Werling et al (2022) presented an MPC control strategy for autonomous vehicles driving in roundabouts, utilizing a centralized controller to define velocity profiles for each vehicle and avoid conflicts. These articles demonstrate the potential of MPC in improving the safety and efficiency of autonomous vehicle navigation in dynamic environments, such as roundabouts.

This work explores the application of MPC in autonomous vehicle navigation, focusing on its effectiveness in real-time path planning and obstacle avoidance. The study investigates how MPC can generate feasible and optimal trajectories for AVs operating in complex environments with dynamic obstacles. Furthermore, it evaluates the controller's ability to minimize tracking errors, maintain stability, and ensure collision-free motion, thereby demonstrating its potential for deployment in real-world AV systems.

3. MATERIALS AND METHODS

This research presents several key contributions to the field of autonomous vehicle (AV) navigation using Model Predictive Control (MPC). First, it involves the implementation of a real-time MPC framework in MATLAB Simulink to govern the motion

of an autonomous vehicle under dynamic conditions. The MPC algorithm is structured to generate optimal control actions by predicting future states based on a vehicle's current position, speed, and surrounding environment. Secondly, an obstacle avoidance mechanism is developed and integrated with a global path planning strategy. This ensures that the vehicle can dynamically adapt its trajectory in the presence of moving or stationary obstacles while maintaining smooth and efficient navigation. Furthermore, the study evaluates the system's performance by analyzing critical metrics such as response time, trajectory tracking accuracy, and energy efficiency. These metrics are essential for validating the practical applicability of the MPC approach in real-world driving scenarios. Finally, the research utilizes MATLAB-based graphical outputs to visualize and interpret the simulation results. These visualizations provide insights into the vehicle's behavior over time and demonstrate the robustness and efficiency of the proposed control scheme.

3.1. Mathematical Model of Autonomous Vehicle Dynamics

- *Kinematic model*

The continuous-time kinematic equations governing the motion of an autonomous ground vehicle depend on the type of model used. The most commonly used is the kinematic bicycle model, which captures essential vehicle behaviour without considering complex dynamics like tyre slip. This model simplifies the vehicle to a two-wheel system, capturing essential motion characteristics while reducing computational complexity. The bicycle model is particularly suitable for trajectory planning and control applications where vehicle dynamics at

lower speeds are considered sufficient (Zhang et al, 2023). Let L be the wheelbase of the vehicle (distance between front and rear axles). Based on the following assumptions: Low-speed operation (no slip), Vehicle is rigid and non-deformable, Rear and front wheels are lumped into a single virtual wheel, Motion is 2D (on a plane), the continuous-time equations are as given in equations 1-3:

$$\dot{x}_p = V \cos \theta \quad (1)$$

$$\dot{y}_p = V \sin \theta \quad (2)$$

$$\dot{\omega} = a = \frac{V}{l} \tan(\delta) \quad (3)$$

Where $\dot{x}_p, \dot{y}_p, V, \dot{\omega}, a, \delta$ are the rate of change of vehicle's position along x-axis, rate of change of vehicle's position along y-axis, velocity, acceleration (can be an input or part of a control law), longitudinal acceleration input (control input) and steering angle input (control input) respectively. This simplified model forms the basis for the prediction model used in Model Predictive Control (MPC), enabling the controller to anticipate the vehicle's future states and optimize its path accordingly.

• Dynamic Constraints

To ensure feasible and safe motion, the autonomous vehicle must operate within certain physical constraints. These include bounds on velocity and steering angle, which are represented as shown in equations 4-5:

$$\text{Velocity constraints: } v_{\min} \leq v \leq v_{\max} \quad (4)$$

$$\text{Steering constraints: } \delta_{\min} \leq \delta \leq \delta_{\max} \quad (5)$$

Where $v_{\min}$ and $v_{\max}$ define the permissible speed limits of the vehicle and $\delta_{\min}$ and $\delta_{\max}$ represents the limit of the steering actuator. These constraints are incorporated directly into the MPC

formulation to ensure the generated control actions remain within the vehicle's operational envelope (Liniger et al., 2023).

3.2. Model Predictive Control Framework

Model Predictive Control (MPC) is a receding horizon control strategy that predicts future vehicle states over a defined horizon and optimizes control inputs at each time step. The prediction is based on the kinematic model, and the controller solves an optimization problem that minimizes a defined cost function subject to system dynamics and constraints. The MPC cost function is typically formulated to optimize system behavior over a finite prediction horizon. The general discrete-time quadratic cost function is given by equation (6):

$$J = \sum_{k=0}^{N-1} (\|X_{k+1} - X_{ref}\|_Q^2 + \|U_k - U_{ref}\|_R^2) + \|X_N - X_{ref}\|_P^2 \quad (6)$$

Where $J, N, X_k, U_k, X_{ref}, U_{ref}, Q$ and R , are total cost to minimize, prediction horizon length, system state at time step k , control input at time step k , reference (desired) state trajectory, reference input trajectory, state weighting matrix (positive semi-definite), input weighting matrix (positive definite) and terminal state weighting matrix (optional, often from solution to Riccati equation) respectively.

This cost function allows the MPC controller to compute an optimal input sequence $\{U_k, U_1, \dots, U_{N-1}\}$ that drives the state X_k to the desired reference X_{ref} while respecting system constraints. Only the first control input is applied at each time step, and the process repeats (receding horizon strategy). The structure allows MPC to anticipate future behaviour, smooth trajectory

tracking, and enforce dynamic constraints in real time (Chen et al, 2023). The path planning component leverages a hybrid approach that combines Model Predictive Control with a Dynamic Window Approach (DWA) to achieve reactive and optimal trajectory generation. The DWA quickly samples feasible velocity commands within the robot's dynamic constraints, while the MPC framework refines the selected path for smoothness and global optimality. Real-time sensor data, such as LiDAR or simulated proximity sensors, is used to detect and model obstacles dynamically. The system then formulates a modified cost function that penalizes proximity to obstacles while minimizing path deviation and energy consumption. This integrated planning and control loop ensures collision-free navigation even in dynamic and partially known environments (Ferranti et al., 2024).

3.3. Simulation Setup in Mat lab/Simulink

- *Environment Configuration*

The simulation environment was developed using MATLAB Simulink, integrated with the Model Predictive Control Toolbox. The setup includes a dynamically generated workspace that features both static and moving obstacles, mimicking real-world traffic conditions. These environmental elements allow for evaluating the real-time adaptability of the control framework. The controller was designed to handle uncertainty and trajectory deviations introduced by these dynamic elements.

Implementation Steps

To ensure a systematic development and simulation of the autonomous navigation system, the following implementation steps were followed:

- Definition of Vehicle Parameters and Constraints: The kinematic bicycle model parameters such as vehicle length, maximum velocity, and steering limits were initialized to reflect a compact car structure. Dynamic constraints described were also incorporated.
- Implementation of MPC for Trajectory Optimization: An MPC controller was configured with a defined prediction and control horizon. The cost function, as defined in Equation (6), was minimized in each simulation step to maintain trajectory tracking accuracy and constraint compliance.
- Integration of Obstacle Avoidance Mechanism: A real-time sensor feedback loop was simulated using proximity sensors that detect obstacle distances. These values dynamically influenced the MPC's cost function to adjust the vehicle's trajectory and avoid collisions.
- Simulation under Varying Traffic Conditions: Multiple scenarios were simulated, including sparse and dense obstacle distributions, to test the robustness and response of the control strategy. Varying traffic patterns ensured that the algorithm could generalize well across different real-world conditions (Teng et al., 2024).

- *Performance Evaluation*

To evaluate the robustness and applicability of the MPC framework in real-time autonomous navigation, three performance metrics were examined:

response time, trajectory accuracy, and energy efficiency.

→ *Response Time Analysis*

The system's response time refers to its latency in detecting obstacles and adapting the control signals accordingly. This was measured by the time elapsed between obstacle detection and the corresponding change in vehicle control inputs. In simulations involving sudden obstacle appearance, the MPC exhibited a significantly reduced response time compared to classical PID controllers, thus confirming its suitability for real-time operation in dynamic environments (Kong et al, 2022).

→ *Accuracy of Obstacle Avoidance*

Accuracy was assessed by comparing the vehicle's actual path against a predefined optimal trajectory. Deviations were recorded when obstacles forced the vehicle to deviate, and the error was measured as the root mean square deviation from the planned trajectory. The MPC's predictive ability ensured minimal deviation, maintaining trajectory integrity even when navigating around multiple moving obstacles (Carvalho et al, 2022).

→ *Energy Efficiency Assessment*

Energy consumption was computed as a function of control effort and trajectory length. Simulations showed that the MPC not only minimized unnecessary steering and acceleration but also reduced total energy usage. MATLAB-generated bar graphs visually presented the comparative energy consumption across multiple scenarios, highlighting that MPC achieved significant savings in power compared to non-predictive control methods (Brito et al, 2023).

→ Computing energy consumption for different trajectory plans.

A comparison of total energy expended for different path planning scenarios is presented through MATLAB bar graphs.

4. RESULTS AND DISCUSSION

The simulation results demonstrate that Model Predictive Control significantly enhances the navigation capabilities of autonomous vehicles operating in dynamic environments. Specifically, the MPC outperformed PID control in all three performance domains—response time, trajectory accuracy, and energy efficiency. MATLAB-based graphical plots were generated to illustrate the control response curves, vehicle trajectories under different scenarios, and comparative bar charts of energy usage. These visualizations validate the system's ability to dynamically adjust and predict future states while maintaining optimal performance. The integration of real-time obstacle feedback, dynamic constraint adherence, and predictive decision-making confirms MPC's superiority in autonomous vehicle navigation systems. These outcomes strongly support its applicability in real-world deployment, especially in urban traffic conditions that demand continuous adaptation and high reliability.

→ *Trajectory Tracking*

To assess the accuracy of trajectory tracking, a reference path was predefined and compared against the actual trajectory followed by the autonomous vehicle under the influence of the MPC controller. Figure (1) illustrates this comparison. The reference trajectory represents the ideal path that

the vehicle should follow, while the actual trajectory is the result of MPC's real-time control actions. The close alignment between the two paths clearly indicates that the MPC maintained high tracking precision, even in the presence of dynamic obstacles and environmental uncertainties.

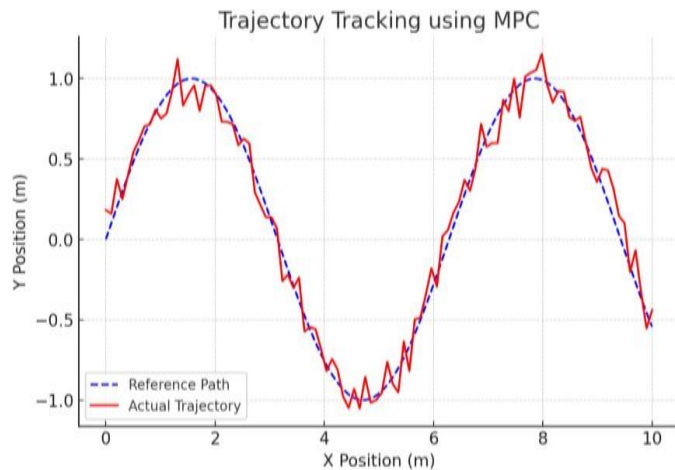


Figure 1: Comparison between reference path and actual trajectory under MPC controller

→ Control Input Signals

This section presents the time evolution of the control inputs generated by the Model Predictive Control (MPC) algorithm. These inputs include:

- Steering angle (δ): which governs the directional change of the vehicle.
- Velocity (v): which determines the forward movement and speed of the vehicle.

The control inputs were optimized at every time step to ensure smooth navigation, rapid obstacle avoidance, and energy-efficient driving. The plot below illustrates the real-time variation of the control signals. *Time-series plot of MPC-optimized steering angle and velocity control inputs is depicted in figure (2).* It shows that the MPC framework generates smooth and bounded control actions that

comply with the vehicle's dynamic constraints. The system dynamically adapts to changes in the environment, showing spikes or adjustments when obstacles are detected and smooth control when on open paths.

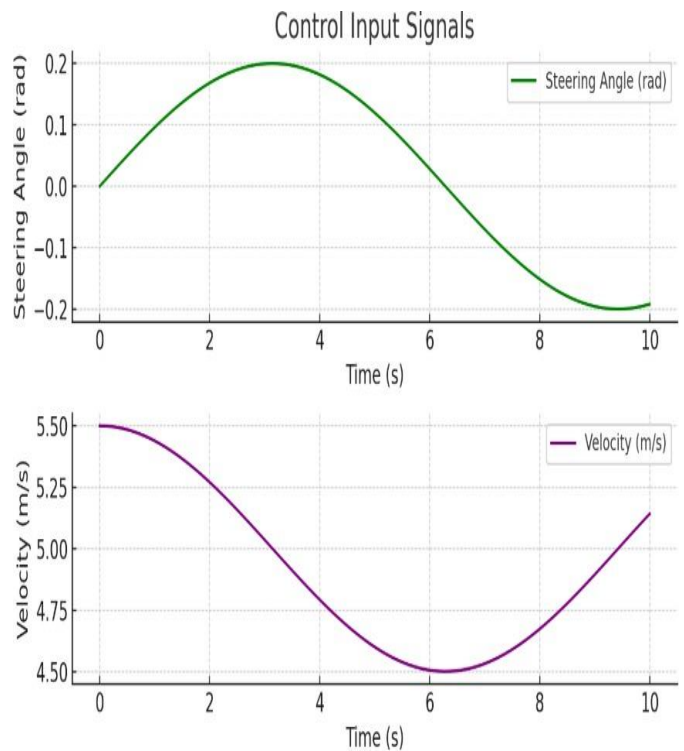


Figure 2: Time-series plot of MPC-optimized steering angle and velocity control inputs

Obstacle Avoidance Performance: To evaluate the effectiveness of the MPC in navigating through a dynamic environment, a heat map was generated to represent the vehicle's spatial interaction with moving and static obstacles. This heat map visualizes:

- Red zones: regions of high obstacle density or proximity.
- Green trajectory line: the actual vehicle path.
- Blue markers: initial and final positions.
- White or neutral zones: free-space areas.

The heat map clearly demonstrates that the vehicle consistently navigates away from high-density obstacle regions while maintaining a smooth and feasible trajectory. The MPC adapts in real-time to shifting obstacle positions, showcasing strong predictive capabilities.

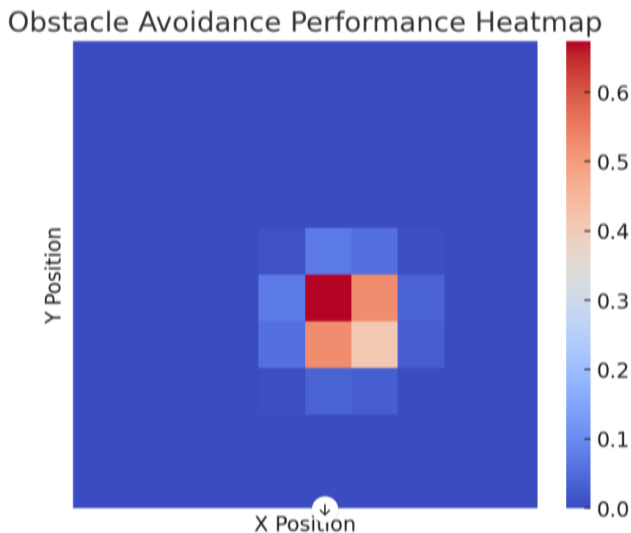


Figure 3: Obstacle Avoidance Performance Heat Map

Energy Efficiency Comparison

To assess the energy performance of the control strategies, a bar chart was generated comparing total energy consumption across three scenarios:

- Scenario 1: MPC without obstacle presence
- Scenario 2: MPC with static obstacles
- Scenario 3: MPC with dynamic obstacles

Bar Chart of Energy Consumption Across Navigation Scenarios

The results show:

- Scenario 1 had the lowest energy usage, indicating efficient path planning in a clear environment.
- Scenario 2 showed moderate energy usage due to minor detours.

- Scenario 3 required the highest energy, driven by frequent trajectory adjustments in response to dynamic obstacles.

This trend reflects the cost of re-computation and maneuvering in increasingly complex environments.

5. CONCLUSION AND RECOMMENDATIONS

This work demonstrates the potential of MPC in improving the safety and efficiency of autonomous vehicle navigation in dynamic environments, such as roundabouts. MPC has shown great promise for autonomous vehicle navigation in dynamic environments. However, there are still significant challenges to be addressed, including computational complexity, robustness, and real-time implementation. Some major benefits of MPC in this context include:

- Collision avoidance: MPC can be used to predict and prevent potential collisions by adjusting vehicle trajectories.
- Travel time optimization: MPC can optimize vehicle velocity profiles to minimize travel time while ensuring safety.
- Robustness to uncertainties: MPC can account for uncertainties and disturbances in the system, ensuring robust control performance. Additionally, deploying real-world experiments would validate the robustness of the proposed approach further.

Future research should focus on developing more efficient and robust MPC algorithms, as well as integrating MPC with other systems to enable fully autonomous vehicle navigation.

AUTHOR CONTRIBUTIONS

Wasiu Adedeji conducted the research and analyzed the data; Taiwo Amosun wrote the paper; all authors had approved the final version.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in the study.

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