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A Development of Time-Varying Weight Model Predictive Control for Autonomous Vehicles

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Abstract— Autonomous vehicles, commonly known as self-driving cars, are rapidly gaining popularity due to their numerous advantages, such as reducing traffic, pollution, and emissions while increasing safety, convenience, and transportation connectivity. In order to accurately track the motion signal, these vehicles are now utilising advanced control techniques, such as model predictive control (MPC). However, the efficiency of MPCs heavily relies on properly tuning their weights. The primary function of the MPC is to recalculate the optimal values for the vehicle control commands, such as desired speed, steering angle, etc., while considering the dynamic model of the autonomous vehicle. The existing linear MPC models cannot reach higher efficiency because of using fixed weights without considering the error. This paper introduces a novel approach for developing an MPC model with a time-varying weights algorithm for autonomous vehicles. The study aims to minimise motion tracking errors such as lateral position and yaw angle errors. Relevant MPC weights are calculated online using fuzzy logic-based units considering the lateral position and yaw angle errors. The proposed linear time-varying MPC was designed and developed using MATLAB software, resulting in improved motion tracking performance with 31.62% and 20.89% reduction of the root means square error of lateral position and yaw angle.

I. INTRODUCTION

The development and implementation of autonomous vehicles have become a key focus for the automotive industry in recent years [1-5]. With significant investments being made towards the research and development of these vehicles, there is growing anticipation for the widespread use of driverless cars. As a result, it is predicted that autonomous vehicles will become a key component of various industries, including transportation, defence, aerospace, and arcology, by 2050 [6]. Also, autonomous vehicles can potentially transform the transportation industry by providing a more cost-effective and safe mode of transportation. Implementing these vehicles in smart cities is expected to play a critical part in shaping the future of urban transportation [7]. Motion simulator platform

can be used for study of autonomous vehicle before going to the real road evaluation of these gadgets [8-13].

An independent vehicle framework enables autonomous vehicle navigation without external guidance. It comprises three components: road detection, motion signal creation, and motion tracking mechanisms [14]. Regulators ensure accurate and reliable motion tracking using geometry-based or kinematic-based models [15]. However, the Stanley controller [16] and pure pursuit [17] are inadequate in handling noise, ambiguity, and high-frequency motion signals. In contrast, kinematic-based controllers incorporate system information, allowing precise control response despite noise and uncertainty [18, 19].

The development of advanced motion tracking systems is a critical attribute of improving the performance of autonomous vehicles. This literature review concentrates on using linear model predictive control (MPC) in autonomous vehicles for lateral motion control. MPC has become a popular approach for addressing the challenges of autonomous vehicle guidance [20-27]. This is mainly due to its effectiveness in managing nonlinear time-varying models and constraints and its ability to operate within the boundaries of acceptable inputs and states. One benefit of using MPC in autonomous vehicles is that it allows for real-time optimisation of the vehicle's trajectory while considering several factors, such as road conditions, traffic, and weather [28]. Linear MPC is a popular choice for controlling the trajectory of autonomous vehicles due to its simplicity and computational load efficiency [29-33]. The study of lateral control in autonomous vehicles aims to make it possible to follow an intended path and set their orientation angles [34]. Numerous controllers, such as PID control [35, 36], fuzzy controller [37-48], optimal control [49-54], and robust backstepping and sliding mode control [55], are developed in order to accomplish this objective. However, these control approaches did not consider the actuators' saturations and physical limits [34]. Using a prediction model, receding horizon optimisation, and feedback correction, MPC is a favourable approach to tackle the issues at hand. This is because it considers input restrictions and state admissibility [56]. An instance of the use of MPC in autonomous vehicles for path planning is a study conducted by Liu et al. [57], where the MPC approach is applied to delivering effective, comfortable and natural manoeuvres. Human vestibular system is responsible for motion sensation, which is situated inside the inner ear of human body [58-61]. A different research project employed a linear time-varying model predictive controller to operate self-driving cars under various driving situations. The controller was able to accurately and

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consistently follow the intended road paths as specified [22, 62-66].

The regeneration of the accurate motion signals with lower lateral position and yaw angle errors, and smooth steering angle variations is necessary to increase the system's efficiency. The currently developed linear MPC [57, 62] uses fixed weights, which reduces the system's efficiency for different driving scenarios. As a result, these models should be tuned based on different motion scenarios to be efficient for every type of motion signal. Also, using fixed weights reduces the system's efficiency in facing abrupt motion signals in hazardous situations. In this study, a linear time-varying weight (LTVW) MPC is developed and developed to eliminate the problems regarding the fixed weights problem. It can change the weights of the MPC based on the online information on lateral position and yaw angle errors to keep the system's errors as low as possible. The fuzzy logic units are developed in this research study to calculate the weights' values while considering the lateral position and yaw angle errors of autonomous vehicles.

Section II presents the proposed methodology, which comprises a fuzzy logic controller, an LTVW MPC, and a model depicting the dynamic behaviour of a four-wheel automobile. The results and associated discourse are revealed in Section III, and the study's conclusions are outlined in Section IV.

II. METHODOLOGY

The proposed method in this research aims to improve the performance of a dynamic vehicle model using a combination of techniques. As shown in Fig. 1, the method contains three principal components: a dynamic vehicle model, a Linear Time-Varying Model Predictive Control (LTVW MPC), and a fuzzy logic controller.

A. Vehicle Dynamic Model

To utilise an MPC model for controller design, creating a vehicle dynamics model is essential. The vehicle's kinematic and dynamic models must be precise to ensure accurate steering angle calculations. A four-wheel vehicle model is employed to generate motion signals for the independent vehicle in this study as it strikes a balance between accuracy and simplicity. The bicycle model considers only the vehicle's lateral and yaw movements, disregarding the chassis' pitch and roll movements. In the bicycle model, the moment of inertia along the z-axis and the mass are represented by rigid bodies, as illustrated in Fig. 2. Derived from the model presented in Fig. 2, the autonomous vehicle system is characterised by three degrees of freedom, or 3-DoF: linear movement along the x-axis and y-axis, and rotation around the z-axis (yaw-angle). The following equations are utilised to determine the autonomous vehicle's movement along the specified axes:

$$\frac{d}{dt} \mathbf{x} = \mathbf{N}\mathbf{x} + \mathbf{M}\mathbf{u} \quad (1)$$

$\mathbf{x}$ and $\mathbf{u}$, which represent the autonomous cars' status vector and input vector signals, respectively, are determined by:

$$\mathbf{x} = [v_y \quad \psi \quad v_x \quad \dot{v}_x]^T \quad (2. a)$$

$$\mathbf{u} = \delta \quad (2. b)$$

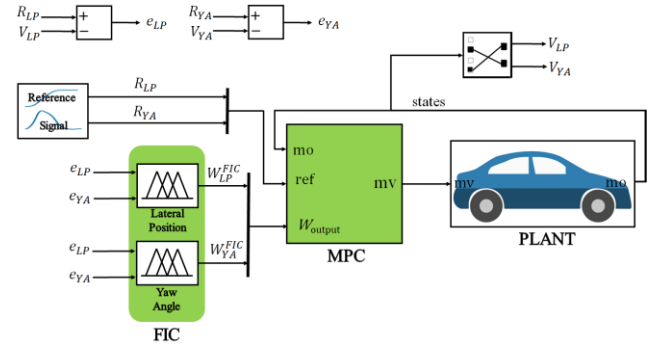


Fig. 1. The linear time-varying model predictive control of the proposed autonomous vehicle, which incorporates fuzzy logic units.

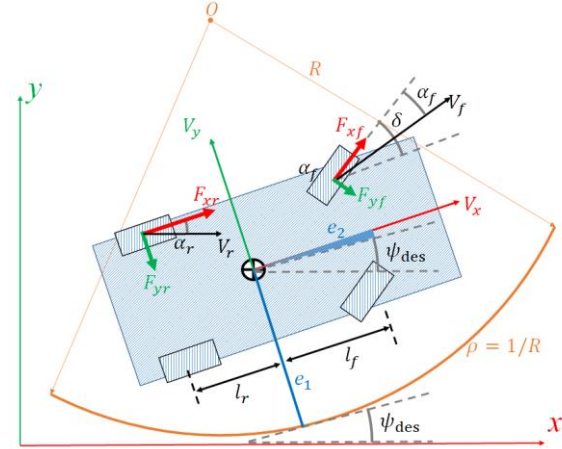


Fig. 2. The vehicle's dynamic model.

$$\rho = 1/R \quad (2. c)$$

Moreover, the vehicle dynamics model's matrices $\mathbf{N}$ and $\mathbf{M}$ are determined as in equations 3. a and 3. b. In these matrices, the variables are, lateral velocity (v_y), longitudinal velocity (v_x), yaw rate ($\dot{\psi}$), longitudinal acceleration ($\dot{v}_x$), automobile steering angle (δ), and road radius (R).

$$\mathbf{N} = \begin{bmatrix} -\frac{2v_x(C_f+C_r)}{m} & 0 & -v_x - \frac{2C_f l_f - 2C_r l_r}{m v_x} & 0 \\ 0 & 0 & 1 & 0 \\ -\frac{2v_x(C_f l_f - C_r l_r)}{I_z} & 0 & -\frac{2v_x(C_f l_f^2 - C_r l_r^2)}{I_z} & 0 \\ 0 & v_x & 0 & 0 \end{bmatrix} \quad (3. a)$$

$$\mathbf{M} = \begin{bmatrix} \frac{2C_f}{m} & 0 & \frac{2C_f l_f}{I_z} & 0 \end{bmatrix}^T \quad (3. b)$$

Eq. (8) describes the parameters used to denote various physical quantities related to a vehicle. These quantities include the total mass of the vehicle (m), its yaw moment of inertia (I_z), the longitudinal distances from the centre of gravity to the front (l_f) and back tyres (l_r), and the cornering stiffness of the front (C_f) and back tyres.

The longitudinal and lateral forces of the tyres are computed using the following formula in the vehicle dynamic model described above:

$$F_{xf} = -C_f s_f \quad (4. a)$$

$$F_{yf} = -C_f \alpha_f \quad (4. b)$$

$$F_{xr} = -C_r s_r \quad (4. c)$$

$$F_{yr} = -C_r \alpha_r \quad (4. d)$$

where s_f , s_r stand for the front and back wheels' tyre slip rates consecutively.

B. Linear Time-Varying Weight Model Predictive Controller

To incorporate the MPC model within the controller, the system's discretised state-space model must be derived, as shown below:

$$\mathbf{x}_m(t+1) = \mathbf{A}_m \mathbf{x}_m(t) + \mathbf{B}_m \mathbf{u}(t) \quad (5. a)$$

$$\mathbf{y}(t) = \mathbf{C}_m \mathbf{x}_m(t) + \mathbf{D}_m \mathbf{u}(t) \quad (5. b)$$

where $T_s=0.1$ (s) is the sampling time, and $\mathbf{A}_m$, $\mathbf{B}_m$, $\mathbf{C}_m$ and $\mathbf{D}_m$ are discretised matrices of the MPC state-space model. It is essential to mention that the input and output rate is constrained. To obtain the states and inputs rates, we need to calculate the difference between the current state and the previous state $\Delta \mathbf{x}_m(t) \triangleq \mathbf{x}_m(t) - \mathbf{x}_m(t-1)$ and $\Delta \mathbf{u}(t) \triangleq \mathbf{u}(t) - \mathbf{u}(t-1)$. This is how we can define the augmented state-space model:

$$\mathbf{x}(t+1) = \begin{bmatrix} \mathbf{A}_m & \mathbf{0} \\ \mathbf{C}_m \mathbf{A}_m & \mathbf{I} \end{bmatrix} \mathbf{x}(t) + \begin{bmatrix} \mathbf{B}_m \\ \mathbf{C}_m \mathbf{B}_m \end{bmatrix} \Delta \mathbf{u}(t) \quad (6. a)$$

$$\mathbf{y}(t) = [\mathbf{0} \quad \mathbf{I}] \mathbf{x}(t) \quad (6. b)$$

$\Delta \mathbf{u}$ and $\mathbf{x}(t) \triangleq \begin{bmatrix} \Delta \mathbf{x}_m(t) \\ \mathbf{y}(t) \end{bmatrix}$ are the control input and state vector of the produced model in Eq (6).

The new model's matrices are represented as $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{C}$. in Eq. (6). Thus, the novel state-space model in equation (6) could be deduced as shown below:

$$\mathbf{x}(t+1) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \Delta \mathbf{u}(t) \quad (7. a)$$

$$\mathbf{y}(t) = \mathbf{C} \mathbf{x}(t) \quad (7. b)$$

The objective of the MPC is to forecast future outputs within a prediction horizon (N_p) by executing control actions within a control horizon (N_c). To estimate the state and output predictions at the n th sample time, the below formula can be utilised:

$$\mathbf{x}(t+1|t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \Delta \mathbf{u}(t) \quad (8. a)$$

$$\mathbf{y}(t+1|t) = \mathbf{C} \mathbf{A} \mathbf{x}(t) + \mathbf{C} \mathbf{B} \Delta \mathbf{u}(t) \quad (8. b)$$

...

$$\mathbf{x}(t+N_p|t) = \mathbf{A}^{N_p} \mathbf{x}(t) + \mathbf{A}^{N_p-1} \mathbf{B} \Delta \mathbf{u}(t) + \mathbf{A}^{N_p-2} \mathbf{B} \Delta \mathbf{u}(t+1) + \dots + \mathbf{A}^{N_p-N_c} \mathbf{B} \Delta \mathbf{u}(t+N_c-1) \quad (8. c)$$

$$\mathbf{y}(t+N_p|t) = \mathbf{C} \mathbf{A}^{N_p} \mathbf{x}(t) + \mathbf{C} \mathbf{A}^{N_p-1} \mathbf{B} \Delta \mathbf{u}(t) + \mathbf{C} \mathbf{A}^{N_p-2} \mathbf{B} \Delta \mathbf{u}(t+1) + \dots + \mathbf{C} \mathbf{A}^{N_p-N_c} \mathbf{B} \Delta \mathbf{u}(t+N_c-1) \quad (8. d)$$

where $\mathbf{x}(t+n|t)$ denotes the state in the n sample time along with the control sample time.

The new vector form of Eq. (8)'s inputs and outputs is known as $\Delta \mathbf{U}$ and $\mathbf{Y}$ where $\Delta \mathbf{U} \in \mathbb{R}^{(N_c \cdot N_{in}) \times 1}$ and $\mathbf{Y} \in \mathbb{R}^{(N_p \cdot N_{out}) \times 1}$, respectively. The sizes of $\Delta \mathbf{U}$ and $\mathbf{Y}$ are N_{in} and N_{out} , respectively.

The model's input-output assessment may then be summarised, and the $\mathbf{f}$ matrix and the $\mathbf{G}$ matrix are defined as follows:

$$\mathbf{Y} = \mathbf{f} + \mathbf{G} \Delta \mathbf{U} \quad (9)$$

$$\mathbf{f} = \begin{bmatrix} \mathbf{C} \mathbf{A} \\ \mathbf{C} \mathbf{A}^2 \\ \vdots \\ \mathbf{C} \mathbf{A}^{N_p} \end{bmatrix} \mathbf{x}(t) \quad (10. a)$$

$$\mathbf{G} = \begin{bmatrix} \mathbf{C} \mathbf{B} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{C} \mathbf{A} \mathbf{B} & \mathbf{C} \mathbf{B} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C} \mathbf{A}^{N_p-1} \mathbf{B} & \mathbf{C} \mathbf{A}^{N_p-2} \mathbf{B} & \dots & \mathbf{C} \mathbf{A}^{N_p-N_c} \mathbf{B} \end{bmatrix} \quad (10. b)$$

To determine the cost function, it is essential to define the reference signal, $\mathbf{R}_{ref}$. The reference signal can be defined using time-invariant or time-varying approaches [67, 68]. The cost function (J), can be defined as follows aiming to decrease the motion tracking error between the reference motion signal, extracted via the AI unit, and the path vehicle is passing:

$$J(\Delta \mathbf{U}) = (\mathbf{R}_{ref} - \mathbf{Y})^T \mathbf{Q} (\mathbf{R}_{ref} - \mathbf{Y}) + \mathbf{U}^T \mathbf{S} \mathbf{U} + \Delta \mathbf{U}^T \mathbf{R} \Delta \mathbf{U} \quad (11)$$

The suggested method involves three weighting matrices for input, output, and input rate denoted as $\mathbf{Q}$, $\mathbf{S}$, and $\mathbf{R}$, respectively. The weights in the output matrix $\mathbf{Q}$ are time-varying and require updating online at each time step. $\mathbf{Q}$ is the weight matrices of the outputs, including the lateral position and yaw angle of the vehicle. $\mathbf{S}$ and $\mathbf{R}$ are the input and input rate weights, which are the steering angle and the rate of steering angle, respectively. The $\mathbf{S}$ and $\mathbf{R}$ weighting matrices remain fixed. The $\mathbf{Q}$ matrix parameters can be conveniently monitored through sensors. The vehicle can generate sufficient input signal (steering angle) to keep the vehicle on the right path with lower errors of lateral position and yaw angle.

B. Fuzzy Logic Controller

The lateral position and yaw angle reference signals are obtained through image processing software by the autonomous vehicle's artificial intelligence component or the information obtained via the GPS unit of the vehicle. The MPC model calculates the optimal input signal (δ) to ensure the autonomous vehicle's precise motion tracking over the prediction horizon. Implementing the system is straightforward, including an LTVW MPC with two weighting parameters: lateral position and yaw angle. The aforementioned parameters are designed to vary online to improve the method's efficiency while motion tracking weights remain fixed. To generate the appropriate weights for the MPC for a lateral position (W_{LP}) and yaw angle (W_{YA}), two fuzzy logic blocks are employed.

Fig. 3a-d show the membership functions of two fuzzy logic blocks that utilise the lateral position error (e_{LP}) and yaw angle error (e_{YA}) as inputs. Fig. 3a illustrates the membership functions of the first input for the vehicle's lateral position error of the fuzzy control unit. Furthermore, the second input's membership function of the vehicle's yaw angle error is shown in Fig. 3b. The input signal is divided into five categories to standardise the errors, from very positive to very negative. The output of the fuzzy blocks includes two weights: the weight of the lateral position (W_{LP}) and the weight of the yaw angle (W_{YA}). The membership functions of the first output of the

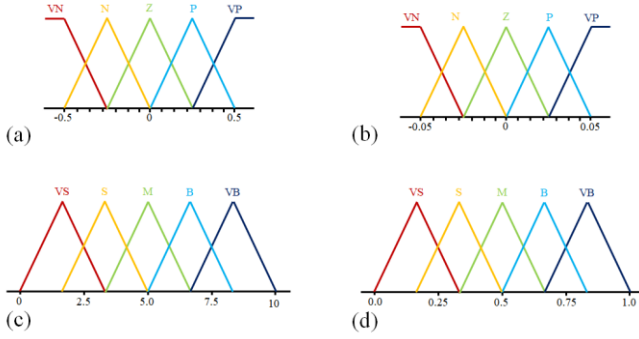


Fig. 3. (a) The fuzzy logic control unit's membership functions for the lateral position error. (b) The membership functions for the yaw angle error in the fuzzy logic control unit. (c) The membership functions for the weight of lateral position output. (d) The membership functions for the weight of yaw angle output.

lateral position fuzzy logic control unit for the weight of lateral position are shown in Fig. 3c. At the same time, Fig. 3d demonstrates the membership functions of the second output of yaw angle fuzzy control unit for the weight of yaw angle.

Various membership functions have been created for different purposes, including triangular, trapezoidal, Gaussian, and sigmoid. On the other hand, in this particular study, triangular membership functions were selected because they have a lower computational load. Additionally, they do not require a large dataset and can be defined asymmetrically. As illustrated in Fig. 3a-d, inputs and outputs have overlapping membership functions. To determine the fuzzy blocks' membership functions, four parameters (e_{LP} , e_{YA} , W_{LP} and W_{YA}) must be specified, as shown in Fig. 3a-d. Mamdani-type fuzzy logic is employed to establish the fuzzy logic rules, utilising the autonomous vehicle's lateral position and yaw angle errors as inputs. The control output is generated using the fuzzy rules presented in Table I.

III. RESULTS AND DISCUSSION

Within this part of the research, two models were created utilising MATLAB software. The initial model is referred to as LTIW MPC, a linear time-invariant weight MPC. As Section II outlines, the second model is referred to as LTVW MPC, which stands for a linear time-varying weight MPC. In order to assess how well the models were performing, three measures were used: mean square error (MSE), which represents the average squared difference between predicted and actual values of a variable; root mean square error (RMSE), which indicates the standard deviation of the differences comparing predicted and actual values; and correlation coefficient (CC), which reflects the linear relationship between two variables, with a range from negative one to positive one.

A test motion path of 15 seconds duration was used to assess the performance of the mentioned methodologies. The road path for this test period is shown in Fig. 4. The road contains one left turn and one right turn between 0 and 5 seconds of motion. At the same time, the autonomous vehicle moves straight without any lane-changing manoeuvres after 5 seconds of motion.

The motion tracking performance of LTIW and LTVW MPCs are compared by analysing the reference and regenerated lateral position and yaw angle, as illustrated in Fig.

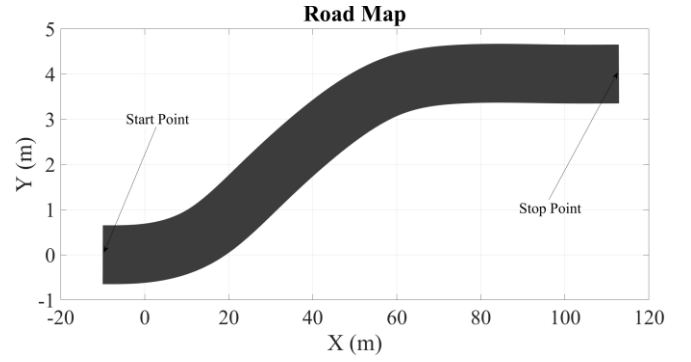


Fig. 4. The reference signal of the autonomous vehicle including motion path along x-y plan.

5a-b. The results in Fig. 5a indicate that the CC factor between the reference and followed lateral position using LTVW and LTIW MPCs are 0.9988 and 0.9972, respectively. The RMSE between the reference and regenerated lateral position using LTVW and LTIW MPCs are 0.0921 (m) and 0.1347 (m) derived from the results presented in Fig. 5a. The results in Fig. 5b indicate that the CC factor between the reference and regenerated yaw angle using LTVW and LTIW MPCs are 0.9874 and 0.9788. The RMSE between the reference and regenerated yaw angle using LTVW and LTIW MPCs are 0.0047 (rad) and 0.0061 (rad), derived from the results shown in Fig. 5b.

Finally, the optimal input signal (steering angle) obtained using LTIW and LTVW MPCs is presented in Fig. 6. Based on the findings of this study, it is evident that the newly proposed method better adheres to avoid the sudden variations in the steering wheel angle when contrasted to the previous method. Based on the represented results in Fig. 6, there was a sudden change in the steering angle (impossible to follow in a real application) using the previous method at 5 seconds of the motion.

To summarise, the experimental findings suggest that the LTVW MPC can produce more precise motion tracking for autonomous vehicles when compared to the LTIW MPC. Therefore, using the proposed techniques can increase the accuracy and performance of future autonomous vehicles, which can result in enhanced road safety.

IV. CONCLUSION

Autonomous vehicles are increasingly becoming popular as a solution to improve safety and efficiency in transportation. With the potential to be applied in different domains, such as aviation, military, and intelligent cities, there is a need for advanced motion tracking systems to enhance the accuracy of these vehicles. In this regard, the present study proposes the

TABLE I
FUZZY CONTROL RULES FOR LATERAL POSITION WEIGHT OF MPC

W_{LP}	e_{LP}	VN	N	Z	P	VP
e_{YA}	VN	VB	B	M	B	VB
	N	B	S	S	S	B
	Z	M	S	VS	S	M
	P	B	S	S	S	B
	VP	VB	B	M	B	VB

VN: very negative; N: negative; Z: zero; P: positive; VP: very positive.

VN: very near; N: near; M: middle; F: far; VF: very far.

VS: very small; S: small; M: medium B: big; VB: very big.

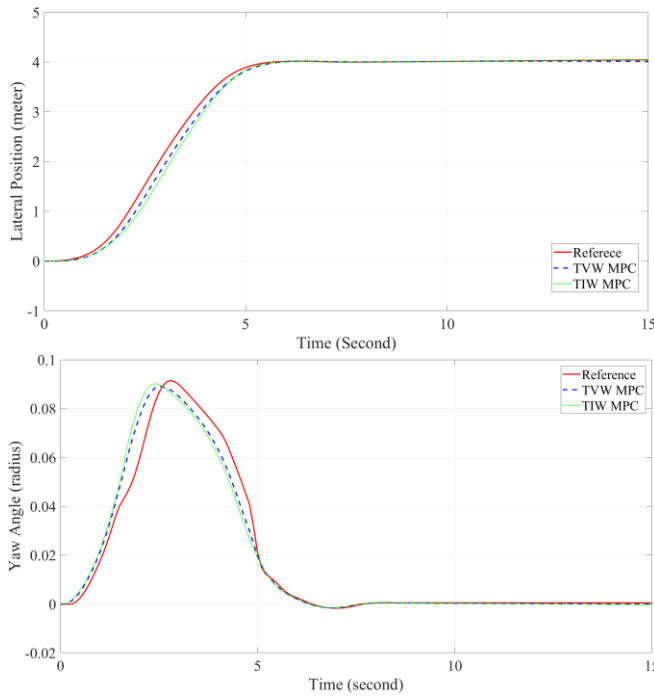


Fig. 5. The reference and followed motion using LTIW and LTVW MPCs along (a): lateral position; (b): yaw angle.

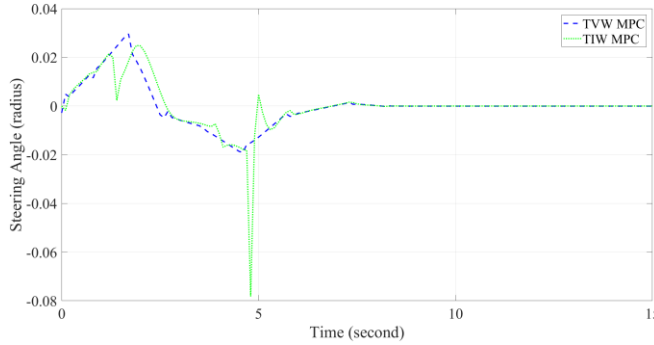


Fig. 6. The optimal extracted input signal (steering angle) using LTIW and LTVW MPCs.

LTVW MPC model, which utilises a four-wheel dynamic model and considers various weights, including inaccuracy in response to abrupt motions and various driving scenarios, to improve motion tracking accuracy. Compared to the LTIW MPC-based tracking system, which has inaccuracy in response to abrupt motions and various driving scenarios, the LTVW MPC model addresses these problems and provides higher efficiency in minimising motion tracking errors. Properly tuning the MPC weights reduces tracking errors and enhances accuracy. The main objective of the LTVW MPC model is to track the lateral position and yaw angle of autonomous vehicles to increase the controller unit's efficiency while considering motion-tracking errors. Two fuzzy logic units have been developed to find the optimal weights of the MPC model. These fuzzy logic units generate optimal weights of lateral position and yaw angle using motion tracking errors. By applying fuzzy logic units to verify optimal weights, the adaptability of the MPC model is enhanced, making it more reliable in various driving scenarios. The development of advanced motion tracking systems, such as the LTVW MPC model, could lead to a broader range of applications for autonomous vehicles and make them an even more viable

solution for transportation in the future. Finally, the LTVW MPC model is a promising solution for improving the accuracy of motion tracking in autonomous vehicles. This model considers various weights, including inaccuracy in response to abrupt motions and different driving scenarios, and utilises fuzzy logic units to determine optimal weights. With the increasing demand for autonomous vehicles, the development of advanced motion-tracking systems could enhance the safety and efficiency of autonomous transportation, making it a more reliable future transportation solution [69]. Also, machine learning and meta-heuristic optimisation methods can be employed to increase the system's efficiency [70-80].

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