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ORIGINAL RESEARCH

High-level decision-making for autonomous overtaking: An MPC-based switching control approach

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Abstract

The key motivation of this paper lies in the development of a high-level decision-making framework for autonomous overtaking maneuvers on two-lane country roads with dynamic oncoming traffic. To generate an optimal and safe decision sequence for such scenario, an innovative high-level decision-making framework that combines model predictive control (MPC) and switching control methodologies is introduced. Specifically, the autonomous vehicle is abstracted and modelled as a switched system. This abstraction allows vehicle to operate in different modes corresponding to different high-level decisions. It establishes a crucial connection between high-level decision-making and low-level behaviour of the autonomous vehicle. Furthermore, barrier functions and predictive models that account for the relationship between the autonomous vehicle and oncoming traffic are incorporated. This technique enables us to guarantee the satisfaction of constraints, while also assessing performance within a prediction horizon. By repeatedly solving the online constrained optimization problems, we not only generate an optimal decision sequence for overtaking safely and efficiently but also enhance the adaptability and robustness. This adaptability allows the system to respond effectively to potential changes and unexpected events. Finally, the performance of the proposed MPC framework is demonstrated via simulations of four driving scenarios, which shows that it can handle multiple behaviours.

1 | INTRODUCTION

Autonomous overtaking is one of the most common yet challenging driving maneuvers, improving trip efficiency by avoiding a slower or stationary preceding vehicle (see [1–10]). In the early years of autonomous vehicle research, the primary focus was predominantly on trajectory planning and tracking. Chai *et al.* [3] proposed several optimization frameworks for solving a series of vehicle trajectory planning problems. The approaches of using a gradient operation [11], a swarm intelligent algorithm [12], a fuzzy adaptive strategy [2], and a deep neural network [13] have been explored to enhance the search capability. These optimisation-based approaches gained considerable attention and found practical applications in the field of path planning.

In general, there are three sequential steps in the control architecture for autonomous vehicles (see Figure 1). A perception module fuses sensor readings to increase the reliability of information on both the environment and the status of the autonomous vehicle. The decision maker uses the perception outputs to make a decision from a set of possible choices, such as {"*Following lane*", "*Slowdown*", "*Stop*", "*Overtaking*"}. Based on the decision, the path planner generates a reference path that is followed by the low-level controller. In other words, decision making, path planning, and motion control constitute a complete control scheme [14].

Decision-making is responsible for evaluating potential collision risks of each possible maneuver based on current traffic states and then making an appropriate decision with minimised collision risks. The existing studies on decision-making can be roughly categorised into three categories, that is, rule-based methods [15–19], learning-based schemes [20–24] and Monte Carlo Tree Search (MCTS) [25–28]. For instance, Wang et al. [15] proposed a predictive maneuver-planning method

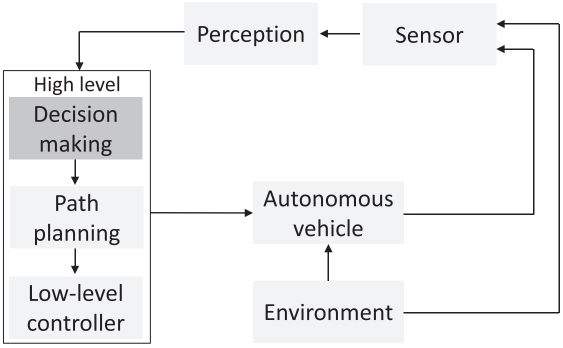

FIGURE 1 The control architecture. The grey shaded block shows the component discussed here.

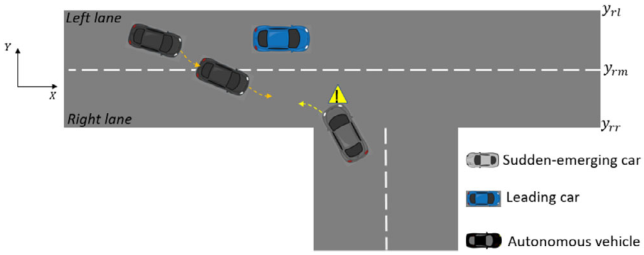

FIGURE 2 Autonomous overtaking with the emerging traffic.

for autonomous vehicle navigating in public highway traffic based on pre-defined switched rules. Jula et al. [18] proposed a rule-based minimum safety spacing calculation method in lane-changing and lane-merging scenarios based on vehicle kinematics. This rule-based method has gained widespread adoption in various applications such as risk assessment in trajectory planning [29], maneuver modelling [30], and overtaking [31]. An integrated rule-based decision-making and motion control framework was presented in [19] to achieve emergency avoidance in complex driving scenarios. However, rule-based methods have several drawbacks. For example, the approach is error-prone, and correct behaviour can only be guaranteed through exhaustive testing. Due to the nature of driving and road conditions, it is impossible to anticipate and account for all possible scenarios during the design stage. Any oversight or omission can lead to potentially dangerous consequences such as colliding with popping up oncoming vehicles, as illustrated in Figure 2. In contrast, Johansson et al. [20] investigated a deep reinforcement learning method for decision-making in the high level. Although this approach yields a promising performance, there is still a concern about how to guarantee collision-free during both the training and the deployment process by the virtue of reinforcement learning methods. Learning-based methods depend on the training scenarios and it is hard to use them in safety-related applications since it is very difficult to obtain data for all possible dangerous cases [23, 32, 33].

In addition, MCTS, a promising method for solving complicated sequence optimisation problems, has also shown its advantages in solving decision-making for unmanned vehicles [25–28]. For example, a cooperative motion planning algorithm for autonomous highway driving was developed in [25] using MCTS, which relies on a manually designed cooperative cost function. This method can handle multiple vehicle interactions in a merging scenario in the simulator without requiring inter-vehicle communication. A deep-MCTS algorithm for vision-based autonomous driving was presented in [26], which can predict driving maneuvers to help improve the stability and performance of driving control. Although MCTS yields promising performance by summing costs *of distance to other road users* into final cost function, there is still concern about how to guarantee the specification of a minimum safe distance between the autonomous vehicle and other road users, thereby improving safety margins in highly dynamic and uncertain environments. Hence, it is a vital task to integrate safety constraints into the decision-making process to ensure that the autonomous system operates safely in all situations.

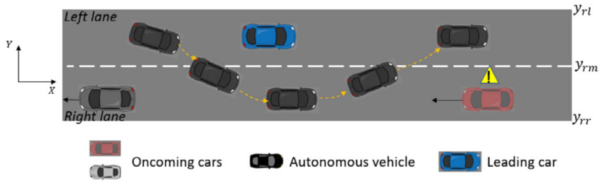

FIGURE 3 Autonomous overtaking with the oncoming traffic.

The autonomous vehicle controller needs to make complex decisions regarding how and where to drive. Especially, it becomes even more challenging when autonomously overtaking a leading vehicle on two-lane country roads in the presence of oncoming vehicles. For example, the autonomous vehicle has lower priority on the opposite lane. This means that the autonomous vehicle always needs to give way to oncoming vehicles. In addition, if the distance from the front car is too small, the field of view of the autonomous vehicle becomes partially blocked. However, if the distance from the front car is too large, the overtaking time would be quite long, resulting in more uncertainties and a prolonged duration during the overtaking maneuver. As illustrated in Figure 3, there are several stages as follows: (1) Depart from the original lane. (2) Occupy the opposite lane to drive past a slow moving (or stationary) vehicle travelling in the same direction. (3) Return to the original lane. The success of overtaking on such a road is significantly affected by many factors, for example, the wide range of natural/traffic conditions (e.g. the layout of the road, visibility), the distance between the autonomous vehicle and the surrounding ones whose behaviours could be widely varying. Moreover, both the longitudinal and lateral motions are involved in this process.

To complete the overtaking maneuver successfully and safely, the autonomous vehicle has to evaluate the available gaps in the opposite direction. This necessitates the autonomous vehicle to drive on the path of potential oncoming vehicles for a significant period of time, often at high speeds [6, 7, 9]. In addition, the information of leading vehicle's trajectory and road boundaries are also required. This means that the overtaking process must satisfy many constraints simultaneously, and this property also brings many more challenges for completing overtaking maneuvers safely, especially on a single-lane two-direction road.

Therefore, it is important to properly make a series of overtaking decisions that improve the trip efficiency and simultaneously satisfy the safety in the high level. The decision-maker is then integrated effectively with a trajectory planning module at the low level to successfully complete overtaking maneuvers.

To effectively deal with the aforementioned challenges and provide an alternative solution, model predictive control (MPC)-based optimisation methods are receiving significant attention because they can generate an optimal path/decision by solving an input and state constrained optimisation problem based on the latest available information in a receding prediction horizon fashion (see [16, 34–47]). This means that MPC method is applicable in real time and can avoid moving obstacles. For example, Dixit et al. proposed a high-level decision-making process based on the MPC method in [44], and this algorithm was executed in the absence of surrounding vehicles. A finite state machine was employed as a high-level decision-maker in [16], where MPC was chosen as a trajectory planner. Reference [45] investigated a multi-mode switching longitudinal autonomous driving system based on MPC, which is serving as the upper-level controller. While these papers did not consider oncoming vehicles (as depicted in Figures 2 and 3), in practice, however, it is inevitable that a vehicle may emerge suddenly on the opposite lane from a crossing road after overtaking is initiated (see Figure 2), or the sensors of the autonomous vehicle did not detect an oncoming vehicle (e.g. due to a limited sensor range or partially blocked field view of the sensors) before executing the overtaking action.

To tackle two-way overtaking problems which may encounter oncoming vehicles, a number of works have been reported, which can be roughly divided into two categories, that is, mechanism-based and learning-based models. The mechanism-based models mainly use risk-related indices for overtaking decisions. Game theory, as a representative mechanism-based approach, has been widely embraced for modelling human decision-making in driving, especially the mutual dependence between the interacting drivers (e.g. [48–50]). Although the game-based approach is promising, as [49] pointed out, there are still many improvements to be made for game-based driving decision models, for example, the sufficient traffic data for modelling, the proper design of payoff function based on understanding how drivers value different objectives, and so on. On the other hand, in recent years, many learning-based models have been proposed to describe overtaking decision (e.g. DQN model [51], hidden Markov model [52], RL [53], DRL [20]). For example, Johansson et al. [20] designed a trajectory planner based on a DRL method using a discrete action space, where these discrete actions are connected to a low-level controller to complete the control of the autonomous vehicle. However, due to the limited control accuracy of the discrete action space, it cannot guarantee collision-free during training and execution. Reference [53] used a risk-based approach to estimate risk states during RL training, and a MCTS was also used to reduce unsafe behaviours of the agent while training. In general, learning-based models have shown powerful capabilities in describing complex driving behaviours, especially when high-quality driving data are available. A drawback of learning-based models is that the learned decision strategies/policies can have difficulty in situations not covered by the training episodes. Therefore, it is very challenging to develop a reliable and robust decision-maker that is able to not only guarantee safety but also perform overtaking in an optimal manner under diverse traffic conditions. Motivated by the above-mentioned observations and recognising the abundance of excellent works in lower-level path planning and dynamics control (see, e.g. [2, 3, 11–13, 54–56]), this paper specifically focuses on decision-making at a higher level for autonomous overtaking under two-lane country roads subject to oncoming vehicles by integrating optimisation methods and switching control techniques.

Here, we are interested in, for a given traffic scenario, how to make a right decision and when to perform overtaking quickly while guaranteeing safety. We develop a process to represent the relationship between the high-level decisions and real control inputs for the vehicles with the help of the concept of switched systems. During the prediction horizon, the control inputs (i.e. the steering angle and the acceleration of the autonomous vehicle) are updated based on the optimal action made by the MPC-based decision-maker. That is, the inputs are regarded as a switched controller and the optimal decision variable is regarded as a switching signal. A cost function for online optimisation is proposed where a coupled term on the relative distance (i.e. the distance between the autonomous vehicle and the oncoming one) and velocity tracking error is also included. This optimisation is repeatedly solved based on the latest available information of the traffic, giving the autonomous vehicle the ability to quickly respond to changes or unexpected events.

The main contributions of this paper are summarised as follows. First, as a contrast to conventional pre-defined rule-based methods, our approach seeks to streamline the decision-making process in autonomous overtaking. We achieve this by incorporating switching techniques and abstracting the decision-making under complex environmental conditions through an MPC-based framework that effectively captures interactions with other road users. Furthermore, the introduced switched system serves as a bridge, connecting high-level decisions to the actual control inputs implemented on the autonomous vehicle at the lower level. Consequently, we can select the safe and optimal action to execute maneuvers. Second, the proposed method can deal with dynamic environments, as well as avoiding collisions. Furthermore, the performance of the proposed approach is validated within four typical driving scenarios, containing a stopped/moving leading vehicle or oncoming vehicles. This demonstrates its feasibility, effectiveness and adaptivity when operating in a dynamic and uncertain traffic environment.

The rest of this paper is organised as follows: In Section 2, problem formulation for autonomous overtaking on two-lane country roads with oncoming vehicles is introduced. A decision-making framework based on MPC and switching approaches is proposed in Section 3, while four driving scenarios are set to verify the effectiveness of the proposed decision-making framework in Section 4. Finally conclusions are discussed in Section 5.

Notations. The set of real numbers is denoted by $\mathbb{R}$. The set of integers is denoted by $\mathbb{Z}$. $\mathbb{R}_{>0} := (0, \infty)$. $\mathbb{Z}_{>0}$ denotes the set of positive integers. x^T denotes the transpose of x.

2 | PROBLEM FORMULATION

Here, we only consider the optimal decision-making for the high-level control design of autonomous overtaking for a two-way road in the presence of oncoming vehicles or other unexpected events (e.g. emerging vehicles or changing behaviours of other vehicles). We propose a high-level decision-making framework by integrating an MPC-based optimisation method and switching control approaches. The decision variables include following lane, slowdown, stop, and overtaking. This allows us to initiate, execute, hold or even abandon an overtaking maneuver. To enable the design of the high-level control system, representations of the autonomous vehicle and its surrounding environment are required. This includes a simplified vehicle model, physical and safety constraints, performance specification, and information about oncoming vehicles, all of which will be introduced in this section.

2.1 | Vehicle model

When high-level decision-making for autonomous vehicles is of concern, a kinematic model is widely used due to its low parameter dependency [57], described as

$$\begin{aligned}\dot{x} &= v\cos\theta,\\ \dot{y} &= v\sin\theta,\\ \dot{\theta} &= \frac{v}{l}\tan\varphi,\\ \dot{v} &= a,\end{aligned} \tag{1}$$

where $z = [x, y, \theta, v]^T$ are the states of the model and $u = [\varphi, a]^T$ are control inputs. Specifically, (x, y) are the coordinates of the centre point of the rear axle, θ is the heading angle of the vehicle body with respect to the x axis, v is the linear forward velocity, φ is the steering angle of the front wheel with respect to the vehicle's longitudinal line and a is the longitudinal acceleration. l is the distance between the front axle and the rear axle, which can be seen from Figure 4. To facilitate the high-level decision-making, the link between the kinematic model and the MPC-based high-level decision-making is realised by determining the control variables $u = [\varphi, a]^T$ using each corresponding decision variable. This means that the model switches into different modes based on the different decision variables. Therefore, we can represent the system as a switched system, where the decision variable defines the switching mode. We take advantage of this representation in the sequel to build up the link between the high-level decisions and low-level real control inputs applied to the autonomous vehicle. More details will be discussed in Section 3.

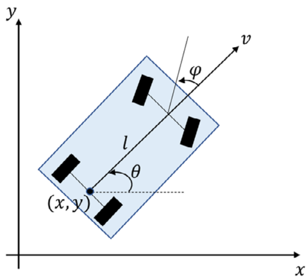

FIGURE 4 Kinematic model for a rear-wheel driving car.

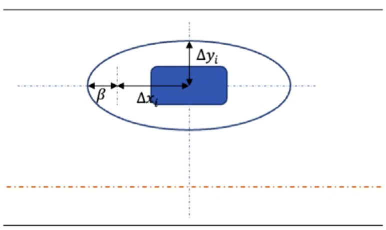

FIGURE 5 The illustration of an elliptical constraint.

To successfully complete the overtaking and ensure the safety, it is important to abstract the behaviour of both the autonomous and surrounding vehicles, model the road layout, and carefully incorporate all the information into the decision-making process. This includes taking into account all safety constraints.

2.2 | Constraints

1) *State/Control variables constraints*: To take physical limitations and other constraints of the autonomous vehicle into consideration, the following constraints are considered:

$$\begin{aligned}&y \in [y_{\min}, y_{\max}],\ \theta \in [\theta_{\min}, \theta_{\max}],\ v \in [v_{\min}, v_{\max}]\\ &\varphi \in [\varphi_{\min}, \varphi_{\max}],\ a \in [a_{\min}, a_{\max}].\end{aligned} \tag{2}$$

2) *Safety constraints*: Inspired by [40], to keep a safe distance between the autonomous vehicle and any nearby Vehicle i with position (x_i, y_i), we introduce an elliptical constraint of the form:

$$\left(\frac{x - x_i}{\Delta x_i + \beta}\right)^2 + \left(\frac{y - y_i}{\Delta y_i}\right)^2 \geq 1, \tag{3}$$

where $\Delta x_i, \Delta y_i$ are calculated by incorporating the geometry (length and width) of Vehicle i and the autonomous vehicle (see Figure 5). These are assumed available from sensing. β is an optional tuning parameter to manipulate the behaviour of the proposed optimisation approach.

2.3 | Performance indexes

1) *Tracking performance indexes*: As shown in Figures 2 and 3, the autonomous vehicle needs to return to the original lane after

finishing the overtaking maneuver. Assume that the desired trajectory is (V_{lref}, Y_{lref}), representing the tracking reference signal of the left lane. Then, the corresponding tracking indexes are designed as follows:

$$J_{trv} = \gamma_1 (v - V_{lref})^2 \tag{4a}$$

$$J_{try} = \gamma_2 (y - Y_{lref})^2, \tag{4b}$$

where constants $\gamma_1, \gamma_2 > 0$. J_{try} guides the autonomous vehicle into the centre of the *left lane*.

2) *Road boundary indexes*: We consider two lanes defined by three boundaries: left, y_{rl}, middle, y_{rm}, and right, y_{rr}, ones (see Figures 2 and 3). During overtaking maneuvers, a vehicle must stay inside the edges of the road. This is ensured here by using barrier functions that are designed such that the boundaries of the road have the highest (i.e., $+\infty$) potential and the centret of the lane has the lowest potential (see, e.g. [58] and [44]). Depending on the stage of the overtaking manoeuvre, we define two barrier functions based on a widely used barrier function in literature.

- When overtaking is not happening, the autonomous vehicle stays in the original lane, and we only need to consider the *left boundary* and the *middle boundary*. Hence, the road potential function is given as follows:

$$J_{roadlm} = \frac{1}{2}\eta_m \sum_j \left(\frac{1}{y - y_{rj}}\right)^2, \tag{5}$$

  where η_m is a scaling factor and y_{rj} is the y-coordinate of the jth road edge with $j \in \{l, m\} := \{left\ boundary, middle\ boundary\}$.

- When overtaking is happening, the autonomous vehicle is able to go across the middle boundary, while the boundaries of *left boundary* and *right boundary* need to be concerned. Thus, the road potential function is

$$J_{roadlr} = \frac{1}{2}\eta_r \sum_j \left(\frac{1}{y - y_{rj}}\right)^2, \tag{6}$$

  where η_r is a scaling factor and $j \in \{l, r\} := \{left\ boundary, right\ boundary\}$. Figure 6 shows a plot of this potential for a y-axis cross-section of a two-lane road under different scaling factors.

2.4 | Autonomous overtaking process description

Let q be the discrete decision of the autonomous vehicle. More specifically, $q \in \{1, -1, -2, 2\} := \{following\ lane,\ slowdown,\ stop,\ overtaking\}$. Let $(X_{ri}^{OV}, Y_{ri}^{OV})$ be the position of oncoming Vehicle i on the opposite right lane, which provides a sketchy path reference of the vehicle i of concern as an input to the low-level controller of

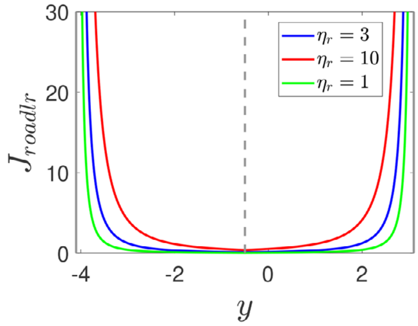

FIGURE 6 Road edge potentials. Three vertical grey lines mark lane dividers dashed line and road edges.

the autonomous vehicle. After taking into account all the constraints and specifications as described above, the overall performance index is given by

$$J(q) = \frac{q^2 - 4}{-3} J_{roadlm} + \frac{q^2 - 1}{3} J_{roadlr} + J_{try} + J_{pv}, \tag{7}$$

where J_{roadlm},J_{roadlr} and J_{try} are given in (5), (6) and (4), respectively. The safety requirement during the overtaking is reflected by J_{pv}. It describes the relative distance between the autonomous vehicle and the oncoming one and the velocity tracking error, given by

$$J_{pv} = \frac{q^2 - 4}{-3} \frac{1}{\gamma_3 |x - X_{ri}^{OV}| + \epsilon} J_{trv}, \tag{8}$$

where $\gamma_3 > 0$ and ϵ is a small positive number to avoid the denominator being zero in the calculation.

Remark 1. Driving on the *left lane* is the goal of the autonomous vehicle, so tracking the desired trajectory should be taken into consideration in the whole overtaking process. That is, there is no q coupled on J_{try} in (7). Moreover, the first two terms $\frac{q^2-4}{-3} J_{roadlm}$ and $\frac{q^2-1}{3} J_{roadlr}$ of (7) correspond to the road boundary constraints mentioned in Section 2.2. In fact, "$\frac{q^2-4}{-3}$" could be changed to any other functions of q as long as it equals to 1 and 0, when $q = \pm 1$ and $q = \pm 2$, respectively. Similarly, $\frac{q^2-1}{3}$ could be also changed.

With the above problem formulation, the overtaking process on a two-way road is described as follows. When the autonomous vehicle is running on the original lane and approaching the desired velocity, both J_{trv} and $|x - X_{ri}^{OV}|$ are decreasing. This means that $\frac{J_{trv}}{|x - X_{ri}^{OV}|}$ does not play a main role in the performance index. Therefore, $q = 1$, rather than $q = \pm 2$, minimises cost $J(q)$ given in (7). When the sensor detects that the distance between the autonomous vehicle and the leading vehicle is closing to the safe distance, and the opposite lane does not allow the autonomous vehicle to initiate overtaking manoeuvers, the optimal solution to (7) is $q = -1$ (*slowdown*). In this case, J_{trv} is increasing, while $|x - X_{ri}^{OV}|$ is still decreasing. Correspondingly, we have that $\frac{J_{trv}}{|x-X_{ri}^{OV}|}$ is getting bigger and bigger, which plays a main role in the performance index. Therefore, to minimise the total cost function, q equals to ± 2. In other words, when the opposite lane is available for overtaking, decision $q = 2$ (*overtaking*) is obtained; when the opposite lane is busy, action $q = -2$ (*stop*) is obtained. When the autonomous vehicle restarted after executing $q = -2$ (*stop*) action, J_{trv} plays a main role and action $q = 2$ (*overtaking*) is obtained, since oncoming vehicles have passed. When overtaking process is in proceeding, that is, $q = 2$, the distance $|x - X_{ri}^{OV}|$ is getting bigger (since all oncoming vehicles are driving away from the autonomous vehicle) and the value of J_{trv} is around zero. Then, $\frac{J_{trv}}{|x-X_{ri}^{OV}|}$ does not play a main role. Hence, the optimal decision $q = 1$ (*following lane*) is made according to other terms in the performance index (7) and the autonomous vehicle returns to the original lane. It shall be highlighted that the above decision-making process continuously execute with all the updated information of the surrounding traffic. This allows the autonomous vehicle to respond to the changing environment in a safe and rational way, which will be explained further and demonstrated in simulation studies.

Remark 2. We consider only the relative distance in X-direction between the autonomous vehicle and the first oncoming vehicle, which does not drive pass the autonomous vehicle. That means $x \leq X_{ri}^{OV}$ when consider the direction of the autonomous vehicle as positive direction.

3 | DECISION-MAKING BASED ON MPC AND SWITCHING APPROACHES

3.1 | Switching control approach

The main purpose of the MPC approach is to find the optimal high-level decision consequence by repeatedly solving an online constrained optimisation problem. In this subsection, we demonstrate that the high-level decision-making can be represented as a switched system. Specifically, we treat the decision-making as a switching control process that facilitates the autonomous vehicle switching from one sub-operation mode to another one. For each sub-operation mode, we define specific pairs of control inputs with respect to decision variables applied on the vehicle. Under these pairs of control inputs, the autonomous vehicle exhibits different behaviours that could be described by the kinematic model which is given by (1), but with different control inputs with respect to different decision variables. This will be presented by the following model (9). This approach enables us to link the high-level decision (such as *slowdown* or *overtaking*) to lower-level behaviours and status of the autonomous vehicle (e.g. position, velocity). Furthermore, it also allows us to evaluate the relationship between the autonomous vehicle and other vehicles (e.g. leading or oncoming vehicles) to ensure safety and other desirable properties.

TABLE 1 The control inputs $u_{q(k)}(k)$, $k \in \mathbb{Z}_{\geq 1}$, in the predictive kinematic model and its relationships with decision variables.

$(\varphi_{q(k)}(k), a_{q(k)}(k))$	logical conditions
$(0, c_2)$	$q(k) = 1$ & $v(k) < V_{lref}$
(0,0)	$q(k-1) \neq -2$ & $q(k) = 1$ & $v(k) = V_{lref}$
$(0, c_2)$	$q(k-1) = -2$ & $q(k) = 1$
$(0, -c_1)$	$q(k) = -1$
$(-c_4, c_2)$	$q(k) = 2$ & $x - X_l^{LV} \leq X_{el}$ & $y \geq -y_f$
$(0, c_2)$	$q(k) = 2$ & $x - X_l^{LV} \leq X_{el}$ & $y < -y_f$
(c_3, c_2)	$q(k) = 2$ & $x - X_l^{LV} > X_{el}$ & $y \leq y_z$
$(0, c_2)$	$x - X_l^{LV} > X_{el}$ & $y > y_z$
$(\varphi(k-1), 0)$	$q(k) = -2$

More precisely, we first discretize the system (1) by using Euler method with sampling time T_s. Hence, the system (1) can be rewritten as

$$z(k+1) = f_{q(k)}(z(k), u_{q(k)}(k)), \tag{9}$$

where $z(k) = [x(k), y(k), \theta(k), v(k)]^T$, $u_{q(k)}(k) = [\varphi_{q(k)}(k), a_{q(k)}(k)]^T$ are determined by decision variable $q(k)$ with $q(k) \in \{1, -1, -2, 2\}$ that can be interpreted as the switching modes and $f(0, 0) = 0$. Moreover, the control and state sequences must satisfy

$$z(k) \in \mathbb{Z} \tag{10a}$$

$$u_{q(k)}(k) \in \mathbb{U}, \tag{10b}$$

where $\mathbb{Z}$ is a subset of $\mathbb{R}^4$ and $\mathbb{U}$ is a subset of $\mathbb{R}^2$, each set containing the origin in its interior.

Remark 3. In this study we assume that the autonomous vehicle cannot reverse, *that is*, $v(k) \geq 0$ for all $k \in \mathbb{Z}_{\geq 1}$. In addition, due to safety reasons, the overtaking maneuvers must be finished as soon as possible. To sum up, the constraints on the decision variable $q(k)$ are summarised as

$$q(k+1) \neq \begin{cases} -1, & q(k) = \pm 2, \\ -2, & q(k) = 1. \end{cases} \tag{11}$$

Here, we mainly focus on how to obtain the sequence of optimal decision action $q^*(k)$ on the high level. Therefore, to give a sketchy tracking reference to the low-level control of the autonomous vehicle, based on the optimal decision $q^*(k)$, we use the logic shown in Table 1 to update control inputs $u(k)$ in the predictive model. Note that (X_l^{LV}, Y_l^{LV}) is the position of the leading vehicle in the *left lane*.

In Table 1, constants $X_{el}, y_f, y_z \in \mathbb{R}_{>0}$ and $c_1, c_2, c_3, c_4 \in \mathbb{U} \cap \mathbb{R}_{>0}$ are to be determined later. In Table 1, for the second case when $q(k) = 2$, that autonomous vehicle runs on the *right lane* for a while with steering angle $\varphi = 0$. Noting that, the focus of this paper is not on path planning and trajectory following, a simple rule-based low-level control (given in Table 1) is used to capture and represent the behaviour of the autonomous and other vehicles for the purpose of decision-making. Once an action such as overtaking or lane-following is decided, the command will be passed to a lower-level path planning module that will generate a realistic path based on more detailed models and other information using optimisation or other search tools. This path will be used as a trajectory reference for the lowest level controller to follow.

3.2 | MPC-based framework

During the overall maneuver, the constraints (2) and (3) should always be satisfied. Let $(X_{rj}^{OV}(k), Y_{rj}^{OV}(k))$ and $V_{rj}^{OV}(k)$ be the position and the longitudinal speed of the oncoming Vehicle j at instant kT_s, respectively. Then, the prediction for the position of the oncoming Vehicle j at time $(k+1)T_s$ is calculated as follows:

$$\begin{aligned} X_{rj}^{OV}(k+1) &= X_{rj}^{OV}(k) + V_{rj}^{OV}(k)(k-1)T_s \\ Y_{rj}^{OV}(k+1) &= Y_{rj}^{OV}(k). \end{aligned} \tag{12}$$

Similarly, given the position $(X_l^{LV}(k), Y_l^{LV}(k))$ and the longitudinal speed $V_l^{LV}(k)$ of the leading vehicle at instant kT_s, the prediction of its position at time $(k+1)T_s$ is given as

$$\begin{aligned} X_l^{LV}(k+1) &= X_l^{LV}(k) + V_l^{LV}(k)(k-1)T_s \\ Y_l^{LV}(k+1) &= Y_l^{LV}(k). \end{aligned} \tag{13}$$

Thus, the overall optimisation problem is formulated as follows:

$$\min_{q(k)} \sum_{i=0}^{N-1} J(q(i;k)) \tag{14a}$$

$$s.t.\ \ z(i+1;k) = f_{q(i;k)}(z(i;k), u_{q(i;k)}(i;k)) \tag{14b}$$

$$z(i;k) \in \mathbb{Z},\ u_{q(i;k)}(i;k) \in \mathbb{U} \tag{14c}$$

$$q(i;k) \in \{1, -1, -2, 2\} \tag{14d}$$

$$q(i+1;k) \neq \begin{cases} -1, & q(i;k) = \pm 2 \\ -2, & q(i;k) = 1 \end{cases} \tag{14e}$$

$$\left(\frac{x(i;k) - X_l^{LV}(i;k)}{\Delta X + \beta}\right)^2 + \left(\frac{y(i;k) - Y_l^{LV}(i;k)}{\Delta Y}\right)^2 \geq 1 \tag{14f}$$

$$\left(\frac{x(i;k) - X_{ri}^{OV}(i;k)}{\Delta X + \beta}\right)^2 + \left(\frac{y(i;k) - Y_{ri}^{OV}(i;k)}{\Delta Y}\right)^2 \geq 1 \tag{14g}$$

ALGORITHM 1 Implementation of hierarchical framework

/*High-level decision-making*/

1) Initialisation: At initial time step, i.e., $k = 0$, initialize the state $z(0) = [x(0), y(0), \theta(0), v(0)]^T$. Given parameters $\gamma_1, \gamma_2, \gamma_3, \eta_m, \eta_r, \epsilon$, and sampling time T_s.
2) Find the optimal decision $q^*(k)$ that gives the minimum value of the cost function (14a) and subject to the physical and safety constraints (14b)–(14g).
3) Execute the first decision $q^*(i;k)$, $i = 0$.

/*Lower-level path planning process*/

1) Check the value of the optimal decision variable q^* transmitted from high level.
2) Choose control inputs $u_{q^*} = [\varphi_{q^*}, a_{q^*}]^T$ for switching system (9) based on Table 1.
3) Feedback the physical information of autonomous vehicle to high level, and then high-level decision-making framework will re-solve the optimisation problem (14) to calculate the new optimal decision passed to the lower level.
4) $k \leftarrow k+1$ and go to step 2) of high level.

where $J(q(i;k))$ is defined in (7), $u_{q(i;k)}(i;k)$ is given in Table 1 and N is the planning horizon.

After solving the above constrained optimisation problem, the following optimal decision sequence can be achieved

$$q^*(k) = \left[q^*(i;k), q^*(i+1;k), \ldots, q^*(i+N-1;k)\right]^T. \tag{15}$$

For each MPC update step, only the first value in the control sequence $q^*(0;k)$ is implemented as the decision action to the autonomous vehicle. At the next time step $(k+1)$, a new optimisation problem is solved over a shifted prediction horizon again with the updated state $z(0;k+1) = z^*(1;k)$. This can be summarised in **Algorithm 1**.

Remark 4. The formulation (14) shows that, to facilitate the decision design in autonomous overtaking, we abstract the decision-making process under a complex environment where interactions with other road users are captured. This safety-constrained solution allows constraints to be specified to ensure that the minimum safe margin between the ego vehicle and other road users is respected (i.e. refer to (14f)-(14g)) despite the behaviour of the other road users not being fully predictable. This formulation enables us to formulate the generation of safe and optimal decisions in uncertain and dynamic environments.

Remark 5. The optimisation problem formulation in Equation (14) differs from the conventional MPC-based trajectory planning problem. Our approach treats decision-making as a switching control process based on various high-level decision commands. Consequently, analysing the duration problem and stability of the proposed framework becomes a challenging task. It is important to note that the main contribution of the paper is to propose this new high-level decision-making framework by integrating MPC and switching control approaches and demonstrate its efficiency. However, detailed theoretical analysis will be our future work. This framework establishes a crucial connection between high-level decision-making and the autonomous vehicle's lower-level behaviour and status, enabling trajectory planning at the lower level for overtaking maneuvers. The core concept of this paper can be seen as a benchmark for researchers interested in designing high-level decision-making frameworks using various optimisation-based methods.

4 | TESTING DRIVING SCENARIOS

In this section, we illustrate the effectiveness of the proposed MPC-based decision-maker through four simulated practical traffic scenarios. Here, we consider the discrete decisions of the autonomous vehicle in the high level by using integer variables. Therefore, the formed optimisation problem can be regarded as mixed-integer programming (MIP). Because YALMIP supports several MIP solvers, all the driving scenarios are built and tested on MATLAB platform with YALMIP Toolkit [59]. The central component in the optimisation problem is the decision variables, and these variables are represented in YALMIP by *sdpvar objects*. The optimisation problem resulting from the integration of the YALMIP solver and the conventional MPC solving process is typically addressed using a receding horizon strategy. In this approach, only the first computed sample of the control input within the prediction horizon is applied to the system, while the remaining samples are discarded. Subsequently, the process is iteratively repeated, adapting to an updated optimisation problem based on the new initial conditions at the next sample. The main idea of the implementation of the proposed high-level decision-making framework is given in Figure 7.

4.1 | Testing environment

For all the driving scenarios, we use Driving Scenario Designer provided by MATLAB to set the testing environment (e.g. see Figure 8). The initial value of the autonomous vehicle is set as $z_0 = [3m; 1.3m; 0rad; 15m/s]^T$. Both lanes are set to be 3.6-m wide and all the vehicles are 1.9-m wide. Other information about the lanes are given in Table 2.

Next, we will present four driving scenarios in details. The initial positions and velocities of surrounding vehicles in different scenarios are given in Table 3.

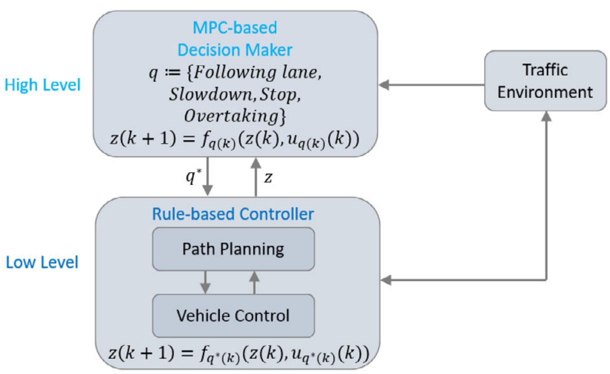

FIGURE 7 Implementation of the proposed high-level decision-making framework.

FIGURE 8 The testing environment designed by Driving Scenario Designer.

TABLE 2 Reference information of the *left lane* and *right lane*, and boundaries of lanes as shown in Figure 2.

Lanes	Y_{lref}	V_{lref}	Y_{rref}
Values	$1.3(m)$	$25(m/s)$	$-2.3(m)$
Boundaries	y_{rl}	y_{rm}	y_{rr}
Values	$3.1(m)$	$-0.5(m)$	$-4.1(m)$

Scenario I: The autonomous vehicle starts on the *left lane* and its sensors detect that there is one leading vehicle moving slowly on the *left lane*, and there is no oncoming vehicle on the *right lane*. The autonomous vehicle needs to overtake the leading one by occupying the opposite road without any collisions.

Scenario II: The leading vehicle is parked on the *left lane*. The oncoming vehicle is approaching at a high speed on the opposite direction.

Scenario III: The leading vehicle is not in stationary but moving forward slowly. Different from Scenario I, the oncoming vehicle is not far from the autonomous one.

Scenario IV: Different from the above three scenarios, in this case, we consider a dynamic environment. Besides the parked leading vehicle, we consider two oncoming vehicles: one is a typical fast-moving vehicle which is not far from the autonomous vehicle, while the other one emerges suddenly (e.g. from the crossing road [see Figure 2]). In addition, to verify the effectiveness of our MPC-based method, in this scenario, we compare with the existing rule-based method proposed in paper [19]. This benchmarked rule-based method concludes four decision variables (i.e. initialisation, acceleration, emergency breaking and quick lane change), and it works very well for addressing overtaking problem in a static environment. However, it may not be flexible when it deals with dynamic environments.

Moreover, the parameters required by the proposed framework are selected as follows:

- Prediction horizon: $N = 5$
- Sampling time $T_s = 0.5(s)$
- Parameters in cost functions and in constraints are given in Table 4.

4.2 | Simulation results

- In Scenario I, we set the overall simulation time to 12 s. The simulation results are shown in Figures 9-I, 10, and 11. It can

TABLE 3 The initial positions and velocities of surrounding vehicles in different scenarios.

Scenarios	I	II	III	IV
Leading	($70\ m; 1.3\ m; 6\ m/s$)	($60\ m; 1.3\ m; 0\ m/s$)	($52\ m; 1.3\ m; 6\ m/s$)	($70\ m; 1.3\ m; 3\ m/s$)
Oncoming 1	–	($140\ m; -2.3\ m; -20\ m/s$)	($39\ m, -2.3\ m; -15\ m/s$)	($104\ m; -2.3\ m; -25\ m/s$)
Oncoming 2	–	–	–	($101\ m; -139.8\ m; -25\ m/s$)

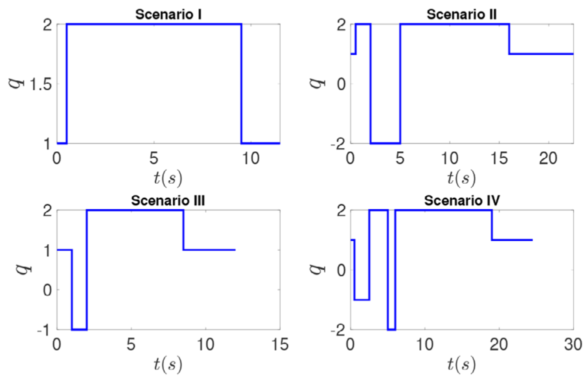

FIGURE 9 Time histories of decisions in four scenarios.

TABLE 4 Parameter specification.

Weights	Values	Parameters	Values	Parameters	Values
γ_1	167	$l\ (m)$	3	$c_1\ (m/s^2)$	3.5
γ_2	228	$\epsilon\ (m)$	10^{-5}	$c_2\ (m/s^2)$	1.5
η_m	3	$\beta\ (m)$	1	$c_3\ (m/s^2)$	0.008
η_r	3	$\Delta X\ (m)$	4	$c_4\ (m/s^2)$	0.009
γ_3	0.016	$\Delta Y\ (m)$	1.6	$y_f\ (m)$	−1.9
–	–	–	–	$y_z\ (m)$	0.83
–	–	–	–	$X_{el}\ (m)$	0.5

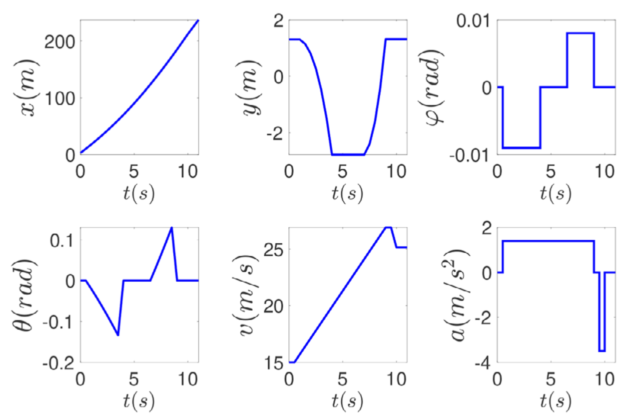

FIGURE 10 The time histories of states and control inputs of the autonomous vehicle in Scenario I.

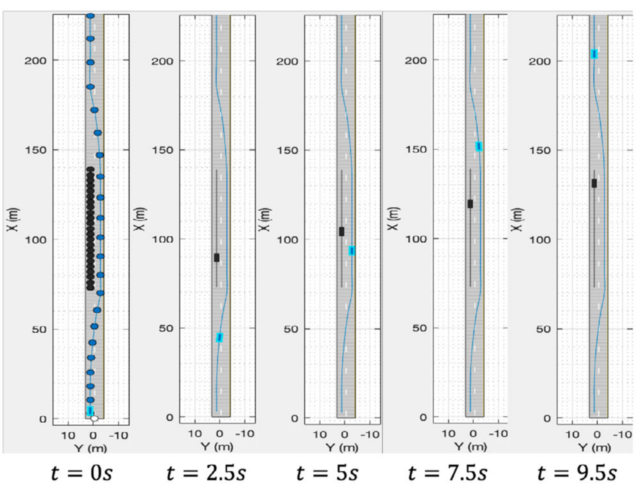

FIGURE 11 A series of screenshots for the overtaking process in Scenario I.

be seen from Figure 9-I that $q(0) = 1$ and the autonomous vehicle starts to change to the opposite lane to overtake the slowly-moving leading vehicle at 0.5 s (i.e. $q(1) = 2$) since the sensor does not detect the oncoming vehicle in the whole overtaking process (see Figure 11). From Figure 9-I, we can see that the autonomous vehicle returns to the original lane after 9 s, that is, $q(19) = 1$. That is, the overall overtaking maneuvers last for 9 s. This paper mainly focuses on the high-level decision-making by assuming there are well-designed lower-level path planning and trajectory following. Therefore, only a simple rule-based low-level controller is implemented in the simulations to illustrate the effectiveness of our high-level decision-making on MATLAB Driving Scenario Designer platform and also which is why we obtain non-smooth results (e.g. see heading angle θ in Figure 10). In real implementation, much detailed and smooth paths will be generated by the path planning module after a high-level decision, which is generated by the high-level decision-maker and passed to the path planning layer. A series of screenshots of the overtaking process can be seen in Figure 11.

- In Scenario II, the overall simulation time is 23 s. According to the settings of this scenario, the simulation results are shown in Figures 9-II, 12, and 13. Figure 13 is used to illustrate the overtaking process. At the beginning, the autonomous vehicle accelerates to track the desired velocity on the original lane. After 0.5 s, the sensors of the autonomous vehicle detect that there is a vehicle parked on the lane, so the autonomous vehicle decides to overtake (i.e. $q(1) = 2$). However, as shown in Figure 13, the opposite lane has been occupied by an oncoming vehicle that is close to the autonomous vehicle. Thus, due to the safety constraints (3), the autonomous vehicle automatically finds the optimal solution to (14), stops (*i.e.,* $q(4) = -2$) and waits for future gaps (see Figure 9-II and the velocity of the autonomous vehicle in Figure 12). From Figures 9-II, 12, and

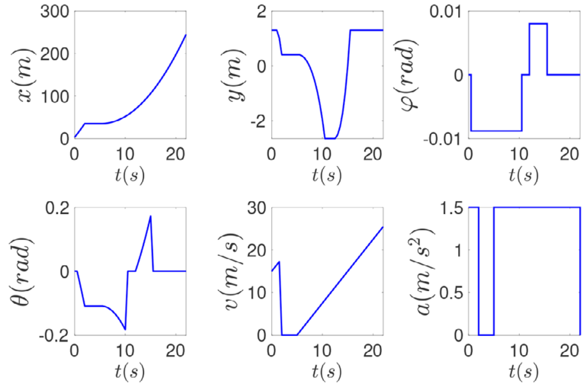

FIGURE 12 The time histories of states and control inputs of the autonomous vehicle in Scenario II.

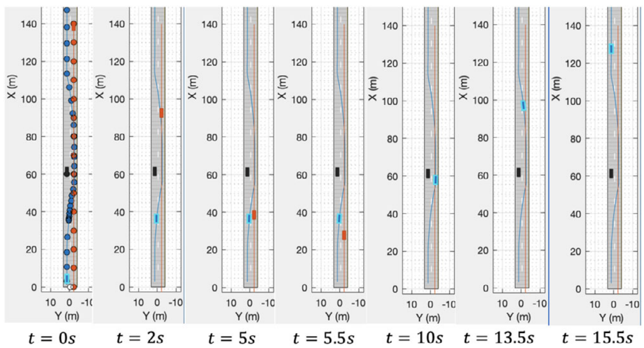

FIGURE 13 A series of screenshots for the overtaking process in Scenario II.

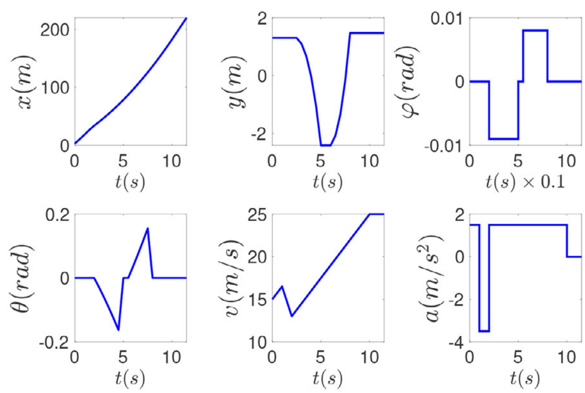

FIGURE 14 The time histories of states and control inputs of autonomous vehicle in Scenario III.

13, we know that the autonomous vehicle decides to re-start overtaking (i.e. $q(10) = 2$) at 5s (i.e. the waiting time is 3 s) when the opposite lane is free, and it goes back to the original lane when the high-level decision changes from "*overtake*" to "*following lane*" at 15 s.

- In Scenario III, the overall simulation time is 12.5 s, and the simulation results are shown in Figures 9-III, 14, and 15. When the autonomous vehicle detects that there is a slowly moving leading vehicle in front of it and the opposite lane is busy, the autonomous vehicle decides to slow down $q = -1$ first (see Figures 9-III and 14) until the oncoming vehicle bypasses it 1.5 s later, which makes the opposite lane clear (see the second screenshot in Figure 15). Hence, the autonomous vehicle automatically restarts overtaking (i.e. $q(4) = 2$). After 7 s, the autonomous vehicle bypasses the leading vehicle and returns back to the original lane; hence, $q(17) = 1$. This overtaking process can be seen in Figure 15.
- The simulation results of Scenario IV are shown in Figures 9-IV, 16, and 17 with 25 s simulation time. From Figure 17, one can see that the left lane is occupied by a slower vehicle and the opposite lane is busy with oncoming vehicles. Therefore, initially the autonomous vehicle decides to slow down (i.e. $q(1) = -1$), and this coincides with human behaviours as human drivers usually slow down first to see whether the leading vehicle will accelerate or not before fully stops (i.e. $q = -2$). When $t = 2.5$ s, oncoming vehicle 1 bypasses; hence, the autonomous vehicle makes the decision to start to overtake the leading vehicle (i.e. $q(5) = 2$). From Figures 9-IV and 17, one can see that during the overtaking process, another oncoming vehicle emerges suddenly (e.g. from the crossing road) at $t = 5$ s and the autonomous vehicle makes emergency stop ($q(10) = -2$) and gives way to

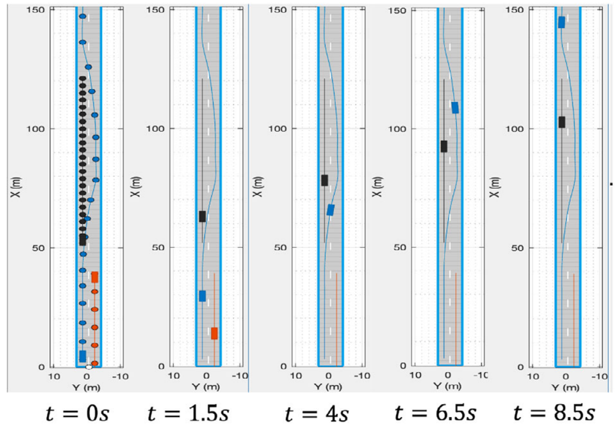

FIGURE 15 A series of screenshots for the overtaking process in Scenario III.

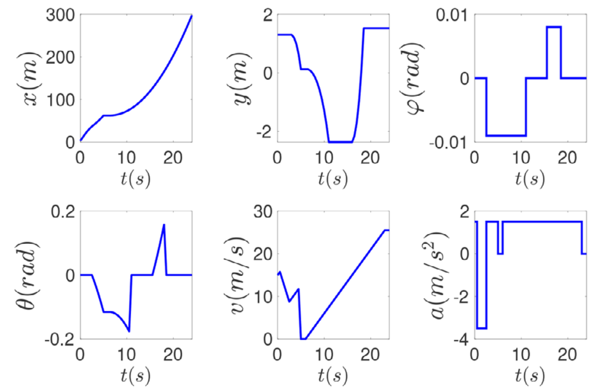

FIGURE 16 The time histories of states and control inputs of the autonomous vehicle in Scenario IV.

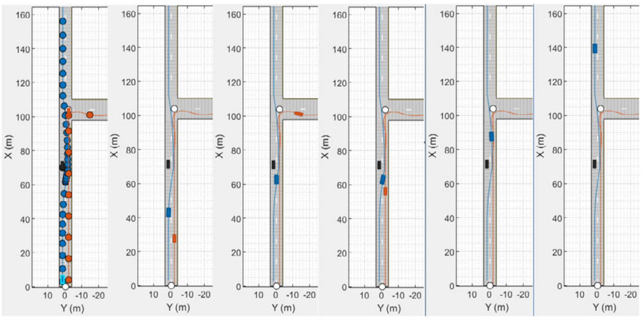

FIGURE 17 A series of screenshots for the overtaking process under the proposed model predictive control (MPC)-based framework in Scenario IV.

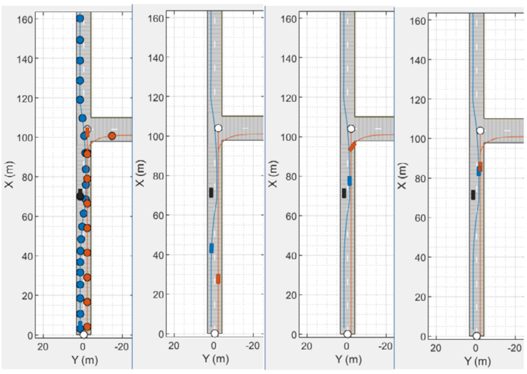

FIGURE 18 A series of screenshots for the overtaking process under rule-based framework [19] in Scenario IV.

oncoming vehicle 2. After about 1.5 s, the opposite lane is free and the autonomous vehicle re-starts the overtaking (i.e. $q(12) = 2$) and it returns back to the original lane at $t = 19$ s (i.e. $q(38) = 1$). The results in this scenario demonstrate that the proposed framework is able to cope with sudden-emerging vehicles in the dynamic environment. However, when we use the existing benchmarked rule-based method proposed in paper [19] to make a decision for such a dynamic environment in the high level, it has collision dangerous, as can be seen in Figure 18 around $t = 6$ s.

Remark 6. Here, we mainly focus on the high-level decision-making framework, and we assume that the low level can perfectly execute the command from the high level. For example, in the high level, we set prediction horizon $N = 5$ and sampling time $T_s = 0.5$. By using Matlab command "tic; toc", it can be easy to check that the maximum computational time for calculating the optimal decision at each time step is 0.35 s (except for the computational time of the first time step, which is 3.1 s due to the initialisation of the algorithm), which is less than the sampling time of 0.5 s. Hence, the real-time applicability of the proposed algorithm can be achieved.

5 | DISCUSSION

Our simulation results display the autonomous behaviour under different practical traffic scenarios on two-lane country roads. Just like a human driver, the autonomous vehicle is content to slow down to see whether the leading vehicle will accelerate or not. If the leading vehicle is moving reasonably close to our desired speed, we may consider the *effort* of overtaking not worth it. However, if the leading vehicle's speed is below tolerance, the automatic behaviour is to overtake, but only if the opposite lane is clear of oncoming vehicles; Otherwise, the autonomous vehicle will keep the same speed as the leading vehicle to wait for a further safe gap to re-start overtaking.

The constraints and cost function given in Section 2 all work together to generate the above behaviour. This interplay, however, necessitates that the weighting parameter values must be chosen holistically. One procedure for parameter selection is to select a few of the parameters as *independent*, with others assigned progressively. For example, inspired by [44] and [58], for a 3.6-m wide lane with normalised parameters, γ_1, γ_2 can be chosen as 167 and 228, respectively, and γ_3 can be chosen as 0.016. η_m and η_r can be chosen based on the desired overlap of road edges and the width of vehicle (see, e.g., Figure 6). For safety constraints (3), the larger the β, the more conservative the algorithm. Conversely, the smaller the β, the more progressive the algorithm. In addition, for a wider lane, it is allowed to chose larger Δy_i.

It is well-known that determining the appropriate duration for behaviours poses a significant challenge in long-term behavioural planning problems. The motion planners employed in autonomous driving vehicles typically comprise a behaviour planner and a trajectory planner. The role of the behaviour planner is to make high-level decisions based on the output of perception and prediction, which involves extrapolating perception outputs to future timestamps. During the duration of the planning horizon, typically ranging from 5 to 10 s into the future (as illustrated in [60, 61]), the trajectory planner leverages the decisions of the behaviour planner and a coarse trajectory to generate a smooth trajectory at a lower level. Therefore, such a challenge is dealt by not only high-level decision-making, but also the lower-level control. Our paper mainly focuses on the framework design of high-level decision-making. The sampling time used in the high level is the time period to update a decision and it is usually greater than that in the low level. Similar to human driving, high-level decision-making is relatively slow in autonomous driving and it is not desirable to change decisions like overtaking too frequently. If the behaviours of surrounding vehicles change, the low-level path planning would automatically adjust the planned path accordingly. That is, the final trajectory outputted by the trajectory planner might differ significantly from the one generated by the behaviour planner. However if necessary, we could change the sampling time. In our future work, we will tackle this challenge by constructing a hierarchical framework.

6 | CONCLUSIONS

This paper has presented a high-level decision-making framework designed to enable safe and optimal decision-making for autonomous overtaking maneuvers in dynamic environments, particularly on two-lane country roads with oncoming vehicles. The proposed decision-making process integrates with the lower-level trajectory planning model to execute overtaking maneuvers effectively. Ensuring the correctness of decisions relies on establishing a strong connection between high-level decision-making and the behaviour and status of the autonomous vehicle. To achieve this, we abstract the behaviours of both the autonomous vehicle and surrounding vehicles, incorporating them into an MPC-based decision-making framework, which is further enhanced with switching control methods.

While we have showcased the effectiveness of our proposed framework through four numerical simulations, including a comparison to the benchmarked rule-based method, analysing theoretical properties of the algorithm, such as convergence, remains challenging. In the future, we intend to employ a more dependable platform to investigate real-world scenarios and adapt our proposed method accordingly, ensuring guaranteed performance. Moreover, theoretical analysis will be conducted.

AUTHOR CONTRIBUTIONS

Xue-Fang Wang: Conceptualization; data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft. **Wen-Hua Chen**: Conceptualization; funding acquisition; investigation; project administration; resources; supervision; writing—review and editing. **Jingjing Jiang**: Conceptualization; formal analysis; investigation; methodology; resources; supervision; validation; visualization; writing—review and editing. **Yunda Yan**: Investigation; resources; software; validation; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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