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Review

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Distributed model predictive control for unmanned aerial vehicles and vehicle platoon systems: a review

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Abstract

This paper reviews the application of distributed model predictive control (DMPC) for autonomous intelligent systems (AIS) with unmanned aerial vehicles (UAVs) and vehicle platoon systems. DMPC is an optimal control method that formulates and solves optimization problems to adjust control strategies by predicting future states based on system models while managing constraints, and this technique has been applied to an increasing number of industrial areas. As the essential parts of AIS, UAVs and vehicle platoon systems have received extensive attention in the civil, industrial, and military fields. DMPC has the ability to quickly solve optimization problems in real-time while taking into account the prediction of the future state of the system, which fits in well with the ability of AIS to predict the environment when making decisions, so the application of DMPC in AIS has a natural advantage. This paper first introduces the basic principles of DMPC and the theoretical results in multi-agent systems (MASs). It then reviews the application of DMPC methods to UAVs and vehicle platoon systems. Finally, the challenges of the existing methods are summarized to offer insights to advance the future development of DMPC in practical applications.

Keywords: Distributed model predictive control, autonomous intelligent systems, multi-agent systems, unmanned aerial vehicles, vehicle platoon systems

1. INTRODUCTION

With the rapid development of communication technology and computer science, the deep integration of complex systems and sensing decision-making has gained unprecedented development [1,2]. Autonomous intelligent systems (AIS) are capable of environmental sensing, target detection, and cooperative control through the integration of advanced control, communication modules, and sensing technologies. They have the ability to autonomously plan actions, share resources, and operate remotely to complete tasks [3]. AIS is increasingly being used in civil and industrial fields, such as logistics and transportation [4], power system inspection, and ocean exploration, as well as military fields [5], including demining and blasting, battlefield surveillance, and combat confrontation. Their unique capability to replace humans in complex and high-risk environments renders them invaluable tools. However, as task demands grow in difficulty and complexity, single unmanned systems face limitations in information access and problem-solving capacity. It is necessary for AIS to deal with current difficulties through a distributed approach, which offers advantages such as spatial distribution, parallel task execution, and fault tolerance. AIS has become a new trend in future research due to its comprehensive information acquisition and ability to realize intelligent interaction and processing in response to mission requirements, compared to single-unmanned systems.

The AIS must perceive the environment to perform autonomous planning, and the prediction part of planning can be realized by optimizing the future state through the distributed model predictive control (DMPC) method. As an optimal control algorithm based on an optimization problem that can handle constraints efficiently, DMPC is widely used in power systems [6], chemical processes [7], urban transportation [8], and manufacturing systems [9]. As a distributed online rolling computation algorithm, DMPC allows AIS to navigate physical and environmental constraints, making it increasingly popular in AIS applications.

As the crucial components of AIS, the cooperative control of unmanned aerial vehicles (UAVs) and vehicle platoon systems has received much attention. UAVs play a vital role in several fields, such as disaster relief, environmental monitoring, logistics, transportation, and military surveillance. Through cooperative control, UAVs can quickly and efficiently cover large areas, perform complex missions, and enhance the response speed and success rates of missions [10–12], and vehicle platooning systems achieve efficient fleet management, reduce traffic congestion, and save energy consumption in various scenarios such as freight transportation, autonomous driving, and traffic management in modern urban environments, thus improving transportation efficiency and road safety [13–15]. The difference between UAVs and vehicle platoon systems is that UAVs operate in a three-dimensional airspace, relying on technologies such as GPS, inertial navigation systems, and radar. In contrast, vehicle platoons operate in a two-dimensional road network, responding to traffic regulations, road conditions, and other vehicles, often using vehicle-to-everything (V2X) communications and light detection and ranging (LiDAR) technologies. UAVs have a more limited range due to battery limitations, while vehicle platoons are more accessible to refuel or recharge and have a longer range. However, UAVs and vehicle platoon systems are similar in several ways, e.g., both involve cooperative control of multiple independent units and require real-time decision-making and communication to achieve common goals; both require real-time control in a dynamic and uncertain environment to ensure efficient operation and safety; both need to consider physical and network security. Despite some differences, UAVs and vehicle platoon systems share commonalities in core technologies such as cooperative control, multi-subsystems communication and path optimization, all of which can be effectively handled under the framework of DMPC. Meanwhile, considering the significance of the cooperative operation between UAVs and vehicle platoon systems in both civil and military fields, an overview of the two systems can help to promote the integration of the two fields, inspire researchers to explore the cooperative operation of these two systems and promote the development of integrated solutions in AIS.

Although existing review articles have covered a wide range of research on DMPC in different application scenarios, such as smart grids [16–18], networked control systems [19], autonomous ground vehicles (AGVs) [20],

each has specific focuses and limitations. For example, Arauz *et al.* concentrated on the application of DMPC in network control problems, with special emphasis on its vulnerabilities and defense mechanisms in network security [19]. On the other hand, Yu *et al.* comprehensively reviewed the application of model predictive control (MPC) in single and multiple AGVs [20]. Notably, Negenborn *et al.* surveyed and categorized a wide range of DMPC methods, offering insights into the historical development and research trends of these methods [21]. However, none of these reviews have specifically addressed the application of DMPC to two critical domains - UAVs and vehicle platoon systems nor have they discussed the unique challenges and future research directions for DMPC within these systems.

In contrast to existing reviews, this review systematically introduces the basic fundamentals of DMPC and its theoretical achievements in multi-agent systems (MASs), with a unique focus on the application of DMPC in two AIS subsystems: UAVs and vehicle platoon systems. It also highlights the shortcomings and challenges of the existing methods in practical applications and discusses the direction of future research to promote DMPC in UAVs and vehicle platoon systems. This review presents the basics of DMPC with theoretical foundations in MASs in Section 2. Sections 3 and 4 review the DMPC applications in UAVs and vehicle platoon systems, respectively. Section 5 discusses the existing shortcomings and challenges of the DMPC approach for AIS. Finally, the conclusion is provided in Section 6.

2. PRELIMINARY FOR DMPC

Before introducing the application of DMPC in UAVs and vehicle platoon systems, this section will introduce the basics of DMPC and the advances of its theoretical research in MASs.

2.1 MPC

MPC is derived from optimal control, which computes for a sequence of control inputs by optimizing a cost function containing information about the system's states and control inputs at a future time and explicitly handling the constraints imposed on the system [22]. MPC employs a rolling optimization strategy, which optimizes over a finite time horizon. Considering a discrete-time system $x(t+1) = f(x(t), u(t))$ as an example, where the system is sampled at a specific sampling instant t, and the currently sampled state information $x(t)$ is used as the initial state based on the model of the system to predict the state of the system in the prediction horizon $[t, t + N]$. Simultaneously, a constrained open-loop optimization problem is solved for a given system cost function to obtain a set of control input sequences. The first control input in this sequence is then applied to the actual controlled system. The new state of the system is obtained by sampling at the next sampling instant $t + 1$, and this process is performed repeatedly. The specific process is shown in Figure 1.

MPC has been widely used in linear systems [23,24] and nonlinear systems [25,26], but it is not the focus of this paper. There are quite a few foundations for MPC research, such as robust MPC methods to cope with external disturbances [27–29], tracking MPC methods to achieve the designed control objectives [30,31], and economic model predictive control (EMPC) methods considering economic costs in the actual production process [32]. Recently, the data-driven MPC methods were proposed by Berberich *et al.*, and a rigorous theoretical analysis was given [31,33,34]. For more information about the advances in theoretical research on MPC and the application of MPC methods in robotics, UAVs, and other systems, readers can refer to Ref. [35–39].

2.2 DMPC

As the scale of engineering systems increases, the applicability of traditional MPC methods diminishes. Instead, the DMPC method has received more attention for its excellent capability of dealing with complex large-scale systems characterized by high dimensionality, multiple subsystems, constraints, and targets. Unlike the centralized architecture of traditional MPC methods, DMPC decomposes the global system into several subsystems and formulates a local optimization problem for each subsystem, allowing the complex optimization
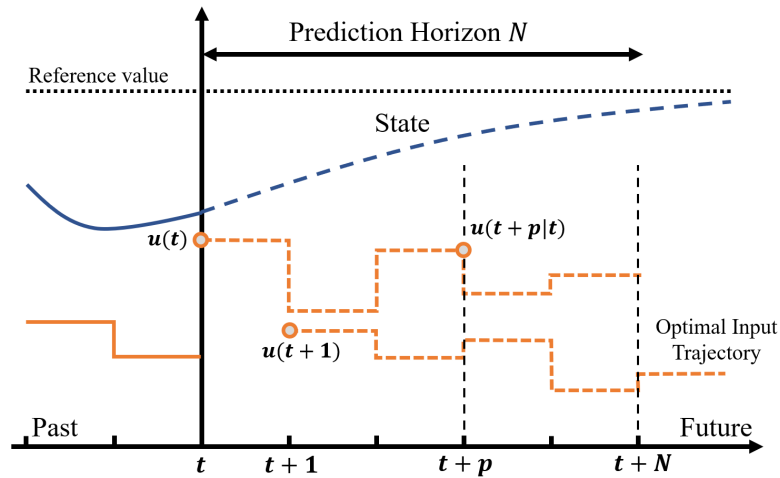
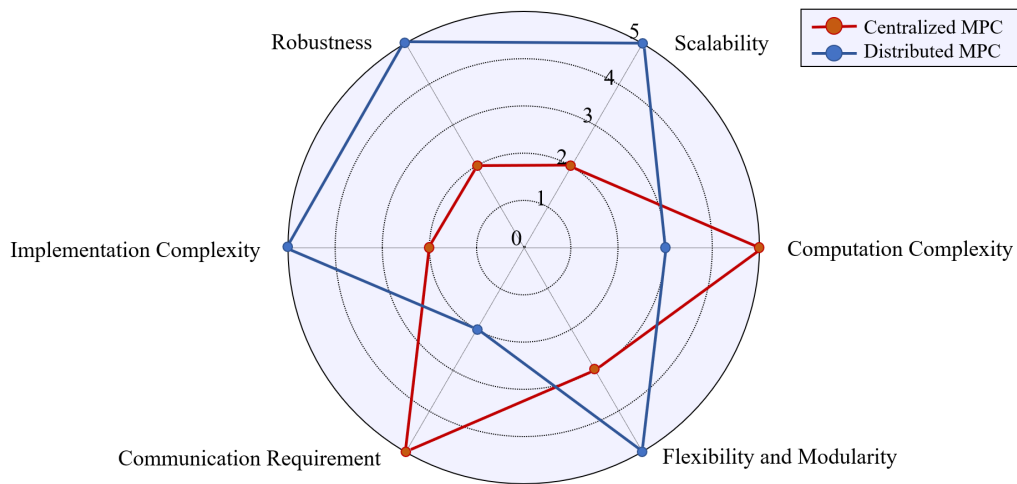**Figure 1.** MPC strategy. MPC: Model predictive control.

Figure 2. Quantitative comparison of key performances between centralized MPC and DMPC. MPC: Model predictive control; DMPC: distributed model predictive control.

problem of a large-scale system to be divided into simple subproblems. This approach significantly reduces the scale and computational complexity of individual optimization problems[40]. A quantitative comparison of some key performances between centralized MPC and DMPC is shown in Figure 2. With the DMPC strategy, information can be exchanged between subsystems, and interaction is also allowed between the local model prediction controllers of each subsystem. The structure of DMPC is schematically illustrated in Figure 3.

In the following, a commonly used DMPC standard framework will be introduced, including the determination of optimization problem, cost function, and information transmission in DMPC.

2.2.1 Optimization problem
A general discrete system is taken as an example to introduce the optimization problem of DMPC:

$$x_i(t + 1) = f_i(x_i(t), u_i(t), x_{-i}(t)) \tag{1}$$

where $x_i(t) \in \mathbb{R}^{n_i}$, $u_i(t) \in \mathbb{R}^{m_i}$ denote the state and control input vector of the subsystem i, respectively, and $x_{-i}(t)$ represents the state of the subsystem that has information interaction with subsystem i. Furthermore,
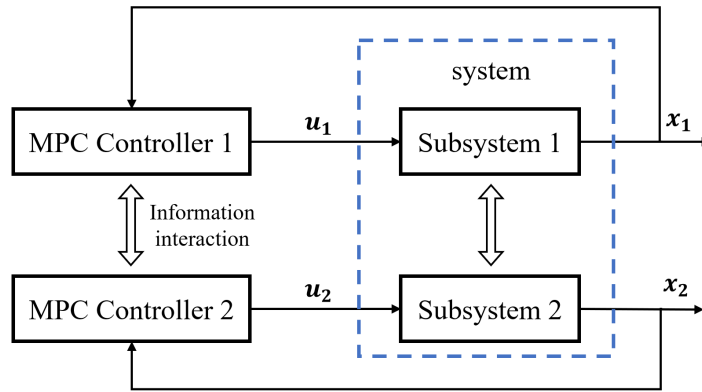
Figure 3. DMPC structure. DMPC: Distributed model predictive control.

the system states and the control inputs must satisfy the constraints: $x_i(t) \in \mathbb{X}_i$ and $u_i(t) \in \mathbb{U}_i$, respectively, where $\mathbb{X}_i$ and $\mathbb{U}_i$ are convex sets containing the origin.

In DMPC, each subsystem optimizes only its local cost function, and its local optimization problem is given as:

$$\min_{u_i(t+s|t)} J_i(x_i, u_i, x_{-i}) \tag{2}$$

$$s.t. \quad x_i(t+s+1|t) = f_i(x_i(t+s|t), u_i(t+s|t), x_{-i}(t+s|t)) \tag{2a}$$

$$x_i(t|t) = x_i(t) \tag{2b}$$

$$x_i(t+s|t) \in \mathbb{X}_i \tag{2c}$$

$$u_i(t+s|t) \in \mathbb{U}_i \tag{2d}$$

$$x_i(t+N|t) \in \mathbb{X}_f^i \tag{2e}$$

where $s = 1, ..., N - 1$, $J_i(x_i, u_i, x_{-i})$ is the objective cost function of the problem, and $x_i(t+s|t)$ is the state predicted at instant t for the instant $t+s$. The terminal term $x_i(t+N|t) \in \mathbb{X}_f^i$ is often used to ensure the stability of the system.

2.2.2 Cost function
The cost function J_i defines the control objectives of the system and guides the direction of the optimization process. However, since different tasks have varying requirements, the design of the cost function must be adapted to specific application scenarios. For instance, in UAV formation control, the cost function may prioritize maintaining formation shape and avoiding collisions, whereas in vehicle platooning, it might emphasize speed coordination and fuel efficiency. Therefore, the formulation of the cost function should not only be consistent with the overall objectives of the control system but should also accurately reflect the specific demands of a given task, thereby enabling efficient and cooperative control in a complex system. The following is a common form of DMPC cost function:

$$J_i = \sum_{s=0}^{N-1} l(x_i(t+s|t), u_i(t+s|t)) + V_c(x_i(t+s|t), x_{-i}(t+s|t)) + V_f(x_i(t+N|t)) \tag{3}$$

Here, $l(x_i(t+s|t), u_i(t+s|t))$ represents the stage cost at the instant $t+s$, and $V_c(x_i(t+s|t), x_{-i}(t+s|t))$ denotes the coupling cost term that containing the state of both subsystem i and its neighbors. Additionally, in DMPC, it is often necessary to include a coupling cost that incorporates information about neighboring subsystems in the cost function. The information transmission between the neighbors will be introduced in the following sections.
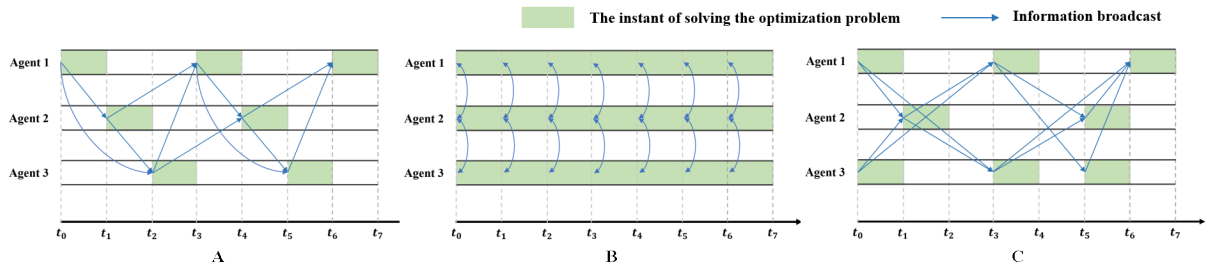
Figure 4. Information interaction between subsystems and the sequence of solving optimization problems. (A) sequential solving and transmission; (B) synchronous solving and transmission; (C) asynchronous solving and transmission.

2.2.3 Information transmission

In DMPC, the interaction of information between subsystems and the sequence of solving the optimization problem is critical for achieving efficient cooperative control. Typically, the sequence of optimization problem solving and transmission can be categorized into three approaches: The first is sequential solving and transmission, where each subsystem sequentially solves the problem in a predetermined order and transmits the results to other related subsystems. The advantage of this approach lies in its clear flow and easy-to-implement sequence control, but it may lead to delays in the overall system. The second approach is synchronous solving and transmission, where all the subsystems start solving simultaneously and transmit the information at the same instant, which minimizes the latency but requires high communication and computational resources. The third approach is asynchronous solving and transmission, where each subsystem independently completes the solving and transmission on its own time scale, allowing for a certain degree of non-simultaneity and thus increasing system flexibility. To illustrate the different characteristics of these approaches more intuitively, Figure 4 presents the sequences of optimization problem-solving and information transmission in the DMPC strategy for a MAS with three agents as an example.

In DMPC, subsystems usually need predictive state information of their neighbors at the current moment in the length of the prediction horizon N to construct the optimization problem. There are generally two main approaches to constructing this predicted state information. The first method is that the neighbor first constructs a complete sequence of predicted states that satisfies the required length of the current subsystem, and then transmits this information to the needed subsystem. The advantage of this approach is that the subsystem can directly utilize the complete information for computation, although it may impose a significant data transmission burden. The second approach is that the neighbor transmits only a part of the necessary state information while the receiver subsystem performs specific calculations based on the received data to construct the necessary neighboring state sequence. This approach can reduce the burden of data transmission, but may require additional computational resources and more complex algorithm design to ensure that the constructed state information can satisfy the requirements of control accuracy. These two methods of information construction enable DMPC to achieve efficient and accurate information interaction and cooperative control in complex systems.

Moreover, existing DMPC algorithms can be classified based on the topology of the transmission network, the information exchange protocols used among local controllers, and the type of cost function considered in the local optimization problem. Depending on whether or not the performance metrics of other subsystems are included in the local cost function, DMPC algorithms can be categorized into coordinated and uncoordinated approaches. Specifically, if each local controller holds global information and minimizes the global cost function, it is referred to as coordinated DMPC[41-43]. Conversely, if each local predictive controller possesses local information, considers the information of its neighbors in the network topology, and uses the information of its neighbors as useful information for its local optimization problem and minimizes the local cost function, it is referred to as uncoordinated DMPC[44-48]. Compared with coordinated DMPC, in uncoordinated DMPC,

each local controller only needs to exchange information with its associated subsystems, which have lower network requirements. Since uncoordinated DMPC only improves its performance during the optimization process, the overall performance of the system is weaker than that of the coordination algorithm based on the global cost function, but it has more flexibility for the control of each subsystem. In most uncoordinated DMPC, local controllers generally use parallel computation to solve the optimization problems of each subsystem simultaneously[46]. When controllers operate asynchronously, a corresponding communication strategy for asynchronous transmission is necessary[47,48]. In the UAVs and vehicle platoon systems targeted in this paper, most of the studies are based on uncoordinated DMPC.

2.2.4 Computational complexity
To analyze the computational complexity of DMPC, it is first necessary to distinguish between linear and non-linear systems. In linear systems, the computational complexity of DMPC is relatively low due to the availability of efficient solution methods, such as linear programming (LP) or quadratic programming (QP), which have polynomial-time computational complexity. In contrast, DMPC problems for nonlinear systems necessitate the utilization of nonlinear programming (NLP) methodologies, which are inherently more intricate since the solution process entails a greater number of iterative procedures and possesses a higher computational complexity. Furthermore, as the system state dimension increases and the prediction horizon lengthens, the computational complexity rises. An increase in state dimension results in a larger state space, necessitating greater computational resources for state prediction and optimization at each time step. Additionally, a longer prediction horizon expands the size of the optimization problem, as computations must be performed over a more extended prediction horizon, significantly increasing the computational burden. However, a longer prediction horizon also offers enhanced control performance. Therefore, it is necessary to balance control accuracy and computational complexity to ensure that the system can be optimized and controlled in real-time within a reasonable timeframe.

2.2.5 Scalability
The scalability of coordinated and uncoordinated DMPC schemes, as discussed in the previous section, will be analyzed in the following. For coordinated DMPC, each local controller needs to optimize the local cost function and consider the global information. This implies that as the number of subsystems increases, the computational burden of the controller will increase with the global information. In contrast, most uncoordinated DMPC schemes exhibit better scalability. In uncoordinated DMPC, each local controller only optimizes its local cost function, so the increase in the number of subsystems does not directly affect the computational complexity of each controller. However, although the computational burden does not increase, the rise in the number of subsystems may result in each subsystem interacting with more neighboring systems, increasing the frequency of information exchange and the amount of communication. As the system grows in size, more complex communication networks may introduce additional burdens, such as delayed information delivery and data loss. Therefore, in the application of large-scale systems, despite the superior performance of uncoordinated DMPC in terms of computational complexity, it is still necessary to address the challenges posed by increasingly complex communication topologies to ensure the overall performance and reliability of the system.

Since DMPC methods vary considerably when applied to different physical systems and task requirements, this paper will first briefly review the theoretical results of DMPC to MASs in the following subsection. These results can be utilized in the control of UAVs and vehicle platoon systems, as discussed in this paper.

2.3 DMPC in MASs
This section provides a brief review of the theoretical research on DMPC in MASs, dividing the research problems into three key aspects: the existence of disturbances, limited communication and computing resources, and network unreliability.

2.3.1 The existence of disturbances

In MASs, different agents collaborate through communication to achieve the given task objectives. As the system becomes larger and more complex, deviations from the actual system during modeling and identification become inevitable. Simultaneously, the complex system is increasingly influenced by the external environment, and these disturbances can be classified as external disturbances. A key research direction in this context is the development of robust DMPC strategies to counter external disturbances. The min-max MPC method, which generates optimal control sequences for the system under the "worst-case" disturbance scenario to ensure robust stability, was first proposed by Campo *et al.*[49]. Jia *et al.* later extended this method to closed-loop DMPC systems by taking feedback control information into account[50]. Wei *et al.* proposed the min-max DMPC method with a self-triggered scheme for the case of multiple parameter uncertainties and external disturbances to achieve robust control under communication delays[47].

In addition, the robust MPC based on "tube" proposed by Mayne is also a classical approach to deal with disturbance[51]. In MASs, for instance, Li *et al.* utilized the tube method to satisfy local robust constraints and applied a modified alternating direction method of multipliers (ADMM) to solve the optimization problem[52]. For disturbed leader-follower systems, Li *et al.* proposed a fully inclusive control algorithm based on tube-DMPC to deal with the problem that the follower may break away from the convex packet under disturbance[53]. Based on the DMPC method and the tube-based auxiliary controller, Li *et al.* realized the robust control of the MASs[54].

2.3.2 Limited communication and computing resources

In the communication process of MASs, communication resources are usually limited due to network bandwidth constraints. Additionally, the computational ability of subsystems in distributed architectures is generally weak, and their computational resources are valuable. While event-triggered control is a better choice in terms of reducing the number of communications and optimization problem solving, for perturbed systems, achieving better control while saving computational resources is a direction of great interest. Zou *et al.* proposed an event-triggered scheme using the information of neighbors to achieve a balance between resource usage and control performance for MASs subject to bounded disturbance[48]. Yang *et al.* also proposed a similar adaptive event-triggered DMPC scheme[55]. In addition, self-triggered DMPC schemes have gradually received attention due to the reduction of the number of samples in the system. Zhan *et al.* studied the application of a self-triggered scheme in linear MAS consensus[56], and Mi *et al.* solved the dynamically decoupled MAS collaboration problem[57]. Both Wei *et al.* and Wang *et al.* applied the self-triggered scheme to nonlinear MASs[47,58]. Based on the disturbance observer and self-triggered DMPC scheme, Yang *et al.* similarly achieved the collaborative control of nonlinear MASs[59].

2.3.3 Network unreliability

The agents interact with the physical environment, communicate local information, and update the information of their neighbors, which requires connectivity, reliability, and security of the communication networks. DMPC-based control methods also need to take network security issues into account. Velarde *et al.* proposed a resilient DMPC control strategy that considers insider attacks[60]. Ananduta *et al.* introduced an iterative DMPC strategy to mitigate the effects of false data injection attacks[61]. Many studies regard denial of service (DOS) attacks as a data loss problem for MASs. For example, Dai *et al.* proposed a resilient robust DMPC scheme based on an extended sequence transmission strategy to eliminate the adverse effects under DOS attacks[62], and Chen *et al.* designed a similar event-triggered DMPC scheme[63]. Wei *et al.* proposed a novel scheme for detecting distributed attacks using the DMPC method to achieve consensus of linear MASs under adversarial attacks[64].

To address the vulnerability of network communication, Hahn *et al.* designed a robust DMPC scheme for affine dynamical subsystems under communication delays[65]. Su *et al.* addressed the tracking consistency problem

Table 1. Research of DMPC-based UAVs considering multi-mission scenarios

Research	Trajectory optimization	Formation control	Collision avoidance	Communication restrictions	Disturbance and fault
Bo *et al.* [74]	✓		✓		
Qi *et al.* [75]	✓		✓	✓	
Yang *et al.* [76]	✓		✓		
Hu *et al.* [77]	✓		✓		
Yu *et al.* [78]	✓		✓		
Gräfe *et al.* [79]	✓		✓		✓
Li *et al.* [80]	✓		✓		
Zheng *et al.* [81]	✓		✓		
Chai *et al.* [82]	✓		✓	✓	
Richards *et al.* [83]	✓		✓		
Zhang *et al.* [84]		✓	✓		
Chi *et al.* [85]		✓	✓		
Zhou *et al.* [86]	✓	✓	✓	✓	
Chen *et al.* [87]		✓	✓	✓	
Wen *et al.* [88]		✓			✓
Yuan *et al.* [89]		✓		✓	✓
Li *et al.* [90]	✓	✓	✓		
Niu *et al.* [91]	✓		✓	✓	
Sun *et al.* [92]		✓	✓		
Jiang *et al.* [93]	✓		✓		

DMPC: Distributed model predictive control; UAVs: unmanned aerial vehicles.

by designing a DMPC strategy for linear MASs affected by disturbance and time-varying communication delays [66]. Wang *et al.* designed an event-triggered DMPC scheme to solve the cooperative control problem for MASs with disturbance, input delays, and communication delays [67]. Franzè *et al.* used the concept of reachability analysis to solve the leader-follower formation control problem under the data loss conditions in MASs [68]. Yang *et al.* utilized Bernoulli distribution to describe the packet loss phenomenon and selected the prediction horizon of MASs based on an event-triggered scheme to achieve cooperative control [69].

3. DMPC FOR UAVS

UAVs have been widely adopted as an emerging technology due to their high flexibility, mobility, and ease of deployment [10]. Given the uncertainty of UAV application scenarios and the complexity of target missions, it is often challenging for an individual UAV to meet evolving mission requirements. UAVs can be controlled in a distributed way, thus realizing that individuals collaborate to perceive the surrounding environment together and complete multiple complex tasks as a whole through information sharing, intelligent collaboration, and autonomous decision-making [70,71]. Current research demonstrates that, based on the communication links between UAVs, UAVs can rapidly and accurately perform complex tasks such as cooperative path planning, target exploration, and formation control. Additionally, in the military domain, UAVs play a crucial role in essential tasks such as reconnaissance and strikes [72]. For instance, the U.S. Air Force announced the Small UAV System Flight Plan in 2016, strategically confirming the future value of small UAVs and clarifying the concept of UAV swarm operations [73], the importance of UAVs continues to grow.

The DMPC method has recently received much attention due to its excellent ability to handle constrained optimization problems and fast computational capability. However, the research on the application of DMPC to UAVs still needs to be completed. The following sections provide an overview of the application of DMPC to UAVs in three key areas: trajectory optimization, formation control, and collision avoidance. In addition, Table 1 summarizes the existing research on DMPC-based UAVs considering multi-mission scenarios.

3.1 Trajectory optimization
When UAVs operate in coordination, optimizing their generated paths to enhance mission efficiency while reducing overall energy consumption is crucial. The DMPC method can find the optimal paths under envi-

ronmental constraints based on its ability to minimize the cost function and deal with the constraints, so the use of the DMPC method to provide real-time solutions for UAVs has received more and more attention.

Bo *et al.* considered UAV kinematics and collision avoidance constraints to develop a trajectory planning strategy based on DMPC, which achieved better real-time performance and more optimal trajectories compared to traditional trajectory optimization methods [74]. Qi *et al.* utilized the DMPC method as a framework to design tracking trajectory optimization for ground targets, and introduced the Nash game method in the optimization solution process, then verified the feasibility of the proposed scheme by simulation [75]. Similarly, Yang *et al.* also designed an online trajectory planning strategy based on the DMPC method [76], and Lun *et al.* investigated the application of UAVs as communication relay nodes for maritime vessels, and simulations verified that the designed DMPC algorithm was able to optimize energy costs while achieving UAVs trajectory planning [94]. The optimization problem designed by Ao *et al.* combined the A* algorithm with Nash optimization, significantly reducing the solution size of the optimization problem while ensuring high accuracy of the generated trajectories [95].

Most of the aforementioned DMPC methods focus on basic trajectory optimization, but more complex trajectory planning tasks must account for obstacles, dynamic target tracking, and other challenging scenarios. Hu *et al.* considered the movement of the target, obstacles obstructing the line of sight, and energy constraints of the UAVs, and designed a DMPC strategy that balances optimization and prioritization, and experimentally verified the effectiveness of the UAVs in tracking targets in urban environments [77]. Yu *et al.* also considered real-time target tracking and combined the adaptive difference algorithm with Nash optimization, and the DMPC was globally optimized with the help of Nash optimization, which improved the accuracy of target tracking [78]. Gräfe *et al.* reduced the computational complexity and network traffic required for the DMPC method based on an event-triggered scheme while ensuring the safety and reliability of the generated trajectories [79]. Yin *et al.* used a DMPC method to generate trajectories to achieve a stable network connection between the UAVs and the ground control stations [96]. Notably, Luis *et al.* utilized online DMPC to generate trajectories of small UAV swarms in real-time and efficiently compute non-collision trajectories in mission scenarios through an on-demand collision avoidance method. The proposed method was shown to reduce flight time by approximately 50% on average in UAV point-to-point transition missions compared to the buffered voronoi cells (BVC)-based collision avoidance method. Meanwhile, the activation function was designed to detect any interference to the UAV, and an event-triggered replanning-based strategy was also devised. The algorithms involved were finally applied to a range of solid UAVs, from 2 to 20, and simulations were conducted to verify the effectiveness of the algorithms under a variety of scenarios, including obstacle-free transitions and transition tasks with static obstacles [97]. Another key research on DMPC is the aerial robot swarms designed by Soria *et al.*, whose objective functions included separation, propulsion, direction, and control. The quadrotor adjusted its flight trajectory based on interactive information, and the practical experiments with five quadrotors successfully demonstrated the safe flight of multiple drones in complex environments [98].

The search task, as a critical operation often performed by UAVs, is closely related to trajectory optimization. It is essential to ensure that the generated trajectories can effectively cover search areas while reducing energy consumption to meet various mission requirements in real-time. The DMPC-based search trajectory generation has been studied in some literature. Du *et al.* and Yao *et al.* developed UAV search trajectory optimization strategies by combining graph theory [99] and target probabilistic graph [100] under the DMPC framework, respectively. Trajectory optimization becomes particularly challenging in complex environments with unknown obstacles and communication interference. Hence, Li *et al.* proposed an adaptive guidance DMPC method to reduce exploration loss and improve exploration efficiency [80]. Chai *et al.* used Voronoi diagrams to replan the search trajectory in real-time, avoiding the collision between repeated search and UAVs, and still achieved better performance in communication-constrained environments [82]. It is worth mentioning that Zheng *et al.* applied DMPC to UAV collaborative area search by taking the neighbor prediction path as a parameter

and distributing the overall search objective function in the constraints between UAVs[81]. Simulation results demonstrated that their algorithm effectively improves search efficiency and verifies the scalability as the number of UAVs increased from 8 to 20.

3.2 Formation control

The importance of UAV formation control lies in its ability to enhance mission efficiency and execute tasks such as search, surveillance, and rescue through coordinated formation. Maintaining formation also ensures safe distances between UAVs, safeguarding their operational safety. Research on UAV formation control using the DMPC method began with Richards *et al.* in 2004, who proposed a robust DMPC scheme for cooperative UAVs that avoided collisions by satisfying robust constraints. This strategy was significantly less computationally expensive than centralized algorithms and achieved superior tracking control performance[83]. Subsequently, Ru *et al.* achieved formation reconfiguration control based on UAVs with different missions, using multi-objective game theory combined with the DMPC method to realize autonomous formation reconfiguration[101]. Based on the DMPC framework, Bian *et al.* proposed an algorithm for fast formation control of UAVs on circular trajectories, effectively improving the convergence ability of the formation with lower computational consumption[102].

In addition, formation flight in complex situations is widely concerned; considering the different tasks of heterogeneous UAV formation and collision avoidance in formation movement, Zhang *et al.* designed a DMPC scheme based on adaptive differential evolution[84]; Jiang *et al.* designed cost functions for leader, coordinator and follower UAVs, respectively, in heterogeneous UAVs, and simulations verified the feasibility of the designed DMPC strategies under the tasks of formation and retention, and insertion of new UAVs into the formation[103]. Chi *et al.* achieved safe UAV formations using the particle swarm optimization (PSO) algorithm combined with the DMPC method[85], while Liu *et al.* realized rapid formation and maintenance of UAVs based on the DMPC method, demonstrating both stability and feasibility[104]. For military applications, formation reconfiguration plays an essential role in performing military missions, such as attacking enemy military targets and searching for targets; Zhou *et al.* used the DMPC method while considering communication constraints to achieve UAVs that break through defenses under stealthy conditions[86]. Another related and intriguing issue is collaborative payload transportation. For instance, Wehbeh *et al.* designed a system model connecting quadcopters with payloads and compared centralized MPC and DMPC schemes[105]. Simulation experiments proved the effectiveness of the designed algorithm.

Recently, as DMPC has been more widely utilized in UAV formation control, existing studies have begun to consider the constraints of objective factors previously neglected in the literature, such as the limitations of the communication network, external disturbance, and errors due to model inaccuracies. Considering the actual situations of communication failure, Chen *et al.* designed a formation control algorithm based on relative position information about the relative distances and angles between UAVs, and then realized formation control based on the DMPC method in the presence of communication disturbances and information inaccuracies[87]. Wen *et al.* designed a two-layer MPC scheme for UAVs, where the outer layer used a DMPC strategy to generate optimal control vectors, which combined with the inner layer's tube-based MPC, reduced control errors in UAV formation subjected to disturbance[88]. Yuan *et al.* proposed a DMPC-based data transmission structure to accelerate the convergence of a six-degree-of-freedom UAV formation, with simulations employing data transmission delays following a Gaussian distribution[89]. The designed unidirectional structure was shown to play a crucial role in system convergence, demonstrating the applicability of the proposed DMPC algorithm.

Encirclement is a tactic used to restrict a target by changing the formation of a group of UAVs. Its purpose is to maintain surveillance and prevent enemy targets from escaping or to protect friendly targets[106], and the process of encirclement can be viewed as a process of formation change and maintenance. Marasco *et al.* developed a strategy to encircle both moving and static targets using a circular formation based on the DMPC

method[107]. Based on the designed DMPC algorithm, Hafez *et al.* first considered the task allocation strategy in the UAVs in the simulation by estimating the trajectory cost of the target and minimizing the task time. The encirclement effect demonstrated the effectiveness of two UAV teams in encircling stationary and moving targets[108].

3.3 Collision avoidance

When UAVs perform trajectory optimization and formation control, constructing a safe flight trajectory is fundamental to achieving cooperative control. Effective collision avoidance strategies can ensure that UAVs do not collide with obstacles and other aircraft, thus ensuring the integrity of the equipment, reducing the probability of accidents, and improving mission efficiency[109].

In previous research, such as that by Richards *et al.*[83], Bo *et al.*[74], and Zhang *et al.*[84], when optimizing trajectories and maintaining UAV formations based on the DMPC method, the safety of the formation was ensured by imposing safety or collision avoidance constraints. In addition, Li *et al.* addressed the collision problem at a low cost by designing a collision management unit and designing cooperative collision avoidance rules based on angle changes[90]. It is worth mentioning that D'Amato *et al.* designed an MPC-based collision avoidance system and incorporated the right-of-way rules from the International Civil Aviation Organization (ICAO) to make UAV behavior predictable and compatible with human decision-making. The prediction unit was designed to predict potential collisions and calculate the required constraints, and the simulation results verify the effectiveness and scalability of their scheme[110].

Niu *et al.* designed UAVs to predict the motion trajectories of their neighbors to avoid collisions in situations where communication was impossible, demonstrating the effectiveness of the proposed scheme in scenarios involving no communication and multiple obstacles[91], Sun *et al.* also adopted a similar approach and employed the improved Quatre algorithm to enhance the stability of UAV formation[92]. Jiang *et al.* developed a terminal condition to satisfy the collision avoidance algorithm for DMPC-based UAV formation control, aiming to reduce the conservatism of collision-free safe trajectories[93].

4. DMPC FOR VEHICLE PLATOONS

Ground vehicles are common tools of transportation and play a significant role in people's lives. With the rapid development of sensors, control systems, and computer technology, expectations for vehicle performance have risen. Research on ground vehicles has focused on AGV platoons due to their potential to reduce traffic congestion, improve traffic efficiency, enhance vehicle safety, and save energy[20,111]. The effectiveness of vehicle platoons in maintaining safety and saving fuel has been experimentally demonstrated by the PATH program in California[112], the Energy ITS program in Japan[113], and the GCDC program in the Netherlands[114].

The primary objective of a vehicle platoon is to synchronize the movement of a group of vehicles by assigning a control role to each vehicle and exchanging information between vehicles to ensure that appropriate safety distances are maintained between adjacent vehicles[111]. However, this method has limitations that make it challenging to maintain a stable platoon. The advancement of communication technology enables vehicles in a platoon to communicate through wireless or self-organizing networks. This facilitates the design of effective collaborative control strategies, improving the stability and efficiency of the platoon while ensuring smooth cooperative control and operation. Figure 5 shows four typical communication methods used in vehicle platoons of a front vehicle 0 and N rear vehicles[115]. In addition, all of these communication topologies shown in Figure 5 can be converted to unidirectional communication.

Considering a vehicle platoon with a leader, the objective of the platooning is for each following vehicle i to maintain an appropriate distance from the follower vehicles and the leader vehicle while following the leader
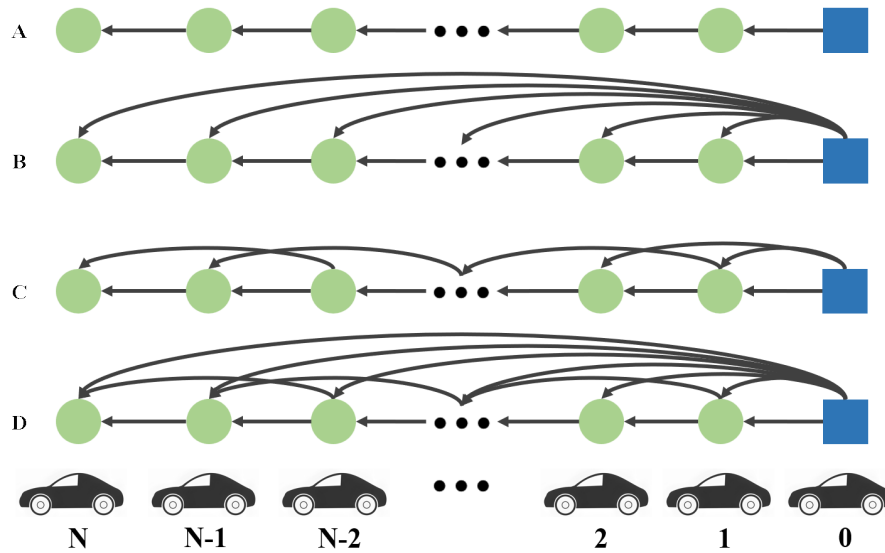
Figure 5. The directed communication topologies used in vehicle platoon. (A) PF topology; (B) PLF topology; (C) TPF topology; (D) TPLF topology. PF: Predecessor-following; PLF: predecessor-leader following; TPF: two-predecessor following; TPLF: two-predecessor-leader following.

at a speed of v_0. This objective can be given mathematically as:

$$\begin{cases} \lim_{t \to \infty} ||v_i(t) - v_0(t)|| = 0 \\ \lim_{t \to \infty} ||s_{i-1}(t) - s_i(t) - d_{i-1,i}|| = 0 \\ \lim_{t \to \infty} ||s_i(t) - s_0(t) - d_0|| = 0 \end{cases} \tag{4}$$

where $d_{i-1,i}$ is the desired distance between neighboring vehicles, and d_0 is the desired distance between a follower vehicle and the leader vehicle. To control vehicle platoon using the DMPC scheme, local information interaction at each vehicle node is required. This approach achieves collaborative motion globally while adhering to the constraints outlined in Equation (4).

4.1 Strategy for platooning

In the DMPC scheme, distributed controllers are deployed in each vehicle to collaborate in solving the constrained optimal control problem (COCP) for platooning over a finite time horizon and to exchange information via vehicle-to-vehicle communication links.

Maxim *et al.* set the constant speed of the leader and established the control strategy for the remaining vehicles; each vehicle was controlled by the DMPC method[116]. Lu *et al.* demonstrated the stability of vehicle platoon under unidirectional communication topology for heterogeneous vehicles by designing a cost function based on the difference between the states of a vehicle and its neighboring vehicles[117]. Similarly, Ma *et al.* achieved stable control of heterogeneous vehicles using an output feedback-based DMPC strategy[118]. Zheng *et al.* presented the trajectory error-based cost functions for heterogeneous vehicles with dynamic coupling; this design ensured stability through equality-based terminal constraints subject to spatial geometric constraints[115]; similar studies have appeared in the research of Qiang *et al.*, they designed a two-layer control architecture, using vehicles with odd numbers as the first layer, sending information to vehicles with even numbers, and ensuring the distance and same speed of vehicles through sequential calculation[119]. In addition, Yu *et al.* considered using the Nash optimal DMPC algorithm for platooning, which employed the Nash optimal algorithm to solve the decentralized problem and achieve Nash equilibrium for all vehicles[120]. To keep the required control rate at the same level as the communication rate, Liu *et al.* proposed a non-iterative DMPC scheme for vehicle platooning, which ensured the stability of the closed-loop system through the linear matrix inequality technique

and had compatibility constraints between the neighboring vehicles [121]. The simulation verified the effective control of the vehicle platooning in the presence of joining and leaving vehicles.

Similar to the factors to be considered by DMPC in UAVs, computational resources and computational speed determine the ability of the vehicle platoon to deal with emergencies quickly. To solve the problem of shortage of computational resources, Bai *et al*. designed a parallel DMPC method based on the ADMM, which used the Lagrange multiplier method and the dual decomposition technique [122]. For a mixed fleet of autonomous vehicles and human-driven vehicles, Zhan *et al*. proposed the ADMM-based DMPC method to obtain the global optimal solution of the local controller for the sub-platoons, which significantly reduced the computational consumption [123].

To operate vehicle platoons on real roads, it is essential to account for the fact that the speed of the leader vehicle is time-varying to adapt to the road conditions. To address this problem, Maxim *et al*. proposed a DMPC method for tracking the leader vehicle [124]. On the other hand, Yan *et al*. analyzed the stability and feasibility of the DMPC method for vehicle platooning systems [125]. Qiang *et al*. addressed the problem of coupled state vehicles with distance constraints and cost functions, which computed the state-coupled set for decoupling constraints and solved the DMPC optimization problem when the information of the leader vehicle is unknown [126]. Simulation results demonstrated that the proposed algorithm can ensure stable tracking between vehicles even when the lead vehicle has variable inputs.

4.2 Robustness of platooning

Most research on DMPC-based vehicle platoon control assumes an accurate model. However, model uncertainty, sensor noise, and environmental disturbances can adversely affect the accuracy of the DMPC scheme. Additionally, communication delays and data transmission losses during vehicle-to-vehicle information exchange can further degrade platooning performance. Therefore, robust DMPC schemes should be developed to maintain system stability under these uncertainties.

Luo *et al*. addressed the problem of disturbances and modeling errors in vehicle platoon systems, employing the proportional multiple integral (PMI) observer techniques with unknown inputs to limit the deviation between the actual systems and nominal systems [127]. For the same situation, Ju *et al*. also proposed a stochastic DMPC scheme and verified the effectiveness of the control scheme in the presence of model uncertainties [128]; Yin *et al*. combined Taguchi's robustness with stochastic DMPC scheme to reduce the negative impact of uncertainty on the performance of platooning [129]. For the vehicle platoon systems subjected only to additive disturbances, Luo *et al*. proposed a robust DMPC scheme for tracking virtual time-varying trajectories for non-complete vehicle platoon systems [130], and Chen *et al*. utilized local and neighbor uncertainty distribution information to collaboratively handle coupled probabilistic constraints in vehicle platoon systems. Based on the designed self-triggered mechanism, a constraint tightening strategy was implemented in the optimization problem to ensure the stability of the systems at the triggering moment. Simulation experiments were also conducted in a vehicle platoon system with five vehicles to verify the effectiveness of the algorithm in the case of queue control and emergency braking [131]. In addition, Mousavi *et al*. considered uncertain resources in dynamic environments, incorporating the evolution of vehicles and the environment into the planning strategy, resulting in a general framework consisting of estimation, prediction, and planning [132].

In recent years, research has increasingly focused on data-driven approaches to effectively address inaccuracies in modeling heterogeneous vehicle platoon systems. The basic principle of data-driven modeling is to use the input and output data of the system to construct the system model, and data-driven DMPC methods have been recently investigated by Huang *et al*. [133], Zheng *et al*. [134] and Kohler *et al* [135]. The basic principle of data-driven modeling is to use the input and output data of the system to construct the system model, and data-driven DMPC methods have been recently investigated by Zheng *et al*. [134] and Kohler *et al*. [135]. Based on this

method, Huang *et al.* added a variable for estimating the global consensus distributed across each agent in the optimization problem and actively compensated for the communication delay based on input-output data. The simulation results demonstrated the convergence of the auxiliary variables with the system output, verifying the effectiveness of the designed algorithm under communication delay[133]. Wu *et al.* established a data-driven model using subspace identification for a heterogeneous vehicle platoon to achieve stability under the DMPC method[136]. It is worth mentioning that Zhan *et al.* mapped the nonlinear model to a high-dimensional linear space based on the theory of the Koopman operator, and designed a neural network framework based on extended dynamic mode decomposition (EDMD) to approximate the Koopman operator. The simulation experiment used 25 vehicles, and the centralized MPC and DMPC methods were used, respectively. The results showed that DMPC can reduce the computational cost. The method has a faster convergence speed than the traditional nonlinear DMPC method[137].

When data losses occur during the communication of vehicle platoons, such as packet losses and communication delays, it is crucial for vehicle platoon control to estimate the lost data and accurately continue the mission. Wang *et al.* addressed data estimation under packet loss by designing a DMPC scheme that solves invariant sets and feedback control laws[67]. Pauca *et al.* used the information received by the vehicle at the previous moment to alleviate packet losses caused by wireless communication networks that exchanged information between vehicles[138]. In scenarios where inter-vehicle communication is limited and communication delays exist, Xu *et al.* used buffers and delay compensators to reduce the interference caused by non-ideal communication[139]. Wang *et al.* designed an event-triggered scheme based on state errors and input delays and proposed a compensation scheme for input and communication delays[67]. Similarly, Maxim *et al.* and Yan *et al.* designed DMPC schemes to achieve stable control of vehicle platoons in the presence of time-varying communication delays[124,125].

4.3 Security of platooning

When a vehicle platoon is traveling on a roadway, preventing collisions is paramount to ensuring passenger safety, and recent research has focused on enhancing the safety of vehicle platoons. Mohseni *et al.* considered the non-holonomic property of the vehicle platoons while predicting the behavior of other vehicles, and designed a cooperative DMPC scheme with predictive collision avoidance features to ensure collision avoidance even when the vehicle deviates from the desired trajectory[140]. Liu *et al.* considered the interactions between vehicles and their neighbors, and by analyzing the data of expressway naturalistic driving, the authors summarized the characteristics from aggressive driving behaviors to cautious driving behaviors, and designed collaborative strategies for different driving behaviors. Notably, the proposed DMPC scheme was validated through hardware-in-the-loop simulation, demonstrating its ability to safely perform tasks such as following a vehicle and changing lanes in high-risk situations[141]. In addition, the safe merging problem of heterogeneous vehicle platoons is studied by Liu *et al.*[141]. By designing the collision safety constraints, Gratzer *et al.* ensured the stability of the vehicle platoon during sudden braking maneuvers[142]. In the research of Franzè *et al.*, vehicle platoons could flexibly adjust their topologies in the presence of obstacles, thus ensuring the safe operation of the systems[143].

Ensuring network security is also crucial for vehicle platoons, as vehicle-to-vehicle information transmission is vulnerable to malicious intrusions and cyber-attacks, which can threaten the stability of the platoon and potentially lead to human injury and property loss. Chen *et al.* established a dynamic event triggering scheme with DoS attack sensing capability, where the event triggering threshold was adjusted according to the DoS attack duration and vehicle states. The evolution of vehicle positions, spacing, and speeds in the formation under different event-triggering parameters and DoS attack durations were verified through simulation, demonstrating the resilience and reliability of the designed DMPC algorithm in addressing security challenges[144]. Lyu *et al.* designed a communication topology safety response system that incorporates the DMPC method and demonstrates that it can effectively ensure the stability and security of the vehicle platoons under cyber-attacks[145].

Zeng *et al.* developed a resilient DMPC framework for vehicle platoons under Byzantine attacks, which detected unreliable information based on the resilient set and previously transmitted information, and achieved excellent performance with guaranteed safety[146].

5. CHALLENGES AND FUTURE

The previous sections reviewed the application of DMPC methods in UAVs and vehicle platoon systems, but significant theoretical and implementation challenges remain. This section summarizes the challenges and future of DMPC methods in practical application.

5.1 Security control

The DMPC method has shown great potential in UAVs and vehicle platoon systems, but its safety issues cannot be ignored. Due to the dependence of DMPC on network physical systems, there is a risk of nonmalicious failures, such as communication delays and data loss, which may lead to system instability. In addition, the distributed nature of DMPC makes it vulnerable to network attacks, especially deception attacks[147,148] and interrupt attacks[149]. Attackers can tamper with control signals or disrupt communication networks, seriously affecting system performance and potentially causing recursive feasibility and stability issues.

To address these security challenges, researchers have proposed various network security control methods and fault tolerant control (FTC) technologies. These approaches are designed to maintain system stability by detecting, identifying, and mitigating the effects of network attacks. For example, a design based on robust DMPC can improve the security margin of the system in the face of network attacks, ensuring the integrity of input signals[144]. In addition, the FTC method mitigates security issues caused by malicious agents by actively isolating faulty subsystems[150]. In Section 4.3 of the previous text, a brief statement was made regarding the network communication security control issues of vehicle platoon systems. However, the security control issues of UAVs and vehicle platoon systems based on DMPC still require further research. In recent years, emerging technologies such as cloud computing and blockchain have also demonstrated the potential to enhance the security of DMPC[151,152]. The cloud-based MPC framework can utilize encryption technology to keep data encrypted during transmission and processing, thereby preventing data leakage and attacks[153]. Meanwhile, blockchain technology has the potential to provide a secure distributed information exchange platform for MASs, thereby further enhancing the ability of the system to resist attacks[154]. In the future, the development of DMPC methods will rely on the combination of stronger network defense mechanisms and FTC methods. The incorporation of cutting-edge technologies such as cloud computing and blockchain will be critical in developing more secure and resilient distributed control systems, particularly for applications with stringent security requirements, such as UAVs and vehicle platoon systems.

5.2 Data-driven control

Most of the existing DMPC methods are based on accurate system models, but considering the difficulty in obtaining models in actual systems or the use of imprecise and unstable models, there are significant differences between theoretical and actual results. Data-driven control, by contrast, is a method that does not depend on an exact system model. It generates control inputs through a designed algorithm based on data obtained by the system over a period of historical time, which can solve the current problem of DMPC relying on an exact model. Kohler *et al.* designed a linear data-driven DMPC scheme with dynamic coupling features based on Willems' Fundamental Lemma[135,155]. Additionally, researchers have proposed scalable data-driven DMPC schemes[156] for large-scale systems, dissipative behavior-based data-driven DMPC schemes[157], and data-driven DMPC schemes for direct current (DC) microgrids[158] and complex traffic network management[159]. In addition, Fawcett *et al.* successfully achieved robust motion control of quadruped robots in complex environments by combining behavioral system theory with distributed data-driven predictive control technology[160], which demonstrated the effectiveness of data-driven methods in different systems. As noted earlier,

the application of data-driven DMPC in vehicle exhaust systems to handle solutions with uncertain dynamics has gained significant attention[136,137]. In summary, data-driven DMPC has shown outstanding performance in handling dynamic responses and optimizing control of unknown complex systems, demonstrating its extensive potential and development prospects in multiple fields. However, in current data-driven DMPC research, how to ensure that robust data-driven DMPC methods can be obtained even if the data is unreliable or partially missing still needs to be studied.

In addition to traditional data-driven DMPC control schemes, there is growing interest in data-driven DMPC approaches based on learning methods. Gros *et al*. demonstrated that reinforcement learning (RL) could achieve stable MPC control under model uncertainty and also studied the presence of disturbances[161,162]. Mallick *et al*. extended this work to MASs, implementing RL and deployment of DMPC as a function approximator[163]. Similarly, Liu *et al*. designed a neural network-based DMPC approximator that successfully reduced the computational burden of DMPC in large-scale systems[164]. Another learning-based approach utilizes deep learning, such as combining long short-term memory (LSTM) units with MPC schemes to reduce energy consumption[165], using deep belief networks to find the optimal control list for MPC for sewage treatment[166], and combining autoencoders with MPC for automatic power generation control[167]. Notably, Salzmann *et al*. implemented real-time onboard tracking control for quadcopters using deep learning and MPC[168]. However, there have been limited achievements in combining DMPC schemes with deep learning. Yin *et al*. combined LSTM units with convolutional neural networks (CNN) for feature extraction and prediction of offshore wind farms, and then used DMPC for control[169]. D'Alfonso *et al*. used deep RL combined with DMPC to achieve vehicle exhaust control[170]. Given the powerful ability of deep learning to capture system features, especially in complex nonlinear and large-scale systems, its combination with DMPC can significantly enhance the dynamic modeling capability of the system. In the future, it is essential to focus on the computational efficiency and dynamic adaptability of data-driven DMPC solutions to enable their application in a broader range of scenarios, such as UAVs and vehicle platoon systems.

5.3 Practical limitations
In addition to considering the theoretical challenges of DMPC, it is also crucial to address the practical challenges that arise during the implementation of DMPC in UAVs and vehicle exhaust systems. A primary challenge is hardware limitations, as actual system models are often nonlinear, requiring nonlinear model predictive control (NMPC) methods instead of linear MPC calculations in most cases. Compared to the most advanced non-predictive methods, NMPC imposes significantly higher computational demands, making it difficult to deal with the nonlinear optimization problems on vehicles and UAVs with limited processing power[171]. This issue is more prominent in UAVs with more limited memory and computing resources. Additionally, some hardware components may impose further constraints on the construction of MPC problems, thereby affecting the feasibility of these problems. Some constraints require the design of DMPC strategies with higher computational efficiency and lower power consumption. With further development of hardware and nonlinear optimization solvers[172,173], as well as computational research based on field programmable gate arrays (FPGA)[174,175] and microprocessors[176], running NMPC algorithm with nonlinear fully dynamic models on embedded computers has become easier to compute. However, obtaining more efficient solutions to reduce hardware limitations remains an open problem.

Communication delay presents another critical challenge. In distributed control systems, particularly in UAVs and vehicle platoon systems, effective communication is essential for coordination. Sections 2.4 and 4.2 in the previous text have discussed some situations where communication delays and packet loss occur in UAVs and vehicle platoon systems. Due to factors such as signal attenuation, channel congestion, and external radio interference, data transmission may be delayed or lost, which can degrade the performance of DMPC, leading to suboptimal control actions or even system instability, thereby jeopardizing the safety of the systems. Therefore, it is crucial to incorporate robust communication protocols and consider delay compensation techniques

within the DMPC framework, and there have been numerous theoretical studies that have taken into account communication delays or packet loss situations[66,67,177,178]. However, in practical implementation, due to the limitations of hardware to some extent, few studies have verified the practical effectiveness of theoretical DMPC schemes through hardware-in-the-loop simulations[179]. This issue merits further consideration in future research.

Environmental factors also play an essential role in the practical deployment of DMPC. Uncertain dynamic environments, such as constantly changing weather conditions, obstacles in forests or complex terrains, sudden road accidents, and occasional pedestrians in UAVs and vehicle platoon systems, present significant challenges to the safety and robustness of DMPC strategies. The DMPC strategy must be adaptable and resilient to possible uncertain situations to ensure safe and reliable operation in real-world scenarios. For MPC-based approaches, Lindqvist *et al.* proposed a method for UAVs to quickly handle dynamic obstacles. However, there are still limitations in relying on motion capture systems to detect obstacles clearly[180]. Batkovic *et al.* designed the auto drive system for cycling based on the model predictive flexible trajectory tracking control (MPFTC) framework to deal with unforeseen road emergencies[181]. In a distributed scenario, obstacle avoidance trajectory planning in complex environments for UAVs has been proposed[98]. Additionally, scenario-based MPC methods have emerged as a potential solution to the challenges posed by changing environments[182], which can introduce factors such as terrain into the prediction range and adjust the control strategy in advance to maintain the system performance in changeable environment[183]. Furthermore, methods based on machine learning[168,184] or RL[161,185] can make the system robust to dynamic environments through online learning and adaptive strategies, and also have the potential to be applied to participate in designing DMPC strategies in dynamic environments.

The design of DMPC performance parameters, such as the state weight matrix and control weight matrix, plays a crucial role in determining the effectiveness and efficiency of control strategies. These parameters significantly influence the behavior of the system, affecting its stability, robustness, and convergence speed. However, traditional methods for designing these parameters often rely on human expertise and intuition, introducing a degree of randomness and subjectivity into the algorithm implementation process. Although RL-based parameter update methods have demonstrated the ability to achieve desired control effects even with imprecise parameters[161], designing an adaptive parameter adjustment scheme suitable for different systems or using learning-based methods such as RL and neural networks to find better parameters and apply them well to practical systems is still worth further research.

6. CONCLUSIONS

This paper reviews the application of DMPC methods in UAVs and vehicle platoon systems. These systems rely on communication to exchange information and coordinate tasks such as trajectory planning, formation control, and platoon control through DMPC methods. Additionally, considering the robustness and security of AIS, DMPC methods must address complex environmental constraints, external disturbances, and cyberattacks. While there is a foundation of research on these issues, further investigation is needed to address more practical and complex mission scenarios. This paper also summarizes the challenges faced by existing DMPC methods in AIS. However, the work presented here has its limitations. The application examples provided in this paper aim to help readers understand current research directions and challenges, and to inform future work.

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Authors' contributions
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Yan H is an Editorial Board Member of the journal *Intelligence & Robotics* and the guest editor of the Special Issue "Robot System Intelligentization and Application: Learning, Control and Decision", while the other authors have declared that they have no conflicts of interest.

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