CIT. Journal of Computing and Information Technology, Vol. 31, No. 4, December 2023, 203–218
doi: 10.20532/cit.2023.1005769

Distributed Computing Optimization in Unmanned Aerial Vehicle Swarm Cooperative Networks

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The Unmanned Aerial Vehicle (UAV) swarm cooperative networks across diverse domains present significant challenges in management and control to maximize collaborative efficiency, particularly in applications for large-scale and dynamic environments where real-time coordination is essential. This challenge has led to the development of a UAV swarm cooperative network flow prediction model, facilitating the strategic anticipation of network dynamics. A novel algorithm for distributed, finite-time cooperative control is introduced, grounded in this model. This algorithm optimizes the operational efficiency and control precision of UAV systems, while simultaneously augmenting the collaborative efficiency and stability of the UAV swarms. It marks a significant advancement in distributed computing strategies, offering a viable solution for the real-time coordination challenges in extensive UAV swarm cooperative networks. The proposed approach leverages multi-agent technology, integrating spatial-temporal constraints, location limitations, and path selection in cooperative behavior for dynamic and effective network management. This study not only enhances the understanding of UAV swarm dynamics but also contributes to the practical application of UAV swarms in areas requiring precise coordination and robust network stability.

ACM CCS (2012) Classification: Computing methodologies → Parallel computing methodologies → Parallel algorithms → Massively parallel algorithms

Keywords: UAV swarm, cooperative network, flow prediction model, distributed control, multi-agent technology, system stability

1. Introduction

The recent shift of UAV swarm cooperative networks from theoretical exploration to practical implementation has manifested considerable potential across diverse sectors [1–4]. Such networks have found applications ranging from military reconnaissance and strike missions to commercial endeavors like environmental monitoring, agricultural spraying, and urban delivery, where their unparalleled efficiency and benefits are evident [5]. At the same time, in the area of operational efficiency enhancement, robustness in task execution, and resource utilization efficiency, the UAV swarm cooperative networks are recognized as playing a pivotal role. Additionally, these networks are instrumental in fostering technological innovation. The significance of these networks in contributing to the future landscape of intelligence and automation is undeniable. As technological advancements continue and application scenarios broaden, the distinctive value of UAV swarm cooperative networks is anticipated to be increasingly prominent across diverse fields. A pivotal challenge, however, is the effective management and control of these UAV swarms to maximize collaborative effects, particularly in real-time coordination within expansive, dynamic environments [6–9]. Consequently, the formulation of an efficient distributed computing optimization strategy has become imperative.

Research in UAV swarm cooperative networks provides robust theoretical underpinnings for the extensive deployment of UAV systems, thereby enhancing their functionality across various fields [10, 11]. These networks bolster system redundancy and robustness, ensuring stability and reliability even in the event of individual UAV failures [12]. Moreover, optimizing distributed computing strategies within such networks is fundamental to augmenting the execution efficiency and control precision of UAV systems, catering to the requirements of more complex and advanced scenarios [13].

Current research methodologies in UAV swarm cooperative networks often fall short in meeting the real-time needs of large-scale UAV swarms and intricate dynamic environments [14-17]. Typically, these methods rely on fixed network topologies and predefined UAV states, which are subject to continual variation in real-world settings [18]. Furthermore, the optimization process frequently demands substantial computational resources, rendering it impractical for actual applications [19–23]. Critically, these methods tend to overlook the interactions and collaborative behaviors among UAVs, thus constraining the practicality and accuracy of optimization outcomes.

This study examines distributed computing optimization strategies within UAV swarm cooperative networks. In Section 2, the introduction of a UAV swarm cooperative network flow prediction model is detailed. This model facilitates real-time control over the UAV swarm cooperative networks by forecasting future network dynamics and assessing the effects of various candidate decision sequences on control. Thereafter, Section 3 delves into the application of multi-agent technology. Each UAV unit is characterized as an agent within this context. The multi-agent model for the UAV swarm is then constructed, drawing upon the networks' topology and the inter-agent coupling relationships. Subsequently, a distributed, finite-time cooperative control algorithm is designed. This algorithm facilitates distributed control during UAV swarm cooperative behavior, significantly improving the collaborative efficiency of the UAV swarm. The research proposes an efficient, real-time distributed computing optimization strategy, targeting to overcome the challenges faced by existing methodologies in managing large-scale UAV swarm cooperative networks.

A comparative analysis was conducted on the performance of various algorithms, encompassing deep Q-network (DQN), graph isomorphism networks (GIN), graph attention networks (GAT), and the novel method proposed in this study. This analysis focused on three critical performance indices: simulation time, time required for collaborative control, and the acceleration ratio in optimization computation. The findings indicated that the algorithm proposed in this research surpassed the comparative algorithms across multiple performance evaluation metrics. Notably, in terms of the time required for collaborative control and the optimization computation acceleration ratio, the introduced method demonstrated not only heightened efficiency but also enhanced stability. These results suggest that the algorithm presented in this research facilitates more rapid completion of control tasks and more effective acceleration of computation processes, thus offering more reliable and efficient performance in practical applications.

2. UAV Swarm Cooperative Network Flow Prediction Model

In this research, a comprehensive dynamical prediction of future UAV swarm cooperative networks was undertaken. This entailed the development of theoretical models and the execution of simulation experiments. The dynamics of UAV motion and the efficiency of task execution were scrutinized, with a particular emphasis on spatial-temporal constraints and the integration of location-based limitations to guarantee operations within safe perimeters. Furthermore, the study addressed the functionality of dynamic rule updates, enabling real-time modification of the UAV swarm's state and facilitating prompt UAV responses to both environmental shifts and the activities of adjacent UAVs. The influence of cooperative behavior, particularly in path selection, on the overall efficacy of the group was also a key focus. A notable application in disaster relief scenarios demonstrated that strategic path selection significantly accelerates UAVs' deployment to critical areas for search and rescue efforts. By examining these facets, the research provides a detailed assessment of control effectiveness within UAV swarm cooperative networks, laying a substantial theoretical groundwork for prospective implementations. The consideration of the time window and spatial scope is imperative in UAV swarm task execution. Spatial-temporal constraints, as defined in this model, entail the scheduling and control of the UAV swarm within the bounds of these temporal and spatial requirements, thereby facilitating more precise predictions of UAV swarm dynamics.

Furthermore, environmental and terrain factors often impose location restrictions on UAV swarms. Such restrictions, when integrated into the prediction model, refine the accuracy of UAV swarm dynamics forecasts. The dynamic nature of interactions and collaborative behaviors in UAV swarm cooperative networks necessitates real-time updates and adjustments. Update rules, as established in this model, manage the UAV swarm by accommodating these dynamic changes, which are integrated into the prediction model to ensure greater accuracy in forecasting UAV swarm dynamics. Path selection in collaborative behavior, a critical aspect influencing collaborative effectiveness, involves strategic scheduling and control of the UAV swarm to optimize collaborative outcomes.

Rolling prediction, a pivotal technique employed in this model, involves forecasting the next moment's state based on current state and input, followed by the generation and application of corresponding control decisions. This iterative process continues until all predictions and decisions are completed. Analysis of these aspects highlights rolling prediction as a crucial method within the UAV swarm cooperative network flow prediction model, facilitating real-time control of UAV swarm cooperative behavior. Control decisions within the rolling prediction time domain include:

- Decision generation. Predicting the UAV swarm's state for the subsequent moment based on the current state and input, and generating control decisions in response to the predicted state and prevailing environmental conditions. These decisions may encompass parameters such as flight path, speed, and altitude.
- Decision execution. Applying these control decisions to the UAV swarm at the next moment, thereby influencing UAV flight control. This stage ensures the smooth progression of collaborative behavior and task execution.
- Decision update. Post-execution, the state and input of the UAV swarm are updated based on actual outcomes and environmental changes, laying the foundation for future prediction and decision generation.
- Decision optimization. Throughout the prediction and decision-making process, control decisions are continuously optimized in response to actual outcomes and environmental changes, aiming to maximize collaborative efficiency and task execution effectiveness of the UAV swarm.

The UAV swarm cooperative signal adaptive control challenge is fundamentally a multi-constraint nonlinear optimization issue. This complexity arises from the multitude of constraints that govern UAV swarm collaborative behavior, encompassing, but not restricted to, spatial-temporal constraints, location limitations, update protocols, and pathways for collaborative actions. The inherent nonlinearity of this control problem is a direct consequence of the dynamic and intricate nature of UAV swarm behavior. The utilization of prediction control is particularly beneficial in this context. It considers future states and environmental shifts within a predetermined time frame, which allows for more logical and optimized control decisions. Importantly, this approach integrates a variety of constraint conditions into the optimization process, ensuring comprehensive compliance with these conditions. Therefore, the prediction control of UAV swarm cooperative network flow, as proposed in this study, effectively redefines the UAV swarm cooperative signal adaptive control challenge into a solvable multi-constraint nonlinear optimization problem within a finite time domain. This transformation facilitates efficient and real-time cooperative control of UAV swarms.

To optimize collaborative efficiency, enhance system stability and reliability, and minimize energy consumption while ensuring quality and timely completion of collaborative tasks, key factors influencing optimization objectives are identified. These encompass UAV performance attributes like flight speed, altitude, payload capacity, and endurance, all of which impact the UAV swarm's collaborative efficiency and energy consumption. Environmental factors such as terrain, weather, and air currents influence the UAVs' flight path and speed, affecting both collaborative efficiency and energy consumption. Task requirements, comprising urgency, complexity, and spatial distribution, impact the scheduling and control of the UAV swarm, thus influencing collaborative efficiency and task completion quality. Additionally, cooperative strategies involving UAVs' collaborative behavior patterns and path selection affect both the collaborative efficiency and system stability of the UAV swarm.

In the prediction model, the current control step is denoted by jv, and the predicted cooperative state of the UAV swarm, including position and speed, is represented by $\hat{a}(jv)$. The predicted control input sequence is indicated by $\hat{\imath}(jv)$. At the $j + m$ moment within the prediction time domain, this is represented by $L_u(j + m)$. In scenarios of emergency tasks, the number of UAVs on the u-th flight path is considered, with the flight path count in the cooperative network denoted by W. The duration of an emergency task at the j-th moment under the k-th cooperative mode on the u-th path is represented by $h_{u,k,j}$, with the lower and upper limits of this emergency task time being $h^{\mathrm{MIN}}{}_u$ and $h^{\mathrm{MAX}}{}_u$, respectively. The task cycle is represented by V_u, and the task scheduling loss time is denoted by M_u. The number of cooperative modes on the u-th flight path is indicated by B_u, and the efficiency difference of the cooperative mode at the j-th moment on the u-th path is denoted by $\phi_{u,j}$. The sequence of cooperative modes on the u-th flight path is represented by P_u, with the k-th cooperative mode on this path denoted by $og_{u,k}$. Consequently, within the prediction time domain B_O, the optimization objective function of the model's prediction control is defined:

$$\underset{\hat{\imath}}{MAX}\, K\left(\hat{a}(j_v), \hat{\imath}(j_v)\right) = \sum_{i=1}^{W} \sum_{j=j_v}^{j_v+B_o-1} L_u(j+1) \tag{1}$$

$$\text{s.t.} \quad h_u^{MIN} \le h_{u,k,j} \le h_u^{MAX} \tag{2}$$

$$\sum_{k=1}^{B_u} h_{u,k,j} = V_u - M_u \tag{3}$$

$$0 \le \varphi_{u,j} \le V_u - M_u \tag{4}$$

$$P_u \in \left\{ og_{u,k} \middle| k = 1, 2, ..., B_u \right\} \tag{5}$$

Figure 1 presents a schematic diagram illustrating the rolling time domain definition utilized in the prediction model developed for this study. This dynamic timeframe, known as the rolling time domain, spans from the present moment to a pre-set future moment. The UAV swarm's future cooperative state is predicted based on its current state and input, taking into account the dynamic behavior patterns of the swarm, collaborative task requirements, and environmental influences. These predictions form the foundation for subsequent control decisions. Within the prediction time domain Bo, the future cooperative state of the UAV swarm is denoted by $\hat{a}(jv)$, while the control input is represented by $\hat{\imath}(jv)$:

$$\begin{aligned} \hat{a}(j_v) = \big[& a(j_v+1 | j_v), \\ & a(j_v+2 | j_v), ..., \\ & a(j_v+B_o | j_v) \big] \end{aligned} \tag{6}$$

$$\begin{aligned} \hat{\imath}(j_v) = \big[& i(j_v | j_v), \\ & i(j_v+1 | j_v), ..., \\ & i(j_v+B_o-1 | j_v) \big] \end{aligned} \tag{7}$$

To maintain continuity and stability in control, it is essential that decision variables outside the control time domain $B_v (B_v < B_o)$ mirror the con-

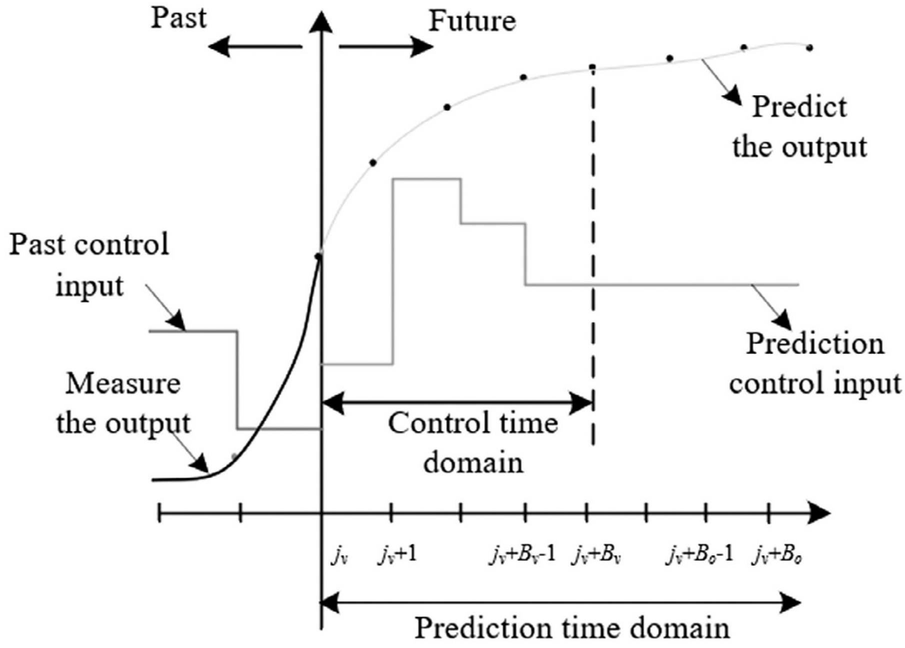


Figure 1. Definition of the rolling time domain.

trol variables of the preceding moment, as delineated in the model. This is critical to prevent significant instantaneous changes in the flight state of UAVs, such as position, speed, and direction, which could pose risks of damage or danger. The decision variables for the current moment, therefore, should not substantially deviate from those of the previous moment:

$$\hat{i}\left(j_v + j \mid j_v\right) = \hat{i}\left(j_v + B_v - 1 \mid j_v\right), \quad j = B_v, \ldots, B_o - 1 \tag{8}$$

The following formula redefines these control variables:

$$\hat{i}\left(j_v\right) = \left[i\left(j_v \mid j_v\right), i\left(j_v + 1 \mid j_v\right), \ldots, i\left(j_v + B_v \mid j_v\right)\right] \tag{9}$$

By resolving this model, the optimal control sequence $\hat{\imath}(j_v)$ is ascertained. This sequence delineates the coordinated actions the UAV swarm should undertake over a future period to meet predefined task objectives. This process involves considering the collaborative relationships among the UAV swarm members, alongside the constraints imposed by task requirements on UAV behavior. Building upon the optimal control sequence generated, its first element $i^*(j_v|j_v)$, representing the optimal control decision for the current moment, is applied to the UAV swarm. It is crucial to ensure that control instructions are transmitted to each UAV in a timely and accurate manner, and that each UAV operates in compliance with these instructions.

Following the execution of control decisions, new state information of the UAV swarm is gathered through sensors and other devices. This information is crucial as it forms the initial state for the subsequent prediction cycle. In this iterative process, the consideration of environmental changes is imperative, as these may significantly impact the state of the UAVs. Thus, the real-time updating of state information becomes a necessity. The prediction time domain is methodically advanced, maintaining the continuity and stability of the prediction to avoid any discontinuities. The methodology outlined in Figure 2 represents a dynamic, iterative process, necessitating continual adjustment of control strategies based on the latest state information. This approach is essential for optimizing the collaborative behavior of the UAV swarm, ensuring the effective execution of the task at hand.

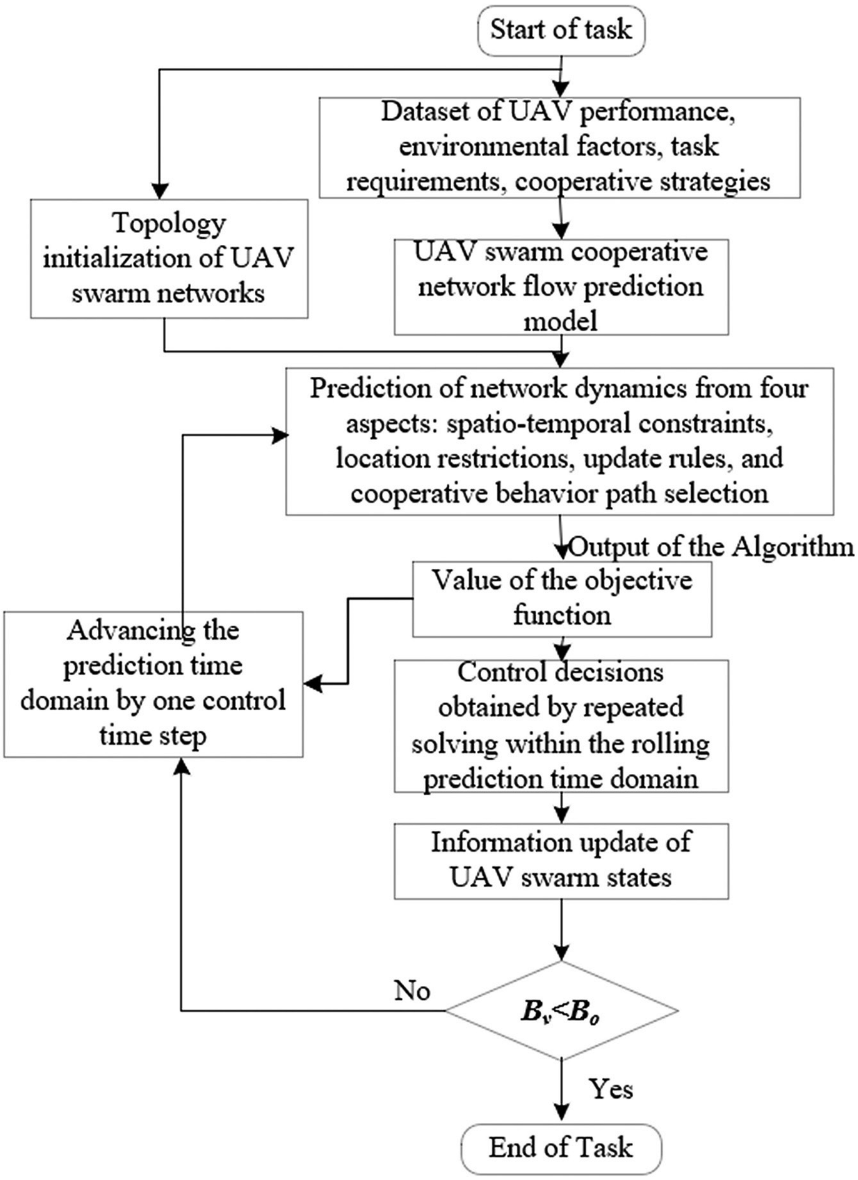


Figure 2. Flowchart of UAV swarm cooperative network flow prediction.

3. Distributed Finite-time Cooperative Control of UAV Swarms

In this study, a distributed finite-time cooperative control method for UAV swarms is proposed to augment their adaptability and robustness, particularly in complex and variable environments and task requirements. This method conceptualizes each UAV unit as an agent within a multi-agent model, enabling distributed control. Consequently, each UAV is capable of making autonomous decisions based on its state and the states of proximate UAVs, obviating the necessity for centralized control by a central node. Such a distributed approach significantly enhances the UAV swarm's adaptability and robustness, equipping it to adeptly manage diverse and dynamic environmental and task challenges. Furthermore, this method's control process is confined to a finite timeframe, rather than an indefinite duration, ensuring that objectives are attained within a specified period. This attribute is particularly beneficial for tasks where time is a critical factor.

In the developed multi-agent model for UAV swarms, each UAV is regarded as an autonomous agent, collectively constituting a sophisticated network system. Nodes in this network symbolize individual UAVs, while edges represent interactions between them, mirroring the UAV swarm's cooperative network topology. The interaction relationships among UAVs are inherently dynamic; alterations in the network's structure occur as UAVs either complete their tasks and depart from the group or as new UAVs are integrated. This dynamic nature enables the UAV swarm to more effectively adapt to changes in environmental conditions and task requirements. It is defined that when UAV unit u is coupled with UAV unit k, the value of $\hat{S}_{uk}$ is set to 1; otherwise, it remains 0. Simultaneously, the parameters $\hat{\imath}_u = i_u / l_u$, $\hat{j}_u = j_u / l_u$, and $\hat{f}_u = f_u / l_u$ are introduced, leading to the formulation of the following expression for the multi-agent model:

$$\begin{cases} \dot{z}_u = c_u \\ \dot{c}_u = \hat{\imath}_u + \hat{j} \sum\limits_{k=1,\, k\neq u}^{b} \hat{s}_{uk} \left[\left(z_k - z_u \right) + m_u \left(k - u \right) \right] \\ + \hat{f}_u \sum\limits_{k=1,\, k\neq u}^{b} \hat{s}_{uk} \left(c_k - c_u \right) - E\left(c_u \right) \end{cases} \tag{10}$$

Figure 3 illustrates the UAV-based wireless sensor device system utilized in the study. During collaborative behavior, the UAV swarm gathers state information from all UAV units through wireless sensor devices. The system constructs a speed-distance curve from this data, which is essential for ensuring the safety and precision of the UAV swarm's collaborative maneuvers. The expression for this curve is as follows:

$$\dot{z}_e\left(y\right) = c_e\left(y\right) \tag{11}$$

Additionally, the distance and speed differences between each UAV unit, denoted as u, and the curve are defined, enhancing the model's accuracy in depicting UAV dynamics:

$$\begin{cases} \tilde{z}_u = z_u - z_e + \sum\limits_{l=1}^{u-1} m_l \\ \tilde{c}_u = c_u - c_e \end{cases} \tag{12}$$

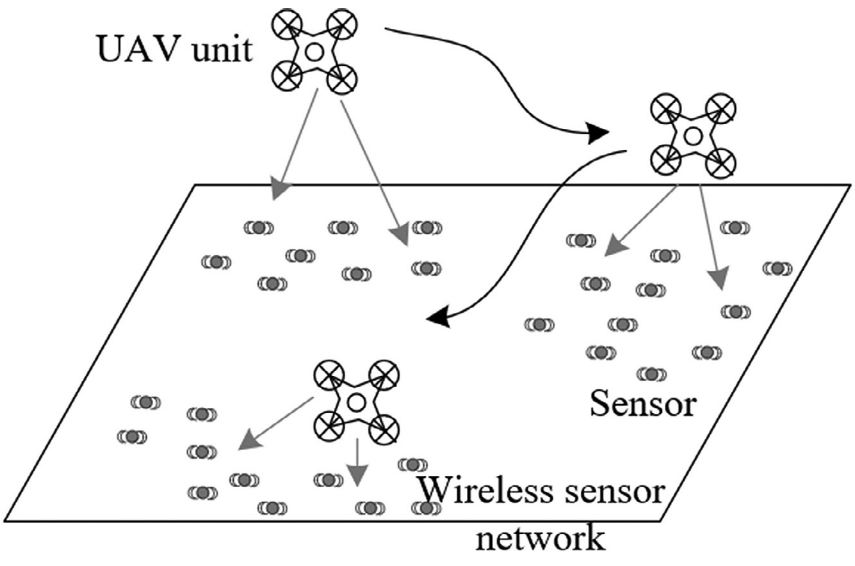


Figure 3. UAV-based wireless sensor device system.

The distributed finite-time cooperative control method for UAV swarms, developed in this study, primarily aims to establish a finite-time control law $\hat{\imath}_u(y)$ for each UAV unit. This law is based on information from neighboring UAV units, and its key objectives are twofold.

First, it ensures that the speed of all UAV units becomes uniform within a finite period. Uniform speed across all units is fundamental for effective group cooperative behavior. When all UAVs operate at a consistent speed, the swarm can move coherently along the predetermined route and speed, which is vital for avoiding disarray and inefficiency in group behavior. Rapid response capability in the control algorithm is crucial for promptly aligning the velocities of all UAVs, thereby enhancing task execution efficiency.

Second, the method aims to maintain optimal safe distances between consecutive UAV units. This is critical for ensuring the safety of UAVs during task operations. The model defines a range of safe distances, represented by $(-g_2, g_1)$, within which the UAVs must operate. Balancing these distances is essential for maximizing the UAV swarm's coverage and operational efficiency while preventing collisions and maintaining effective internal communication and collaborative behavior. Precise control is required to achieve this balance, with the initial distance between adjacent UAV units within the safe range forming the basis for the swarm's control objectives:

$$\begin{cases} \lim\limits_{y\to Y}\sum\limits_{k\neq u}\left|c_k - c_u\right| = 0 \\ \lim\limits_{y\to Y}\sum\limits_{u=1}^{b}\left|c_k - c_u\right| = 0 \\ \lim\limits_{y\to Y}\left|z_1 - z_e\right| = 0 \\ \lim\limits_{y\to Y} r_u(y) = 0,\ u = 1, 2, ..., b-1 \\ -g_2 < r_u(y) < g_1, \forall y > 0 \end{cases} \tag{13}$$

To realize the control objectives previously delineated, this study defines o_1, o_2, ω_1, and ω_2 as positive constants. The variable s_{up} is assigned a value of 1 when u equals 1, and 0 in other instances. Subsequently, a finite-time distributed control law, aligned with the stated control objectives, is formulated:

$$\begin{aligned} \hat{\imath}_u = {} & o_1 \sum_{c_k\in B_u} s_{uk}\,\mathrm{sig}\left(\tilde{z}_k - \tilde{z}_u\right)^{s_1} + \\ & o_2 \sum_{c_k\in B_u} s_{uk}\,\mathrm{sig}\left(\tilde{c}_k - \tilde{c}_u\right)^{s_2} \end{aligned} \tag{14}$$

The parameters σ_1 and σ_2 are set within the ranges of $(0, g_1)$ and $(0, g_2)$, respectively. In scenarios where c_k belongs to B_u, the value of s_{uk} is assigned 0. Alternatively, s_{uk} is defined as follows in other circumstances:

$$s_{uk} = \begin{cases} \dfrac{2g_1\sigma_1 - \sigma_1^2}{g_1^2 - \left(\tilde{z}_k - \tilde{z}_u\right)^2} - o_1^{-1}\hat{s}_{uk}\hat{j}_u \\ IF\quad u>k\quad AND\quad g_1 - \sigma_1 < \left(\tilde{z}_k - \tilde{z}_u\right) < g_1 \\ IF\quad u<k\quad AND\quad -g_1 - \sigma_1 < \left(\tilde{z}_k - \tilde{z}_u\right) < -g_1 + \sigma_1 \\ \dfrac{\sigma_2^2}{\left(g_2 - \left|\tilde{z}_k - \tilde{z}_u\right|\right)^2} - o_1^{-1}\hat{s}_{uk}\hat{j}_k \\ IF\quad u>k\quad AND\quad -g_2 < \left(\tilde{z}_k - \tilde{z}_u\right) < -g_2 + \sigma_2 \\ IF\quad u<k\quad AND\quad g_2 - \sigma_2 < \left(\tilde{z}_k - \tilde{z}_u\right) < g_2 \\ 1 - o_1^{-1}\hat{s}_{uk}\hat{j}_u,\ EL \end{cases} \tag{15}$$

Employing the aforementioned finite-time distributed control law facilitates the realization of efficient collaborative behavior within the UAV swarm. By achieving uniformity in speed across all UAV units and maintaining specified maximum and minimum safe distances, the group's overall efficiency and safety are significantly enhanced. This approach underscores the importance of finely tuned control mechanisms in optimizing the collaborative dynamics of UAV swarms.

4. Experimental Results and Analysis

Figure 4 presents a comparative analysis of the number of UAVs per flight path at each control time step. This figure is instrumental in evaluating the performance of the UAV swarm cooperative network flow prediction model, a cornerstone of this study. The model's ability to predict future network dynamics and assess the efficacy of potential decision sequences facilitates real-time control over the UAV swarm cooperative network. The data, as illustrated in Figure 4, reveal that the number of UAVs in-

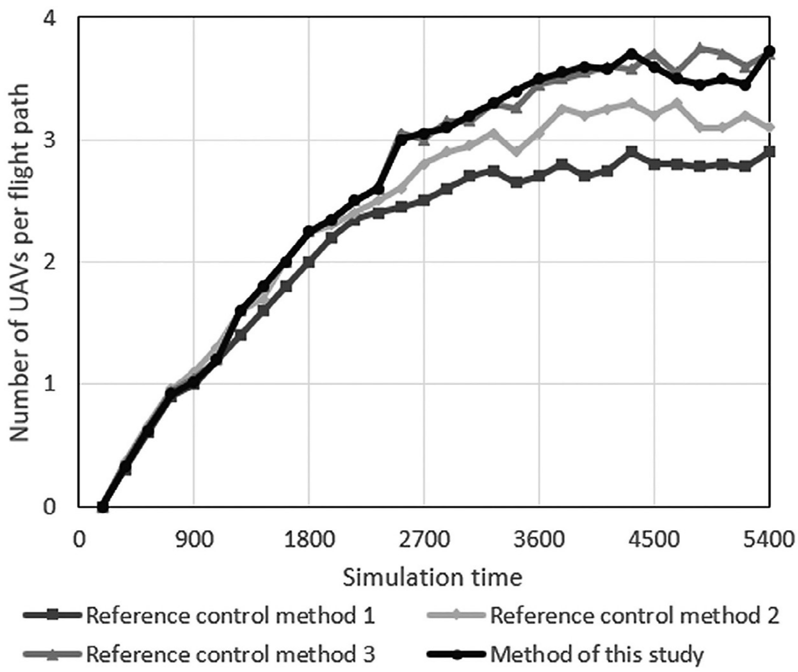


Figure 4. Comparative analysis of the number of UAVs per flight path at each control time step.

creases over time across all algorithms, albeit with varying rates and degrees of stability. Initial simulation results show comparable performance among the four algorithms. However, as the simulation progresses, a discernible divergence emerges, with the approach of this study (represented by the black line) demonstrating a clear lead over the other methods. The DQN algorithm (dark gray line), GIN algorithm (light gray line), GAT algorithm (gray line) exhibit fluctuations but generally trail behind the method proposed in this study. The analysis underscores the superiority of the model developed in this study, particularly in its capacity to manage increasing numbers of UAVs and maintain stability, thereby affirming its effectiveness in real-time network control.

Figure 5 offers a comparative analysis of the number of UAVs on each flight path across four distinct algorithms. Represented are the DQN algorithm (dark gray line), GIN algorithm (light gray line), GAT algorithm (gray line), and the method developed in this study (black line). The analysis reveals that the method of this study, as indicated by the black line, consistently achieves higher flight distances across most control strategies while maintaining an optimal number of UAVs. This performance suggests that the UAV swarm cooperative network flow prediction model proposed herein effectively balances extended flight distances with the management of UAV numbers, aligning with the objectives of cooperative swarm behavior. Furthermore, minimal fluctuations in the black line on the *z*-axis, indicative of the number of UAVs per flight path, signify a stable UAV count under varying control strategies. This stability is a testament to the robustness of the control strategies and the predictive accuracy of the model. Thus, it is inferred that the model excels not only in facilitating extended flight distances but also in ensuring stability and reliability in UAV number management. These attributes affirm the suitability of this study's model for UAV swarm cooperative network flow prediction and management, offering effective and real-time control for future network dynamics.

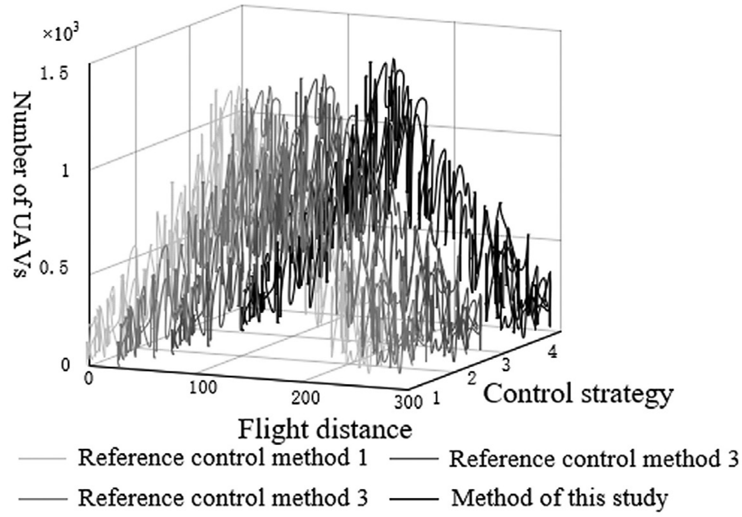


Figure 5. Comparative analysis of the number of UAVs on each flight path.

Figure 6 presents a comparative assessment of the degree of improvement achieved by the algorithm developed in this study relative to other algorithms. The horizontal axis indicates the range of improvement degrees, while the vertical axis reflects the level of enhancement over the DQN and GAT algorithms. The improvement of this study's algorithm over the DQN algorithm is represented by the light gray bar, and its enhancement relative to the GAT algorithm is depicted by the dark gray bar. The data clearly demonstrate that the method proposed in this study exhibits substantial advancements over both the DQN and GAT algorithms across various improvement ranges. Notably, in scenarios with improvements of 60% or higher, this study's method distinctly surpasses the DQN algorithm. Similarly, in the 30%-60% improvement range, it achieves a greater level of enhancement compared to the GAT algorithm. Collectively, these results affirm that, in most instances, the algorithm introduced in this study realizes significant improvements over both the DQN and GAT algorithms. This highlights the substantial efficacy of the prediction model introduced in this study, particularly in scenarios requiring higher degrees of improvement, thereby demonstrating its superior performance capabilities.

Figure 7 illustrates the time efficiency in cooperative control among different algorithms, including the DQN, GIN, GAT, and the method proposed in this study. As simulation time progresses, the black line, representing this study's method, consistently manifests a lower duration for cooperative control compared to the other algorithms. This gap in efficiency widens as the simulation advances, indicating a sustained period of stability. These observations suggest that the method developed in this study not only excels in the efficiency of cooperative control but also maintains this efficiency consistently over time.

Figure 8 provides an analysis of the optimization computation speedup ratios across various algorithms at differing points in the simulation timeline. Here, the DQN algorithm is represented by light gray bars, the GIN algorithm by dark grey bars, and this study's method by gray bars. The speedup ratio is a critical metric for assessing algorithmic optimization performance, with higher ratios indicating substantial gains in computational speed relative to a given benchmark. The figure clearly shows that the method developed in this study consistently exhibits the highest speedup ratios at every simulation point, markedly surpassing both the DQN and GIN algorithms. This data strongly suggests that the prediction model of this study significantly excels in computational optimization, offering enhanced speeds that facilitate more efficient cooperative control in UAV swarm operations, especially under demanding real-time conditions. The effectiveness of this method, as depicted, plays a pivotal role in enabling UAV swarms to perform tasks rapidly and accurately in complex environments, highlighting the superiority and practical applicability of the proposed model.

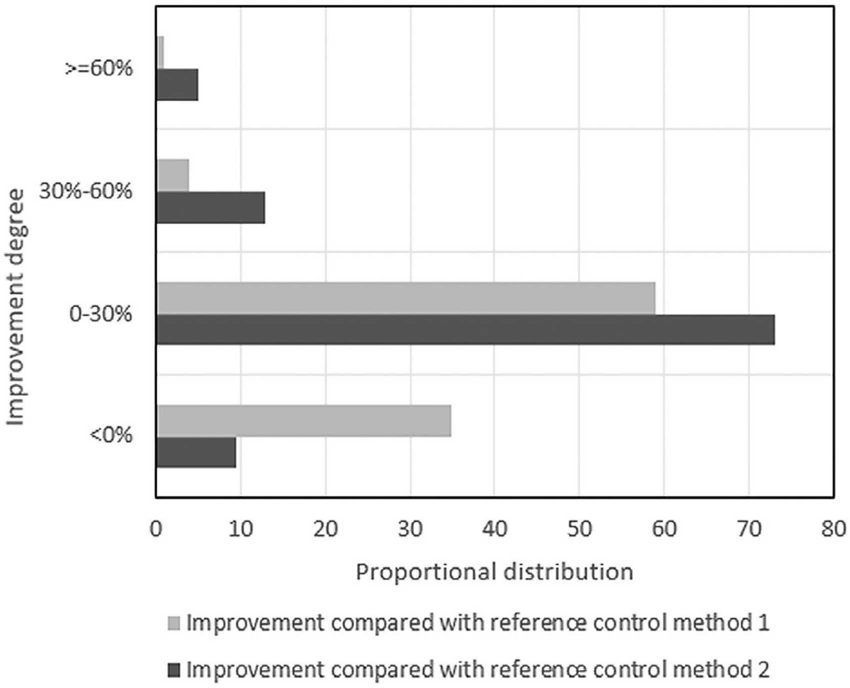


Figure 6. Comparison of the improvement degree achieved by the proposed algorithm relative to other algorithms.

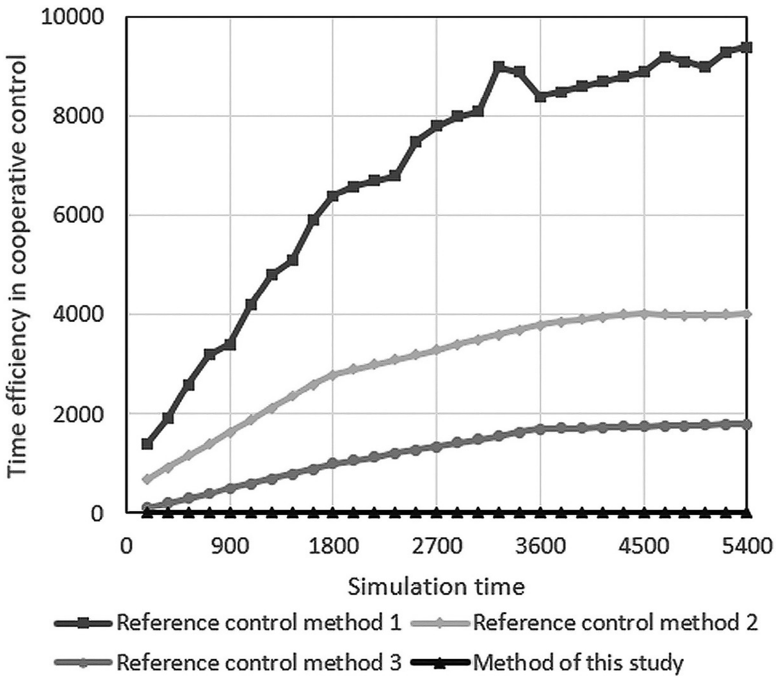


Figure 7. Time efficiency in cooperative control among different algorithms.

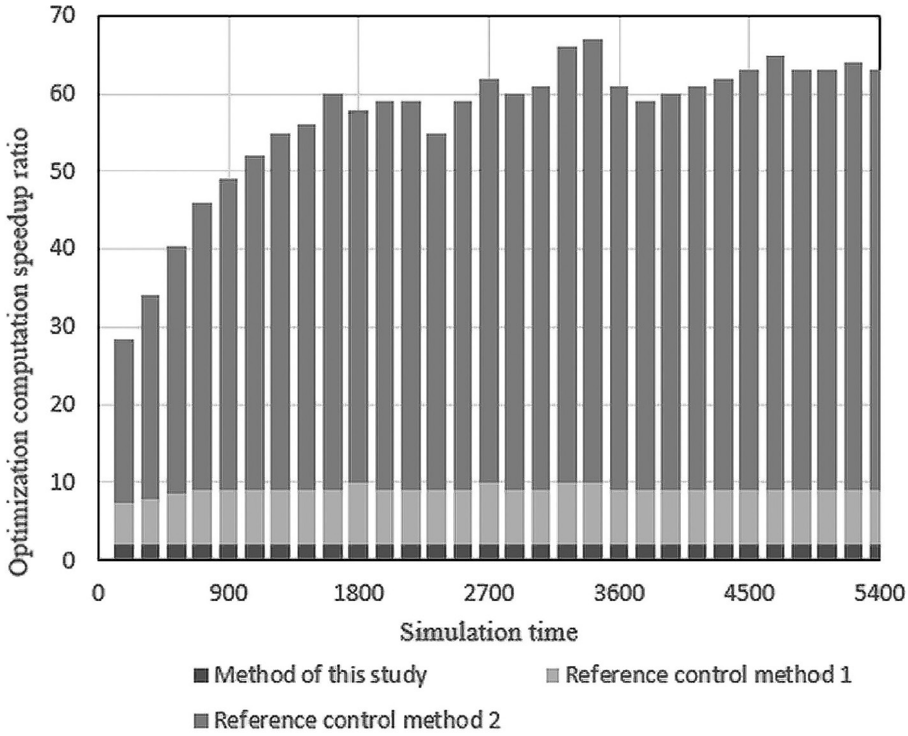
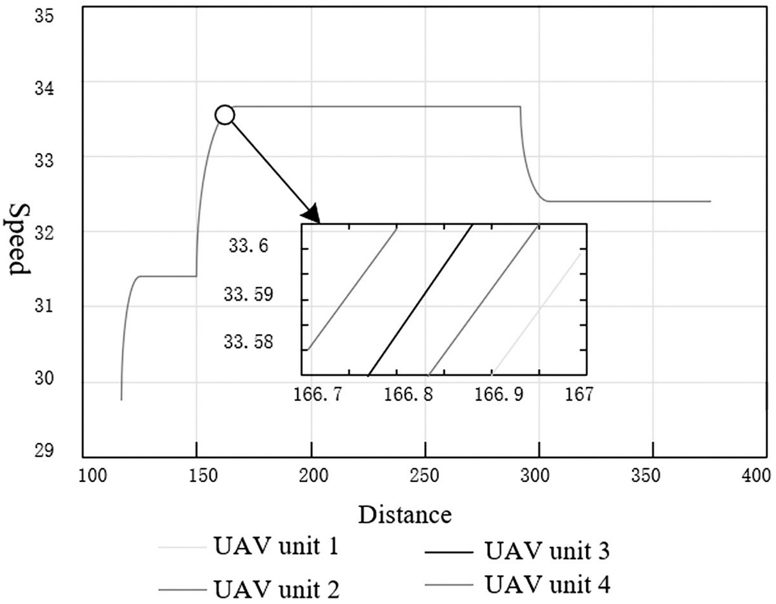


Figure 8. Comparison of optimization computation speedup ratios for cooperative control.

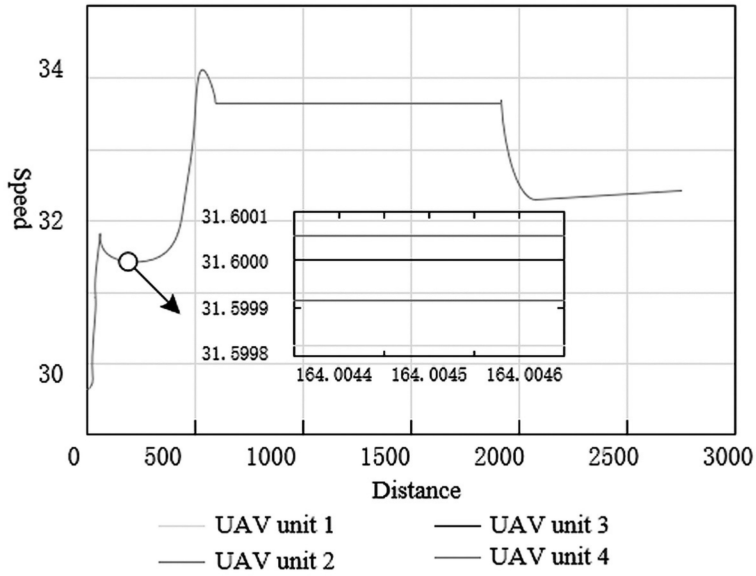
Figure 9 focuses on the speed-distance curves under different task scenarios, showcasing the performance of the distributed finite-time cooperative control algorithm devised in this study. The curves exhibit a notable jump in speed, stabilizing thereafter, indicative of a strategic shift in cooperative control, such as adjusting speed near target points. Throughout most of the trajectory, the speed remains consistent, suggesting that the UAV swarm maintains stable task execution post-initial adjustments, a hallmark of effective cooperative control. Minimal variations in speed across different curve segments imply the algorithm's capability to uphold uniform speed during UAV progression, thereby sustaining cooperative efficiency, even under finite-time stability constraints. The efficacy of the proposed cooperative control algorithm is evident across various tasks, maintaining stable speed and task execution, thereby underscoring its rapid response and robust control characteristics essential for efficient and reliable UAV swarm operations.

5. Conclusion

This study has focused on addressing the challenges in managing and controlling the flow of UAV swarm cooperative networks, with the objective of achieving efficient cooperative control of UAV swarms. A UAV swarm cooperative network flow prediction model was developed, grounded in the real-world demands of UAV cooperative behavior. Utilizing multi-agent technology, each UAV unit was conceptualized as an intelligent agent. By considering the topology and coupling relationships within the UAV swarm cooperative network, a comprehensive multi-agent model was constructed. Subsequently, a novel distributed finite-time cooperative control algorithm was formulated based on this model. The prediction model, designed in this study, endeavors to anticipate future network dynamics and assess the effectiveness of control decisions. This approach facilitates real-time governance of the UAV swarm cooperative network. It efficiently resolves control decisions within a dynamic pre-



(a) Task 1.



(b) Task 2.

Figure 9. Speed-distance curves under different task scenarios.

diction time domain, accounting for variables such as spatial-temporal constraints, location limitations, and choices in cooperative behavior pathways. Additionally, the cooperative control algorithm, underpinned by multi-agent technology, enables distributed control amidst UAV swarm cooperative behavior, markedly improving the swarm's collaborative efficiency.

A thorough experimental analysis was conducted, comparing various algorithms, including DQN, GIN, GAT, and the approach introduced in this study, across different metrics such as simulation time, cooperative control duration, and optimization computation speedup ratios. The findings revealed that the method proposed in this study outshined in multiple evaluation aspects, especially in terms of cooperative control efficiency and computational optimization, when benchmarked against other algorithms.

In conclusion, the UAV swarm cooperative network flow prediction model and the distributed finite-time cooperative control algorithm proposed in this study demonstrate not only theoretical innovation but also practical efficacy, as evidenced in experimental validations. These advancements hold substantial promise for enhancing the intelligent management and control of UAV swarm cooperative behavior, with potential applications extending to military, monitoring, rescue operations, and other relevant domains.

In this study, the proposed algorithm's contribution to enhancing the real-time collaborative control efficiency of UAV swarms is recognized. However, it is acknowledged that the research encompasses certain limitations. The model, potentially idealized, may not fully encompass the myriad uncertainties prevalent in complex environments, such as climate variations and signal interference. Furthermore, the scalability and robustness of the algorithm in expansive UAV networks necessitate additional validation. Prospective research endeavors could focus on refining the model for greater realism in dynamic, complex environments. This entails optimizing the algorithm for augmented efficacy in larger-scale networks and bolstering its resilience to uncertainties and potential malfunctions. Additionally, the exploration of more sophisticated distributed computing frameworks is warranted, aiming to manage the extensive data and high computational demands characteristic of collaborative tasks involving UAV swarms more efficiently.

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Received: November 2023
Revised: January 2024
Accepted: January 2024

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