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A Low Latency Clustering Method for Large-Scale Drone Swarms

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ABSTRACT Large-scale drone swarms are expected to play an important role in information acquisition, rescue search and joint fire strikes. These swarms usually adopt a clustering structure to control formation flight for fast and stable communication. Effective clustering can improve the transmission efficiency and task execution ability of the network. On the basis of uniform clustering, we establish a model with the number of unmanned aerial vehicles (UAVs) and the number of cluster heads (CHs) as variables to minimize the communication latency. Using conditional criteria, the communication delay is minimized to solve the relationship between the number of drones and the number of CHs, and this model is for clustering. A simulation platform is built with OPNET to evaluate the impact of different numbers of CHs on the network performance. According to the proposed scheme, the optimal number of CHs for 500, 300, 100 UAVs is 31, 24, 14, respectively. In the case of specific simulation parameters, these optimal numbers of CHs can achieve excellent performance in terms of delay and packet loss rate. This result has value in drone swarms clustering applications.

INDEX TERMS Drone swarms, formation flight, clustering method, communication delay.

I. INTRODUCTION

Drone swarms are the typical application on mobile ad hoc networks (MANET) in the aviation field and are composed of numerous UAVs [1]. With the development of intelligent, low-cost and miniaturized UAVs, the application of drone swarms has become an extremely important research direction such as for coordinated reconnaissance and target surveillance [2], [3]. A group of UAVs instead of one single UAV leads to many advantages such as extending the mission coverage, ensuring a reliable ad-hoc network, or enhancing the operation performance [4]. A drone swarm usually encompasses a control ‘, which includes three layers: 1) Sensor layer. It contains various sensors carried by UAVs to collect raw data for specific targets. 2) Information processing layer. It makes up of communication module, which filters the useful information of the raw data through the information exchange between the UAVs and performs effective information fusion. 3) Decision-making layer. According to information fusion, the current situational awareness is formed, so that drone swarms can be accurately controlled.

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In the 8 years from 2011 to 2018, the Strategic Capabilities Office (SCO), the Defense Advanced Research Projects Agency (DARPA) and the Office of Naval Research (ONR) proposed the Perdix micro-UAV project, the Distributed Battle Management (DBM) project, the Collaborative Operations in Denied Environment (CODE) project, the Gremlins project, the System of Systems Integration Technology Experimentation (SoSITE) project, the Low-cost UAV Swarming Technology (Locust) project, the Loyal Wingman project and the offensive bee colony Offensive Swarm-Enabled Tactics (OFFSET) project. These large-scale drone swarm projects cover scenarios such as coordinated reconnaissance, target surveillance, integrated relay of heaven and Earth, and saturated firepower strikes [5], [6]. They have the ability to change operational modes; reduce operational costs; and improve operational flexibility, mobility, invulnerability, and strategic position.

The factors of the operational environment are complex and changeable, and combat chances are rare and fleeting [7]. Information and instructions need to be quickly transmitted to each UAV for sharing and interaction. If information and instructions do not arrive in time, the UAVs cannot respond quickly to adjust to battlefield situations, which may lead to the failure of the entire mission and irreparable damage [8]. Therefore, minimizing the wireless communication delay provides a basis on the drone swarms can complete their specified tasks [9].

The real-time performance of wireless communication can be considered in two aspects. First, the development of a new wireless technology (5G), protocol standards and intelligent hardware increases the bandwidth, signal transmission and reception rates [10]. Second, ensuring low latency communication under the same wireless technology, protocol standards and hardware level by the reasonable layout of the network topology of drone swarms [11]. In [12], a tractable method was proposed for the 3D deployment of drone base stations and solved the problem of cell association with the goal of minimizing the latency of drone users. The clustering structure shown in Fig.1 is suitable for large-scale drone swarms [13]. The self-organizing drone network forms a plurality of clusters by a clustering algorithm [14], with each cluster is composed of a cluster head (CH) and some cluster members (CMs). These CHs form the high layer virtual backbone network and provide two critical functions: 1) direct communication between cluster heads, and 2) medium for cross-cluster communication. The CMs in the same cluster communicate directly through one hop, but the data to be transmitted between clusters are first sent to the CH, from where they are sent to the CH of the cluster where the destination node is located through the virtual backbone network [15]. The CH then transmits to the destination node to achieve cross-cluster communication.

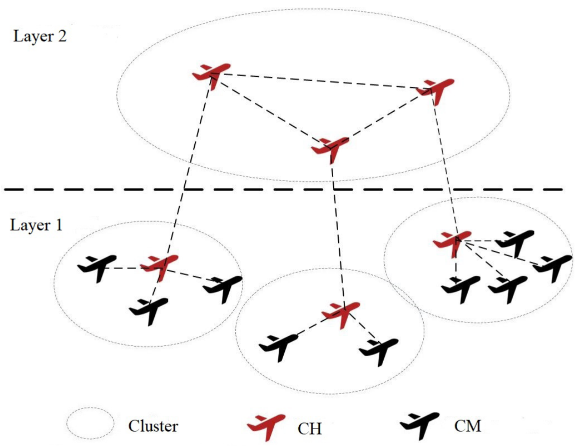


FIGURE 1. Two layer cluster hierarchy of UAV swarms.

The rest of paper is organized as follows: The section II introduces related work on clustering algorithms for drone swarms. In section III, a new clustering method is proposed, which involves conditional assumptions, process derivation, application process and working frame. Section IV evaluates the performance of our proposed method and section V concludes the paper.

II. RELATED WORK

Drone swarms are characterized by high-speed mobile nodes and dynamically changing topology [16]. Minimizing communication delay by reasonable clustering is highly significant to scientific engineering models and applications.

Currently, there are many clustering algorithms for drone swarms, such as the lowest-ID, highest-degree and weight-based clustering algorithms (WCA) [17]. In the previous two clustering algorithms, a node is elected as CH if it has the lowest ID or the highest connectivity [18]. The WCA is based on the use of a combined several parameters like the node degree, distances with all its neighbors, node speed and the time spent as a CH. For the same purpose, the authors in [19] proposed a time division multiple access (TDMA) system based on minimum ID clustering, which was applied to increase the capacity management of wireless networks in the vehicle-mounted ad hoc network. Alinci *et al.* [20] studied some clustering schemes from different performance indicators. In [21], a multihop clustering scheme is proposed to improve the stability of the clustering of vehicle clusters. In [22], a multi-parameter weighted clustering algorithm is introduced to improve the clustering of drones, network stability and survival rate. Fahad *et al.* [23] proposed a clustering algorithm based on gray wolf optimization, which can provide a robust routing protocol to ensure reliable information transmission. In [24], a clustering algorithm based on ant colony optimization for VANETs is proposed to extend the lifetime of clusters. The work in MANET [25] developed a clustering algorithm by proposing to use coalition game theory, identifying coalitions to clusters and players to nodes, where nodes take decision whether to leave or not their current coalition based on the coalition values.

Due to the limited energy and computing power of a single UAV, it is impossible for the UAV to guarantee the best working state anytime and anywhere. On the one hand, some experts are working to reduce the energy consumption of drones. The work in [26] studied a novel cache-enabled UAV framework in cloud radio access network that can meet the mobile user's quality-of-experience (QoE) requirement while minimizing the transmit power of the UAVs. On the other hand, more studies have been conducted on the impact of residual energy and load balancing factors on communication efficiency. To solve the problem of routing instability caused by battery residual energy and nodes mobility, a proposed scheme uses energy aware cluster formation and cluster head election based on the glowworm swarm optimization algorithm in [27]. In [28], limited battery energy and the high mobility of UAVs represent two main problems, the authors addressed these problems by means of efficient clustering. First, the transmission power of the UAVs was adjusted to save the energy consumption during communication. Second, the K-means clustering algorithm was adopted for CHs election to enhance the cluster lifetime and reduce the routing overhead. To optimize the number of clustering as well as energy dissipation in nodes, a clustering algorithm by using multi-objective particle swarm optimization algorithm is presented in [29], this method provides an energy-efficient solution and reduces the network traffic. In [30], the authors introduced the cluster head selection algorithms for FANET to achieve stable connection of UAVs and reduction of energy consumption. In [31], a center-based clustering algorithm is proposed, where self-organized VANETs form stable clusters and decrease the status change frequency of vehicles on highways. In [32], the authors proposed a cross-layer based lightweight reliable and secure multicast routing protocol for MANET to solve route failures, link failures, packet losses due to network overloading. The CHs are elected based on residual energy, link stability, and remaining bandwidth.

Indeed, these studies have been done based on setting some criteria to designate certain drones as CHs. In this paper, a novel method based on uniform clustering is presented. The focus of our work is realizing low latency communication by adjusting the number of CHs. For the election criteria of the CHs, it is possible to select any suitable algorithm among the lowest-ID, highest-degree, weight-based and coalition game clustering algorithms. With the development of technology and increasing demand, the UAV cluster hardware load computing power will become more powerful, the routing algorithms will become more intelligent, and the communication content will become more diverse. The model still have strong universality and will meet the current and future UAV needs.

III. METHOD CONSTRUCTION

A. CONDITIONAL ASSUMPTIONS

This paper is based on CH election and proposes a clustering optimal value model from a mathematical point of view. In this model, the input variable is the total number of drones, and the output is the number of CHs, which can lower the global network communication delay. The global network communication delay divide the delay into several parts: queuing delay, transmission delay and propagation delay. Since the electromagnetic wave has the same speed in the air, the distance between the source node and the destination node is the same, so the propagation delay can be approximated as a constant. The paper mainly consider the influence of the queuing delay and transmission delay.

The clustering model needs to take into account both intracluster and intercluster routing, which is an optimal balance problem. The model considers the communication delay as the only performance reference indicator to solve the cluster optimal value problem in a large-scale UAV cluster using a uniform clustering mode. As shown in Fig.2, the cross-cluster communication model is derived from the following definitions.

1) **DEF 1:** The total number of drones is N, the number of CHs is n, the number of UAVs per cluster is N/n, the global communication delay is T, the intracluster communication (where both the source node and the destination node are in the same cluster) delay is T_i, and the intercluster communication (where the source node and the destination node are in different clusters) delay is T_o;
2) **DEF 2:** The reception rate and transmission rate of all drones are constants λbps and μbps, respectively.
3) **DEF 3:** The probability that any node of the UAV cluster sends information to the other nodes is equal, the size of the transmitted data packet is a constant $m bits$, and the number of destination nodes is used to represent the number of data packets;
4) **DEF 4:** C_i represents the ith cluster and CH_i represents the CH of the ith cluster in the UAV clustering structure.
5) **DEF 5:** S is a data sending node, and D is a data destination node.

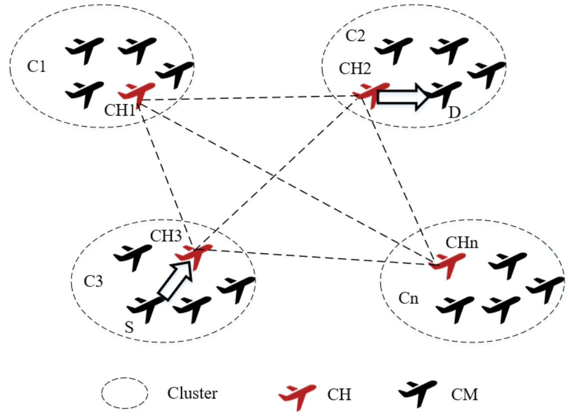


FIGURE 2. Two layer cluster hierarchy of UAV swarms.

B. PROCESS DERIVATION

The global network delay of drone swarms includes intracluster delay and intercluster delay. TDMA technology is adopted at the MAC layer, the entire system bandwidth for an interval of time is equally assigned to each drone. In addition, we supposed that the chances of each UAV receiving the message are equal, so the number of UAVs is used to represent the traffic. Since the UAV sends data to UAVs other than itself, the global traffic is $N-1$, the intracluster traffic is $N/n-1$, and the intercluster traffic is $N-N/n$. The ratio of the intracluster traffic to global traffic η_i is:

$$\eta_i = \frac{N-n}{n(N-1)} \tag{1}$$

The ratio of intercluster traffic to global traffic η_o is:

$$\eta_o = \frac{n-1}{N-1} \cdot \frac{N}{n} \tag{2}$$

S sends an m bits packet, the transmission rate at μbps, and the network delay T is the sum of the queuing delay T_q and the transmission delay T_t.

$$T = T_q + T_t \tag{3}$$

1) QUEUING DELAY

In order to calculate T_q, an M/M/1 queue model [33] is adopted to represent the queue length for a single UAV. The average time spent waiting in the queue denotes the queuing delay. The queuing delay of drone swarms includes intracluster queuing delay and intercluster queuing delay. The model is characterized by the following assumptions:

(i) The reception rate according to a Poisson process with parameter λbps, for $t \geq 0$, the probability density function is:

$$f(t) = \lambda e^{-\lambda t} \tag{4}$$

(ii) UAV service time, s, has an exponential distribution with parameter μbps, for $s \geq 0$, the probability density function is:

$$g(s) = \mu e^{-\mu s} \tag{5}$$

And thus, by (4) and (5), the queue utilization, $\rho = \lambda/\mu$ represents the average proportion of time which the UAV is occupied. And $\rho < 1$ for the queue to be stable in a drone.

(iii) UAV nodes follow the principle of FIFO data processing.

(iv) The buffer is of infinite size, and queue congestion is not considered.

Proposition. The probability that there n packets in the queue is:

$$P_n = \rho^n(1-\rho) \tag{6}$$

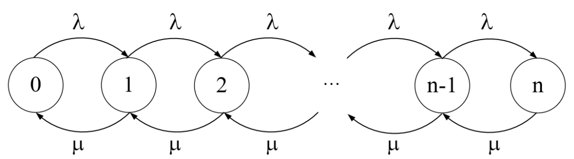


FIGURE 3. The state in the queue process.

The state space diagram for the queue is shown as Fig.3. In a steady state, the expected number of transitions from n-1 up to n must equal the number of transitions from n down to n-1.

$$\lambda P_{n-1} = \mu P_n \tag{7}$$

This is a geometric series, thus

$$P_n = \rho^n P_0 \tag{8}$$

To solve for P_0, observe that

$$\sum_{n=0}^{\infty} P_n = 1 \tag{9}$$

$$P_0 = 1-\rho \tag{10}$$

For each drone node, the expected number of packets in the queue is:

$$\begin{aligned} L_d &= \sum_{n=1}^{\infty}(n-1)P_n = \sum_{n=1}^{\infty}(n-1)\rho^n(1-\rho) \\ &= \rho(1-\rho)\sum_{n=1}^{\infty}(n-1)\rho^{n-1} = \frac{\rho^2}{1-\rho} \\ &= \frac{\lambda^2}{\mu(\mu-\lambda)} \end{aligned} \tag{11}$$

The queuing delay faced by each drone can be calculated as below:

$$T_d = \frac{L_d}{\lambda} = \frac{\lambda}{\mu(\mu-\lambda)} \tag{12}$$

The intracluster queuing delay T_{di} is:

$$T_{di} = T_d \tag{13}$$

The intercluster queuing delay includes the delay from S to CH3, the queuing delay from CH3 to CH2 and the queuing delay from CH2 to D. Thus, the intercluster queuing delay T_{do} is:

$$T_{do} = 3T_d \tag{14}$$

the queuing delay can be obtained as follows:

$$T_q = T_{di} + T_{do} = \frac{4\lambda}{\mu(\mu-\lambda)} \tag{15}$$

2) TRANSMISSION DELAY

T_t represents the time drone takes to push the packets onto the link, including intracluster transmission delay T_{ti} and intercluster transmission delay T_{to}.

$$T_t = T_{ti} + T_{to} \tag{16}$$

The intracluster transmission delay T_{ti} is:

$$T_{ti} = \frac{m}{\mu/((N/n)-1)} \cdot \eta_i \tag{17}$$

The intercluster transmission delay includes the transmission delay from S to CH3, the transmission delay from CH3 to CH2 and the transmission delay from CH2 to D. These values are $m/(\mu/((N/n)-1))$,$m/(\mu(n-1))$ and $m/(\mu/((N/n)-1))$,respectively. Thus, the intercluster transmission delay T_{to} is:

$$T_{to} = (\frac{m}{\mu(n-1)} + 2 \cdot \frac{m}{\mu/((N/n)-1)}) \cdot \eta_o \tag{18}$$

Combining (1), (2), (16), (17) and (18), the transmission delay can be obtained as follows:

$$T_t = \frac{nN(n-1)^2 + 2N(N-n)(n-1) + (N-n)^2}{n^2(N-1)} \cdot \frac{m}{\mu} \tag{19}$$

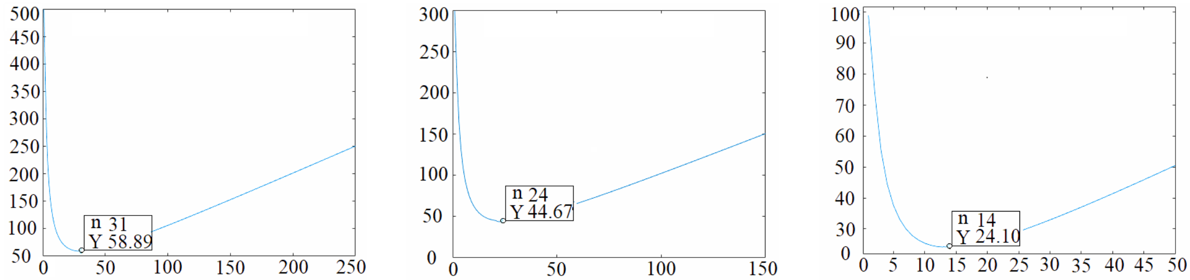
3) NETWORK DELAY

By (3),(15) and (19),the global network delay can be represented:

$$\begin{aligned} T &= T_q + T_t \\ &= \frac{nN(n-1)^2 + 2N(N-n)(n-1) + (N-n)^2}{n^2(N-1)} \cdot \frac{m}{\mu} \\ &\quad + \frac{4\lambda}{\mu(\mu-\lambda)} \end{aligned} \tag{20}$$

Because m, μ and λ are both constants,this article converts the extreme points of T about n into the new function Y, where

$$Y = \frac{nN(n-1)^2 + 2N(N-n)(n-1) + (N-n)^2}{n^2(N-1)} \tag{21}$$



(a) 500 Nodes (b) 300 Nodes (c) 100 Nodes

FIGURE 4. Relationship between Y and the number of CHs. The horizontal axis (X axis) and the vertical axis (Y axis) represent the number of CHs and the value of Y. According to III-A, The coordinate points marked by the box indicate that the minimum Y is achieved when the number of CHs is at this value.

The first derivative of Y to n is found, and $\frac{\partial Y}{\partial n} = 0$, obtaining a total of three extreme points:

$$n_1 = \frac{\sqrt{8N+1}-1}{2},\ n_2 = \frac{-\sqrt{8N+1}-1}{2},\ n_3 = 1 \quad (22)$$

n_2 and n_3 are invalid values, so the function has only one valid extreme point n_1. In addition, $\frac{\partial^2 Y}{\partial n^2} > 0$, Y is a concave function here, so is global communication delay T, and n_1 is a minimum value point. At this time, the global communication delay is the smallest at this point, that is, the optimal number of CHs. And we name it n_o.

Considering the actual clustering situation, the number of CHs should be $[2, N/2]$. Taking $N = 500$, 300 and 100, draw the relationship between Y and n by MATLAB, and mark the effective extreme points.

The trends of the three graphs in Fig. 4 are exactly the same. And the figures exhibit that when the numbers of nodes $N = 500$, 300 and 100, the optimal numbers of CHs $n_o = 31$, 24 and 14 are the lowest points. The corresponding minimum global communication delays are $(\frac{58.89m}{\lambda} + \frac{4\lambda}{\mu(\mu-\lambda)})$, $(\frac{44.67m}{\lambda} + \frac{4\lambda}{\mu(\mu-\lambda)})$ and $(\frac{24.10m}{\lambda} + \frac{4\lambda}{\mu(\mu-\lambda)})$, respectively.

C. APPLICATION PROCESS

In section III-B, the clustering optimal number model of a large-scale UAV cluster is obtained, but it should be noted that N, n, and N/n in the model should be integers. The drone swarms system continuously adjusts the optimal number of CHs according to the change of the number of drones. When the heuristic method is applied to the clustering of drone swarms, the process operation is shown in Table.1.

When the total number of UAV nodes is known, the number of cluster heads is calculated according to the model, and rounding is performed to calculate the number of cluster heads and the number of members per cluster. This minimizes the global communication delay in the case of the number of drones and optimizes network performance.

D. WORKING FRAME OF THE PROPOSED METHOD

Figure 5 depicts the workflow of proposed method in the whole communication mechanism. When the drone swarms generate communication requirements and need to transmit data, the system obtains the current number of swarms through information exchange statistics. Thus, the current optimal number of CHs can be calculated according to the proposed scheme. Then, these datagrams are separately transmitted within the intracluster and intercluster based on the division of the destination IP address. Finally, the drone swarms complete the low latency data communication in the current situation.

TABLE 1. Operation flow.

Operation flow
Input: number of UAVs(N)
Calculate the optimal number of CHs (n_o) according to equation 7
If n_o is an integer
Calculate N/n
if N/n is an integer
Acquire clustering result
else
$round(N/n)$
Acquire clustering result
else
$round(n_o)$
Calculate $N/round(n_o)$
if $N/round(n_o)$ is an integer
Acquire clustering result
else
$round(N/round(n_o))$
Acquire clustering result
End

IV. PERFORMANCE EVALUATION

A. SIMULATION DESIGN

The paper uses OPNET 14.5 to certify the optimal clustering number with ad hoc on-demand distance vector (AODV) routing. In the case of a fixed number of drone swarms, the different numbers of CHs and optimal clustering number of CHs are selected as simulation comparisons to show that the clustering method has the lowest communication delay. The simulation development steps using OPNET are as follows:

1) **Step 1:** Design the node model and link model, and build a wireless network simulation scenario.

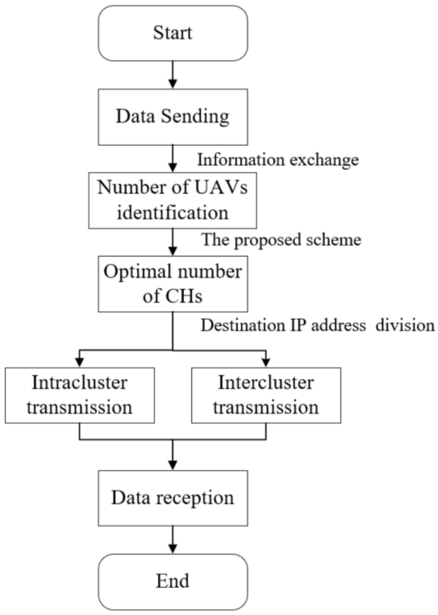


FIGURE 5. Flow chart for the proposed scheme.

2) **Step 2:** Set the simulation parameters and statistical parameters.
3) **Step 3:** Perform parameter optimization simulation and analyze the simulation results.

Fig.6 shows the clustering scene of a drone swarm built by OPNET. The red hexagon represents a cluster. The mobile nodes in the cluster denote the moving drones. Each cluster randomly elects a node as the CH, and the CHs form the internet backbone.

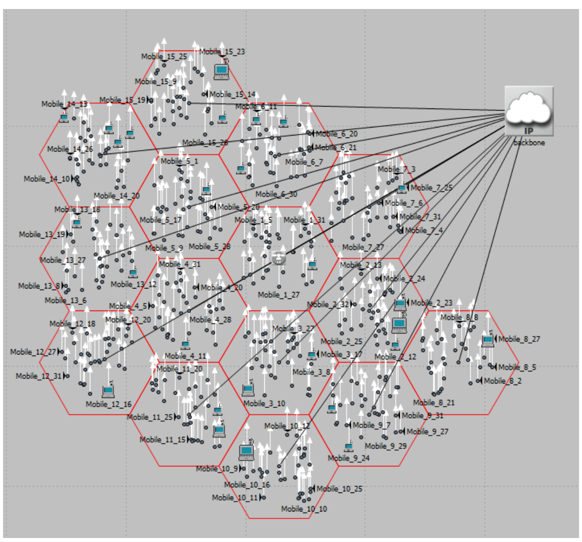


FIGURE 6. The clustering network scenario.

B. PARAMETER SETTINGS

To prove the correctness and adaptability of the clustering method, the parameters and configurations of simulation scenarios are presented in Table 2. As shown in the second row, we select $N = 500$, 300, and 100 as the number of large-scale drone swarms. In the third row, these bold numbers 31, 24, 14 represents the optimal number of CHs in the presence of 500, 300, 100 UAVs according to the proposed method. Other numbers of CHs are chosen as the comparison. We establish corresponding scenarios for five different CHs with OPNET. After the parameters and configurations are set, the communication delay and packet loss rate are selected as the result statistics. Then, the simulation is performed for each scenario for 30 minutes.

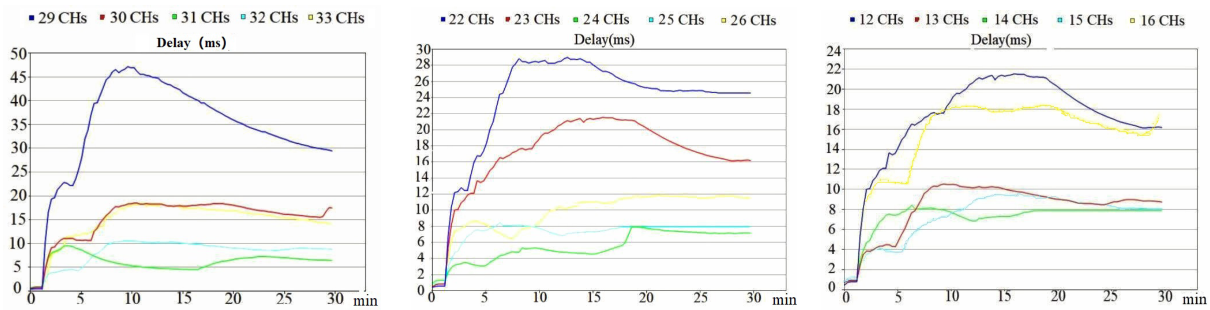
TABLE 2. Simulation scenarios setting.

Parameter	Value
Number of UAVs (N)	500 300 100
Numbers of comparison CHs (n)	29/30/**31**/32/33 22/23/**24**/25/26 12/13/**14**/15/16
Simulation area	10000x10000 sq.m.
Routing protocol	AODV
Wireless mode	802.11b
Multiple access technology	TDMA
Packet size	1024 B
Number of data sending nodes	10
Number of data receiving nodes	Global
UAVs moving speed	5 m/s
Maximum data transfer rate	11 Mbps

C. SIMULATION RESULTS

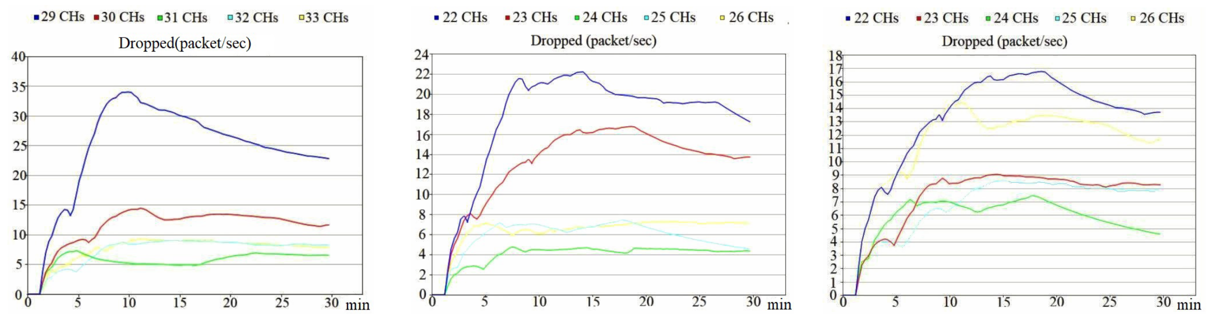
To analyze the performance of the proposed method, communication delay and packet loss rate are selected as statistical results. In Fig.7 and Fig.8, the horizontal axis represents 30 minutes of simulation time, and the vertical axis represents communication delay and packet loss rate of the wireless network, respectively.

1) Communication delay. It means the delay between the first sent byte and the last received byte, which includes transmission delay, process queue delay and propagation delay. The simulation results show that the communication delay increases rapidly with the start of the data transmission, and then decreases slightly after reaching the peak value, gradually becoming but continuing to fluctuate within a certain range. Minimizing communication delay is the goal of the proposed method. According to the proposed method, the optimal numbers of CHs are $n_o = 31$, 24, and 14 in the cases of $N = 500$, 300, and 100, respectively. In Fig.7 (a), (b) and (c), it is evident that the optimal number of CHs achieves the lowest communication delay after the curves are stable. At the same time, the closer the number of optimal CHs is, the lower the corresponding communication delay, which suggests that the clustering model is a concave function at the optimal number of CHs; that is, the clustering method implements low latency communication. It is well known that the more the number of drones, the longer the



(a) 500 Nodes (b) 300 Nodes (c) 100 Nodes

FIGURE 7. Delay comparison with different number of CHs. The curve for each color represents the communication delay that a different number of CHs brings during the simulation.



(a) 500 Nodes (b) 300 Nodes (c) 100 Nodes

FIGURE 8. Packet loss rate comparison with different number of CHs. The curve for each color represents the packet loss rate that a different number of CHs brings during the simulation.

communication delay will be. Fig.7 (a), (b) and (c) also demonstrate this phenomenon.

2)Packet loss rate. It refers to the ratio of the number of data packet lost in the communication process to the number of data groups sent, which represents the integrity of data from sending to receiving. The simulation results show that the packet loss rate maintains the similar trend as the communication delay. The packet loss rate increases rapidly with the start of the data transmission, and then decreases slightly after reaching the peak value, gradually becoming but continuing to fluctuate within a certain range. According to the method, the optimal numbers of CHs are $n_o = 31$, 24, and 14 in the cases of $N = 500$, 300, and 100, respectively. The optimal number of CHs has the lowest packet loss rate after the curves are stable. It can be concluded that the clustering method guarantees low latency while also having a minimum packet loss rate. Meanwhile, Fig.8 (a), (b) and (c) illustrate that the packet loss rate becomes higher as the number of UAVs increases.

V. CONCLUSION

This paper presents a low latency method based on uniform clustering for large-scale drone swarm. CHs play an important role in managing intercluster and intracluster communication. In the proposed scheme, the relationship between the number of CHs and communication delay is derived by mathematical to determine the optimal clustering model. By optimizing total number of CHs in the network, the communication delay is minimized. Besides, the novel method makes it compatible with any existing clustering algorithm, and reduces the wireless communication delay by deriving an optimal number of CHs. The effectiveness of the approach are exhibited with the help of simulation results. Simulation results show that the method can guarantee a low communication delay and low packet loss rate, ensuring low latency communication as well as a low packet loss rate during transmission. Moreover, this method can dynamically guide drone swarms to perform rapid clustering in real time. If some UAVs are destroyed or temporarily added, causing changes in the number of drone swarms, the model can still quickly calculate the optimal number of CHs, thereby dividing and adjusting the drone cluster to ensure real-time dynamic information transmission. Overall, this method can ensure reliable and low latency network communication and realize network optimization management.

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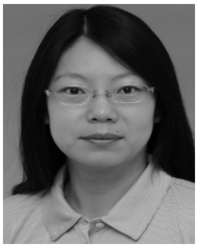

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