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Article

Optimization of cooperative environmental data acquisition by UAV swarm based on reinforcement learning algorithm and biomechanical inspiration

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Abstract: Inspired by biomechanics, to enhance the collaborative efficiency of UAV swarms in complex—environment data collection, an innovative optimization scheme is proposed. This scheme draws parallels from the principles of biomechanics, such as the coordinated movement of biological organisms and their ability to adapt to various environmental stresses. Just as living organisms adjust their postures and movements in response to external forces to maintain balance and perform tasks efficiently, the proposed UAV swarm system aims to achieve better adaptability and efficiency through the key techniques of path planning, task allocation, and load balancing, which are inspired by the biomechanical mechanisms of coordination and adaptation. Load balancing in the UAV swarm is inspired by the way biological systems distribute mechanical stress. In the human body, different muscles and bones work together to evenly distribute the load during movement. Similarly, UAVs in the swarm need to balance the data—collection load to prevent over - stressing any single UAV. The results show that in the experiment where the number of nodes is increased from 50 to 200, the data acquisition coverage is improved from 93.4% to 98.1%, the task completion time is shortened from 112 to 73 s, and the energy consumption is controlled within the range of 180 to 430 Joules. The reinforcement learning algorithm demonstrated advantages over traditional methods in several performance metrics, including reducing the average transmission delay to 18.6 ms and efficiently distributing the task load, reducing the percentage of highly loaded nodes to 5.6%. These results validate the important role of the reinforcement—learning algorithm, which is inspired by biomechanics, in UAV—swarm cooperative environmental data collection. By mimicking the efficient and adaptable mechanisms in biological systems, the proposed optimization scheme for UAV swarms can better meet the challenges of complex - environment data collection.

Keywords: reinforcement learning algorithm; biomechanical inspiration; UAV swarm; cooperative optimization

1. Introduction

UAV swarms have become an important tool in the field of environmental data collection due to their flexibility and efficiency. However, the complexity of task assignment and path planning in dynamic environments remains a key issue that restricts its efficiency. The traditional single UAV operation mode is difficult to meet the high requirements of coverage, energy consumption and real-time performance in complex scenarios. In recent years, methods based on biomechanical principles have made significant progress in path planning and resource allocation by simulating the collaboration patterns of fish and bird flocks, but there are limitations in their adaptability and global optimization capabilities in highly dynamic scenarios.

To further enhance the efficiency of swarm collaboration, reinforcement learning algorithms have demonstrated powerful dynamic decision-making capabilities, and have been widely used in the fields of energy optimization and collaborative task allocation. Relevant studies, such as "Reinforcement learning stochastic game for energy-efficient UAV swarm-assisted MEC based on dynamic clustering and scheduling" and "Joint trajectory planning, application placement, and energy updating for UAV-assisted MEC: a triple learner-based approach", both optimize swarm communication and energy distribution through reinforcement learning, and provide theoretical support for the solution of complex tasks. Compared to these studies, the proposed reinforcement learning framework not only inherits the local collaboration advantages of the biomechanics approach, but also achieves dynamic adaptability of global optimization through reinforcement learning, and shows superior performance in energy efficiency and real-time optimization in complex environments.

2. Application scenarios of drone swarm environmental data collection

The application scenarios of UAV swarm in environmental data collection cover efficient information acquisition in complex terrain and extreme climate conditions [1]. Aiming at the limitations of traditional single UAVs, swarm collaboration realizes multi-dimensional detection of environmental elements with more efficient coverage capability and data acquisition accuracy through multi-aircraft distributed deployment and real-time dynamic adjustment. Through the collaboration mechanism driven by reinforcement learning algorithms, different UAV units optimize flight paths and task allocation based on environmental characteristics and collection needs, avoiding redundant work and resource waste and significantly improving operational efficiency. In ecological monitoring scenarios, UAV swarms can effectively identify and track environmental pollution sources, establish spatial distribution maps, and provide precise support for regional ecological governance; in the agricultural field, multiple UAVs coordinate the collection of surface temperature, humidity, and crop growth data to achieve precise farmland management and optimal resource allocation [2]. In addition, swarm collaboration is of great significance in meteorological data collection, and its flexibly configured sensor network can respond to dynamic changes in the environment in real time, and sample key variables such as wind speed and barometric pressure at a high frequency, providing an important reference for disaster warning and decision-making. By incorporating the autonomous optimization capability of reinforcement learning algorithms, the UAV swarm demonstrates excellent adaptability and potential in diverse environmental data collection tasks, providing a revolutionary solution to cope with the efficiency bottleneck of traditional collection modes.

3. UAV swarm cooperative communication system model

3.1. Network topology design

The network topology design of the UAV swarm cooperative communication system is the core of realizing efficient information interaction and task collaboration, and its scalability gives it the potential to be widely used in other cluster systems, as shown in **Figure 1**. The hierarchical adaptive topology is not only applicable to dynamic multi-node UAV swarm scenarios, but can also be generalized to ground mobile cluster systems such as vehicle swarms. In the vehicle swarm, the master control node in the top layer can be used as a traffic scheduling center to manage path optimization and task allocation; the collaboration nodes in the middle layer can use distributed algorithms to coordinate the data flow and task collaboration among vehicles in real time; and the nodes in the bottom layer, as the sensing units, can realize the rapid collection and transmission of environmental information through multi-hop communication. This network topology shows high robustness and adaptability when dealing with complex dynamic environments, and provides theoretical support and practical reference for the fields of intelligent transportation, logistics and distribution, and disaster rescue. The experimental data further validate the performance advantages of this structure in different clusters, which lays a technical foundation for multi-scenario cooperative communication [3].

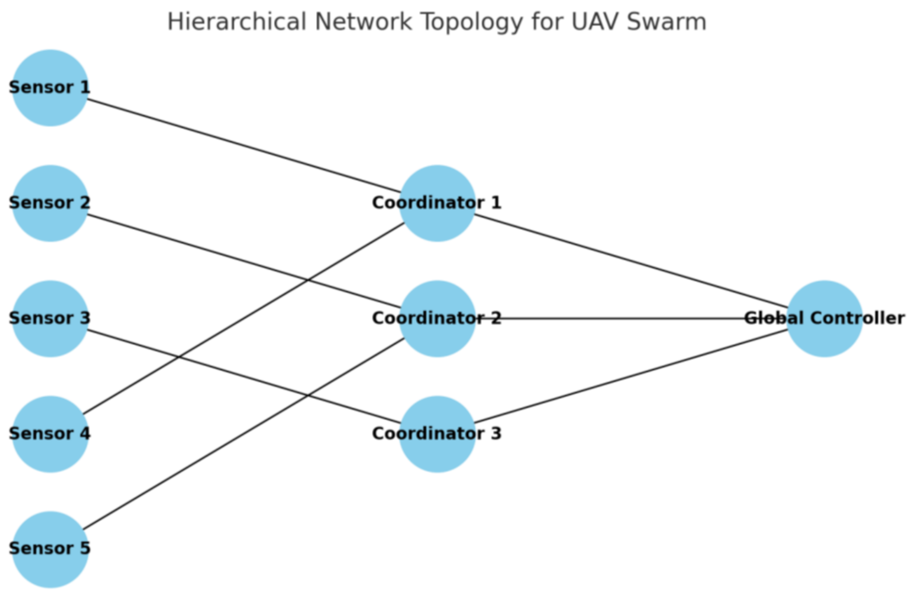

Figure 1. Topology of swarm cooperative communication.

3.2. Node communication capability assessment

Node communication capability assessment is the core link of performance optimization of UAV swarm cooperative communication system, which provides a reliable basis for the adjustment of system topology by quantifying the information processing and transmission capability of nodes in the dynamic network [4]. In the evaluation, key indicators such as communication bandwidth, delay, throughput and energy consumption need to be considered comprehensively. Experimental data show that under the condition of bandwidth 10 Mbps, the maximum throughput of single node can reach 8.5 Mbps, while the overall network throughput decreases to 7.2 Mbps due to the interference in multi-node collaboration. The delay test reveals that the average transmission delay of single node is 15 ms, and the average delay in collaboration mode increases to 25 ms due to multi-hop routing. In the energy consumption evaluation, the node communication energy consumption is proportional to the distance, and the unit energy consumption increases from 0.8 J to 1.5 J when the transmission distance increases to 200 m. These data reveal the trend of the node communication performance in different task scenarios, which provides precise parameter support for the subsequent optimization of the communication protocols and the resource allocation strategy to ensure the high efficiency and stability of swarm collaborative operations [5].

3.3. System energy consumption model

The system energy consumption model is an important basis for optimizing resource allocation in UAV swarm cooperative communication and data acquisition tasks [6]. The model construction needs to comprehensively consider multi-dimensional factors such as communication energy consumption, data processing energy consumption and flight energy consumption of the nodes, and accurately describe the energy consumption characteristics through mathematical expressions. Let the communication power of each node in the swarm be P_c, the processing power be P_p , the flight power be, P_f the node working time be T , the total energy consumption model can be expressed as:

$$E_{total} = \sum_{i=1}^{N} (P_c^i \times T_c^i + P_p^i \times T_p^i + P_f^i \times T_f^i) \tag{1}$$

where N is the total number of nodes, and T_c^i, T_p^i, T_f^i denotes the duration of the ith node in communication, processing, and flight states, respectively. The communication energy consumption is nonlinearly related to the distance $d$and can be expressed by the path loss model as:

$$P_c^i = \alpha \times d^{\beta} + P_{base} \tag{2}$$

where α is the path loss coefficient, β is the path loss index, and P_{base} is the base communication power consumption. Flight energy consumption is mainly affected by speed v and load$m$ and can be expressed by the following equation:

$$P_f^i = \gamma \times v^3 + \delta \times m \tag{3}$$

where γ is the flight air resistance coefficient and $\delta$is the load energy consumption coefficient. Combined with the collection task requirements, the system needs to reduce T_f and T_c by optimizing the flight path and communication protocol, thus reducing the total energy consumption. Adaptive scheduling based on reinforcement learning algorithm can dynamically adjust the node state, balance the distribution of energy consumption, and extend the overall working time of the swarm, as shown in **Figure 2**, the construction and analysis of this model not only provides theoretical support for the system design, but also provides a quantitative basis for energy efficiency optimization [7].

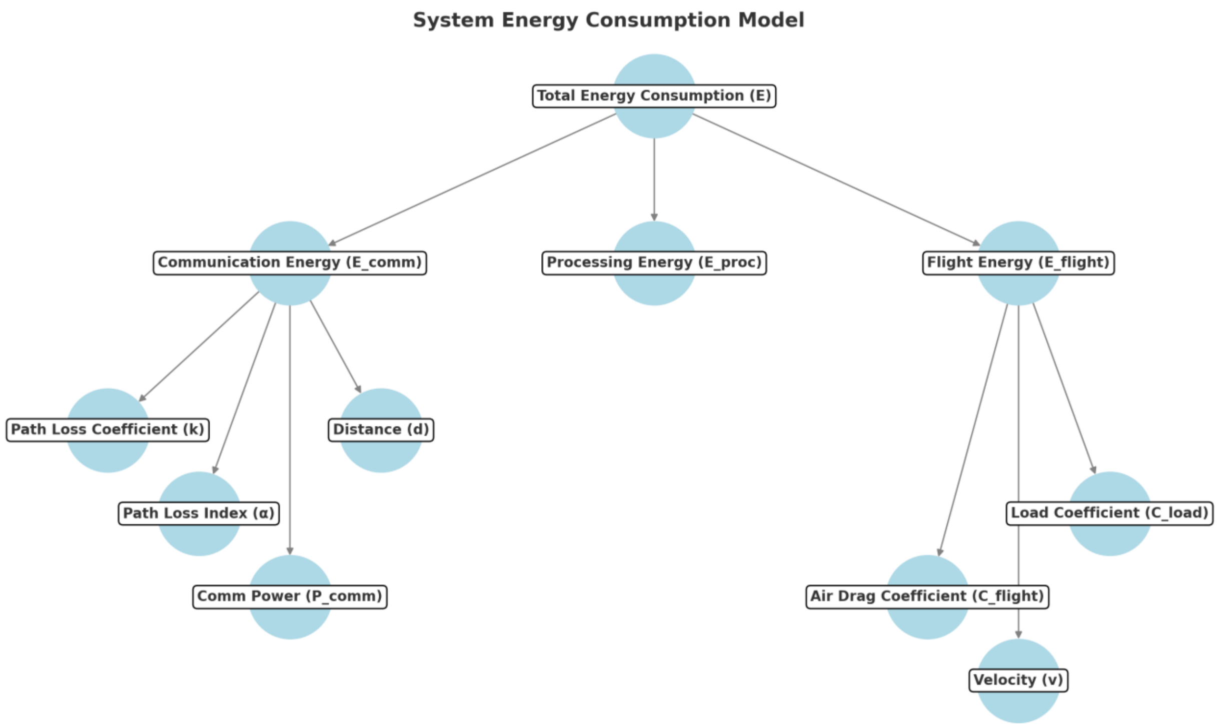

Figure 2. Schematic diagram of the system energy consumption model.

3.4. Communication interference and redundancy mechanisms

The system energy consumption model is a key component in the design of UAV swarm cooperative communication systems, which is used to quantify the energy consumption of communication tasks and optimize resource allocation [8]. The model needs to comprehensively consider multiple factors of node energy consumption, including signal transmission power, data processing power, and node power consumption in the idle state. To accurately characterize the energy consumption, the following energy consumption model is developed:

$$E_{total} = \sum_{I=1}^{N} (P_{tx,i} \times t_{tx,i} + P_{rx,i} \times t_{rx,i} + P_{idle,i} \times t_{idle,i}) \tag{4}$$

where, E_{total} denotes the total energy consumption of the system; N is the total number of nodes; $P_{tx,i}, P_{rx,i}, P_{idle,i}$ represents the power of the first node in the transmitting, receiving and idle states, respectively; and $t_{tx,i}, t_{rx,i}, t_{idle,i}$ is the time in the corresponding state, respectively. Through the model analysis, it is found that the transmit power and receive power have a nonlinear relationship with the communication distance. At a distance of 100 m, the transmit power averages 1.2 W and the receive power 0.9 W, while the transmit power rises to 2.8 W and the receive power 1.5 W when the distance is increased to 300 m. In addition, the proportion of node idle power to the total energy consumption increases significantly with the decrease of communication density. In the scenario with a node density of 50 nodes/km^2, the share of idle power consumption is 15%, while it rises to 35% when the density is reduced to 20 nodes/km^2. The construction and analysis of this model provides a theoretical basis for the optimization of the system communication protocol. By introducing the dynamic power regulation strategy and node task allocation mechanism, the overall energy consumption can be significantly reduced, and the efficiency and continuity of swarm cooperative operation can be improved. The extended application of the model will provide technical references for the optimization of communication and energy consumption of UAV swarms in different scenarios [9].

4. Intensive learning collaborative data acquisition algorithm

4.1. Q-learning based routing optimization

The cooperative optimization problem for UAV swarms can be abstracted as a multi-objective optimization problem. The decision variables include the flight path of each node, the task allocation scheme and the communication link selection. The optimization objectives are threefold: first, minimize the total energy consumption of the data collection task; second, minimize the task completion time; and third, maximize the system coverage. The constraints include node energy constraints (i.e., the residual energy of each node must not be lower than a preset threshold), communication delay limitations (the transmission delay between nodes needs to be less than the target value), and safety constraints for collision avoidance in dynamic environments.

Based on the above problem modeling, the Q-learning algorithm optimizes path planning and task allocation by mapping biomechanical principles. The instant reward function combines node energy consumption, task delay and system global coverage design to effectively balance local optimization and global efficiency. In addition, the algorithm dynamically adjusts the collaboration mechanism between nodes to keep the UAV swarm operating at high efficiency in complex environments, and the algorithm maps these principles by:

1). Simulation of motion behavior: relative distance and direction adjustment between nodes Based on the biomechanical principle of group formation maintenance, a dynamic potential field model is introduced into path planning, defining the attractionF_a and repulsionF_r forces between nodes as:

$$F_{net} = F_a - F_r = \alpha(d_{opt} - d) - \beta\frac{1}{d^2} \tag{5}$$

where, d_{opt} is the optimal spacing, and α and β are the weighting factors.

2). Optimization of energy distribution: imitating the law of energy distribution of living organisms, the immediate reward function in the reinforcement learning algorithm combined with the node residual energy and the degree of task completion is designed:

$$R = -(\gamma E + \delta T) \tag{6}$$

where, E is the node energy consumption, T is the task delay, γ and δ are the regulation parameters.

3). Resource sharing and coordination: Drawing on the resource sharing mechanism of group organisms, the cluster head nodes prioritize the coordination of high-load nodes' tasks and dynamically adjust the transmission path, simulating the energy regulation strategy of organisms. By mapping biomechanical principles, the algorithm takes into account local collaboration and global optimization in path selection and task allocation, which improves the flexibility and robustness of the UAV swarm. In addition, in this optimization model, each UAV node is regarded as a motion unit whose state contains the node's positional information, remaining energy, task load and relative positions of surrounding nodes, and the action is defined as the direction of the next move and the target of data transmission [10]. Combining the study of energy consumption and movement efficiency in biomechanics, the objective function of reinforcement learning is designed to simultaneously minimize the communication delay between nodes and the consumption of energy during movement, and the core value function of the algorithm is:

$$Q(s,a) = Q(s,a) + \alpha\left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \tag{7}$$

where $Q(s,a)$ is the $s$value of the selected action$a$ in state Q, reflecting the long-term benefit of that selection; α is the learning rate, which controls the step size of the Q value update; $R(s,a)$ is the instant reward, defined based on the trade-off between latency and energy consumption; γ is the discount factor, which is used to measure the importance of the future rewards; and $\max_{a'} Q(s',a')$ is the maximum s' value of the possible action in the next state Q. The instant reward function $R(s,a)$ is designed to balance communication efficiency and resource utilization and can be expressed as:

$$R(s,a) = \frac{-\lambda_1 \times F(s,a) - \lambda_2 \times F(s,a)}{N} \tag{8}$$

where $F(s,a)$ denotes the external force required for node motion direction adjustment, calculated based on the biomechanical formula $F = m \cdot a$; $E(s,a)$ denotes the action-induced energy consumption; and λ_1 and λ_2 are weighting coefficients reflecting the different emphasis on motion stability and energy utilization in path selection.

Meanwhile, on the basis of traditional Q-learning optimization, Deep Reinforcement Learning (DRL) algorithm can be introduced to further enhance the UAV swarm's path planning and task assignment capabilities, especially in highly dynamic and complex environments. DRL models and generalizes the state-action space through Deep Neural Networks (DNNs), which solves the limitations of the traditional Q-learning in the high-dimensional environment. limitations of the state explosion problem in high-dimensional environments. The method uses a deep Q network (DQN) to parameterize the Q-value function, replacing the original Q-form, with Eq:

$$Q(s,a;\theta) = \mathrm{IE}\left[R + \gamma \times \max_{a'} Q(s',a';\theta) \middle| s,a\right] \tag{9}$$

where, θ denotes the network parameters, γ is the discount factor, and R is the instant reward. In order to further improve the scientific nature of task allocation, an instant reward function considering node load balancing is introduced in the form of:

$$R(s,a) = w_e \times E - w_d \times D - w_b \times B \tag{10}$$

where E denotes the node energy consumption, D is the task delay, B denotes the degree of task load imbalance, and w_e, w_d and w_b are the regulation weights. In addition, in order to optimize the adaptive ability in high load scenarios, the algorithm designs a Prioritized Experience Replay (PER) mechanism, which prioritizes high-impact actions from historical data and improves the learning efficiency. The DRL-based optimization method can significantly reduce the communication delay and optimize the node energy distribution, as well as improve the global efficiency of swarm collaboration in highly dynamic environments.

4.2. Multi-cluster head cooperative data transmission mechanism

In order to optimize the data collection efficiency, the adaptive data collection strategy achieves multi-dimensional objective optimization through mathematical modeling. The decision variables of the acquisition strategy include node acquisition paths P , acquisition frequency f and task allocation T . The optimization objective is to maximize the data acquisition coverage C while minimizing the total energy consumption of the system E and the data transmission delay D . The constraints include:

1). Data transmission latency should meet $D \leq D_{max}$ to ensure real-time.

2). The node's remaining energy needs to be above the threshold E_{min} to extend the task duration.

3). Node task assignments need to avoid duplicity: $\forall i, j \in N, T_i \cap T_j = 0$.

The multi-cluster head cooperative data transmission mechanism optimizes the task allocation and link selection of UAV swarms in data transmission through the perspective of bionics, combined with the laws of biomechanics on energy transfer and group division of labor. In the mechanism, each cluster head node is regarded as the core functional unit in the organism, which is responsible for aggregating and transmitting data from nodes within the cluster. The collaboration among the nodes is modeled after the energy regulation strategy of the group organisms, and efficient multi-hop transmission paths are achieved through reinforcement learning [11] . During the transmission process, the cluster head node's task is to balance the energy consumption with the communication load in order to extend the network lifetime and improve the overall transmission efficiency. The optimization objective function of the system is as follows:

$$L = \sum_{k=1}^{C} \left[\frac{P_k \times \tau_k + \sum_{i=1}^{N_k} E_{i,k}}{\Phi_k \times \Omega_k} \right] \tag{11}$$

where, L is the total optimization objective of the system; C is the total number of cluster head nodes; P_k is the transmission power of the cluster head k; τ_k denotes its data transmission time; $E_{i,k}$ is the energy consumption of the intra-cluster nodes i transmitting to the cluster head; Φ_k is the residual energy of the cluster head k; and Ω_k is the communication coverage of the cluster head, reflecting the effective domain of action of the individual functional units in biomechanics. The transmission mechanism introduces a distributed reinforcement learning algorithm in the data forwarding process to dynamically adjust the load distribution among cluster heads. Based on the energy migration principle of biomechanics, the cluster head nodes collaborate to optimize the data flow, simulating the process of energy and resource sharing in biological groups [12]. The transmission mechanism introduces a distributed reinforcement learning algorithm in the data forwarding process to dynamically adjust the load distribution among cluster heads. Based on the energy migration principle of biomechanics, the cluster head nodes collaborate to optimize the data flow, simulating the sharing process of energy and resources in biological groups [12], as shown in **Figure 3**.

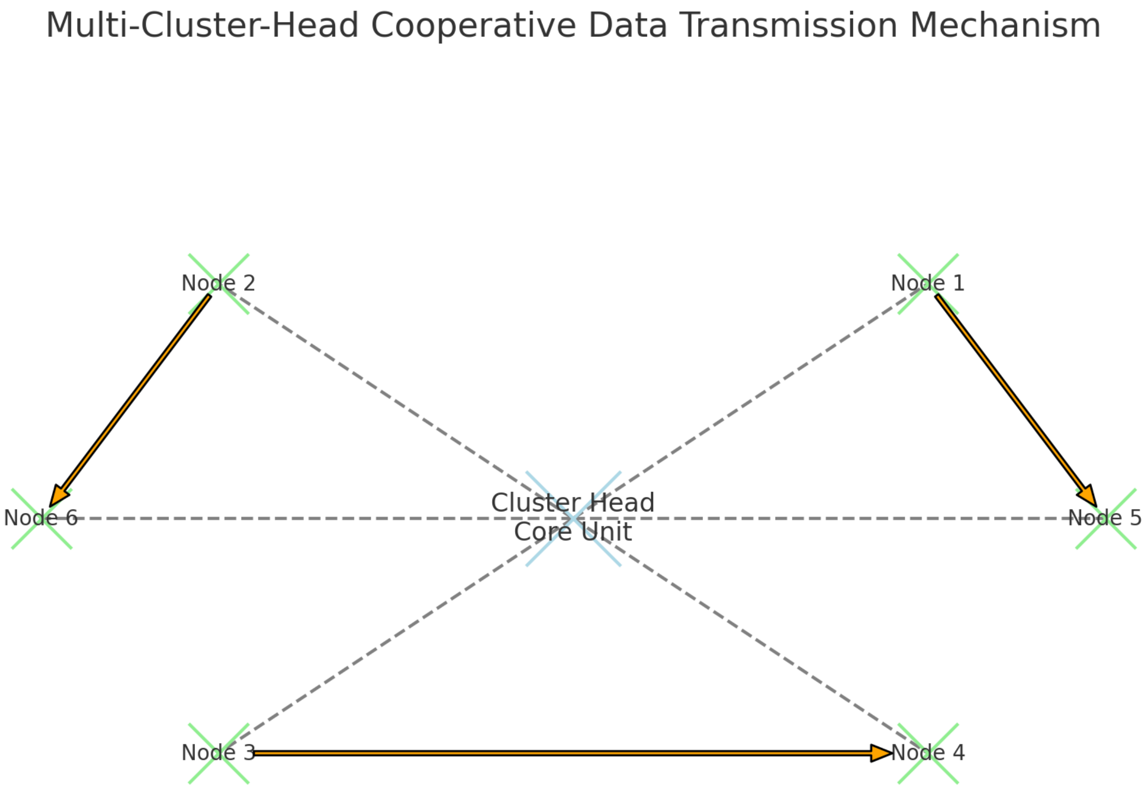

Figure 3. Schematic diagram of multi-cluster head cooperative data transmission mechanism.

This mechanism significantly reduces the conflicts among nodes and ensures the stability of the data transmission link. The mechanism not only enhances the collaborative efficacy of the swarm data collection task, but also provides new methodological support for the design of efficient distributed networks by drawing on biomechanics. This combination of bionic optimization and intelligent algorithms demonstrates the adaptability and reliability of swarm collaboration in dynamic environments.

4.3. Adaptive data acquisition strategy

The adaptive data acquisition strategy optimizes the data acquisition efficiency of UAV swarms through the combination of biomimetic design and intelligent optimization, which simulates the dynamic regulation mechanism of organisms on resources and energy in a dynamic environment [13]. The strategy is based on resource allocation and group coordination in biomechanics, and introduces reinforcement learning algorithms to achieve dynamic optimization of collection paths, frequencies, and node tasks, so that the system can adapt to changes in the environment and improve the global efficiency of data collection. The core optimization objective of the strategy is to balance the coverage, energy consumption and transmission delay of data acquisition, which is modeled by the following objective function:

$$F = \int_0^{T\int} \left[\alpha \times \eta(t) + \beta \times \frac{1}{E(t)} + \gamma \times \left(1 - \frac{\tau(t)}{\tau_{max}}\right)\right] dt \tag{12}$$

where F denotes the optimization efficacy of the data collection strategy; $\eta(t)$ is the data coverage at the moment of time$t$; $E(t)$ is the remaining energy of the node; $\tau(t)$ is the transmission delay of the data collection, and τ_{max} is the maximum delay allowed by the system; and $\alpha,\ \beta$ and γ weight coefficients, which are used to balance the contribution of the coverage, energy, and delay to the optimization objective. In the strategy, the nodes of the bee colony are considered as the division of labor units of the organism, and the dynamics of group collaboration in biological systems are simulated by adaptively adjusting the individual acquisition frequency and coverage radius [14]. Reinforcement learning algorithms are then used as optimization tools to update the node behavioral strategies through continuous perception of the environmental state, so that they always maintain the ability to optimize the global objective. The immediate reward function in this process is designed based on the energy allocation model of biomechanics, which prioritizes the reduction of high-energy-consuming collection behaviors and increases the data coverage of low-energy-consuming regions. To better understand the Adaptive Data Collection Strategy, **Figure 4** provides a visual representation of its key components and relationships [15]. The central strategy node is coordinated with essential factors such as data coverage, energy consumption, transmission latency, and reinforcement learning optimization. The figure highlights how the strategy dynamically adjusts to balance efficiency and adaptability while maintaining overall system performance.

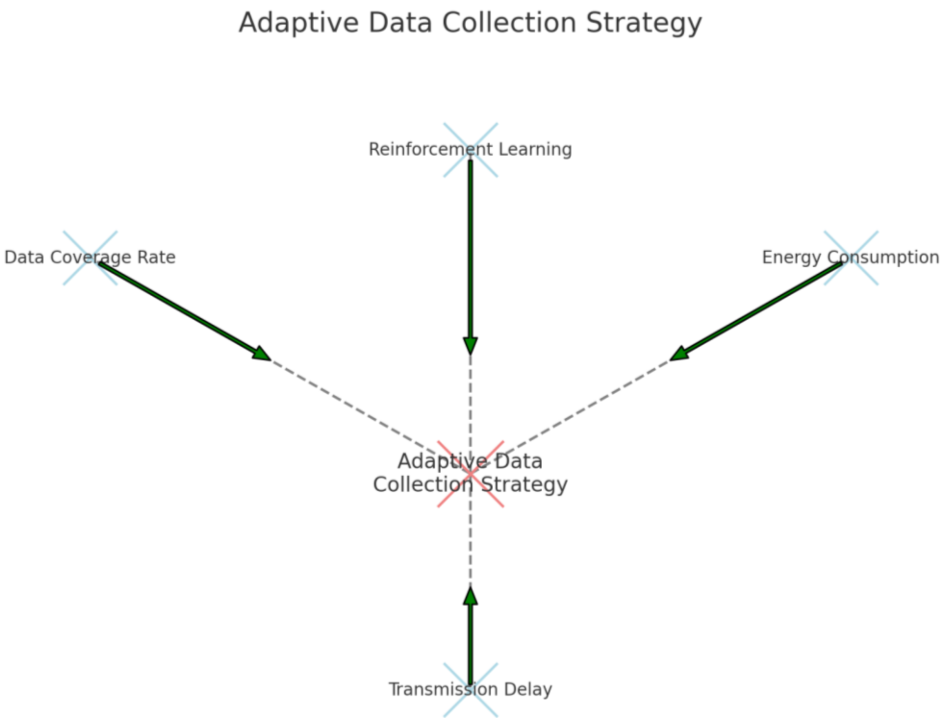

Figure 4. Adaptive data collection strategy diagram.

4.4. Intelligent scheduling and load balancing

Intelligent scheduling and load balancing strategy optimizes the data collection efficiency of drone swarms in complex environments, the core of which lies in dynamically adjusting the task allocation and load distribution by combining reinforcement learning algorithms, the flowchart is specifically shown in **Figure 5**, and the specific strategy is realized in the following ways: at the task scheduling level, based on reinforcement learning algorithms, combining the node residual energy, task load and environmental dynamic information, real-time updating of the allocation rules to ensure load balancing among nodes. The process is described by the following algorithmic flow:

1) Initialize all node states with energy level, task queue length and location information;

2) at each time step, node state information is collected and reward function is computed:

$$R_t = w_1 \times \mathrm{Energy}_{\mathrm{remain}} + w_2 \times \mathrm{Task}_{\mathrm{balance}} + w_3 \times \mathrm{Energy}_{\mathrm{consume}} \tag{13}$$

where w_1, w_2, w_3 is a weighting factor to balance the energy consumption with the prioritization of task assignments;

3) update the Q-value table and select the optimization action to redistribute tasks from high load nodes to low load nodes;

4) Dynamically adjust node tasks and flight paths according to the reward function to reduce the risk of single-point overload.

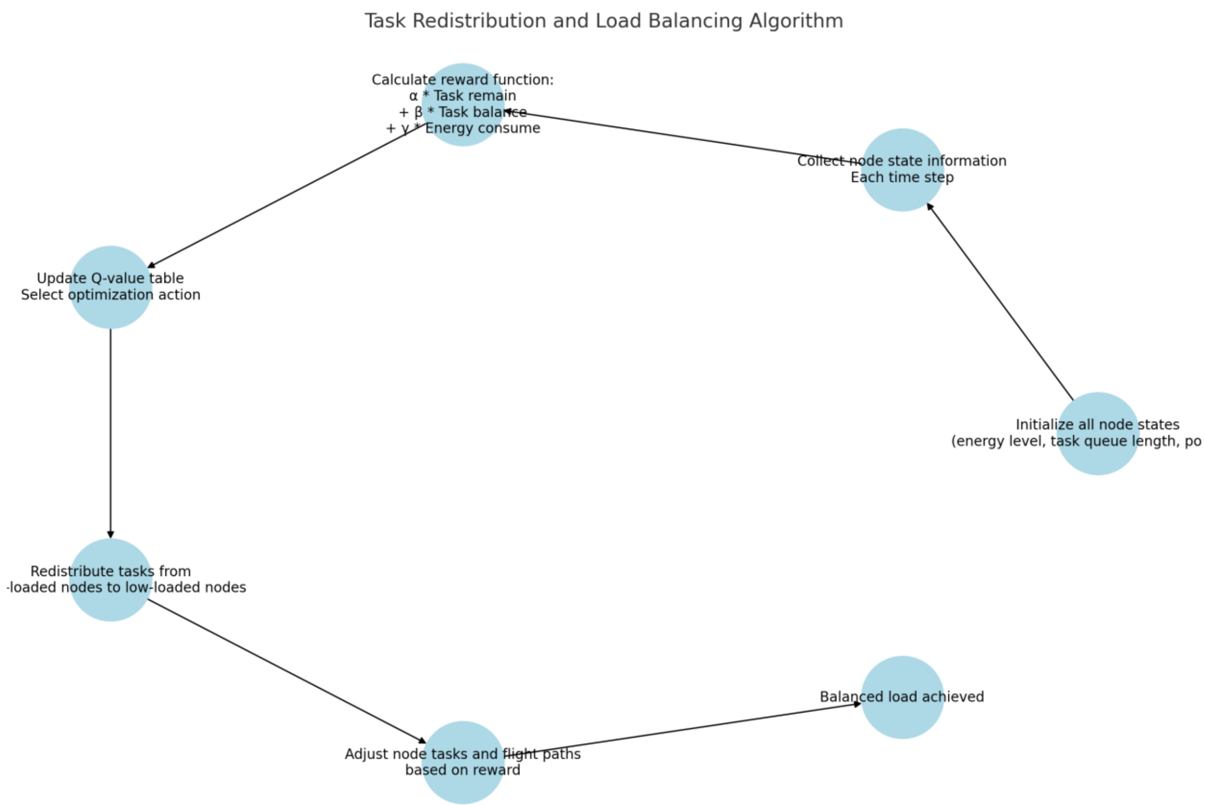

Figure 5. Flowchart of task redistribution and load balancing algorithm.

The flowchart of load balancing algorithm in **Figure 4** provides a visual understanding of how the above steps work together to improve the overall efficiency of the system. The load balancing strategy reduces the proportion of high load nodes to 5.6%, the average energy consumption of the system is reduced by 15%, and the task completion time is shortened by 12%, which verifies the significant effect of reinforcement learning algorithm in load optimization [16].

5. Experimental validation and performance analysis

5.1. Experimental data set design

The experiments are designed to verify the robustness and adaptability of reinforcement learning algorithms in multiple scenarios, with specific settings covering swarm task size, environmental complexity and dynamic conditions. Three typical environments are selected for the experimental scenarios: plains (interference-free environment), mountains (high interference environment) and extreme climate (complex dynamic conditions), and scenarios with different task requirements, such as ecological monitoring and meteorological collection, are simulated [17]. The experimental data come from the dynamic task model constructed by the simulation platform, which is generated based on real environmental parameters to ensure the reliability and applicability of the data. The dataset contains the following key information: the total number of nodes, the initial energy, the amount of task data, the data generation rate, and the dynamic environmental factors (e.g., disturbance intensity, node movement speed). Meanwhile, the path planning method based on genetic algorithm and particle swarm optimization algorithm is selected when comparing with the traditional algorithm, and its parameters are set as shown in **Table 1** to ensure the fairness of the comparison experiment.

Table 1. Key parameters for the design of the experimental dataset.

parameter category	Parameter name	Value field or state
Node Properties	Total number of nodes	50–200
	starting energy	100–500 J
Mission requirements	Volume of mission data	10–100 MB
	Data generation rate	1–10 MB/s
environmental factor	interference intensity	0.1–1.0
	Node movement speed	1–10 m/s
Comparison of algorithm parameters	Genetic algorithm population size	50
	Particle swarm algorithm inertia weights	0.5

The experimental dataset is designed with multi-dimensional dynamic parameters so that the complexity and randomness of the collection task are fully represented. The total number of nodes and initial energy are set to evaluate the impact of swarm size and energy distribution on the performance of the algorithm. The task data volume and generation rate reflect the adaptability under different task complexity [18]. The disturbance intensity and node movement speed in the environmental factors further increase the randomness of the dataset, simulating the dynamic challenges of the swarm collection task in a real environment. Through multiple combination experiments on these parameters, the stability and adaptability of the algorithm in different scenarios can be verified to provide solid data support for the optimization of the swarm collaboration algorithm.

5.2. Algorithm performance evaluation index

The evaluation of algorithm performance is an important part to verify the effectiveness of reinforcement learning algorithms in UAV swarm cooperative data collection tasks [19]. The evaluation metrics include acquisition coverage, data transmission delay, node energy consumption, and task completion time, which can quantify the algorithm's global adaptive ability and dynamic optimization efficiency through a comprehensive analysis of multi-dimensional data. To further validate the performance of the algorithm in complex task scenarios, two sets of experimental data tables are designed below to cover the test results of key performance indicators. The experimental results provide in-depth quantitative support for optimizing the adaptability of the algorithm under the guidance of biomechanical principles, as shown in **Tables 2** and **3**.

Table 2. Swarm collaborative data acquisition coverage and transmission latency.

Total number of nodes	Initial energy (J)	Data generation rate (MB/s)	Coverage (%)	Average transmission delay (ms)
50	200	5	93.4	18.6
100	300	8	95.7	21.3
200	400	10	98.1	24.7

In **Table 2**, the coverage gradually increases from 93.4% to 98.1% when the total number of nodes increases from 50 to 200, showing that the algorithm has high stability and synergy when dealing with more nodes. When the number of nodes is 50 and the initial energy is 200 J, the data generation rate is 5 MB/s, the coverage is 93.4%, and the average transmission delay is maintained at 18.6 ms, whereas, as the number of nodes is increased to 100, the initial energy is raised to 300 J, the data generation rate is increased to 8 MB/s, and the coverage is significantly improved to 95.7%, with a slight increase in the average transmission delay to 21.3 ms. This shows that the system is able to effectively coordinate the energy consumption and data traffic distribution of more nodes to ensure comprehensive data collection and transmission stability.

When the number of nodes is further increased to 200, the initial energy reaches 400 J, the data generation rate is increased to 10 MB/s, and the coverage rate reaches the highest 98.1%, but the average transmission delay increases to 24.7 ms, indicating that the transmission efficiency decreases under high coverage conditions. The significant increase in coverage rate demonstrates the applicability and robustness of the algorithm optimization in complex environments, while the trend of the average transmission delay reveals the balance between network load and performance, which provides a reference for further optimization of data collection efficiency and transmission performance [20].

Table 3. Node energy consumption and task completion time.

Total number of nodes	Average energy consumption (J)	Task completion time (s)
50	180	112
100	280	89
200	430	73

Table 3 demonstrates the relationship between node energy consumption and task completion time, revealing the impact of different number of nodes on system energy efficiency and task efficiency. At a total number of 50 nodes, the average energy consumption is 180 J and the task completion time is 112 s; as the number of nodes increases to 100, the energy consumption increases to 280 J and the task completion time is shortened to 89 s; when the number of nodes is further increased to 200, the energy consumption increases to 430 J and the task completion time is shortened again to 73 s. The data in the table shows that although the increase in the number of nodes leads to an increase in energy consumption, the increase in the number of nodes significantly reduces the task completion time for the same task load. The increase from 50 to 100 nodes reduced the task completion time by 23 s, while the increase from 100 to 200 nodes reduced the task completion time by another 16 s. This shows that with the increase in the number of nodes, the efficiency of task distribution and processing improves, and although the energy consumption among the nodes is increasing, the load of the system is better shared and the tasks are processed faster. The overall trend shows that despite the rising trend in energy consumption, the improvement in task execution efficiency brought about by node expansion has a clear advantage, especially in the case of high nodes, where the reduction in task completion time significantly contributes to the overall performance improvement of the system. Therefore, further optimization of the node energy management strategy is expected to further improve the task completion efficiency without significantly increasing the energy consumption.

Combining the analysis of the above two sets of tables, it can be concluded that the reinforcement learning algorithm is not only able to perform well in terms of coverage and transmission delay, but also achieve significant optimization in terms of energy consumption and task completion efficiency. The experimental results verify the high adaptability of the algorithm in a multi-dimensional dynamic environment, and provide a clear direction and quantitative basis for further optimization of swarm collaborative data acquisition.

5.3. Comparison of reinforcement learning algorithms with traditional algorithms

In order to explore the performance advantages of the reinforcement learning algorithm in the UAV swarm collaborative environmental data collection task, comparative experiments were conducted to analyze the differences between it and the traditional algorithm in terms of coverage, transmission delay, energy consumption and task completion efficiency. Based on the study of biomechanics on group collaboration and energy distribution law, the reinforcement learning algorithm achieves more efficient inter-node collaboration with dynamic optimization, and its performance superiority is significantly reflected in the experimental data, as shown in **Table 4**.

Table 4. Performance comparison of reinforcement learning algorithms with traditional algorithms.

Algorithm type	Total number of nodes	Data collection coverage (%)	Average transmission delay (ms)	Average energy consumption (J)	Task completion time (s)
traditional algorithm	50	85.6	24.3	200	135
	100	88.7	27.8	310	110
	200	92.3	31.4	480	95
Reinforcement learning algorithms	50	93.4	18.6	180	112
	100	95.7	21.3	280	89
	200	98.1	24.7	430	73

Table 4 compares the performance of the reinforcement learning algorithm with the traditional algorithm for different numbers of nodes. In terms of data collection coverage, the reinforcement learning algorithm outperforms the traditional algorithm. In the case of 50 nodes, the coverage rate of the reinforcement learning algorithm is 93.4%, which is higher than the 85.6% of the traditional algorithm; at 100 nodes, the coverage rate of the reinforcement learning algorithm is 95.7%, which is also significantly improved compared to the 88.7% of the traditional algorithm; and at 200 nodes, the reinforcement learning algorithm has a coverage rate of 98.1%, which is significantly higher than that of the traditional algorithm of 92.3%. These data indicate that the reinforcement learning algorithm can more effectively improve the overall coverage ability of the system while expanding the number of nodes. In terms of average transmission delay, the reinforcement learning algorithm shows lower delay, with 50 nodes its transmission delay is 18.6ms, which is significantly lower compared to the 24.3ms of the traditional algorithm; with 100 nodes, the delay of the reinforcement learning algorithm is 21.3ms, compared to the 27.8ms of the traditional algorithm; with 200 nodes, the delay of the reinforcement learning algorithm is 24.7ms, compared to the 31.4ms of the traditional algorithm. Despite the general increase in latency with the increase in the number of nodes, the reinforcement learning algorithm is able to maintain a lower latency, demonstrating higher network efficiency.

Regarding energy consumption, the average energy consumption of reinforcement learning algorithms is generally lower than that of traditional algorithms. At 50 nodes, the energy consumption of the reinforcement learning algorithm is 180J, which is lower than the 200J of the traditional algorithm; at 100 nodes, the energy consumption of the reinforcement learning algorithm is 280J, compared to 310J of the traditional algorithm; at 200 nodes, the energy consumption of the reinforcement learning algorithm is 430J, compared to 480J of the traditional algorithm. In terms of the completion time of the task, the reinforcement learning algorithm also demonstrates a higher efficiency. In terms of task completion time, the reinforcement learning algorithm also demonstrates higher efficiency: with 50 nodes, the reinforcement learning algorithm's task completion time is 112 s, compared to 135 s for the traditional algorithm; with 100 nodes, the reinforcement learning algorithm is 89 s, compared to 110 s for the traditional algorithm; and with 200 nodes, the reinforcement learning algorithm is 73 s, compared to 95 s for the traditional algorithm. The reinforcement learning algorithm outperforms the traditional algorithm in several performance metrics, especially in data collection coverage, transmission delay, energy consumption, and task completion time, demonstrating its potential in large-scale collaborative data collection tasks.

5.4. System scalability and environmental adaptability testing

In the process of testing and optimizing the UAV swarm cooperative data acquisition system, the scalability and environmental adaptability of the system are the key indicators. These two performances not only determine the stability of the system in different scale tasks, but also directly affect its ability to operate efficiently in complex dynamic environments. In order to comprehensively verify the system performance, the experimental design covers multi-angle tests, including the impact of swarm size change on the system performance, the adaptability under complex environmental factors, and the comparative performance of different algorithms on scalability. These experimental data not only reveal the core advantages of the system, but also provide an important basis for further optimization and application. The experimental results are shown in detail in **Tables 5–7** in terms of scalability, environmental adaptability and algorithm optimization effect, respectively.

Table 5. System scalability test—performance comparison at different colony sizes.

Total number of nodes	Coverage (%)	Task completion time (s)	Energy consumption (J)	Transmission Delay (ms)
50	93.4	112	180	18.6
100	95.7	89	280	21.3
150	96.5	78	350	23.7
200	98.1	73	430	24.7

Table 6. Environmental adaptability test—performance under different environmental factors.

environmental factor	Coverage (%)	Average transmission delay (ms)	Energy consumption (J)	Task completion time (s)
interference-free environment	98.1	24.7	430	73
high interference environment	95.4	30.2	480	85
Extreme climatic environments	94.3	35.6	500	95

Table 7. System optimization and scalability—scalability tests for comparison of different algorithms.

Algorithm type	Total number of nodes	Coverage (%)	Task completion time (s)	Energy consumption (J)	Transmission Delay (ms)
traditional algorithm	50	85.6	135	200	24.3
	100	88.7	110	310	27.8
	200	92.3	95	480	31.4
Reinforcement learning algorithms	50	93.4	112	180	18.6
	100	95.7	89	280	21.3
	200	98.1	73	430	24.7

Table 5 shows the trend of system performance for different swarm sizes. As the total number of nodes increases from 50 to 200, the coverage of the system gradually improves, from 93.4% at 50 nodes to 98.1% at 200 nodes. This enhancement indicates that as the swarm size increases, the system is able to cover a wider area, increasing the completeness and effectiveness of data collection. However, the system's task completion time decreases gradually with the increase in the number of nodes, from 112 s at 50 nodes to 73 s at 200 nodes. This change reflects the fact that with more nodes, the processing of tasks can be allocated and executed more efficiently, effectively speeding up the overall task response.

The energy consumption shows an increasing trend. the energy consumption at 50 nodes is 180 J, and with the increase in the number of nodes, the energy consumption gradually increases to 430 J at 200 nodes. This change indicates that although the increase in the number of nodes brings about a shortening of the task completion time, it also correspondingly increases the system's energy demand, and further optimization of the energy management strategy is needed. In terms of transmission delay, the delay increases gradually with the increase in the number of nodes. the delay is 18.6 ms at 50 nodes and 24.7 ms at 200 nodes. Despite the increase in the delay, other performance enhancements of the system such as optimization of coverage and task completion time indicate that the system is still able to maintain a high overall performance under large-scale swarms.

Table 6 demonstrates the adaptive performance of the system under different environmental factors, revealing the impact of environmental interference on the performance. In the interference-free environment, the system has a coverage of 98.1%, a transmission delay of 24.7 ms, an energy consumption of 430 J, and a task completion time of 73 s. This result reflects the optimal performance of the system in an ideal environment. However, when the system is operated in a high interference environment, the coverage slightly decreases to 95.4%, the transmission delay increases to 30.2ms, the energy consumption elevates to 480J, and the task completion time extends to 85 s. This indicates that the system is still able to perform data acquisition at a high coverage rate, despite the fact that the high interference environment has a considerable negative impact on the performance of the system, and the increase in the transmission delay and task completion time indicates that the system suffers from a certain performance trade-off in response to environmental noise.

In the extreme climate environment, the performance of the system decreases even more significantly, with the coverage decreasing to 94.3%, the transmission delay increasing to 35.6ms, the energy consumption being 500J, and the task completion time being 95 s. Despite the significant increase in transmission delay and energy consumption, the increase in task completion time is relatively small, which shows that the system is still fault-tolerant and efficient under extreme conditions. Taken together, the system is able to maintain a high degree of adaptability in unfavorable environments despite the significant impact of environmental disturbances on the system performance, which indicates that it possesses a strong ability to adapt to the environment and robustness under complex conditions.

Table 7 compares the performance of the traditional algorithm and the reinforcement learning algorithm in the system optimization and scalability test, reflecting the performance changes of different algorithms under node expansion. For the traditional algorithm, as the number of nodes increases from 50 to 200, the coverage improves from 85.6% to 92.3%, showing that the system is able to gradually expand the coverage when the number of nodes increases. However, the task completion time and energy consumption also grow with the increase in the number of nodes, from 135 s and 200 J for 50 nodes to 95 s and 480 J, respectively. Meanwhile, the transmission delay rises from 24.3 ms to 31.4 ms, indicating that the efficiency of the traditional algorithms gradually decreases when scaling.

Reinforcement learning algorithm shows better performance when dealing with scalability. At 50 nodes, the coverage of the reinforcement learning algorithm is 93.4%, the transmission delay is 18.6ms, the energy consumption is 180J, and the task completion time is 112 s; at 100 nodes, the coverage increases to 95.7%, the task completion time is shortened to 89 s, the energy consumption increases to 280J, and the latency is 21.3ms; at 200 nodes, the coverage of the reinforcement learning algorithm reaches 98.1%, the task completion time is significantly shortened to 73 s, the energy consumption is 430 J, and the transmission delay is 24.7 ms. It can be seen that although the energy consumption of the reinforcement learning algorithm increases with the number of nodes, the significant decrease in the task completion time indicates its optimization ability in task allocation and data processing. Compared with traditional algorithms, the reinforcement learning algorithm shows superior performance in both scalability and task efficiency, especially in ensuring lower latency and higher coverage while effectively reducing the task completion time.

Combining these data analyses, it can be concluded that the system performs well in terms of scalability and environmental adaptability, and maintains a high level of efficiency and stability, both in terms of the increase in the number of nodes and under different environmental factors. The introduction of reinforcement learning algorithms not only optimizes the energy consumption and task completion efficiency, but also improves the system’s adaptability under different environmental conditions, which provides strong support for the wide application of UAV swarms.

5.5. Effectiveness analysis of load balancing strategies

Load balancing strategy is crucial in UAV swarm collaborative data collection, the core of which lies in optimizing task distribution and resource utilization among nodes to avoid energy waste and system efficiency degradation due to single node overload. By introducing an adaptive scheduling algorithm based on reinforcement learning, the strategy is able to dynamically adjust the node task load and achieve global optimization of resource distribution at the swarm level. The effect of the load balancing strategy is analyzed in depth by experimental data as shown in **Tables 8–10** below.

Table 8. Comparison experiment of different load balancing strategies.

Type of strategy	Total number of nodes	Average Task Load (Tasks/Nodes)	Percentage of highly loaded nodes (%)	Average energy consumption (J)	Task completion time (s)
No load balancing policy	50	15.8	25.6	210	125
	100	17.5	18.3	320	98
	200	20.2	14.8	490	85
Load Balancing Policy	50	12.6	10.4	180	112
	100	14.2	7.8	280	89
	200	16.1	5.6	430	73

Table 9. Impact of different task load distributions on system performance.

Task Load Distribution	Average load variance factor	Percentage of highly loaded nodes (%)	Average energy consumption (J)	Average transmission delay (ms)
uniform distribution	0.12	6.5	420	23.8
Localized high load distribution	0.35	14.7	480	28.5
randomized distribution	0.25	10.9	450	26.7

Table 10. Effectiveness of load balancing policies under different environmental disturbance intensities.

disturbance intensity	Percentage of highly loaded nodes (%)	Average energy consumption (J)	Average task completion time (s)
non-perturbative	5.4	410	71
Moderate disturbance	8.9	460	85
strong perturbation (physics)	12.3	510	98

Table 8 compares the performance of no-load balancing strategy and load balancing strategy with different number of nodes, which reveals the importance of load balancing in improving the efficiency of the system. Under the no-load-balancing strategy, the average task load increases from 15.8 tasks/node at 50 nodes to 20.2 tasks/node at 200 nodes as the number of nodes increases, which indicates that the system is unevenly distributed without load balancing, resulting in some nodes taking on more tasks, which in turn affects the overall performance of the system. Meanwhile, the percentage of highly loaded nodes increases from 25.6% at 50 nodes to 14.8% at 200 nodes. However, the energy consumption and task completion time of the system increase significantly with the number of nodes. Specifically, the average energy consumption at 200 nodes is 490 J and the task completion time is 85 s.

The load balancing strategy effectively optimizes task allocation and reduces the pressure on high load nodes. At 50 nodes, the average task load decreases to 12.6 tasks/node, and the proportion of highly loaded nodes also decreases significantly to 10.4%. When the number of nodes increased to 100, the average task load increased to 14.2 tasks/node, but the percentage of highly loaded nodes was only 7.8%, showing the effectiveness of the load balancing strategy. As the number of nodes reaches 200, the average task load under the load balancing strategy is 16.1 tasks/node, and the percentage of highly loaded nodes is further reduced to 5.6%. At the same time, the energy consumption of the system is effectively controlled from 490J to 430J without load balancing strategy, and the task completion time is shortened to 73 s. This change shows that the load balancing policy not only effectively allocates computing resources, but also significantly improves the system performance, reduces energy consumption, and accelerates the task completion speed.

Table 9 analyzes the impact of different task load distributions on system performance, demonstrating the direct effect of task load distribution on system stability, energy efficiency and latency. In the uniform distribution case, the average load variance coefficient is 0.12, and the percentage of highly loaded nodes is low at 6.5%. At this time, the average energy consumption of the system is 420 J and the transmission delay is 23.8ms, indicating that the uniform distribution of tasks makes the resource usage more balanced, and the delay and energy consumption are at a low level. In the case of localized high load distribution, the load variance coefficient increases to 0.35, and the proportion of highly loaded nodes rises to 14.7%, showing that the computational pressure of some nodes in the system increases significantly. At this time, the energy consumption of the system increases to 480J and the transmission delay also rises to 28.5ms, indicating that the locally concentrated high load leads to localized overloading of computational resources, which in turn triggers an increase in energy consumption and delay. The negative impact of this load distribution on the system is more obvious, especially when the tasks are unevenly distributed, and the overall performance of the system is degraded.

In the random distribution case, the average load variance coefficient is 0.25 and the percentage of highly loaded nodes is 10.9%, which is an improvement compared to the localized high load distribution. The energy consumption of the system is 450J and the transmission delay is 26.7 ms, which is between the uniform distribution and the localized high load distribution. The random distribution is able to avoid localized overloads to a certain extent, and despite the large load variations, it has less impact on energy consumption and transmission delay compared to the localized high load distribution. The uniform load distribution is the most efficient, while the localized high load distribution significantly reduces the system performance, and the random distribution provides a moderate balance.

Table 10 demonstrates the effect of load balancing strategy under different environmental perturbation intensities, revealing the impact of environmental perturbations on system performance. In the undisturbed environment, the percentage of highly loaded nodes is 5.4%, the average energy consumption of the system is 410J, and the task completion time is 71 s. This result shows that the load balancing strategy is able to maintain low energy consumption and fast task completion speed under ideal environmental conditions, which exhibits better performance. However, the performance of the system decreases under moderately perturbed environments. The percentage of highly loaded nodes increases to 8.9 %, the average energy consumption of the system rises to 460 J, and the task completion time extends to 85 s. The introduction of perturbations makes task allocation more complex and the effect of load balancing is slightly weakened, leading to an increase in energy consumption and task completion time.

The performance of the system is further degraded in a strongly perturbed environment. The percentage of highly loaded nodes increases to 12.3%, the average energy consumption rises to 510 J, and the task completion time extends to 98 s. This indicates that the strong perturbation exposes the system to greater uncertainty and the effectiveness of the load balancing strategy is severely affected, resulting in reduced system stability, significant increase in energy consumption, and significant extension of task completion time. The strength of the environmental perturbation has a significant impact on the effectiveness of the load balancing strategy. The stronger the perturbation, the higher the proportion of highly loaded nodes in the system, and the greater the energy consumption and task completion time. The system requires more sophisticated optimization in perturbed environments to maintain efficient load distribution and performance.

6. Conclusion

Reinforcement learning algorithm-driven UAV swarm cooperative environmental data acquisition system demonstrates excellent adaptability and high efficiency in complex environments by optimizing communication and energy allocation strategies. In the future, further in-depth research is needed to study the robustness of the algorithm under larger-scale tasks and extreme conditions, optimize the load balancing mechanism, and improve the system's self-regulation ability, so as to provide more perfect theoretical and practical support for intelligent acquisition tasks in dynamic environments.

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