Optimizing the Fault Localization Path of Distribution Network UAVs Based on a Cloud-Pipe-Side-End Architecture

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***Abstract*—The currently proposed optimization algorithm for cooperative fault inspection of distribution network UAVs struggles to accurately detect fault points quickly, leading to low inspection efficiency. To address these issues, we investigate a new fault localization path optimization algorithm for distribution network UAVs based on a cloud-pipe-edge-end architecture. This architecture employs multiple drones for coordinated control, allowing for the simultaneous detection of suspected fault areas. Communication links facilitate interaction at both the drone and system levels, enabling the transmission of fault diagnosis information. Fault defects are identified, and the information is analyzed within an edge computing framework to achieve precise fault localization. Experimental results demonstrate that the proposed algorithm significantly enhances detection speed and accuracy, providing robust technical support for UAV operations.**

***Keywords*—Cloud-pipe-edge-end architecture; distribution network UAV; cloud-edge collaboration; edge computing**

I. Introduction

With the continuous development of high and new technology, UAVs are more and more widely used in various industries. With the support of IoT technology, UAV, as a new type of electric power inspection tool, has the advantages of wide inspection range, high efficiency, low cost, etc., and has been widely used in power systems. Therefore, it is necessary to continuously improve the distribution network UAV inspection and fault location system, optimize the flight path planning and positioning algorithms to adapt to the development needs of the power system, and improve the fault location accuracy and inspection efficiency. At present, the path planning of distribution network UAVs mainly adopts the rule-based method, which is simple and easy to implement but cannot adapt to the complex environment and task requirements. The study in [1] uses YOLOv5 machine vision technology to optimize the planning of unmanned aerial vehicle inspection paths, which requires control and coordination of multiple unmanned aerial vehicles. However, this method does not have a supporting multi-objective unmanned aerial vehicle cluster control technology, making it difficult to achieve multi-path collaborative planning. The study in [2] uses an adaptive multi heuristic ant colony algorithm to improve the problem of missing local path planning for unmanned aerial vehicles. It sets threshold restrictions on pheromones and uses adaptive heuristic function factors to transition the states of all nodes in the inspection path, achieving local path planning. However, when facing complex inspection environments, the overall path planning of this method is easily affected by local factors, resulting in path redundancy and increased time consumption. The study in [3] adopts the fast search random tree RRT algorithm to randomly generate connections through task nodes, analyze the distance between the path and obstacles, and plan the path of multi UAV collaborative tasks, which has certain feasibility in shortening the flight path distance. But the search range of this algorithm is limited, which will have an impact on the running time of the drone. In response to the above shortcomings, this article proposes a drone cluster control technology based on cloud management edge architecture to optimize the planning of fault location paths for distribution network drones. The establishment of cloud management side end architecture for joint control of multiple UAVs, the determination of suspected fault areas through synchronous detection, and the analysis of fault information in the edge computing logic framework can achieve cluster control and optimal path planning for distribution network UAVs, accurate fault diagnosis and location, effectively remedy the shortcomings of multi UAV patrol in complex environments, such as the difficulty of coordination and long control time, and provide new ideas and methods for the application of UAVs in power patrol and other fields.

II. Research Method

A. Distribution Network UAV Inspection Control based on Cloud-Pipe-Side-End Architecture

1) Cloud pipe edge technology architecture: Cloud-managed edge-end architecture is an architecture that combines cloud computing, edge computing, and end devices to realize efficient management and control of IoT devices [4]. In cloud-pipe-edge-end architecture, cloud computing is responsible for storing and processing large amounts of data and providing various applications and services; edge computing is responsible for processing data close to the data source in order to reduce the latency and cost of data transmission; and end devices are responsible for collecting and transmitting data.

Cloud-pipe-side-end architecture is an emerging architecture that provides new ideas and methods for the development of the Internet of Things, and the application of this technology to the distribution network UAV inspection system has the following advantages:

a) Improve efficiency: By distributing computing and storage resources on different levels, the efficiency and response speed of the system can be improved.

b) Reducing cost: By processing data on edge computing nodes, the delay and cost of data transmission can be reduced.

c) Improve reliability: By distributing computing and storage resources on different levels, the reliability and fault tolerance of the system can be improved [5].

d) Expanding application scope: By combining cloud computing, edge computing, and terminal devices, the application scope of IoT can be expanded.

2) Cloud edge cooperative UAV inspection control system: UAVs play an essential role in power systems in distribution network fault inspection and line monitoring. However, UAV inspection and control systems usually face challenges such as large data volume, high transmission latency, and limited computational resources. In order to solve these problems, the cloud-pipe-side-end architecture is applied to the UAV inspection and control system. The structural framework of the cloud-edge cooperative UAV inspection control system based on the cloud-pipe-edge-end architecture is shown in Fig. 1.

a) Cloud platform: The cloud platform is responsible for storing and processing a large amount of data generated during UAV inspection [6]. It provides robust computation and storage capabilities that enable in-depth analysis and processing of data, as well as a variety of applications and services, such as data visualization, mission planning, and flight path optimization.

b) Edge nodes; Edge nodes are located at the edge of the network, close to UAVs and sensors. They are responsible for processing and analyzing the data collected by UAVs in real time to reduce the delay of data transmission; edge nodes can also perform some critical control tasks, such as flight control, mission assignment, etc.

c) UAV terminal: The UAV terminal includes the UAV itself and various sensors, which are responsible for collecting data and transmitting them to the edge node or cloud platform [7]. The UAV terminal can also receive control commands and perform corresponding tasks.

Through the cloud-pipe-edge architecture, the UAV inspection and control system can realize efficient data processing and transmission. The cloud platform provides powerful computing and storage capabilities, the edge node reduces the delay of data transmission, and the UAV terminal ensures real-time data collection and task execution [8]. It brings higher efficiency, reliability, and scalability for UAV distribution network inspection and fault localization and provides better support for the application of UAVs in various fields. Fig. 2 shows overall structure of the UAV inspection control system.

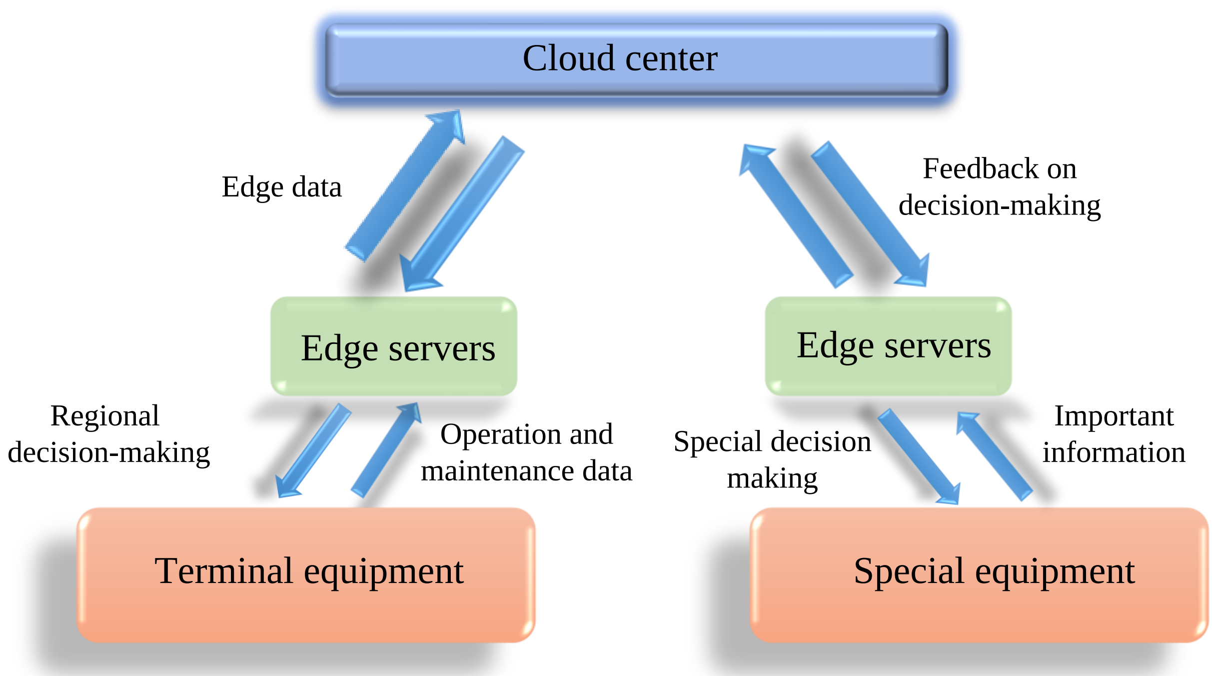


Fig. 1. Technical architecture of cloud-pipe-edge-end architecture.

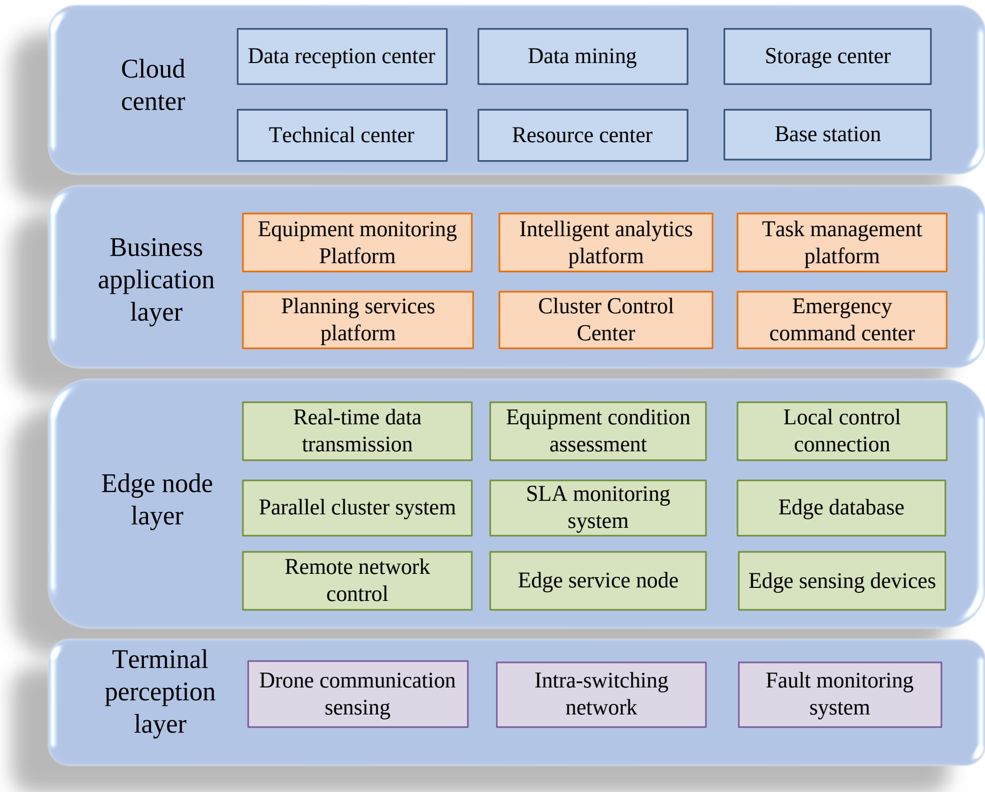


Fig. 2. Overall structure of the UAV inspection control system at the edge of the cloud pipe.

III. Distribution Network Fault Localization UAV Inspection Path Planning

A. Fault Localization based on Edge Computing

In the process of distribution network inspection, the UAV collects distribution network-related localization data, including location information such as lines, equipment, receiving base station, relative distance, etc., by means of the onboard LiDAR sensor. The collected data is transmitted in real time to the grid system server for edge computing [9]. The received edge server data is processed in real time to extract the positional feature information of the edge deployment, and the UAV cognitive edge computing network model is constructed (see Fig. 3).

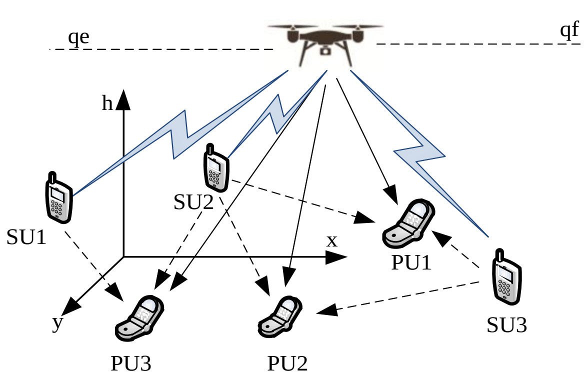


Fig. 3. UAV cognitive edge computing network model.

All servers, distribution network nodes and user terminal location information is imported into the network model, and the UAV inspection channel model is constructed using a three-dimensional Cartesian coordinate system [10]. Assuming that the distribution network node coordinates are represented as (x, y, z), and setting the fixed elevation of the UAV inspection flight as h, the node coordinate channel gain coordinate transformation under the time slot sequence is described as:

$$G_t(x, y, z) = \frac{\Delta g}{h_t^2 + q[y_t] - x_t^2} \tag{1}$$

In the formula, $G_t(x, y, z)$ represents the distribution network node coordinate time slot channel gain result, and Δg is the channel gain amplitude per unit distance. The network model is used to monitor the dynamic information of the UAV inspection and to monitor the faults of the distribution network equipment and lines, and when an abnormal signal location is identified, the fault point is quickly located and marked by comparing the data in the normal state with the currently collected data, and the signal is transmitted to the edge server at the nearest distance [11]. Carrier linear fuzzy adjustment based on real-time UAV position and edge server distance:

$$\begin{bmatrix} N_{0,0} \\ \vdots \\ N_{n-1,n} \end{bmatrix} = \begin{bmatrix} \Delta X_{0,0} & \Delta Y_{0,n} \\ \vdots & \vdots \\ \Delta X_{n-1,n} & \Delta Y_{n-1,n} \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

In the formula, N is the horizontal distance carrier linear correction parameter of the time series data, and ΔX, ΔY are the original coordinate signals of the fault localization point. The distance between the corrected coordinate parameters and the edge server is calculated using the least squares method L_n:

$$(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2 + (z_n - z_{n-1})^2 = L_n^2 \tag{3}$$

The fault localization results are fed back to the UAV inspection control system through edge computing, and the system carries out optimal path planning according to the fault localization information and manipulates the UAV to carry out collaborative inspection and maintenance operations [12].

B. UAV Inspection Path Planning Algorithm

The inspection path power model is constructed according to the UAV flight law, and the pitch angle, yaw angle, and roll angle are calculated during the UAV flight:

$$\begin{cases} \theta = \left[(V_y - V_z)\phi\varphi + v_x F \right] / V_x \\ \varphi = \left[(V_z - V_x)\theta\phi + v_y F \right] / V_y \\ \phi = \left[(V_x - V_y)\theta\varphi + v_z F \right] / V_z \end{cases} \tag{4}$$

In the formula, θ, φ, ϕ represent the pitch, roll and yaw angles of the UAV during flight, V_x, V_y, V_z are the flight acceleration in the horizontal and vertical axes, respectively, v_x, v_y, v_z are the rotor angular velocities corresponding to the sailing directions, and F is the coefficient of the UAV flight moment [13]. Through the Laplace transform, the UAV pitch angle, roll angle, and yaw angle (see Fig. 4) attitude mechanics function matrices are obtained:

$$\begin{cases} \theta(t) / F(t) = \bar{h} / V_y t^2 \\ \varphi(t) / F(t) = \bar{h} / V_z t^2 \\ \phi(t) / F(t) = \bar{h} / V_x t^2 \end{cases} \tag{5}$$

In the formula, t is the UAV timing node parameter, $\bar{h}$ is the ideal altitude for UAV hovering.

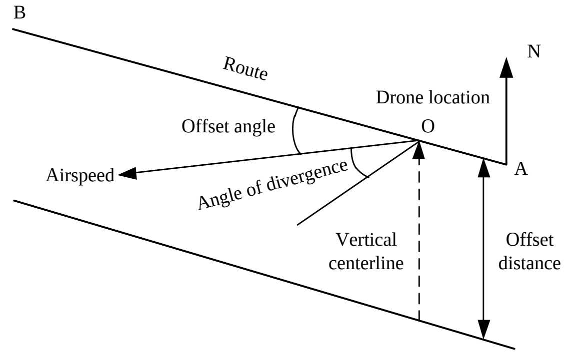


Fig. 4. Schematic of yaw angle attitude mechanics.

The unit angle error correction factor e_{ref} is introduced to correct the error for flight altitude at different attitude angles:

$$\begin{cases} \Delta h_\theta = h(\theta_{ref} - \theta) \cdot e_{ref} \\ \Delta h_\varphi = h(\varphi_{ref} - \varphi) \cdot e_{ref} \\ \Delta h_\phi = h(\phi_{ref} - \phi) \cdot e_{ref} \end{cases} \tag{6}$$

Based on the corrected UAV flight dynamics parameters, a PID tracking controller is utilized for path planning of the inspection nodes:

$$Line_n = \sqrt{\left(free + \alpha L_{on_1} \right)^2 + \left(l_{safe} + L_{on_n} \right)^2} \tag{7}$$

In the formula, $free$ indicates the maximum degree of freedom of the UAV flight path, α is the inspection path safety coefficient, l_{safe} is the inspection safety distance for fault localization, and L_{on_1}, L_{on_n} are the distances from the initial position to the inspection node, respectively. According to the formula, the UAV inspection path can be planned to carry out precise fault point search inspection for distribution network tripping, disasters and other suspected fault segments, with high real-time, high accuracy and fast response, which can improve the operation and maintenance efficiency and reliability of the distribution network [14].

IV. UAV Path Optimization Algorithm based on Cloud Pipe Edge Ends

A. UAV Cluster Control Objective Function

In order to carry out distribution network fault detection more efficiently, multi-UAV cluster control will be used for collaborative inspection, so multi-objective optimization is needed on the basis of the original path planning. Firstly, the shortest distance function between multi-path nodes is obtained by edge computing as:

$$\min L_n = \sum_{n}^{i=1}\left(ql_n + ql_n'\right) + f\left(e_n\right) \tag{8}$$

In the formula, where l_n, l_n' are the straight line length and the actual effective length of the n node distance, q is the distance minimization weighting factor, and $f\left(e_n\right)$ is the error penalty function [15]. The nearest path matching objective function that removes the overlapping area of the node space is obtained by constraining the node in and out of the path edge points:

$$\sum_{n}^{i=0} L_n^i = 0 \mid 1, \forall i = 1, 2\cdots, N, \forall n = 1, 2\cdots, n \tag{9}$$

The directed band-weighted relationship between the number of UAV cluster controls and the total distance of the inspection path can be described as:

$$\min L_{all} = \sum_{N}^{n}\sum_{n}^{i=0}\sum_{n}^{j=0} l_{on}^i h_{nt} \tag{10}$$

The shortest distance between the monitoring points is calculated to match the neighboring nodes in the inspection path, and the directed weighted path (Fig. 5) is obtained schematically as follows:

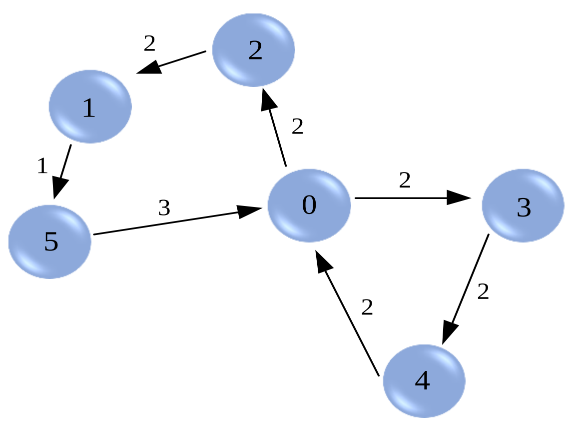


Fig. 5. Schematic diagram of directed weighted paths.

Based on the UAV speed and path distance parameters, the total UAV cluster inspection route time can be predicted:

$$\min T_{all} = \max\left\{\sum_{n \le N}^{i=1} \max\left\{t_i^n \times \left(t_i - e_i\right), 0\right\}\right\} \tag{11}$$

In the formula, where t_i^n is the UAV inspection time per unit distance for line n, and e_i is the time error parameter of the path [16]. The server monitors the flight paths and times of multiple UAVs, and collaboratively monitors the entire UAV cluster through centralized control to achieve efficient inspection tasks.

B. *Multi-objective Function Constraints*

For the UAV range, energy consumption, and load-carrying performance, further optimal efficiency constraints need to be imposed on the multi-objective UAV path[17]. Assuming that all UAVs take the distribution network base control center as the departure starting point, the maximum number of cooperative control UAVs is:

$$\max N = \sum_{n}^{i=1} l_i^n, i = 1, 2\cdots, n \tag{12}$$

Distribution network UAV inspection needs to be conFig.d with relevant sensing and communication devices to collect information on distribution machinery lines and other equipment, as well as monitor and feedback fault problems [18]. The UAV load will affect its flight speed and elevation threshold; in order to achieve optimal path planning, the total amount of UAV load needs to be constrained:

$$\max M = \sum_{n}^{i=0} v_i^n \times m_i, i \in 1, 2\cdots, n \tag{13}$$

In the formula, where v_i^n is the expected optimal speed of path inspection, m_i is the UAV unit distance supportable carrying capacity threshold. According to the UAV endurance performance and inspection path length, the maximum working time of a single UAV is constrained and controlled by considering the UAV startup operation and waiting service time t_i:

$$\max T = \sum_{n}^{i=0} l_i^n v_i^{-n} + \sum_{n}^{i=1} l_i^n t_i \tag{14}$$

For the fault localization process, the UAV path has a dynamic nature, and the particle velocity and position update formulation of the adjacency matrix of the inspection node[19]. Setting the dimension particle of node position as W_n, the extended edge set of particles in the adjacency matrix is $n_k^l = \left[n_k^{l_1}, \cdots, n_k^{l_n}\right]$:

$$n_k^{l_i} = \left[\left\langle n_i, W_n\right\rangle, \left\langle W_n, n_j\right\rangle\right] \otimes k_W \tag{15}$$

The extended edge set data of each node particle can form a Hamiltonian circle in the actual position, and in the Hamiltonian circle constraints, the UAV path can be dimensionally adjusted, and the probabilistic constraints can be imposed on the edge flight speeds of the path nodes in the case where the velocity component v_k^l is.

$$P\left(v_k^l\right) = \left\{\frac{n_i, n_j}{P\left(n_i, n_j\right)}\right\} \tag{16}$$

After the above multi-objective function constraints, the multi-UAV cluster control capability can be strengthened to promote the distribution network fault inspection and localization efficiency [20], reduce the work intensity and error rate, and realize high-precision and high-efficiency fault inspection so as to guarantee safe and stable operation of the power system.

V. Discussion

In order to test the effectiveness of the research method, a comparative experiment is designed to simulate the UAV distribution network fault inspection process and compare and analyze the experimental result data. The distribution network of a power system is taken as the inspection object, and the inspection nodes are set according to the location of the distribution network; the server model of the control center is PC i5-8250U CPU, and the inspection node data are numbered by using VRPTW. Select and adjust the UAV cluster parameters as shown in Table I.

TABLE I. UAV Cluster Test Parameter Settings

Targets	Parameters
UAV SYSID	2、3、5
Number of nodes	20
Path type	zigzag path
UAV2 point set coordinates	HOME (121.441 121 6,31.028 408 30) TARGET1(121.441 269 2,31.028 381 84,10) TARGET2(121.441 308 2,31.028 426 12,10)
UAV3 point set coordinates	HOME (121.441 167 1,31.028 364 30,10) TARGET1(121.441 197 3,31.028 611 22,17) TARGET2(121.441 009 2,31.028 666 81,17) TARGET3(121.441 988 3,31.028 800 62,17)

The operating drone control system automatically formulates the drone inspection plan according to the calculation results of the optimization algorithm, planning the number, starting point, flight path, and other contents of the cluster inspection drone. Adopting vehicle navigation, planning the path navigation of the vehicle to the take-off point of the faulty section, guiding the team members to the survey location to carry out the machine patrol operation, navigating and guiding the team to the landing point of the drone to recover the aircraft after the drone takes off, and real-time according to the faulty search and patrol and localization process of the collection of data situation, and further make the drone response strategy.

A. UAV Fault Location Inspection Time Analysis

This experiment is based on edge computing algorithm support, combined with multi-objective function constraints for path planning and task control of UAV clusters. All drones take the point HOME (121.441 121 6,31.028 408 30) as the starting point for inspection, and the lightweight defect recognition algorithm is deployed at the edge end of the drones to identify the defective faults of the distribution network in real-time and troubleshoot them on site. Through the real-time linkage function, the UAV is maneuvered to return to the flight, upload the fault information, and complete this fault-finding task. The average inspection time of each fault node of the UAV under the support of different algorithms is monitored and counted, and the time parameters of one group, three groups, and five groups of UAV cooperative control are recorded, respectively.

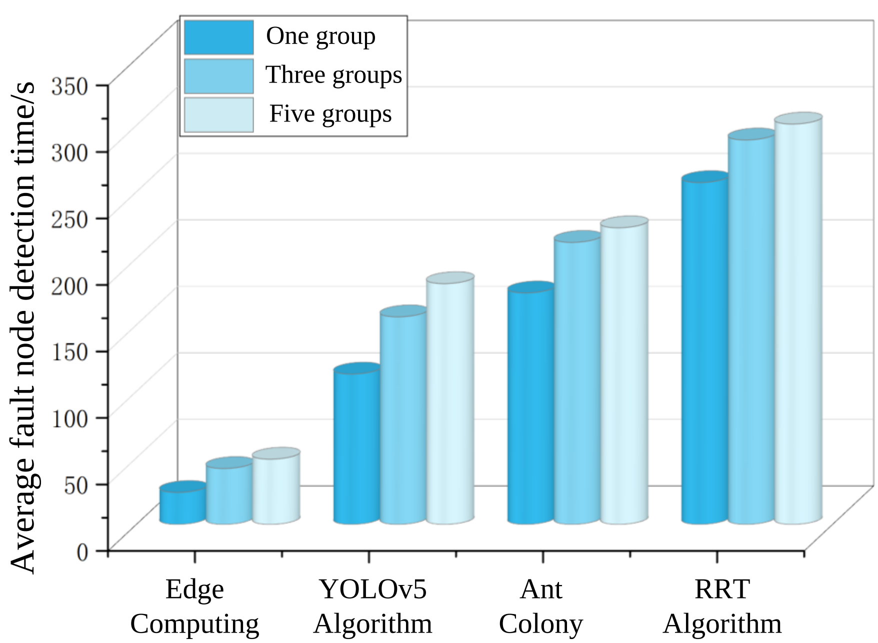


Fig. 6. UAV fault localization inspection time.

From the data in Fig. 6, it can be clearly seen that when controlling a group of drones, the cloud edge collaboration method has a shorter working time for the drones, with an average inspection time of only 24 seconds for a single node. The response time for single drone inspections using the other three traditional methods, such as YOLOv5, exceeds 100 seconds. At the same time, as the number of drones in collaborative control increases, the average inspection time per unit drone has also increased, and the fault detection time is directly proportional to the number of drones. When the number of UAV test groups is 5, the average detection time based on edge computing control is 49 seconds, while the RRT forest algorithm is limited by the search range, and the response speed is slow, and the unit time is up to 301 seconds. This shows that the edge computing method used in this paper for cloud edge collaborative control of UAVs is faster, and the average time for distribution network fault patrol is far lower than the traditional method.

B. UAV Flight Attitude Stability Analysis

According to the UAV flight path dynamics model, the pitch angle, roll angle, and yaw angle of UAV flight will affect the course direction and cause the optimal path offset to a certain extent. Therefore, the UAV attitude offset angle is monitored during the experiment, and the jitter angle range of different flight attitudes of each group of UAVs is counted to analyze the UAV flight stability.

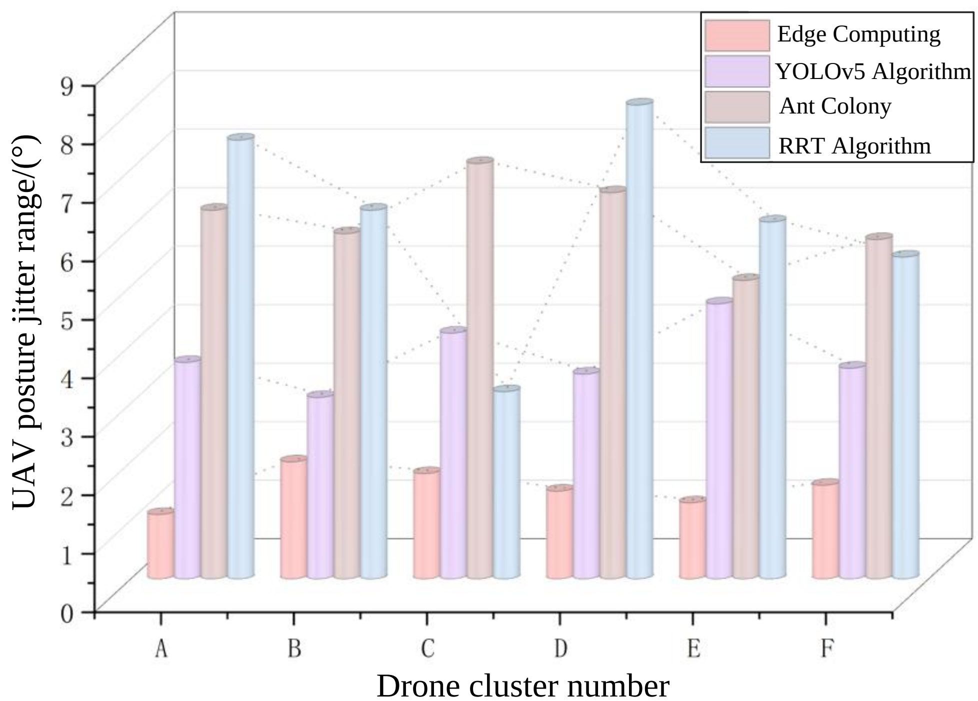
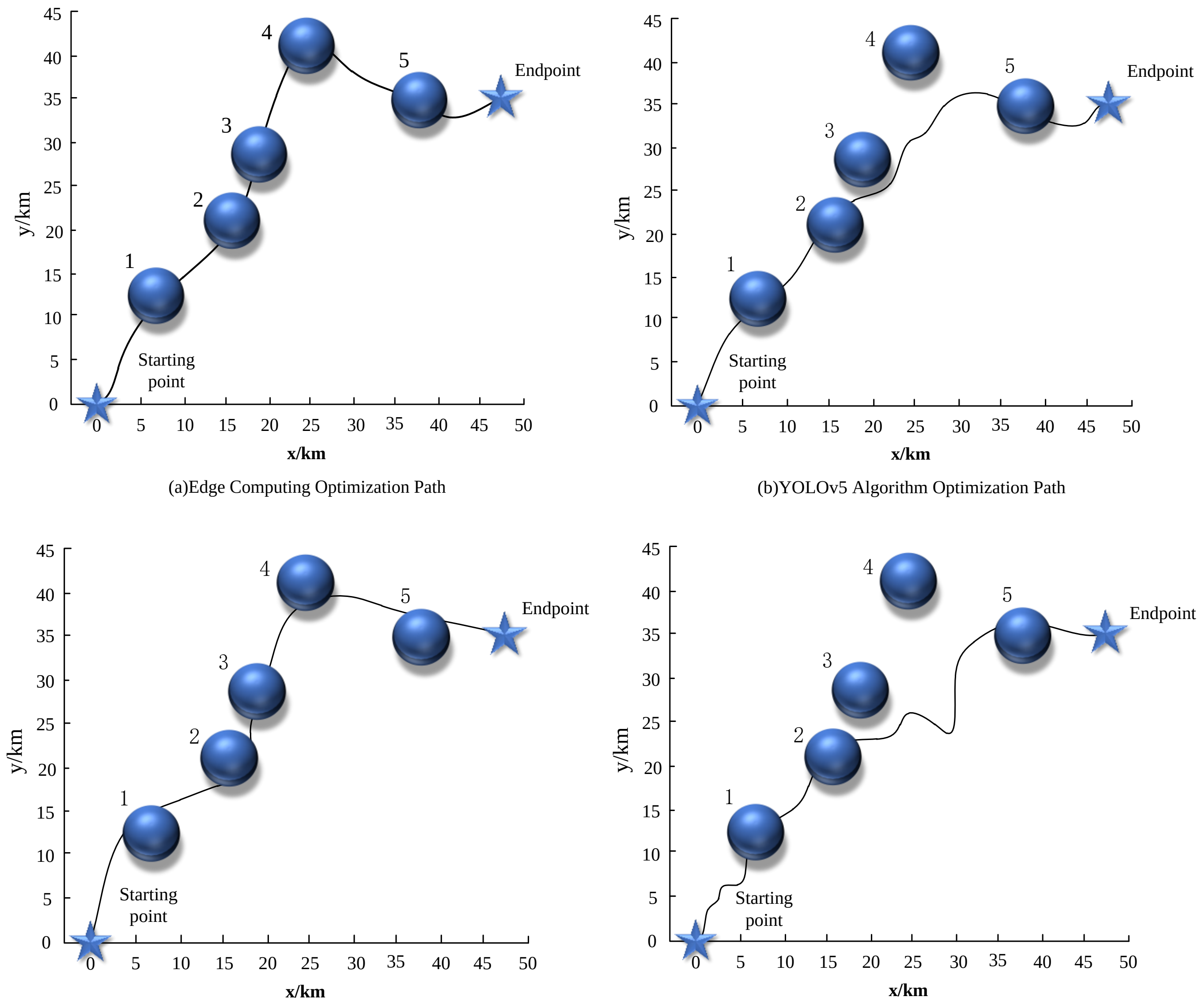


Fig. 7. UAV flight attitude jitter range.

As shown in the Fig. 7, this paper is based on edge computing to construct the power model of the UAV inspection path. The UAV flight angle attitude control is more accurate, and the jitter range of each group's UAV posture is no more than 3°, which has good stability. The control system based on the adaptive ant colony algorithm is less stable. The jitter range of all six groups of UAVs is more than 5°, while the jitter situation of UAVs using RRT forest algorithm path planning has great uncertainty. The jitter offset angle reaches a maximum of 8.1°, and the minimum angle deviation is only 3.2°. In the comprehensive analysis, using the edge computing method for path planning, fully considering the UAV yaw and jitter angle problems, and using power law for path optimization effectively improves the UAV inspection attitude stability.

C. Drone Inspection Path Planning Analysis

Using MATLAB software to simulate the fault location inspection path of the distribution network UAV, a set of path node position coordinates are extracted and imported into the system program, and four groups of UAV flight real-time path coordinate parameters are substituted to obtain the training path visualization image as follows.



(a)Edge Computing Optimization Path

(b)YOLOv5 Algorithm Optimization Path

(c)Ant Colony Algorithm To OPtimize The Path

(d)RTT Algorithm Optimizes The Path

Fig. 8. Comparison of UAV inspection paths.

As shown in Fig. 8, five fault detection points are set in the selected path. The optimized patrol path based on edge computing completely covers five fault points, almost passing through the joint point of the fault center, and there is no redundant path between fault nodes. The YOLOv5 algorithm lacks supporting multi-objective unmanned aerial vehicle cluster control technology, which makes it impossible to achieve collaborative control of multiple unmanned aerial vehicle targets, resulting in path planning missing fault detection points 3 and 4, which does not meet the expected planning and inspection requirements; The path optimization effect of ant colony algorithm is relatively good, achieving fault localization for 5 monitoring points. However, the detection synchronization is poor, and there is a certain lag in information, resulting in a deviation in the inspection path of fault points 1 and 2, only reaching the edge range of the fault point, and there is a certain error in the positioning data; RRT path planning also missed the distant detection points 3 and 4, and did not reach the center range of other fault monitoring points, resulting in low accuracy of fault localization and detection information.

In summary, the fault localization path optimization algorithm for distribution network UAVs with cloud-pipe-edge-end architecture studied in this paper has good application performance, the coordinate information of fault localization is more accurate, and the power model is used to improve the stability of the UAV flight attitude. With the support of cloud-edge cooperative technology, we can better realize multi-objective UAV cluster control, edge computing optimization path coverage is more comprehensive, the unit interval distance is shorter, and it is more advantageous than the traditional method in the distribution network fault inspection and positioning work.

VI. Conclusion

Aiming at the deficiencies in UAV cluster control and path planning, this paper proposes a fault location path optimization algorithm for distribution network UAVs based on cloud-pipe-edge-end architecture. It obtains the following conclusions through theoretical and experimental research:

Based on the cloud-pipe-edge-end technology architecture, the UAV is controlled by cloud-edge cooperative control and interacts with edge nodes to improve the data processing and response rate.

Based on edge computing to process UAV inspection and fault localization data, carrier linear fuzzy adjustment is carried out through the relative distance of edge servers to improve the accuracy of coordinate localization parameters.

Construct a UAV flight dynamics model, analyze UAV posture angle and flight law, and improve the real-time control performance of the path planning system.

Carry out multi-objective path optimization for UAV clusters and constrain the load time and expansion dynamics of the number of UAVs to reduce the error rate of inspection path deviation and obtain the optimal path planning for inspection with high precision and high efficiency.

Through experiments, it is proved that the method studied in this paper has good stability and application efficiency, and more secure and efficient algorithms and technologies will be further explored in future research to improve the accuracy and efficiency of fault location path planning for distribution network UAVs, so as to make a more significant contribution to the intelligent development of the work of UAV inspection and fault detection of distribution network.

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