

UAV Assisted Data Collection for Internet of Things: A Survey

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Abstract—Thanks to the advantages of flexible deployment and high mobility, unmanned aerial vehicles (UAVs) have been widely applied in the areas of disaster management, agricultural plant protection, environment monitoring and so on. With the development of UAV and sensor technologies, UAV assisted data collection for Internet of Things (IoT) has attracted increasing attentions. In this article, the scenarios and key technologies of UAV assisted data collection are comprehensively reviewed. First, we present the system model including the network model and mathematical model of UAV assisted data collection for IoT. Then, we review the key technologies including clustering of sensors, UAV data collection mode as well as joint path planning and resource allocation. Finally, the open problems are discussed from the perspectives of efficient multiple access as well as joint sensing and data collection. This article hopefully provides some guidelines and insights for researchers in the area of UAV assisted data collection for IoT.

Index terms— Unmanned Aerial Vehicle; Wireless Sensor Networks; Data Collection; Internet of Things; Clustering; Data Collection Mode; Path Planning; Resource Allocation; Multiple Access; Joint Sensing and Data Collection; Review; Survey

I. INTRODUCTION

With the development of Internet of Things (IoT), sensors are widely deployed in the scenarios such as intelligent transportation, forest monitoring, smart city and smart ocean. It is estimated that by 2030, the number of sensors in the world will exceed 100 trillion [1]. Hence, the collection of the huge amount of data from sensors faces great challenge. The data collection techniques of IoT require low energy consumption, low delay and high reliability.

Unmanned aerial vehicle (UAV) with wide coverage and high mobility provides new opportunities for data collection of IoT [2, 3]. UAV assisted data collection has the advantages of high agility, high flexibility and low cost. In addition, UAV can collect data in close proximity to sensors, which greatly

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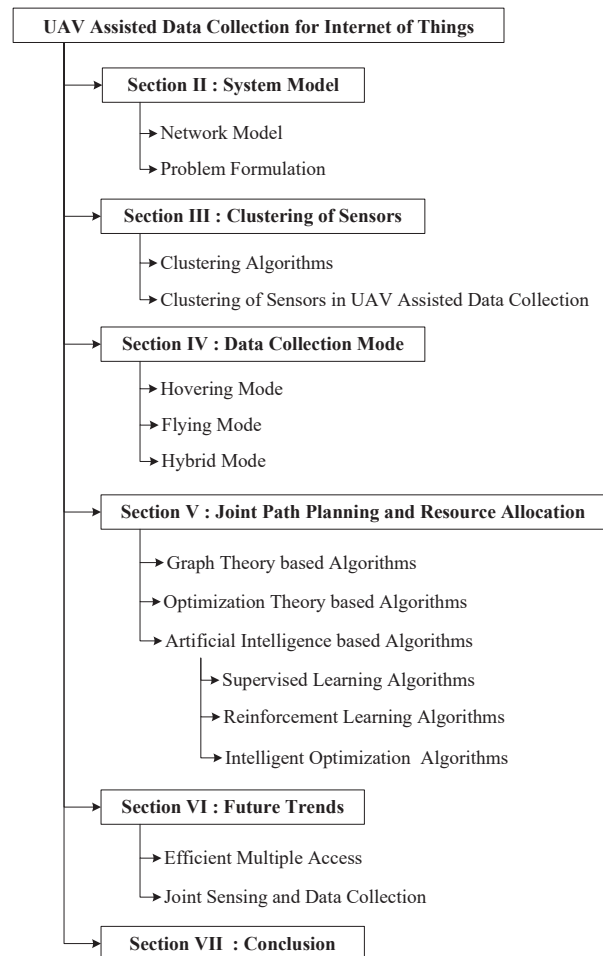


Fig. 1. The organization of this article.

reduces the energy consumption of IoT. The combination of UAV and IoT facilitates timely and effective data collection, especially in the complex, harsh or remote environments [4–8]. As an ideal tool for data collection, UAV assisted data collection for IoT has the following advantages.

- *High efficiency and flexibility of data collection:* UAV reduces the data collection time because its trajectory can be optimized [9–11].
- *Low energy consumption and long network lifetime for IoT:* UAV not only reduces the energy consumption of data transmission in IoT, but also can charge the sensors wirelessly, which collectively improve the network lifetime of IoT [12, 13].

TABLE I
GLOSSARY.

Abbr.	Definition	Abbr.	Definition	Abbr.	Definition
3D	Three-Dimensional.	DRL	Deep Reinforcement Learning.	MTCDs	Machine-Type Communication Devices.
5G	5th Generation Mobile Networks.	FDMA	Frequency Division Multiple Access.	NOMA	Non-Orthogonal Multiple-Access.
ACO	Ant Colony Optimization.	G2A	Ground-to-Air.	PRM	Probabilistic Roadmap
AWGN	Additive White Gaussian Noise.	GA	Genetic Algorithm.	PSO	Particle Swarm Optimization.
AI	Artificial Intelligence.	GBD	Generalized Benders Decomposition.	QoS	Quality of Service.
AoI	Age of Information.	GTOA	Group-based Trajectory Optimization Algorithm.	RL	Reinforcement Learning.
AP	Access Point.	HCP	Hybrid Clustering Routing Protocol.	RSSI	Rreceived Signal Strength Indicator.
BB	Branch and Bound.	Het-IoT	Heterogeneous Internet of Things.	SA	Simulated Annealing.
BCD	Block Coordinate Descent.	HHPS	Hybrid hovering points Selection.	SCA	Successive Convex Approximation.
BRB	Branch Reduction and Bound.	IoT	Internet of Things.	SFLA	Shuffled Frog Leaping Algorithm.
BS	Base Station.	KKT	Karush-Kuhn-Tucker.	SIC	Successive Interference Cancellation.
CH	Cluster Head.	LEACH	Low Energy Adaptive Clustering Hierarchy.	STOA	Segment-based Trajectory Optimization Algorithm.
CP	Data collection Point.	LoS	Line of Sight.	TDMA	Time Division Multiple Access.
CRB	Cramér-Rao Bound.	MA	Memetic Algorithm.	TSP	Traveling Salesman Problem.
CS	Cuckoo Search Algorithm.	MAC	Multiple Access Control.	TSPN	Traveling Salesman Problem with the Neighborhood.
DDPG	Depth Deterministic Gradient Descent.	MDP	Markov Decision Process.	UAV	Unmanned Aerial Vehicle.
DE	Differential Evolution.	MIMO	Multiple Input Multiple Output.	UKF	Unscented Kalman Filter.
DFP	Direct Future Prediction.	MLE	Maximum Likelihood Estimation.	VNS	Variable Neighborhood Search.
DL	Deep Learning.	MM	Majorize-Minimize or Minorize-Maximize.	VoI	Value of Information.
DP	Dynamic Programming.	MPT	Microwave Power Transfer.	WSN	Wireless Sensor Network.

- *Wide coverage:* Due to the high altitude of UAV, there is a higher chance for line of sight (LoS) connections between UAV and sensors, which improves the success probability and coverage of communication [8, 14].

Along with the above advantages, there are also several challenges in UAV assisted data collection.

- *The clustering of sensors and selection of data collection mode:* The deployment and clustering of sensors, as well as the selection of data collection mode will greatly affect the performance of UAV assisted data collection. Hence, there exists a complex air-ground coupling in the optimization of the performance of data collection.
- *Joint path planning and resource allocation of UAV:* The resource allocation problem is coupled with the path planning of UAV, which further complicates the problem of resource allocation.

Therefore, in view of the challenges of UAV assisted data collection, this article provides in-depth survey on three key technologies including the clustering of sensors, the modes of UAV assisted data collection, and the joint UAV path planning and resource allocation.

A. Existing Surveys and Tutorials

Recently, a few related surveys and tutorials have been published. Li *et al.* [15] summarize the UAV communication for 5G/B5G wireless networks. They summarize and review the air-ground integrated network architecture and various 5G technologies implemented on UAV platform. In UAV assisted IoT, media access control (MAC) has a crucial impact on spectrum efficiency and energy efficiency of battery powered sensor networks. In [12], various MAC protocols for UAV assisted IoT are reviewed. Heaphy *et al.* [16] describe the potential application of UAV in forestry. UAV makes up for the shortcomings of satellites and manned aircraft, and collects images with higher temporal and spatial resolution to support forest inventory, health monitoring, silviculture and harvesting operations. Pham *et al.* [17] focus on the application of UAV in traffic data collection. This paper not only compares various UAV operation frameworks and popular platforms, but also applies UAV in speed behavior analysis, gap acceptance and merging behavior. In [18], Dan *et al.* introduce the mode and latest progress of cooperation among various functional components in UAV assisted wireless sensor network (WSN). For large-scale IoT deployed in complex environment, Yang *et al.*

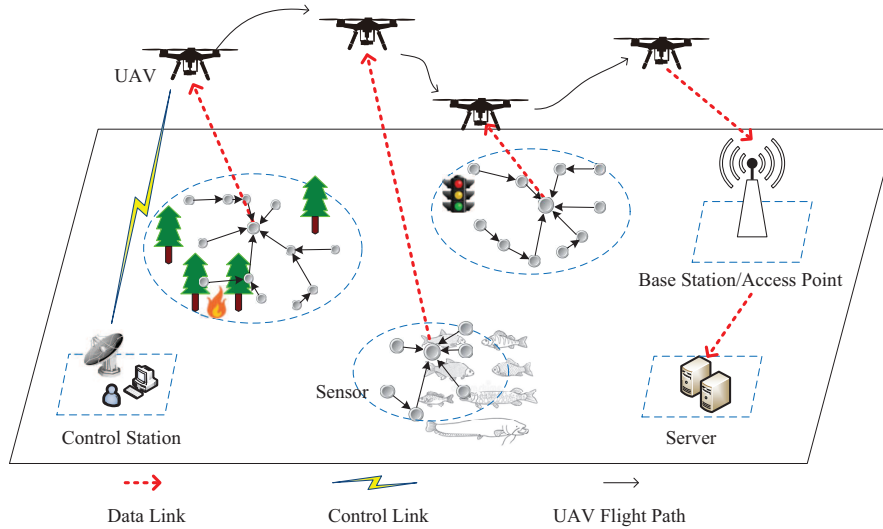


Fig. 2. The system model of UAV assisted data collection.

[19] review four technologies, including sensor deployment, UAV configuration (such as flight speed and radius), UAV path planning and UAV autonomous navigation. However, existing articles have the following limitations.

- There is a lack of investigation and discussion on the data collection modes using UAV.
- The clustering algorithms of sensors are not discussed in details.
- The joint path planning and resource allocation schemes for UAV assisted data collection are not reviewed.

B. Contributions and Organization

This article aims to review the development status and future trends of UAV assisted data collection techniques. To this end, we conduct a comprehensive review on the relevant literatures in recent years. The scenario of UAV assisted data collection is not a simple combination of UAV networking and IoT. They need to cooperate with each other to improve the system efficiency, which is the perspective of this article. The main contributions of this article are summarized as follows.

- Three key technologies of UAV assisted data collection for IoT including the clustering of sensors, the data collection modes, and the joint UAV path planning and resource allocation methods, are reviewed in details.
- The complete solution of UAV assisted data collection including the key technologies such as joint sensing and data collection, clustering of sensors, efficient access of large-scale sensors, and efficient routing in WSN, and joint path planning and resource allocation, is designed. Among these key technologies, efficient multiple access and joint sensing and data collection have a large probability to be the future research trends.

As shown in Fig. 1, the rest of this article is organized as follows. Section II introduces the system model of UAV assisted data collection for IoT. In Section III, the clustering algorithms of sensors are introduced. Section IV investigates three data collection modes, analyzing the advantages and

disadvantages of each data collection mode. Section V reviews the joint UAV path planning and resource allocation methods in details. Section VI discusses the complete solution and future trends of UAV assisted data collection. Finally, Section VI summarizes this article.

II. SYSTEM MODEL

In this section, we introduce the network model and mathematical model in UAV assisted data collection.

A. Network Model

As illustrated in Fig. 2, the network elements of UAV assisted data collection consist of sensor, UAV, control station and server, which are explained as follows.

- *Sensor*: In order to sense the environment, the sensors are deployed and the sensing data are sent to UAV. The type of sensors depends on the application scenarios. For instance, the temperature and humidity sensors are deployed in the forest monitoring scenario.
- *UAV*: The UAV flies above the sensors to collect data, which is then brought back to the server.
- *Control station*: The control station plans UAVs' flight path for efficient data collection.
- *Base station (BS)/Access point (AP)*: The BS/AP collects the sensing data directly from the surrounding sensors, as well as the UAVs.
- *Server*: The server stores and processes the data from sensors.

As shown in Fig. 2, in the scenario of UAV assisted data collection, UAV takes off from a control station and flies above sensors to collect data, such as the potential of hydrogen (PH) and salinity in the ocean, the wildlife and fire in the forest, the traffic and weather in the smart city. Then the UAV delivers the data to the BS/AP and finally returns to the control station. The scheme of UAV assisted data collection aims at high efficiency, low energy consumption and low delay during data collection.

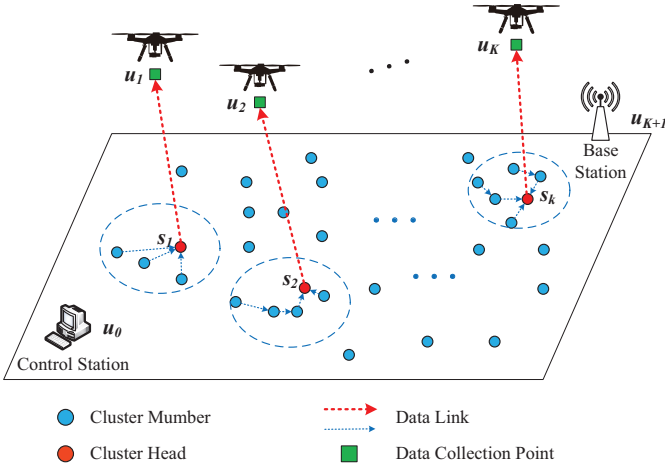


Fig. 3. Optimization of UAV assisted data collection.

In addition, some standard IoT technologies are applied in UAV assisted data collection, such as NB-IoT and LoRa. LoRa can be used as a gateway for UAV assisted data collection to extend the coverage to rural and remote areas [20]. Delafontaine *et al.* [21] present a UAV assisted localization system using LoRa networks in which a UAV is deployed to improve the positioning accuracy of sensor. Because NB-IoT can support large coverage and meet the low-power and low-cost operation of sensors, it is also applied in UAV assisted data collection, such as soil detection [22], city open water monitoring [23] and air quality monitoring [24].

B. Mathematical Model

As shown in Fig. 3, the system of UAV assisted data collection is composed of a UAV, a BS, a control station and M sensors. The set of sensors is denoted by $\mathcal{M} \triangleq \{1, 2, \dots, M\}$. The UAV collects and sends the data of sensors back to the BS. The control station plans the flight path of the UAV and charges the UAV before flight. There are the following assumptions [25, 26].

- *Distribution of sensors:* Sensors are randomly distributed in the target area. Their position coordinates are known and expressed as $s_m = (x_m, y_m, h)^T \in \mathbb{R}^{3 \times 1}$, $m \in \mathcal{M}$. The sensor is equipped with omni-directional antenna and the communication range is r_c .
- *Clustering of sensors:* When the number of sensors is small or the locations are scattered, each sensor can directly upload the data to the UAV. When the number of sensors is large, the sensors need to be clustered. Hence there are two types of nodes, namely, cluster head (CH) and cluster member (CM). The CH collects the data of CMs within the cluster, and is responsible for communicating with the UAV [27].
- *Self-positioning of UAV:* UAV acquires its location via the installed positioning module such as Global Navigation Satellite System (GNSS) module [28].
- *Number and type of UAVs:* The number of UAVs depends on the number of sensors and the amount of data to be collected. The type of UAVs consists of rotor UAV and

fixed-wing UAV [29]. Therefore, three data collection modes, i.e., hovering mode, flying mode and hybrid mode, exist in the literatures.

- *Mobility, energy and capacity of UAVs:* UAV can fly at a fixed altitude H and speed v (When $v = 0$, it means that the UAV is hovering), and V_{max} is the maximum speed that UAV can reach. The maximum flight distance and energy of UAV are L_{max} and E_{max} , respectively [30]. The buffer size of UAV is also taken into account, limiting the amount of data that can be collected.
- *Ground-to-air communication and transmission rate:* There will be LoS channel between sensors and UAV with a certain probability. This probability depends on the environment and the angle between the sensor and the UAV. As shown in [26, 31], the probability of LoS transmission is

$$P_{\text{LoS}}(s_m, u) = \frac{1}{1 + a \exp[-b(\theta(s_m, u) - a)]}, \quad (1)$$

where $\theta(s_m, u)$ is the angle between the sensor s_m , $m \in \mathcal{M}$ and the UAV at position $u \in \mathbb{R}^{3 \times 1}$. a and b are environmental parameters, which mainly depend on the ratio of building area to total land area, the average number of buildings in a unit area and the height of buildings [26]. Then the transmission rate between the sensor s_m and the UAV located at u is [32]

$$R(s_m, u) = B \log_2 \left(1 + \frac{|h(s_m, u)|^2 P_m}{N_0} \right), \quad (2)$$

where B is the channel bandwidth, $h(s_m, u)$ is the channel gain between UAV and the sensor, P_m is the transmit power of each sensor when communicating with UAV, N_0 is the power of additive Gaussian white noise.

Combined with the model in Fig. 3 and the above assumptions, it is assumed that M sensors in the IoT are divided into K clusters, expressed as $\mathcal{K} \triangleq \{1, 2, \dots, K\}$. Each cluster has only one CH s_k , and the sensors in the cluster can communicate with each other. The goal of UAV is to collect data from the CHs quickly and efficiently. In order to achieve this goal, the distance, flight time, and energy consumption for path planning need to be jointly optimized [19]. Meanwhile, the data collection mode between UAV and CH, such as hovering mode, flying mode and hybrid mode, has an impact on the efficiency of data collection [33]. Taking hovering mode as an example, the UAV collects data of CH s_k at the data collection point u_k , $k \in \mathcal{K}$ [34]. Other data collection modes have corresponding constraints. Before formulating the problem, the following constraints need to be considered.

1) *Sensor energy consumption constraint:* This constraint ensures that the energy consumption of each sensor s_k does not exceed E_k .

$$t_k P_k \leq E_k \quad \forall k, \quad (3)$$

$$P_k > 0 \quad \forall k. \quad (4)$$

In hovering mode, the channel conditions between UAV and sensors remain unchanged, hence the sensor s_k can transmit data with constant transmit power P_k . t_k is the hovering time

of UAV at data collection point u_k .

2) *Data collection constraint*: The sensor s_k needs to meet the minimum data collection requirements r_k .

$$t_k B \log_2 \left(1 + \frac{|h(s_k, u_k)|^2 P_k}{N_0} \right) \geq r_k \quad \forall k. \quad (5)$$

3) *UAV energy consumption constraint*: The total energy consumption of UAV cannot exceed its maximum energy E_{\max} .

$$P_u(0) \sum_{k=1}^K t_k + P_u(v) \frac{\sum_{i=0}^{K+1} \sum_{j=0}^{K+1} x_{i,j} d_{i,j}}{v} \leq E_{\max}, \quad (6)$$

where $P_u(v)$ is the power of UAV flying at constant speed v ($0 < v \leq V_{\max}$) [35, 36], $d_{i,j}$ is the distance from u_i to u_j .

4) *UAV trajectory constraint*: This constraint ensures that the UAV starts from the control station, traverses all data collection points and then returns to the BS.

$$\sum_{i=1}^K x_{i,j} = 1 \quad i \neq j, \forall j \in \mathcal{K}, \quad (7)$$

$$\sum_{j=1}^K x_{i,j} = 1 \quad i \neq j, \forall i \in \mathcal{K}, \quad (8)$$

$$\sum_{j=1}^K x_{0,j} = \sum_{i=1}^K x_{i,K+1} = 1 \quad \forall i, j \in \mathcal{K}, \quad (9)$$

$$x_{i,j}, x_{0,j}, x_{i,K+1} \in \{0, 1\} \quad i \neq j, \forall i, j \in \mathcal{K}, \quad (10)$$

where $x_{i,j}$ is a binary variable. $x_{i,j} = 1$ indicates that the UAV flies from the data collection point u_i to u_j . u_0 and u_{K+1} represent the starting point (control station) and ending point (BS) of the UAV, respectively.

5) *Age of information constraint*: The age of information (AoI) is a performance indicator to measure the timeliness of data. Compared with the latency, AoI includes not only the transmission delay of data packets, but also the waiting time of data packets at the source node and the residence time at the destination node [37, 38]. AoI constraint reveals the requirements for data timeliness.

$$A_j^k \leq A_j^{k,th} \quad \forall k \in \mathcal{K}, j \in \mathcal{J}_k, \quad (11)$$

where A_j^k and $A_j^{k,th}$ are the AoI and its threshold for the j -th uploaded packet of CH s_k , respectively. $\mathcal{J}_k \triangleq \{1, 2, \dots, J_k\}$ is the number of data packets in s_k . Without considering the sampling time and communication overhead, the AoI of the data collected at CH s_k consists of the time of data upload, the time of UAV returning to the data center and the time of data unloading [9, 39]. If the UAV accesses CHs sequentially (from s_1 to s_K), the AoI of the j -th uploaded packet from the CH s_k can be expressed as [9]

$$A_j^k = \sum_{i=k}^K \sum_{j=1}^{J_k} \varsigma_j^i - \sum_{l=1}^{j-1} \varsigma_l^k + \varsigma_0 + \frac{\sum_{i=k}^K \|u_i - u_{i+1}\|}{v}, \quad (12)$$

where ς_j^i is the time of uploading the j -th data packet for the i -th CH, ς_0 is the data unloading time of UAV. For the data packets of CHs not accessed by UAV, the AoI is 0. If further considering the possibility of packet expiration, AoI can be expressed as [40]

$$A_j^k = \begin{cases} \sum_{i=k}^K \sum_{j=1}^{J_k} \varsigma_j^i - \sum_{l=1}^{j-1} \varsigma_l^k + \varsigma_0 + \frac{\sum_{i=k}^K \|u_i - u_{i+1}\|}{v}, & t_j^k < t_j^{k,ex} \\ T_{\text{total}}, & \text{otherwise,} \end{cases} \quad (13)$$

where t_j^k is the time interval from the generation of the j -th data packet of s_k to the completion of data collection by UAV, $t_j^{k,ex}$ is the effective time of the data packet. If the data packet expires, its AoI is set as the overall time for the UAV to complete the task.

The above parameters about queuing delay need to be modified according to the queuing models, such as First-Come-First-Service (FCFS), Last-Come-First-Service (LCFS), priority based and limited buffer strategies [41, 42]. The application scenarios of FCFS, LCFS and priority based model are increasingly sensitive to data timeliness. The scenarios requiring comprehensive data such as agricultural monitoring and marine monitoring often adopt the FCFS model. The LCFS model is more suitable for the scenarios that value the latest data, such as driverless vehicle monitoring and field fire monitoring.

UAV assisted data collection schemes usually aim at maximizing the amount of collected data, minimizing flight time of UAV, minimizing energy consumption of UAV or sensor, minimizing AoI and so on. Overall, there are three key issues in UAV assisted data collection, namely, the clustering of sensors, the data collection mode of UAVs, and the path planning and resource allocation of UAVs. The application and optimization of the three key technologies are helpful to improve the efficiency of data collection, ensure the timeliness of data, as well as save the energy consumption of UAV and sensors. Besides, it is essential to consider the clustering algorithm of sensors and the data collection mode of UAV for an effective path planning algorithm. In the following sections, we will provide a thorough survey on these topics.

III. CLUSTERING OF SENSORS

In this section, we first review the clustering algorithms in conventional sensor network, and then discuss the clustering of sensors in UAV assisted data collection.

A. Clustering Algorithms

When the number of sensors is large, the topology of sensor network becomes complicated and the cost of routing between sensors is relatively large. Therefore, it is necessary to utilize a clustering algorithm to divide the network into several sub-networks. The basic idea of clustering algorithms is to merge neighboring nodes into a cluster and select a CH from each cluster that is responsible for aggregating the data from other sensors in the cluster.

Depending on different performance metrics, there are various clustering algorithms. According to the selection methods

TABLE II
FACTORS AFFECTING CLUSTERING ALGORITHMS.

Reference	Methodologies	Reference	Methodologies
[43]	Select the sensor with the highest power as the cluster head (CH).	[25]	Distributed clustering.
[9]	Affinity propagation.	[27, 44]	K -means clustering algorithm.
[26, 45]	Problem decomposition.	[46]	α -hop clustering algorithm.
[47]	Base station (BS) assisted clustering.		

of CH, the clustering algorithms are classified into deterministic CH selection algorithms, random CH selection algorithms and adaptive CH selection algorithms [48]. According to the control methods of clustering algorithms, the clustering algorithms can be classified into distributed clustering algorithms, hybrid clustering algorithms and centralized clustering algorithms [49].

The widely applied clustering protocol is the low energy adaptive clustering hierarchy (LEACH) because of its simplicity [50]. More specifically, at the beginning of LEACH, each sensor generates a random number between 0 and 1. If the number is greater than a given threshold, it is selected as CH. Then, the CH broadcasts a packet to other sensors in the same network. Each node decides which cluster to join according to the strength of the received signal, and transmits a feedback packet to the CH in a time division multiple access (TDMA) manner. With LEACH, the energy consumption of each sensor is distributed evenly by periodically switching the CHs, thereby prolonging network lifetime [48]. Recently, there are some literatures to improve LEACH [50–52]. Basavaraj and Jaidhar [53] propose a new threshold by calculating the average remaining energy of sensors, the average distance between sensors and BS, and the optimal number of CHs. In the scenario of UAV assisted data collection, since LEACH randomly selects CH, some sensors with less energy may be selected, so that the communication with the UAV cannot be completed. Chen and Shen [54] comprehensively consider the factors such as the residual energy and the communication range of sensor to select CH, which extend the network life. The malicious node may be selected as CH under LEACH. Therefore, Wang *et al.* [55] improve LEACH and apply UAV to collect sensor information such as energy and ID, so as to avoid selecting the sensor affected by malicious node as CH.

B. Clustering of Sensors in UAV Assisted Data Collection

In the scenario of UAV assisted data collection, due to the limited energy of UAV, the energy consumption brought by the flight of UAV needs to be reduced. A large number of clusters will reduce the energy consumption within the cluster to forward data, but will increase the energy consumption of UAV for flight. In contrast, a small number of clusters will reduce the energy consumption of UAV during flight, but the energy consumption of sensors will increase. Therefore, it is necessary to jointly optimize the energy consumption of sensors, the energy consumption of UAV, clustering of sensors and CH selection, path planning of UAV [44]. The clustering

methods of sensors used in relevant literatures are shown in Table II.

Chen *et al.* [43] and Salih *et al.* [25] consider the energy constraints of sensors for clustering. Chen *et al.* [43] select the sensor with the highest power as the CH to extend the lifetime of sensors. The data forwarding rule in the cluster is that only when the value of information (VoI), which is highest when an event first occurs and decays with time, is greater than a certain threshold, the sensors in the cluster will send the data to the CH, thereby greatly reducing the energy consumption of the sensors. Salih *et al.* [25] utilize a distributed clustering method to minimize the average sending distance from the sensors in the cluster to the CH. In order to minimize the AoI, Tong and Moh [9] jointly optimize the CH selection and flight path of UAV, in which an algorithm based on affinity propagation is used to determine the locations of the CH and the associated sensor.

In addition, most of the literatures considers the energy consumption of sensors, flight time of UAV and path planning in the clustering algorithms. Ebrahimi *et al.* [44] and Alfattani *et al.* [27] apply the k -means clustering algorithm, and update the sensors in the cluster through iterations. Sujit *et al.* [45] and Ghorbel *et al.* [26] decompose the joint UAV path planning and energy consumption optimization problem into several sub-problems. In [45], the initial problem is decomposed into the sub-problems of finding clusters, connecting clusters, route planning, and UAV path planning. Ghorbel *et al.* [26] decompose the problem into three sub-problems: optimizing the position of CH, assigning sensors into clusters and UAV path planning. The α -hop clustering algorithm designed by Wu *et al.* [46] adjust the hop number in each cluster to reduce energy consumption and delay. A large α determines small number of clusters, which reduces the UAV path and decreases the flight time. When α is relatively small, each cluster is small, which reduces energy consumption of data forwarding in sensor network. Haider *et al.* [47] apply UAV to get the remaining energy of sensors, channel conditions and the distance between sensors. Then the BS utilizes these information from UAV and determines which sensors are CHs, which greatly extends the lifetime of the sensors.

IV. DATA COLLECTION MODE

According to the movement status of UAV during data collection, the data collection modes are classified into three types, namely, hovering mode, flying mode and hybrid mode. Their characteristics are summarized in Table III. Table IV is a summary of the literatures on the three data collection modes.

TABLE III
COMPARISON OF DATA COLLECTION MODES.

Data collection mode	Hovering at data collection point (CP)	Continuing data collection after passing through CP	Energy consumption	Flight time	The AoI of data collected from sensors
Hovering mode	√	×	High	High	Low
Flying mode	×	√	Low	Low	High
Hybrid mode	√	√	Medium	Medium	Medium

¹ √ denotes the existence of the feature, × denotes the absence of the feature

TABLE IV
THE OPTIMIZATION SCHEMES UNDER DIFFERENT DATA COLLECTION MODES.

Data collection mode	Reference	Objective function	Decision variables
Hovering mode	[56]	Minimization of the total task duration.	The number of subregions, hovering point, hovering time of each position, trajectory between hovering points.
	[27]	Minimization of flight time of UAV.	The number and trajectory of UAV.
	[13]	Maximum of minimum energy of sensors after data collection.	Hovering point, residence time of UAV.
	[9]	Minimization of node upload time and flight time of UAV.	Position correlation between sensors and hover points, trajectory of UAV.
Flying mode	[57]	Minimization of flight time of UAV.	Continuous optimization of interval, speed of UAV, transmit power of sensors.
	[58]	Minimization of the weighted sum of energy consumption of UAV and sensors.	Trajectory of UAV, wake-up scheduling of sensors, data collection time.
Hovering and Flying mode	[32]	Minimum of maximum data collection time.	Trajectory of UAV, wake-up scheduling of sensors, sensor association.
	[34]	Minimization of flight time of UAV.	Data collection interval, speed of UAV, transmit power of sensors.
Hybrid mode	[59]	Minimization of battery consumption and Maximization of UAV throughput.	Energy consumption and throughput of UAV, delay of machine-type communications devices (MTCs) tasks, collection and computing efficiency of different priorities.
	[33]	Minimization of the average age of information (AoI).	The age of collected data, data collection mode, energy consumption of each sensor.

A. Hovering Mode

In hovering mode, the UAV stays above the data collection point for a period of time to collect data. The data collection point can be the location of the CH or near the CH. In [56], the entire region is divided into several sub-regions, and UAV hovering over these sub-regions collects data from sensors. Hovering mode can provide relatively stable data transmission, but the energy consumption is relatively large.

The UAV hovering locations and duration have a great impact on the reliable data collection and the shortest flight time. A framework design for IoT based on multiple UAVs is proposed in [33]. This work firstly optimize the number and location of CHs to minimize the data collection time. Then, the number of UAVs and their trajectories are optimized in order to minimize the flight time. And reliable data collection shortens the AoI of data collected from sensors, which is the time that the data is transmitted from sensor to the data center. In [9], in order to minimize the maximum AoI of all sensors, a joint sensor association and path planning strategy is proposed to balance the flight time of UAV and the upload

time of sensors which is affected by the quality of ground-to-air communication link under hovering mode.

In addition, to maximize the lifetime of sensors, the UAV hovering height and duration should be considered. Under the constraints of transmit power of sensors and energy consumption of UAV, Baek *et al.* [13] optimize the hovering point and dwell time of UAV to maximize the minimum energy of sensors during data transmission and energy collection periods.

B. Flying Mode

Under flying mode, when UAV passes through the data collection point, it slows down and collects the data of sensors until it leaves the communication range of the sensors. With the characteristics of moving while collecting data in flying mode, the collection task can be completed quickly. However, if the amount of data is large, the UAV in flying mode may not satisfy the the requirement of timely data collection.

Under flying mode, the shortest flight time is commonly chosen as the objective function. In UAV assisted data collection, it is observed that the optimal speed of UAV is

TABLE V
COMPARISON OF GRAPH THEORY BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Voronoi diagram	[60]	Maximum of minimum residual energy of sensors.	Hovering point, UAV path planning.	×	×	√	×
	[61]	Minimization of flight time of UAV.	UAV task area allocation, UAV path planning.	×	√	√	×
Probabilistic roadmap	[62]	Maximization of the amount of collected data.	UAV path planning.	√	×	×	×
Hilbert curve	[63]	Maximization of data collection rate.	UAV path planning.	√	×	×	×

¹ √ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

proportional to the energy and density of sensors. However, it is inversely proportional to the amount of data to be uploaded. Thus, to minimize the flight time of UAV during data collection, the horizontal distance that the sensors can upload data to the UAV, the speed of UAV, and the transmit power of sensors are jointly optimized in [57] and [34]. In the multi-UAV enabled IoT, Zhan *et al.* [32] focus on the problem of minimizing the maximum completion time of data collection among all UAVs. They jointly optimize the trajectories of UAVs, wake-up scheduling and association for sensors, while ensuring that sensors can successfully upload a given amount of data with limited energy budget.

In the above literatures, the constraint is that the energy of UAV or sensor is limited. Zhan and Huang [58] study the fundamental tradeoff between the energy consumption of UAV and that of all sensors. In order to characterize this tradeoff relation, they formulate an optimization problem to minimize the weighted sum of the energy consumption of UAV and sensors. Then, the trajectory of UAV, mission completion time and wake-up scheduling for all sensors are jointly optimized.

C. Hybrid Mode

The hybrid mode combines the characteristics of hovering mode and flying mode. The UAV stays above the data collection point for data collection. When the UAV flies to the next collection point after a period of time, data collection can still be carried out until the UAV is out of the communication range of the sensor. The energy consumption and flight time under hybrid mode are smaller than that under hovering mode, but larger than that under flying mode. Different data collection modes are usually chosen according to the application scenarios and performance requirements.

The hybrid mode can adjust the data collection mode dynamically according to the energy consumption of UAV. To minimize the average AoI of data collection, Jia *et al.* [33] lower the AoI of data collection under three data collection modes, energy consumption at each node and age evolution of collected data. When the initialized energy of sensor increases, hybrid mode has better performance than the other modes. Because of the limited battery of machine-type communications devices (MTCDs) and UAV, Zhu *et al.* [59] propose a hybrid hovering points selection (HHPS) algorithm

to select the hovering points of UAV with the minimum power consumption of MTCDs.

V. JOINT PATH PLANNING AND RESOURCE ALLOCATION

Path planning of UAV refers to the calculation of the optimal path of UAV from the source to the destination under specified conditions [64]. The UAV path planning has a crucial influence on the performance of data collection. There are various goals for path planning, such as the shortest path, the shortest flight time and the lowest energy consumption of UAV. The characteristics of UAV, such as high mobility and flexible deployment, bring challenges for UAV path planning. Besides, considering the limited energy and radio resources of UAV, the UAV path planning is usually combined with resource allocation to efficiently optimize the resource utilization [65, 66]. Hence, the complexity of joint path planning and resource allocation is high because the decision space is huge.

In this section, according to the techniques in the algorithms, the updating methods, objective functions and so on, we classify the path planning algorithms into graph theory based algorithms, optimization theory based algorithms and artificial intelligence (AI) based algorithms. Then, the relevant literatures of UAV path planning are reviewed in the scenario of UAV assisted data collection.

A. Graph Theory based Algorithms

Graph theory based path planning algorithms include Voronoi diagram algorithm, probabilistic roadmap (PRM) algorithm, Hilbert curve algorithm, and so on. Using graph theory based algorithm, the geographical space where UAV is flying is converted into a graph and the path between source and destination is searched. The comparison of different algorithms is listed in Table V, where the key metrics are explained as follows.

- *Amount of collected data (AoCD)*: The amount of data collected by UAV.
- *Time efficiency (TE)*: The time duration for UAV to complete data collection.
- *Energy efficiency (EE)*: The energy consumption of UAV and sensors in terms of battery or fuel.
- *Age of information (AoI)*: Freshness of collected data, which needs to be distinguished from the latency and

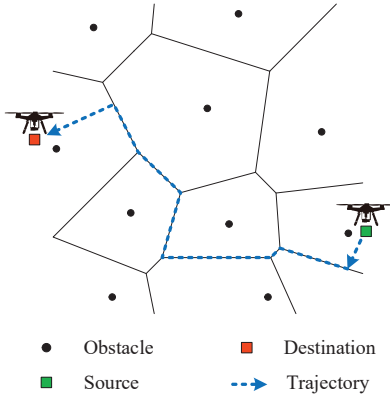


Fig. 4. The principle diagram of Voronoi diagram.

is defined as the time interval between the time when the sensor data is generated and the time when the UAV returns and uploads the collected data to the data center. Specifically, the latency is the time interval between the sending time and the receiving time of data, while AoI is the time interval between the generation time and the use time of data [37–39].

In UAV assisted data collection, AoCD, TE, EE, AoI are the key performance metrics that may be considered in the algorithm design.

1) *Voronoi diagram*: Voronoi diagram, also known as Tyson polygon or Dirichlet diagram, is a set of polygons composed of vertical bisectors connecting two adjacent points, where the points are the obstacles [67, 68]. The advantage of Voronoi diagram is that the generated path is far away from obstacles. Thus collision can be avoided. As shown in Fig. 4, the circular is regarded as the obstacle and the plane is divided in light of the nearest neighbor principle. The point within a polygon is nearest to the obstacle within this polygon compared with other obstacles. Then, the shortest path is searched along the edges of the polygons as the flight path of UAV [69], which is denoted by the dotted line in Fig. 4. The Voronoi diagram can be constructed using four algorithms: incremental algorithm, intersect of half planes, divide and conquer algorithm and plane sweep algorithm [70–72].

Aiming to design the energy-saving path of UAV for data collection, Baek *et al.* [60] modify the Voronoi diagram which determines the optimal hovering point of UAV according to the residual energy of sensors, so as to maximize the minimum remaining energy of sensors, extending the network lifetime. Compared with the path planning of UAV based on Voronoi diagram in [73–75], the total length of flight path of UAV is shortened. However, in practical application scenarios, it is difficult for a single UAV to deal with too many sensors. Wang *et al.* [61] study the cooperative data collection system using multiple UAVs, which applied Voronoi diagram to allocate the collection areas of each UAV. Combined with the optimization of the speed, collection position and transmit power of UAV, the trajectories of multiple UAVs are obtained, which effectively shorten the completion time of data collection.

2) *Probabilistic roadmap*: PRM consists of sampling points and collision-free straight-line edges [76–78], as shown in

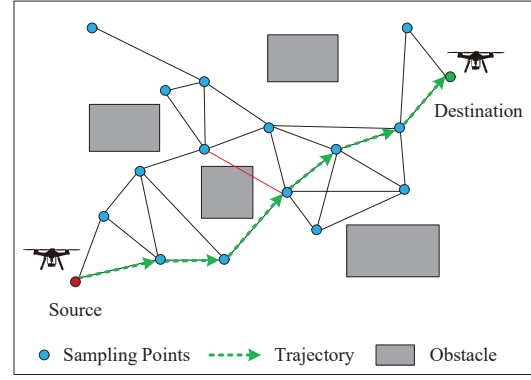


Fig. 5. The principle diagram of PRM.

Fig. 5. The sampling points are selected in the space without obstacles. PRM based path searching algorithm consists of the stages of learning and query. In the learning stage, PRM randomly scatters points in the region to construct an undirected graph. In the query stage, PRM applies the shortest path algorithms to find the flight path of UAV. This method uses relatively few random sampling points to find a solution. And the probability of finding a path tends to 1 with the increase of the number of sampling points.

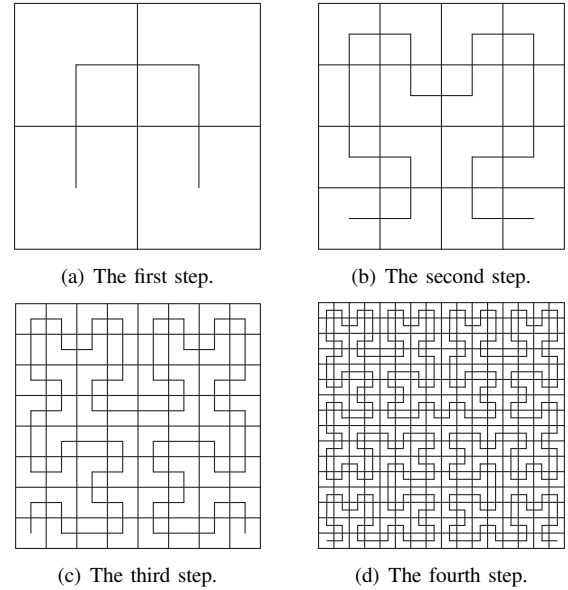


Fig. 6. The first three steps of the Hilbert space-filling curve.

Penicka *et al.* [62] consider the existence of obstacles in UAV assisted data collection. The data collection mission is considered as a physical orienteering problem, which aims at ensuring a feasible, collision-free trajectory to maximize the collected data (reward) with the constraint of energy (budget). The asymptotically optimal sampling-based probabilistic roadmap (PRM*) combined with variable neighborhood search (VNS) algorithm is proposed. The proposed algorithm applies VNS algorithm to expand the initial roadmap with low-density nodes, and the PRM* algorithm is applied to build a shortened collision-free trajectory. The low-density initial roadmap brought an advantage of lower computational

TABLE VI
COMPARISON OF OPTIMIZATION THEORY BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Dynamic programming	[34]	Minimization of flight time of UAV.	Time slot, speed of UAV, transmit power of sensors.	✓	✓	✓	×
	[57]	Minimization of flight time of UAV.	Time slot, transmit power of sensors, data collection interval.	✓	✓	✓	×
	[9]	Minimization of AoI.	The number and location of data collection points, UAV path planning, associations of sensors and data collection points.	×	✓	×	✓
	[33]	Minimization of AoI.	Data collection mode, energy consumption of sensors, age evolution of collected data.	×	×	✓	✓
	[80]	Minimization of the average AoI.	Energy harvesting time, data collection time for each sensor, UAV path planning.	×	×	×	✓
	[81]	Minimization of AoI.	The number of data collection points, transmission priority of sensors, the balance between flight time of UAV and data upload time, UAV path planning.	×	✓	×	✓
Branch and bound	[82]	Maximization of the number of sensors and minimization of the amount of collected data with time constraint.	Radio resource allocation, UAV path planning.	✓	×	×	✓

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

complexity compared with other algorithms with high-density initial roadmaps.

3) *Hilbert curve*: The Hilbert curve plays an important role in image processing, multidimensional data index, and so on, which is a space-filling curve mapping from one-dimensional space to the two-dimensional space [79]. As shown in Fig. 6, a space is divided into subspaces, and the Hilbert curve can pass through all the subspaces. Fig. 6 shows the Hilbert curve from first order to fourth order.

The construction of Hilbert curve is an iteration of the order. The curve is organized by straight lines, and always pass through the center of subspaces. Each subspace is divided into four subspaces in each iteration, such that the curve can have better granularity after iteration. Finally, a curve covering the entire space is formed, which provides the optimal trajectory for the UAV to cover the area of data collection. In [63], a UAV using delay tolerant network protocol is applied to realize data collection in the large-area IoT scenarios without pre-deployed network infrastructure. In particular, Liang *et al.* [63] apply the path planning algorithm based on Hilbert curve to determine the flight path of UAV. The coordinates of sensors are applied as one of the inputs of the algorithm. As shown in Fig. 7, the trajectory generated by the algorithm based on Hilbert curve can traverse all the cells where sensors are deployed and skip the cells without sensors.

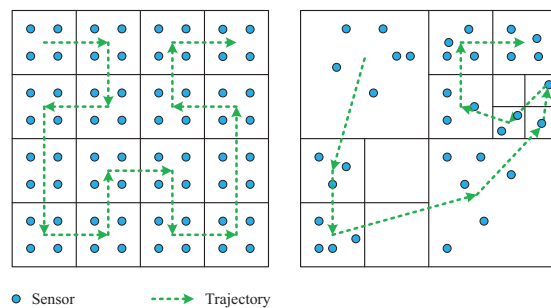


Fig. 7. Trajectory of UAV based on Hilbert curve.

B. Optimization Theory based Algorithms

In the problem of joint path planning and resource allocation of UAV for data collection, the algorithms based on optimization theory, such as dynamic programming (DP), branch and bound, successive convex approximation (SCA), can find the optimal or suboptimal solution. However, for some NP-hard problems, the time complexity is exponential and intolerable. When the decision space is huge, the heuristic methods can be applied to find the feasible solution. Table VI and Table VII compare the literatures using optimization theory based algorithms.

1) *Dynamic programming*: DP is a nonlinear optimization method proposed by Bellman [90]. DP transforms multi-stage decision-making problem into a series of single-stage decision-

TABLE VII
COMPARISON OF OPTIMIZATION THEORY BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Successive convex approximation	[83]	Minimization of propulsion energy consumption of UAV.	Length and curvature of UAV path.	×	×	✓	×
	[84]	Minimum-maximum energy consumption of UAV and sensors.	Communication scheduling between UAV and sensors, transmit power of sensors, UAV path planning.	×	×	✓	×
	[58]	Weighted minimization of energy consumption for UAV and sensors.	UAV path planning, data collection time, wake-up scheduling of sensors.	×	✓	✓	×
	[32]	Minimization of data collection time.	Wake-up scheduling of sensors, UAV path planning.	✓	✓	✓	×
	[85]	Maximum of minimum data collection rate.	UAV time allocation, UAV path planning.	✓	✓	✓	×
	[86]	Maximization of throughput between UAV and sensors.	Resource allocation, UAV path planning.	×	×	×	×
	[10]	Minimization of flight time of UAV.	Resource allocation of sensors, UAV path planning.	✓	✓	✓	×
	[87]	Maximization of power transmission efficiency.	Power of the charging station, UAV path planning, communication scheduling between of UAV and sensors.	×	×	✓	×
	[88]	Maximization of throughput of air-to-ground networks.	Communication scheduling between of UAV and sensors, UAV path planning, transmit power of sensor/UAV-CHs.	×	×	✓	×
Matrix completion	[89]	Minimization of energy consumption of UAV and redundant data.	Sampling point selection, UAV path planning.	✓	×	✓	×

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

making problems [91]. The optimal path can be obtained recursively. According to the types of objective functions, the DP based joint path planning and resource allocation methods are summarized as follows.

- *Minimization of flight time of UAV*

Minimizing the flight time of UAV can fundamentally reduce the energy consumption of UAV. The sensors are deployed in a straight line in [35] and the trajectory of UAV is divided into non-overlapping intervals for data collection. The interval for data collection is optimized using DP to minimize the flight time of UAV. And the optimal speed of UAV and transmit power of sensors are found. Furthermore, Gong *et al.* [57] apply DP to optimize the partition of intervals.

- *Minimization of AoI*

In terms of the average AoI, taking AoI as objective function is better than taking flight time of UAV as optimization objective. Especially when the sensor buffer is limited or data is covered regularly, timely data collection becomes very critical. Jia *et al.* [33] find the best path for UAV by jointly considering the access sequence of sensors and data collection mode. A solution based on DP is proposed to determine the optimal access sequence of sensors and minimize the average AoI. Hu *et al.* [80] decompose the problem of minimizing the average AoI of collected data into time allocation and energy transfer problem, and trajectory of UAV optimization problem.

Different from other models considering that UAV has limited energy and needs to be powered by a BS, Hu *et al.* [80] assume that UAV acting as a mobile power source collects the data of sensors and powers the sensors. However, the algorithms using DP are complex and inefficient when the number of sensors is large.

- *Minimization of maximum AoI or average AoI*

Aiming at the problem of data collection with optimal AoI, sensor association and path planning are jointly optimized to reveal the optimal tradeoff between data transmission time of sensors and the flight time of UAV in [9]. It is verified that the path maximizing AoI is the shortest Hamiltonian path. When the number of data collection points, flight path of UAV and sensors scheduling are jointly optimized, maximum AoI can be greatly reduced. Liu *et al.* [81] study the problem of UAV assisted data collection based on AoI. On the basis of determining the hover point and sensors access sequence of UAV, they use DP to calculate optimal trajectories to minimize the maximum AoI or average AoI.

2) *Branch and bound*: Branch and bound (BB) is a kind of search and iteration method [92, 93]. BB decomposes the given problem into sub-problems iteratively. The sub-problem decomposing process is called branching. The boundary of the sub-problem's objective function is called the bound.

In order to collect data from as many sensors as possible

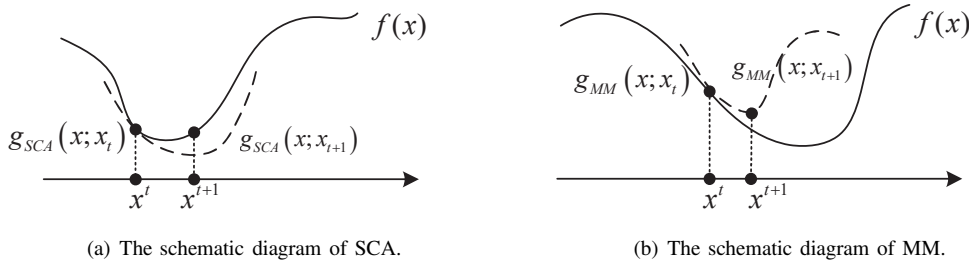


Fig. 8. Comparison of MM and SCA for solving optimization problems.

and ensure a minimum amount of uploaded data per sensor, Samir *et al.* [82] design a high-complexity branch, reduce and bound (BRB) algorithm to find the global optimal solution in relatively small scale IoT. In the BRB algorithm, a set of N non-overlapping hyper-rectangles that cover the optimization problem of maximizing the number of served sensors is maintained. The hyper-rectangle contains all feasible solutions of the optimization model. And three operations, namely, branching, reduction and bounding, are conducted for each iteration in the BRB to improve the lower and upper bounds of the objective function until the difference between the lower and upper bounds is smaller than a predefined value. Accordingly, the hyper-rectangle is constantly reduced to update the upper and lower bounds and remove the part that does not meet the feasible solution.

3) *Successive convex approximation*: SCA transforms the original nonconvex optimization problem into a series of convex optimization problems which can be solved efficiently. As shown in Fig. 8, the principle of SCA is similar to majorize-minimize or minorize-maximize (MM), which can solve a series of convex optimization problems similar to the original problem iteratively [94, 95]. When the final convergence condition is satisfied, the solution is approximately regarded as the solution of the original problem. MM requires that the approximation function $U_{MM}(x_t)$ is the upper bound of the original function at the approximation point, which is one feasible solution of objective function. Besides, SCA requires that the approximation function $U_{SCA}(x_t)$ is convex. Then, we summarize the SCA based joint path planning and resource allocation methods according to the objective functions.

- *Minimization of energy consumption*

The path planning of UAV needs to take into account time and energy consumption. Dong *et al.* [83] firstly propose a mobility model for fixed wing UAV, which is composed of straight line segment and circle segment. And they apply path discretization approach and SCA to optimize the straight circular trajectory to minimize the propulsion energy consumption of UAV on the premise of satisfying the throughput requirements. Zhan and Lai [84] focus on the propulsion energy model of rotary wing UAV. Under the premise of limited UAV energy, they jointly optimize the communication scheduling of sensors, transmit power allocation and trajectory of UAV to minimize the maximum energy consumption of UAV and sensors. For the non-convex problem, an efficient suboptimal solution by applying the alternating optimization and SCA is proposed. In particular, Zhan and Huang [58]

reveal a basic trade-off between the energy consumption of UAV and sensors. In [58], they optimize the trajectory of UAV, data collection time and wake-up schedule to minimize the weighted energy consumption of UAV and sensors. In addition, SCA and block coordinate descent (BCD) techniques are applied to obtain the local optimal solution.

- *Maximization of flight time of UAV*

Zhan and Zeng [32] minimize the completion time of the maximum task of multiple UAVs and ensure that the energy of all sensors are sufficient to upload data. By leveraging bisection method and time discretization technique, the original problem is transformed into a discrete equivalent problem, which contains a finite number of optimization variables. And a Karush-Kuhn-Tucker (KKT) solution is obtained by using SCA. In [10], two orthogonal multiple access schemes, namely, TDMA and frequency division multiple access (FDMA), are designed and compared. Zong *et al.* use a binary search algorithm based on SCA to minimize the completion time of data collection. It is proved that the completion time in FDMA scheme is shorter than that in TDMA scheme.

- *Maximization of the amount of collected data*

In [85], Luo *et al.* propose an efficient iterative algorithm to optimize the 3D path planning and time allocation for UAV. The algorithm jointly utilizes epigraph equivalent representation, variable substitution, equivalent representation by using SCA. In addition, the combination of wireless power transmission and data collection effectively solves the problem of data collection with limited energy. In [96], considering the velocity constraint of UAV, the corresponding transmission scheduling and power allocation for sensors are designed by applying BCD and SCA under the given initial trajectory.

- *Maximization of throughput*

With the goal of maximization of average throughput between UAV and sensors, Sun *et al.* [86] propose a two-tier UAV communication strategy. In the first tier of the strategy, sensors transmit data to their CHs via a multi-channel ALOHA-based random access scheme. And in the second tier, CHs deliver the aggregated data to the UAV through coordinated TDMA. A low complexity iterative algorithm based on SCA is designed to jointly optimize the trajectory and resource allocation of UAV. Under the constraints of UAV mobility and transmit power of sensors or UAV, Hua *et al.* [88] combine transmit power and communication scheduling of sensor or UAV to maximize the total throughput of the system. And they use SCA to obtain the global optimal solution and suboptimal solution maximizing throughput, respectively.

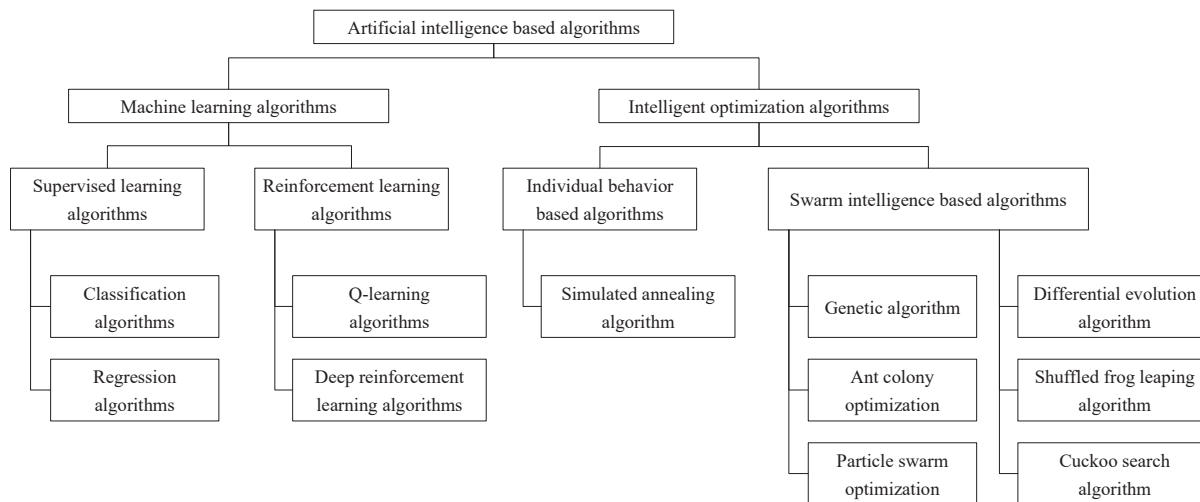


Fig. 9. Artificial intelligence based algorithms for joint path planing and resource allocation.

- *Maximization of power transmission efficiency*

Chen *et al.* [87] introduce the adaptive resonant beam charging system to charge the UAV. In addition to ensuring the quality of service, the power transmission efficiency is maximized by jointly optimizing the trajectory of UAV and the power of charging station. In particular, SCA and Dinkelbach methods are used to deal with the problems of trajectory design and power control, respectively.

4) *Matrix completion method*: Matrix completion uses the observed matrix elements to estimate the unknown elements and recover the entire matrix [97, 98]. These data matrices are usually low rank, and there are some missing data. The problem of low rank matrix completion is to predict those missing data through the observed data and then recover the matrix, using the low rank property of the matrix. Based on the above characteristics, matrix completion method can be used to select the UAV data sampling points and recover the missing data. Because of the high correlation between the collected data, even if the UAV only collects limited amount of data, it can recover the data of the entire monitoring area by exploring the data correlation [99, 100].

Matrix completion method is applied to guide UAV to select data collection points from the perspective of time and space in [89]. The data collected at different positions/times can form a position/time matrix. Taking the location matrix as an example, according to the number of selected sampling points in the row of the sampling points in the location matrix, [89] dynamically adjust the probability of the selected sampling points, which effectively reduces the data redundancy. Based on the results of matrix completion method, ant colony optimization (ACO) is used to minimize the trajectory of UAV. According to the path selection probability, the sampling points are gradually selected by UAV until their number reaches a certain value.

C. Artificial Intelligence based Algorithms

Compared with the traditional algorithms, AI based algorithms can deal with the uncertainty of path planning more effectively and get the approximately optimal solution. AI

based the path planning algorithms are classified into machine learning algorithms and intelligent optimization algorithms. The detailed classification is shown in Fig. 9.

1) *Supervised learning*: A machine learning algorithm is able to acquire knowledge autonomously. According to learning methods, machine learning algorithms can be classified into semi-supervised learning, unsupervised learning, supervised learning, ensemble learning, reinforcement learning (RL) and deep learning (DL). Among them, supervised learning and RL are widely used in UAV path planning. Table VIII compares the literatures using supervised learning based algorithms.

a) *Classification algorithms*: The classification algorithms mainly construct the classification model in the labeled training data, and then classify the new data based on this model. In [101], the path planning problem is modeled as a traveling salesman problem (TSP) with the neighborhood (TSPN). And two trajectory design methods, segment-based trajectory optimization algorithm (STOA) and group-based trajectory optimization algorithm (GTOA), are proposed. STOA calculates the visit order of all sensors and data collection points. While GTOA divides all sensors into clusters and calculates the visit order and locations based on clusters. UAV only needs to pass through the cross region of common transmission region of the grouped sensors. In particular, the sensor that has the largest number of neighbor sensors is selected as CH. The limited flight time of UAV is a challenge for data collection. Aiming to minimizing the total energy consumption of sensors while ensuring data collection through joint optimization of trajectory of UAV, data transmission scheduling of sensors and transmit power. Zhao *et al.* [102] innovatively use non-orthogonal multiple-access (NOMA) in UAV data collection. In addition, the generalized benders decomposition (GBD) is used to decouple sensors scheduling and transmit power.

b) *Regression algorithms*: The regression algorithms extract features from the sample data and predict the continuous target values corresponding to the new data. Chen *et al.* [43] introduce the concept of measurement stream to transform the

TABLE VIII
COMPARISON OF SUPERVISED LEARNING BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Classification algorithm	[101]	Minimization of flight time of UAV.	Height and speed of UAV, link scheduling, UAV path planning.	×	✓	×	×
	[102]	Minimization of total energy consumption of sensors.	Transmission scheduling of sensors, transmit power of sensors, UAV path planning.	✓	×	✓	×
Regression algorithm	[43]	Maximization of the amount of data collected.	Clustering of sensors, value of information (VoI), power of sensors, UAV path planning.	✓	×	✓	×

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

TABLE IX
COMPARISON OF Q-LEARNING BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Q-learning	[103]	Maximization of the amount of data collected.	Time slot, UAV path planning.	✓	✓	×	×
	[104]	Asymptotic minimization of packet loss in IoT.	scheduling of microwave power transfer (MPT) of UAV, UAV path planning.	✓	×	✓	×
	[40]	Minimization of data expiration and loss.	UAV path planning.	✓	×	×	✓
	[105]	Minimization of flight path length of UAV.	UAV collision avoidance, UAV path planning.	×	✓	×	×
	[106]	Minimization of the total energy consumption of UAV.	The real-time amount of data collected, the transmission time between the UAV and aerial BS, UAV path planning.	✓	✓	✓	×

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

traditional RL problem into a supervision learning problem. On the premise of defining VoI, [43] divides all sensors into clusters, and determines the CHs and data forwarding rules according to the power of sensors and VoI. Finally, the UAV collects the aggregated data from CHs. And direct future prediction (DFP) model is applied in the path planning of UAV, so that UAV can deal with multi-objective tasks, maximizing the VoI of collected data and ensuring the UAV charging.

2) *Reinforcement learning algorithms*: RL applies the interaction with the environment to explore the mapping between the optimal state and the action, and finally achieves an optimal strategy and maximizes the cumulative revenue. The training data of supervised learning is generally independent with each other. However, RL deals with sequential decision-making problems, which are dependent with each other in the sequencing. RL is usually applied in obstacle avoidance and path planning of UAV.

a) *Q-learning algorithms*: Q-learning is a model-free RL algorithm using a time-series difference method, which can carry out off-policy learning [117]. Q-learning selects new actions and updates value function. Table IX compares the literatures using Q-learning algorithms. We summarize Q-learning based methods according to the optimization objectives.

- *Maximization of the amount of collected data and mini-*

mization of data loss rate

On the premise that the sensor position is unknown, Cui *et al.* model UAV path planning as a Markov decision process (MDP) in [103], as well as divide the target area into multiple identical rectangular cells. [103] proposes an RL problem to maximize the cumulative amount of data collected and find the optimal trajectory of UAV. Two trajectory optimization algorithms are proposed based on state-action-reward-state-action and Q-learning so that the flight path of UAV can be optimized without the information on the network's topology. However, [103] does not consider energy consumption of UAV and sensors and the packet loss of sensors. In this regard, Li *et al.* [104] use UAV with microwave power transfer (MPT) capability and propose a double-Q learning scheduling algorithm, which jointly optimizes the schedule of MPT and data collection without prior information on battery levels and data queue lengths of sensors. This algorithm effectively minimizes the packet loss of sensors in a long time. Facing the requirement of time-sensitive data collection, Li *et al.* [40] propose an RL method to obtain a minimum-maximum AoI optimal path. And they combine AoI, the deadline constraints of data and Q-learning to optimize the flight path of UAV for the first time. The data loss rate is closely related to the flight time of UAV and the flight order over sensors. The results

TABLE X
COMPARISON OF DEEP REINFORCEMENT LEARNING BASED ALGORITHMS

DRL method	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Deep Q-network (Deep Q-learning)	[107]	Minimization of the weighted sum of AoI, packet drop rate and the energy consumption of UAV.	Random or fixed sampling, buffer management, UAV path planning.	✓	×	✓	✓
	[108]	Minimization of weighted sum of AoI.	Transmission scheduling of sensors, UAV path planning.	×	✓	✓	✓
	[109]	Minimization of buffer overflow and transmission failure of sensors.	Instantaneous waypoint of UAV.	✓	×	×	×
	[110]	Minimization of the average AoI.	Transmission scheduling and energy harvesting of sensors, UAV path planning.	×	×	✓	✓
	[111]	Minimization of flight path length of UAV and maximization of the amount of data collected.	UAV path planning.	✓	✓	×	×
Deep deterministic strategy gradient	[112]	Minimization of AoI under minimum throughput constraints.	Scheduling strategy of UAV, UAV path planning.	×	×	×	✓
	[113]	Minimization of flight time of UAV.	Time window of data collection, priority of sensors, UAV path planning.	×	✓	✓	×
	[114]	Long term freshness of UAV situation awareness.	Resource allocation, UAV path planning.	×	×	✓	✓
	[115]	Minimization of the weighted sum of expected AoI, propulsion energy consumption of UAV and energy consumption of sensors.	Hovering points and flight speed of UAV, transmission scheduling of sensors.	×	×	✓	✓
Proximal policy optimization	[116]	UAV crowdsensing.	The number of UAV and charging station, UAV path planning.	×	×	✓	×

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

show that the optimization method based on RL has low time consumption and data loss rate.

- *UAV collision avoidance and minimization of energy consumption*

Facing the possible collision of multiple UAVs in data collection, Hsu and Gau [105] focus on the collision avoidance algorithm based on RL to obtain an optimal trajectory of UAV. Considering the influence of limited energy and communication resources on flight endurance and data collection of UAV, Ni *et al.* [106] use an RL algorithm to optimize the real-time field data size collected by the on-board camera, transmission time between UAV and aerial BS, flight path of UAV, so as to minimize the total energy consumption of UAV during data collection.

b) *Deep reinforcement learning algorithms*: DL has strong perception, but it lacks decision-making ability. RL has the ability of decision-making, but it lacks perceptual ability. The combination of them, namely, the deep reinforcement learning (DRL), can complement each other and decide the action to maximize revenue [118]. Using DPL to solve the joint optimization problem is also the cutting-edge scheme of

UAV assisted data collection. We compare the literatures using DRL algorithms in Table X and summarize them according to the objective functions as follows.

- *Minimization of AoI*

Modeling DPL problem as MDP is a common method for simplification. [107, 108, 110] all apply a DRL algorithm called deep Q-network (DQN) to achieve the optimal strategy and effectively overcome the disaster of dimensionality. In [107], the data collection problem is modeled as an MDP with final state and action space. Further, the weighted sum of AoI, packet loss rate and energy consumption of UAV is minimized by optimizing the flight path of UAV. Yi *et al.* [108] establish a MDP to find the best flight path of UAV and the transmission scheduling of sensors, so as to minimize the weighted sum of AoI. Liu *et al.* [110] establish an MDP with large state spaces to minimize the average AoI, and the flight path of UAV, transmission scheduling and energy harvesting of sensors are jointly optimized. The simulation results show that the increase of flight time of UAV/transmit power or the decrease of the packet size will reduce the average AoI.

In [112], the UAV assisted vehicular network is considered,

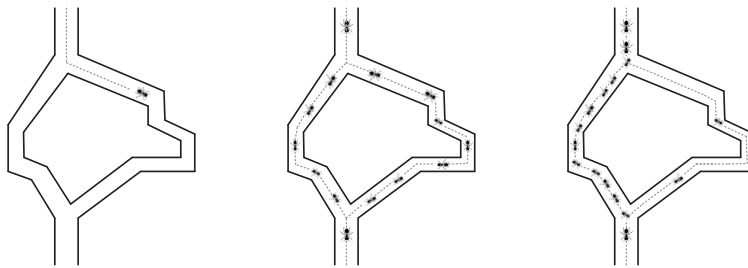


Fig. 10. Illustration of ant colony seeking optimal path in foraging.

where UAVs are used to collect and process the data of sensors. Samir *et al.* develop the deep deterministic strategy gradient (DDPG) to process the trajectory and the scheduling policy of UAVs to minimize the expected weighted sum of AoI. In order to minimize the weighted sum of AoI and the number of sensors as well as energy consumption of UAV, Sun *et al.* [115] comprehensively consider the data collection points, flight speed and bandwidth allocation of UAVs.

- *UAV collision avoidance and minimization of data transmission failure rate*

In order to avoid the possible collisions among UAVs when collecting data from IoT, Liu *et al.* [116] transforms the problem of UAV collision avoidance into a partially observable MDP and present a DRL model named “j-PPO+ConvNTM”. The model can make continuous (path planning) and discrete (data collection and charging) decisions for all UAVs. To minimize the buffer overflow probability of sensors and transmission failure due to the path loss of air-ground channel, Li *et al.* [109] propose a path planning algorithm named Deep Reinforcement Learning based Trajectory Planning. Considering the battery levels and buffer lengths of sensors, the location of UAV and channel conditions, a DRL algorithm is applied in the path planning of UAV to minimize the data loss.

- *Maximization of the amount of collected data*

Considering the limited energy and flight time of UAV, Nguyen *et al.* [111] take minimizing the flight path and maximizing the amount of collected data as the optimization objectives. Through the deep Q-learning and dueling DQL, the UAV can independently decide the next action at each position, so as to obtain a 3D trajectory that can balance the performance of throughput, data collection time and length of flight path. In [119], adopting the full duplex mode, UAV collects data and charges the sensors within its coverage while hovering. A multi-objective optimization problem is proposed, including maximizing the sum data rate and the total harvested energy of sensors as well as minimizing the energy consumption of UAV. The UAV realizes online path planning through a DRL algorithm based on DDPG.

- *Minimization of data collection time*

Bouhamed *et al.* [113] use a combination algorithm of DDPG and Q-learning to minimize data collection time. Furthermore, DDPG is used to realize UAV autonomous navigation in the environment with obstacles, while Q-learning is used to determine the task arrangement of UAV to complete data collection as soon as possible.

- *Minimization of energy consumption*

To minimize the energy consumption of UAV, Fan *et al.* [114] present a freshness function based on AoI and a DRL algorithm that can solve the continuous online decision-making problem involving multiple UAVs. In the rapidly changing environment, the algorithm can markedly reduce energy consumption and AoI.

3) *Intelligent optimization algorithms*: Intelligent optimization algorithms are the combination of random search and local search. In the process of intelligent optimization algorithm, learning strategies are used to obtain the information to effectively find the approximately optimal solution. Then, through a comprehensive searching algorithm, the superiority of the solution is improved.

a) *Individual behavior based algorithms*: Individual behavior based algorithms firstly initialize a feasible solution. Then, the algorithm optimize this feasible solution and probabilistically jump out of local optimum to search the near global optimal solution. Taking simulated annealing (SA) algorithm as an example, it is often used to search the approximately global optimal solution in a large solution space. Different from genetic algorithm (GA), simulated annealing algorithm has the feature of probabilistic jumping out of local optimum, which can accelerate path planning. Table XI compares the literatures using intelligent optimization algorithms.

With a goal of improving the energy efficiency of UAV, Liu *et al.* [120] propose a path planning scheme of UAV based on matrix completion and SA. Firstly, the sampling points with degrees from high to low are selected as dominator sampling points, virtual dominator sampling points and follower sampling points. And all data in the monitoring area is recovered by matrix completion. Then, based on the number and location of selected sampling points, SA is used to determine the visit order of each sampling point. The proposed scheme can reduce the data redundancy by 50% and extend the network lifetime of sensors by 17% compared with the scheme using random sampling point.

b) *Swarm intelligence based algorithms*: Swarm intelligence algorithms consists of GA, ACO, particle swarm optimization (PSO), differential evolution (DE) algorithm, shuffled frog leaping algorithm (SFLA), cuckoo search (CS) algorithm. They applied a large amount of individuals to mimic the solutions. Then, the learning and evolution mechanisms are applied to improve the superiority of solutions.

- *Genetic algorithm*

GA simulates the process of biological evolution. A solution to the problem is expressed as a chromosome. The algorithm

TABLE XI
COMPARISON OF INTELLIGENT OPTIMIZATION BASED ALGORITHMS

Algorithm	Reference	Objective function	Decision variables	AoCD	TE	EE	AoI
Simulated annealing	[120]	Maximization of UAV energy utilization.	UAV path planning, sampling points.	✓	×	✓	×
Genetic algorithm	[27]	Minimization of flight time of UAV.	The number of UAV, the number and location of CHs, UAV path planning.	×	✓	×	×
	[121]	Minimization of energy consumption of UAV hovering and communication.	MTCDs clustering, UAV hovering point, UAV path planning.	×	×	✓	×
	[122]	Minimization of energy consumption of UAV.	UAV path planning.	×	✓	✓	×
Ant colony optimization	[31]	Maximization of the per-node capacity of UAV.	The number of UAV and service cell, UAV path planning.	✓	×	×	×
	[123]	Minimization of flight cost of UAV.	Clustering of sensors, UAV path planning.	×	×	✓	×
Particle swarm optimization	[124]	Minimization of energy consumption of UAV.	Battery capacity, network quality of service (QoS), area coverage, UAV path planning.	×	×	✓	×
Differential evolution	[125]	Minimum-maximum the energy consumption of UAV, BSs and sensors.	Devices transmission schedule, UAV path planning.	×	✓	✓	×
	[126]	Minimization of data collection time.	The selection of CHs, UAV path planning.	×	✓	×	×
Shuffled frog leaping	[127]	Minimization of energy consumption of UAV.	Data collection time, UAV path planning.	×	×	✓	×
Cuckoo search	[59]	Minimization of energy consumption of UAV and sensors.	UAV path planning, UAV hovering point.	×	×	✓	×

¹ ✓ denotes the existence of the feature, × denotes the absence of the feature

² AoCD: Amount of collected data, TE: Time efficiency, EE: Energy efficiency, AoI: Age of information

obtains the most suitable chromosome through the operations of population reproduction, crossover, and mutation, so as to obtain the optimal solution.

To solve the path planning problem of UAV, Alfattani *et al.* [27] firstly optimize the number and locations of CHs. Then, GA is applied to optimize the number and paths of UAVs to minimize the data collection time. Shen *et al.* [121] convert the path planning problem of UAV into a TSP, which is then solved by GA with a goal of minimizing the energy consumption of UAV and sensors. Joseph *et al.* [122] propose GA based path planning of UAV, which minimizes energy consumption of sensors and UAV under the data offloading time windows and communication constraints.

• Ant colony optimization

As shown in Fig. 10, ACO simulates the process that ants find the shortest path during foraging. An ant is regarded as a solution of the path planning problem. Ants spread the pheromone during path searching process and the optimal path accumulates the most pheromone [128]. Thus, the ants are guided to the optimal path, namely, the optimal scheme is searched. In addition, the diversity of ant colony can avoid local optimization.

Aiming at maximizing the per-node capacity of UAV and the amount of collected data, Wei *et al.* [31] adjust the number

of UAVs and service cells, and design two path planning algorithms. Among them, the ACO based path planning algorithm can minimize the time of data collection time and achieve the per-node capacity closer to its theoretical upper bound. Lin *et al.* [123] use precise algorithm and GA to achieve a hierarchical sensor data collection scheme. A path planning algorithm based on ACO is used to improve the scheme to minimize the energy consumption of UAV.

• Particle swarm optimization

PSO originated from the study of birds foraging. Using information sharing mechanism, individuals learn from each other to find food faster [129]. PSO has great advantages in dealing with continuous optimization problems.

In generally, data retrieving and processing are carried out when UAV completes data collection. In these cases, Shi and Xu [124] propose a path planning problem with the constraint called network quality of service (QoS). For the NP hard problem, a PSO based algorithm is used to minimize the flight time of multiple UAVs.

• Differential evolution algorithm

Similar to GA, DE is a kind of intelligent optimization search through the cooperation and competition among individuals in the population [130]. It has strong global convergence performance and robustness, which is mainly used to

solve global optimization problems with continuous variables.

Wang *et al.* [125] study data collection and 3D positioning of sensors. As a mobile data collector and aerial anchor node, UAV assists BSs to realize sensor positioning and data collection of sensors far away from BSs. A DE Algorithm is proposed to optimize UAV path and transmission priority of sensors to minimize-maximize the energy consumption of UAV, sensors and BSs. And the Cramér-Rao Bound (CRB) is derived to evaluate the performance of the algorithm. The final path in the optimization scheme reduces the energy consumption of UAV by 32%. With the selection of optimal CHs and clustering of sensors, Chawra and Gupta [126] propose a meta-heuristic method based on DE to estimate the delay effective path of each UAV to minimize data collection time. The algorithm consists of four steps including initial population generation, mutation, crossover and selection.

- *Shuffled frog leaping algorithm*

SFLA simulates the information sharing and communication of frogs in foraging. It combines the advantages of the memetic algorithm (MA) and PSO [131].

In [127], Kong *et al.* propose an energy efficient algorithm for data collection in sparse sensor network. The improved SFLA is used to further optimize the location and traversal order of data collection points. Then, these orderly data collection points are used to plan the UAV path with minimum energy consumption of UAV. However, the obstacles in the environment are not considered in this paper.

- *Cuckoo search algorithm*

CS algorithm simulates the unique breeding behavior of cuckoo parasitic brood and lvy flight search mechanism to find the optimal solution. It has a better searching performance than GA and PSO algorithm. In the path planning problem, CS can accurately search the global optimal path in a path planning area with fast speed.

Aiming at minimizing the energy consumption of UAV and sensors, Zhu *et al.* [59] propose a hybrid hover location selection algorithm based on a non-service-tolerance mechanism, which ensures that a few highly scattered MTCs are directly served by the BS to reduce the trajectory length of UAV. On this basis, a path planning method based on CS is proposed to jointly optimize the energy consumption and throughput of UAV, the latency of MTCs and data collection efficiency.

VI. FUTURE TRENDS

It is revealed from the above literature review that most literatures focus on the clustering algorithm of sensors and the path planning algorithm of UAV in order to achieve high efficiency, low energy consumption and low delay data collection. However, the following two challenges have not attracted sufficient attention.

- In the large-scale IoT, a large amount of sensors transmit data to UAV, which leads to data congestion.
- UAV assisted data collection may be carried out without the knowledge of the locations of sensors.

For example, in the scenario of ocean monitoring, there are many buoy sensors widely distributed on the sea surface [132], which may lead to transmission conflicts between competing

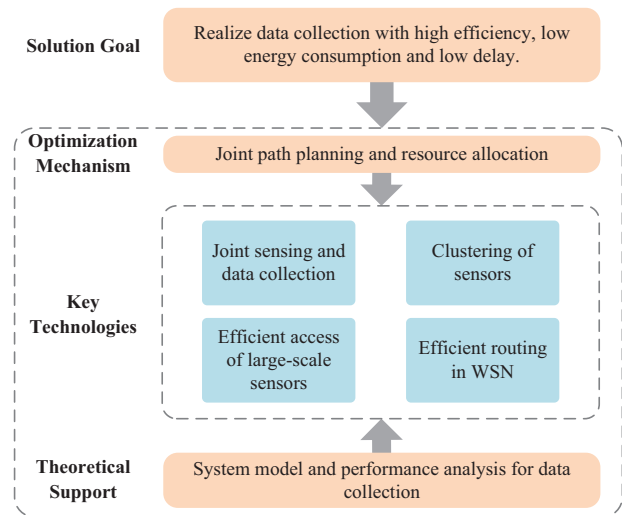


Fig. 11. Scheme of UAV assisted data collection.

sensors. In addition, due to insufficient communication coverage of coastal BSs and high positioning costs such as GPS positioning, it is difficult to obtain the locations of sensors in advance. Similar scenarios include agricultural monitoring and soil monitoring [22–24]. Therefore, we propose a complete solution for UAV assisted data collection in Fig. 11. Joint sensing and data collection, clustering of sensors, efficient access of large-scale sensors and efficient routing in WSN are introduced as key technologies, and joint path planning and resource allocation are applied to provide optimization mechanism with these key technologies.

In the future, we need to focus on but not limited to the following two research trends.

A. Efficient Multiple Access

MAC protocol is designed to satisfy the performance requirements of the network, including solving the potential transmission conflicts between competing sensors, reducing the average packet delay, increasing network throughput, supporting the access of a large number of sensors, balancing energy consumption of UAV and sensors, and so on. The efficient multiple access between UAV and sensors has a crucial impact on the efficiency of data collection and the freshness of data.

In [12], the performance of MAC protocol is improved by scheduling resources in the dimensions of time, frequency and space. Sotheara *et al.* [133] divide the coverage area of UAV into priorities, and sensors access channels according to the priorities of their own regions to reduce transmission conflicts. Due to the limitation of bandwidth, the performance of MAC protocol will reach the bottleneck, especially when the number of sensors is large. The ISM (Industrial, Scientific and Medical) bands including license-free communication frequencies 173 MHz, 433 MHz, 868 MHz and 915 MHz and 2.4 GHz are commonly applied to WSN [134]. In order to expand the bandwidth of WSN, 800/900/1800/2100 MHz of 4G (4th generation mobile communication system) [135] and 5.15-5.85 GHz band of Wi-Fi [136] are also provided for WSN. The

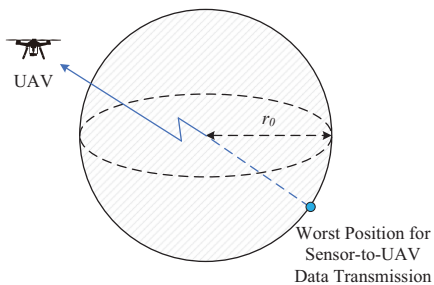


Fig. 12. Data collection with uncertain position of sensor.

application of mmWave in 5G-A (5G Advanced) and Terahertz (THz) in 6G will solve the problem of spectrum shortage [137, 138], which has great potential in providing high data rate and low latency for WSN, providing opportunities for the design of efficient MAC protocol.

When the number of sensors is huge, bandwidth and scheduling schemes cannot always satisfy the requirements of fast and efficient access to channels. In this situation, the NOMA technique is promising to further improve the efficiency of MAC protocol [12, 139]. The combination of UAVs and NOMA can definitely provide high spectral efficiency and support massive connectivity in IoT scenarios [140]. To the best of our knowledge, the investigation on the application of NOMA in UAV data collection is still in its infancy stage [132, 141]. In order to better exploit both the mobility of the UAV and the efficiency of NOMA to improve the UAV assisted data collection performance in ocean observation networks, Chen *et al.* [132] formulated a joint optimization problem of the location of UAV, sensor grouping, and power control in terms of sum rate. When the number of sensors is large, their scheme is able to select sensors with less interference to access the channel, improving the overall performance. Different from [132], the UAV only allows a limited number of nearby devices to be connected to the uplink NOMA network in each time slot, leading to better LoS and successive interference cancellation (SIC) with lower complexity in [141]. Mu *et al.* [142] deploy an intelligent reflecting surface (IRS) to enhance the transmission from UAVs to their intended users while mitigating the interference caused to other unintended users. However, the SIC decoding technology of NOMA may bring large delay, which needs to be solved when designing the NOMA based MAC protocol in the scenario of UAV assisted data collection.

B. Joint Sensing and Data Collection

Sensors are usually randomly distributed in the target area. Most of the existing technologies that support positioning are not suitable for UAV assisted data collection. For example, the cost of installing GNSS chips in a large number of sensors is too high [143]. And the energy consumption of GNSS positioning is high. Therefore, the position information of sensors is generally unknown before data collection. The joint sensing and data collection technology enables the UAV to locate sensors while data collection, as well as satisfying the

requirements of low cost and low energy consumption of the IoT.

However, few literatures take sensing and data collection into consideration together in the scenario of UAV assisted data collection. In order to minimize the maximum energy consumption of all sensors, Wang *et al.* [125] apply a UAV as mobile anchor node and data collector to assist BSs in sensor positioning and data collection. A differential evolution algorithm is proposed to jointly optimize the trajectory of UAV and the transmission schedule of sensors over time. This paper provides a new scheme for the IoT, which realizes low-energy data collection and high-precision 3D positioning. At present, there are many separate studies of UAV assisted sensor positioning and UAV assisted data collection.

1) *UAV assisted sensor positioning*: Due to the flexibility of flight, UAV can select the appropriate position, adjust the posture, and locate the sensors in the target area from different angles, which effectively improves the positioning accuracy. In [144], Xu *et al.* design a target location algorithm based on Unscented Kalman filter (UKF) to improve the accuracy of passive target location of small UAV. The nonlinear target location system with additive white Gaussian noise (AWGN) is considered. The simulation results show that the mean square deviation of the filter estimation error has approached the Cramer-Rao lower bound of the nonlinear system. Han *et al.* [145] propose an autonomous navigation system based on Microcontroller in [144], which obtains the 3D position of the target through the mathematical relationship between the UAV and the ground target. This method significantly improves the accuracy and confidence of measurement. Xu *et al.* [146] propose a positioning method combining maximum likelihood estimation (MLE) and square root volume Kalman filter (SRVKF). The MLE method is applied to locate the unknown sensors. The SRVKF algorithm is then introduced to further improve the positioning accuracy. In particular, the update strategy of threshold selection is used to reduce the influence of nonlinear factors. This method not only improves the positioning accuracy, but also greatly reduces the cost of loading GPS module. In the process of perceptual positioning, data loss or error is inevitable. Due to the uncertainty of wireless signal propagation, Li *et al.* [147] propose an adaptive positioning algorithm combining packet loss rate and received signal strength indicator (RSSI). It makes up for the measurement error without increasing the cost of wireless nodes.

2) *UAV assisted data collection*: For UAV assisted data collection, most studies are carried out under the assumption that the sensor position is known. Generally, key performance indicators such as energy consumption of UAV and sensors, flight time of UAV and AoI will be taken as the objective functions of data collection algorithm. Zhan *et al.* [36] consider the general fading channel model between UAV and sensors and jointly optimize the sensors' wake-up schedule and trajectory of UAV with the goal of minimizing the maximum energy consumption of all sensors. In [148], You and Zhang initially optimize the communication scheduling of sensors and 3D trajectory of UAV in Rician Fading Channel to improve the data collection efficiency. Due to lacking the value of effective fading power, the parameters are approximated by

logic function and solved by BCD and SCA. Han *et al.* [149] take AoI as an index to reveal the freshness of data, and analyze the single IoT device model and the multi-sensor model respectively with first come first service (FCFS) M/M/1 queuing model. In addition, Markov chain is used to predict the amount of collected data and packet loss rate, so as to collect data more efficiently.

In the future, low-power sensing and data collection need to be carried out simultaneously. Meanwhile, because the process of positioning is easily affected by the external environment [150, 151], data collection algorithms with missing location information of sensors or positioning results with large errors need to be designed. Facing the positioning errors, the model of positioning uncertainty is considered in [125]. The initially estimated position coordinates of sensors are taken as the sketchy prior information. Then, the uncertain space of each sensor position is modeled as a sphere with initially estimated position as the center of the sphere. As shown in Fig. 12, it is assumed that the sensor is located furthest from the UAV. B-Spline curves based UAV path is designed, which makes sensors complete the reliable data transmission under the worst data transmission conditions.

VII. CONCLUSION

In this paper, we summarize the scenarios and related technologies of UAV assisted data collection for IoT. The key technologies are reviewed including clustering of SNs, UAV data collection mode, and joint path planning and resource allocation. Hovering mode, flying mode and hybrid mode of UAV are considered. In terms of joint path planning and resource allocation, according to the optimization algorithms used, we review the literatures from the perspectives of graph theory based algorithms, optimization theory based algorithms and AI based algorithms. Finally, we discuss the future trends from two aspects, i.e, efficient multiple access as well as joint sensing and data collection. This article may provide a reference for the research of UAV assisted data collection for IoT.

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REFERENCES

- [1] Ehret and Michael, "The zero marginal cost society: The internet of things, the collaborative commons, and the eclipse of capitalism," *The Journal of Sustainable Mobility*, vol. 2, no. 2, pp. 67–70, 2015.
- [2] S. Liu, Z. Wei, Z. Guo, X. Yuan, and Z. Feng, "Performance analysis of uavs assisted data collection in wireless sensor network," *IEEE 87th Vehicular Technology Conference (VTC Spring)*, pp. 1–5, 2018.
- [3] Z. Wei, Z. Feng, H. Zhou, L. Wang, and H. Wu, "Capacity and delay of unmanned aerial vehicle networks with mobility," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1640–1653, 2019.

- [4] Y. Pang, Y. Zhang, Y. Gu, M. Pan, Z. Han, and P. Li, "Efficient data collection for wireless rechargeable sensor clusters in harsh terrains using uavs," *IEEE Global Communications Conference*, pp. 234–239, 2014.
- [5] R. J. Dobson, C. Brooks, C. Roussi, and T. Colling, "Developing an unpaved road assessment system for practical deployment with high-resolution optical data collection using a helicopter uav," *International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 235–243, 2013.
- [6] B. Zhang, C. H. Liu, J. Tang, Z. Xu, J. Ma, and W. Wang, "Learning-based energy-efficient data collection by unmanned vehicles in smart cities," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 4, pp. 1666–1676, 2018.
- [7] I. Cermakova and J. Komarkova, "Modelling a process of uav data collection and processing," *International Conference on Information Society (i-Society)*, pp. 161–164, 2016.
- [8] C. M. de A. Lima, E. A. da Silva, and P. B. Velloso, "Performance evaluation of 802.11 iot devices for data collection in the forest with drones," *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–7, 2018.
- [9] P. Tong, J. Liu, X. Wang, B. Bai, and H. Dai, "Uav-enabled age-optimal data collection in wireless sensor networks," *IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, 2019.
- [10] J. Zong, C. Shen, J. Cheng, J. Gong, T.-H. Chang, L. Chen, and B. Ai, "Flight time minimization via uavs trajectory design for ground sensor data collection," *16th International Symposium on Wireless Communication Systems (ISWCS)*, pp. 255–259, 2019.
- [11] Z. Wei, X. Liu, C. Han, and Z. Feng, "Neighbor discovery for unmanned aerial vehicle networks," *IEEE Access*, vol. 6, pp. 68 288–68 301, 2018.
- [12] S. Poudel and S. Moh, "Medium access control protocols for unmanned aerial vehicle-aided wireless sensor networks: A survey," *IEEE Access*, vol. 7, pp. 65 728–65 744, 2019.
- [13] J. Baek, S. I. Han, and Y. Han, "Optimal uav route in wireless charging sensor networks," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1327–1335, 2020.
- [14] Z. Wei, H. Wu, S. Huang, and Z. Feng, "Scaling laws of unmanned aerial vehicle network with mobility pattern information," *IEEE Communications Letters*, vol. 21, no. 6, pp. 1389–1392, 2017.
- [15] B. Li, Z. Fei, and Y. Zhang, "Uav communications for 5g and beyond: Recent advances and future trends," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2241–2263, 2019.
- [16] M. Heaphy, M. S. Watt, J. P. Dash, and G. D. Pearse, "Uavs for data collection-plugging the gap," *New Zealand Journal of Forestry*, vol. 62, no. 1, pp. 23–30, 2017.
- [17] H. Q. Pham, M. Comey, K. D. Pham, K. V. Pham, and L. R. Rilett, *Review of Unmanned Aerial Vehicles (UAVs) Operation and Data Collection for Driving*

- Behavior Analysis*. CIGOS 2019, Innovation for Sustainable Infrastructure, 2020.
- [18] P. Dan, F. Stoican, G. Stamatescu, O. Chenaru, and L. Ichim, "A survey of collaborative uavwsn systems for efficient monitoring," *Sensors (Basel, Switzerland)*, vol. 19, no. 21, 2019.
- [19] X. Yang, S. Fu, B. Wu, and M. Zhang, "A survey of key issues in uav data collection in the internet of things," *IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCOM/CyberSciTech)*, pp. 410–413, 2020.
- [20] A. Moheddine, F. Patrone, and M. Marchese, "Uav and iot integration: A flying gateway," *26th IEEE International Conference on Electronics, Circuits and Systems (ICECS)*, pp. 121–122, 2019.
- [21] V. Delafontaine, F. Schiano, G. Cocco, A. Rusu, and D. Floreano, "Drone-aided localization in lora iot networks," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 286–292, 2020.
- [22] G. Castellanos, M. Deruyck, L. Martens, and W. Joseph, "System assessment of wusn using nb-iot uav-aided networks in potato crops," *IEEE Access*, vol. 8, pp. 56 823–56 836, 2020.
- [23] H. Sui, G. Zheng, J. Zhou, H. Li, and Z. Gu, "Application of nb-iot technology in city open water monitoring," *6th International Symposium on System and Software Reliability (ISSSR)*, pp. 95–98, 2020.
- [24] Z. Hu, Z. Bai, Y. Yang, Z. Zheng, K. Bian, and L. Song, "Uav aided aerial-ground iot for air quality sensing in smart city: Architecture, technologies, and implementation," *IEEE Network*, vol. 33, no. 2, pp. 14–22, 2019.
- [25] A. T. Albu-Salih and S. A. H. Seno, "Energy-efficient data gathering framework-based clustering via multiple uavs in deadline-based wsn applications," *IEEE Access*, vol. 6, pp. 72 275–72 286, 2018.
- [26] M. B. Ghorbel, D. Rodriguez-Duarte, H. Ghazzai, M. J. Hossain, and H. Menouar, "Joint position and travel path optimization for energy efficient wireless data gathering using unmanned aerial vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2165–2175, 2019.
- [27] S. Alfattani, W. Jaafar, H. Yanikomeroglu, and A. Yon-gacoglu, "Multi-uav data collection framework for wireless sensor networks," *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, 2019.
- [28] J. Grigulo and L. B. Becker, "Experimenting sensor nodes localization in wsn with uav acting as mobile agent," *IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, vol. 1, pp. 808–815, 2018.
- [29] A. Filippone, "Flight performance of fixed and rotary wing aircraft," *CA*, 2006.
- [30] J. Wang, C. Jiang, Z. Wei, C. Pan, H. Zhang, and Y. Ren, "Joint uav hovering altitude and power control for space-air-ground iot networks," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1741–1753, 2019.
- [31] Z. Wei, Q. Chen, S. Liu, and H. Wu, "Capacity of unmanned aerial vehicle assisted data collection in wireless sensor networks," *IEEE Access*, vol. 8, pp. 162 819–162 829, 2020.
- [32] C. Zhan and Y. Zeng, "Completion time minimization for multi-uav-enabled data collection," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4859–4872, 2019.
- [33] Z. Jia, X. Qin, Z. Wang, and B. Liu, "Age-based path planning and data acquisition in uav-assisted iot networks," *IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, 2019.
- [34] J. Gong, T.-H. Chang, C. Shen, and X. Chen, "Flight time minimization of uav for data collection over wireless sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 9, pp. 1942–1954, 2018.
- [35] X. Mu, Y. Liu, L. Guo, J. Lin, and Z. Ding, "Energy-constrained uav data collection systems: Noma and oma," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 7, pp. 6898–6912, 2021.
- [36] C. Zhan, Y. Zeng, and R. Zhang, "Energy-efficient data collection in uav enabled wireless sensor network," *IEEE Wireless Communications Letters*, vol. 7, no. 3, pp. 328–331, 2018.
- [37] R. D. Yates, Y. Sun, D. R. Brown, S. K. Kaul, E. Modiano, and S. Ulukus, "Age of information: An introduction and survey," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 5, pp. 1183–1210, 2021.
- [38] Z. Fang, J. Wang, C. Jiang, Q. Zhang, and Y. Ren, "Aoi-inspired collaborative information collection for auv-assisted internet of underwater things," *IEEE Internet of Things Journal*, vol. 8, no. 19, pp. 14 559–14 571, 2021.
- [39] Z. Fang, J. Wang, Y. Ren, Z. Han, H. V. Poor, and L. Hanzo, "Age of information in energy harvesting aided massive multiple access networks," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 5, pp. 1441–1456, 2022.
- [40] W. Li, L. Wang, and A. Fei, "Minimizing packet expiration loss with path planning in uav-assisted data sensing," *IEEE Wireless Communications Letters*, vol. 8, no. 6, pp. 1520–1523, 2019.
- [41] S. Kaul, R. Yates, and M. Gruteser, "Real-time status: How often should one update?" *Proceedings IEEE INFOCOM*, pp. 2731–2735, 2012.
- [42] M. Costa, M. Codreanu, and A. Ephremides, "On the age of information in status update systems with packet management," *IEEE Transactions on Information Theory*, vol. 62, no. 4, pp. 1897–1910, 2016.
- [43] J. Chen, F. Yan, S. Mao, F. Shen, W. Xia, Y. Wu, and L. Shen, "Efficient data collection in large-scale uav-aided wireless sensor networks," *11th International Conference on Wireless Communications and Signal Processing (WCSP)*, pp. 1–5, 2019.
- [44] D. Ebrahimi, S. Sharafeddine, P.-H. Ho, and C. Assi,

- “Data collection in wireless sensor networks using uav and compressive data gathering,” *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–7, 2018.
- [45] P. Sujit, D. Lucani, and J. Sousa, “Joint route planning for uav and sensor network for data retrieval,” *IEEE International Systems Conference (SysCon)*, pp. 688–692, 2013.
- [46] Q. Wu, P. Sun, and A. Boukerche, “Unmanned aerial vehicle-assisted energy-efficient data collection scheme for sustainable wireless sensor networks,” *Computer networks*, vol. 165, no. Dec.24, pp. 106927.1–106927.11, 2019.
- [47] S. K. Haider, M. A. Jamshed, A. Jiang, H. Pervaiz, and Q. Ni, “Uav-assisted cluster-head selection mechanism for wireless sensor network applications,” *UK/China Emerging Technologies (UCET)*, pp. 1–2, 2019.
- [48] L. Xu, R. Collier, and G. M. P. OHare, “A survey of clustering techniques in wsns and consideration of the challenges of applying such to 5g iot scenarios,” *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1229–1249, 2017.
- [49] H. E. Xiao-Yu and Y. X. Yao, “Survey of clustering algorithms for wireless sensor networks,” *Computer Knowledge and Technology*, 2017.
- [50] S. K. Singh, P. Kumar, and J. P. Singh, “A survey on successors of leach protocol,” *IEEE Access*, vol. 5, pp. 4298–4328, 2017.
- [51] J. Gnanambigai, D. N. Rengarajan, and K. Anbukkarasi, “Leach and its descendant protocols: A survey.”
- [52] A. Kaur and A. Grover, “Leach and extended leach protocols in wireless sensor network-a survey,” *International Journal of Computer Applications*, vol. 116, no. 10, pp. 1–5, 2015.
- [53] G. N. Basavaraj and C. D. Jaidhar, “H-leach protocol with modified cluster head selection for wsn,” *International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, pp. 30–33, 2017.
- [54] Y. Chen and S. Shen, “A uav-based data collection approach for wireless sensor network,” *7th International Conference on Information Science and Control Engineering (ICISCE)*, pp. 2298–2302, 2020.
- [55] G. Wang, B.-S. Lee, and J. Y. Ahn, “Uav-assisted cluster head election for a uav-based wireless sensor network,” *IEEE 6th International Conference on Future Internet of Things and Cloud (FiCloud)*, pp. 267–274, 2018.
- [56] O. M. Bushnaq, A. Celik, H. Elsayy, M.-S. Alouini, and T. Y. Al-Naffouri, “Aeronautical data aggregation and field estimation in iot networks: Hovering and traveling time dilemma of uavs,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4620–4635, 2019.
- [57] J. Gong, T.-H. Chang, C. Shen, and X. Chen, “Aviation time minimization of uav for data collection from energy constrained sensor networks,” *IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, 2018.
- [58] C. Zhan and R. Huang, “Energy minimization for data collection in wireless sensor networks with uav,” *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, 2019.
- [59] K. Zhu, X. Xu, and S. Han, “Energy-efficient uav trajectory planning for data collection and computation in mmte networks,” *IEEE Globecom Workshops (GC Wkshps)*, pp. 1–6, 2018.
- [60] J. Baek, S. I. Han, and Y. Han, “Energy-efficient uav routing for wireless sensor networks,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 2, pp. 1741–1750, 2020.
- [61] Y. Wang, X. Wen, Z. Hu, Z. Lu, J. Miao, C. Sun, and H. Qi, “Multi-uav collaborative data collection for iot devices powered by battery,” *IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, 2020.
- [62] R. Pnika, J. Faigl, and M. Saska, “Physical orienteering problem for unmanned aerial vehicle data collection planning in environments with obstacles,” *IEEE Robotics and Automation Letters*, vol. 4, no. 3, pp. 3005–3012, 2019.
- [63] H. Liang, W. Gao, J. H. Nguyen, M. F. Orpilla, and W. Yu, “Internet of things data collection using unmanned aerial vehicles in infrastructure free environments,” *IEEE Access*, vol. 8, pp. 3932–3944, 2020.
- [64] Y. S. Jiao, X. M. Wang, H. Chen, and Y. Li, “Research on the coverage path planning of uavs for polygon areas,” in *Industrial Electronics & Applications*, 2010.
- [65] C. Qiu, Z. Wei, Z. Feng, and P. Zhang, “Backhaul-aware trajectory optimization of fixed-wing uav-mounted base station for continuous available wireless service,” *IEEE Access*, vol. 8, pp. 60940–60950, 2020.
- [66] X. Yuan, Z. Feng, W. Xu, W. Ni, J. A. Zhang, Z. Wei, and R. P. Liu, “Capacity analysis of uav communications: Cases of random trajectories,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 8, pp. 7564–7576, 2018.
- [67] X. Chen and X. Chen, “The uav dynamic path planning algorithm research based on voronoi diagram,” *The 26th Chinese Control and Decision Conference (CCDC)*, pp. 1069–1071, 2014.
- [68] W. T. Zhao and J. Y. Peng, “Voronoi diagram-based path planning for uavs,” *Journal of System Simulation*, 2006.
- [69] Y. Zhou, H. Zhao, and Y. Liu, “An evaluative review of the vtol technologies for unmanned and manned aerial vehicles,” *Computer Communications*, vol. 149, no. Jan., pp. 356–369, 2020.
- [70] Qiang, Du, Faber, and Vance, “Centroidal voronoi tessellations: Applications and algorithms.” *Siam Review*, 1999.
- [71] T. Nishida, S. Ono, and K. Sugihara, “Direct diffusion method for the construction of generalized voronoi diagrams,” *4th International Symposium on Voronoi Diagrams in Science and Engineering (ISVD)*, pp. 145–151, 2007.
- [72] M. Berg, M. Kreveld, and M. H. Overmars, *Computational Geometry: Algorithms and Applications*, Computational Geometry: Algorithms and Applications,

- 2008.
- [73] Y. Eun and H. Bang, "Cooperative task assignment/path planning of multiple unmanned aerial vehicles using genetic algorithm," *Journal of Aircraft*, vol. 46, no. 1, pp. 338–343, 2012.
- [74] Y. V. Pehlivanoglu, "A new vibrational genetic algorithm enhanced with a voronoi diagram for path planning of autonomous uav," *Aerospace Science and Technology*, vol. 16, no. 1, pp. 47–55, 2012.
- [75] S. Meguerdichian, F. Koushanfar, M. Potkonjak, and M. B. Srivastava, "Coverage problems in wireless ad-hoc sensor networks," *INFOCOM. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 2001.
- [76] D. Hsu, "On the probabilistic foundations of probabilistic roadmap planning," *International Journal of Robotics Research*, vol. 25, no. 7, pp. 83–97, 2007.
- [77] R. Geraerts and M. Overmars, *A comparative study of probabilistic roadmap planners*, 2003.
- [78] A. A. Ravankar, A. Ravankar, T. Emaru, and Y. Kobayashi, "Hpprm: Hybrid potential based probabilistic roadmap algorithm for improved dynamic path planning of mobile robots," *IEEE Access*, vol. 8, pp. 221 743–221 766, 2020.
- [79] L. Xian, "Four alternative patterns of the hilbert curve," *Applied Mathematics and Computation*, vol. 147, no. 3, pp. 741–752, 2004.
- [80] H. Hu, K. Xiong, G. Qu, Q. Ni, P. Fan, and K. B. Letaief, "Aoi-minimal trajectory planning and data collection in uav-assisted wireless powered iot networks," *IEEE Internet of Things Journal*, vol. 8, no. 2, pp. 1211–1223, 2021.
- [81] J. Liu, P. Tong, X. Wang, B. Bai, and H. Dai, "Uav-aided data collection for information freshness in wireless sensor networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 4, pp. 2368–2382, 2021.
- [82] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, "Uav trajectory planning for data collection from time-constrained iot devices," *IEEE Transactions on Wireless Communications*, vol. 19, no. 1, pp. 34–46, 2020.
- [83] F. Dong, L. Li, Z. Lu, Q. Pan, and W. Zheng, "Energy-efficiency for fixed-wing uav-enabled data collection and forwarding," *IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, 2019.
- [84] C. Zhan and H. Lai, "Energy minimization in internet-of-things system based on rotary-wing uav," *IEEE Wireless Communications Letters*, vol. 8, no. 5, pp. 1341–1344, 2019.
- [85] W. Luo, Y. Shen, B. Yang, S. Wang, and X. Guan, "Joint 3-d trajectory and resource optimization in multi-uav-enabled iot networks with wireless power transfer," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 7833–7848, 2021.
- [86] Z. Sun, Z. Wei, N. Yang, and X. Zhou, "Two-tier communication for uav-enabled massive iot systems: Performance analysis and joint design of trajectory and resource allocation," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1132–1146, 2021.
- [87] W. Chen, S. Zhao, Q. Shi, and R. Zhang, "Resonant beam charging-powered uav-assisted sensing data collection," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 1086–1090, 2020.
- [88] M. Hua, L. Yang, Q. Wu, and A. L. Swindlehurst, "3d uav trajectory and communication design for simultaneous uplink and downlink transmission," *IEEE Transactions on Communications*, vol. 68, no. 9, pp. 5908–5923, 2020.
- [89] X. Liu, H. Song, and A. Liu, "Intelligent uavs trajectory optimization from space-time for data collection in social networks," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 2, pp. 853–864, 2021.
- [90] M. L. Puterman, "Dynamic programming," *Encyclopedia of Physical Science and Technology (Third Edition)*, third edition ed., R. A. Meyers, Ed. New York: Academic Press, pp. 673–696, 2003.
- [91] A. MOKRANE, A. C. BRAHAM, and B. CHERKI, "Uav path planning based on dynamic programming algorithm on photogrammetric dems," *International Conference on Electrical Engineering (ICEE)*, pp. 1–5, 2020.
- [92] E. K. Lee, "Branch-and-bound methods," *Handbook of Applied Optimization*, 2002.
- [93] J. Binney and G. S. Sukhatme, "Branch and bound for informative path planning," *IEEE International Conference on Robotics and Automation*, pp. 2147–2154, 2012.
- [94] Y. Sun, P. Babu, and D. P. Palomar, "Majorization-minimization algorithms in signal processing, communications, and machine learning," *IEEE Transactions on Signal Processing*, vol. 65, no. 3, pp. 794–816, 2017.
- [95] T. Wang and L. Vandendorpe, "Successive convex approximation based methods for dynamic spectrum management," *IEEE International Conference on Communications (ICC)*, pp. 4061–4065, 2012.
- [96] J. Zhang, Y. Zeng, and R. Zhang, "Multi-antenna uav data harvesting: Joint trajectory and communication optimization," *Journal of Communications and Information Networks*, vol. 5, no. 1, pp. 86–99, 2020.
- [97] M. Huang, K. Zhang, Z. Zeng, T. Wang, and Y. Liu, "An auv-assisted data gathering scheme based on clustering and matrix completion for smart ocean," *IEEE Internet of Things Journal*, vol. 7, no. 10, pp. 9904–9918, 2020.
- [98] J. He, G. Sun, Y. Zhang, and Z. Wang, "Data recovery in wireless sensor networks with joint matrix completion and sparsity constraints," *IEEE Communications Letters*, vol. 19, no. 12, pp. 2230–2233, 2015.
- [99] A. Singh, S. Garg, S. Batra, N. Kumar, and J. Rodrigues, "Bloom filter based optimization scheme for massive data handling in iot environment," *Future Generation Computer Systems*, vol. 82, no. MAY, pp.

- 440–449, 2017.
- [100] K. Jin, X. Cheng, X. Ge, and X. Yin, “Three dimensional modeling and space-time correlation for uav channels,” *IEEE 85th Vehicular Technology Conference (VTC Spring)*, pp. 1–5, 2017.
- [101] J. Li, H. Zhao, H. Wang, F. Gu, J. Wei, H. Yin, and B. Ren, “Joint optimization on trajectory, altitude, velocity, and link scheduling for minimum mission time in uav-aided data collection,” *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1464–1475, 2020.
- [102] J. Zhao, Y. Wang, Z. Fei, X. Wang, and Z. Miao, “Noma-aided uav data collection system: Trajectory optimization and communication design,” *IEEE Access*, vol. 8, pp. 155 843–155 858, 2020.
- [103] J. Cui, Z. Ding, Y. Deng, A. Nallanathan, and L. Hanzo, “Adaptive uav-trajectory optimization under quality of service constraints: A model-free solution,” *IEEE Access*, vol. 8, pp. 112 253–112 265, 2020.
- [104] K. Li, W. Ni, B. Wei, and E. Tovar, “Onboard double q-learning for airborne data capture in wireless powered iot networks,” *IEEE Networking Letters*, vol. 2, no. 2, pp. 71–75, 2020.
- [105] Y.-H. Hsu and R.-H. Gau, “Reinforcement learning-based collision avoidance and optimal trajectory planning in uav communication networks,” *IEEE Transactions on Mobile Computing*, pp. 1–1, 2020.
- [106] W. Ni, H. Tian, S. Fan, and G. Nie, “Optimal transmission control and learning-based trajectory design for uav-assisted detection and communication,” *IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1–6, 2020.
- [107] P. Tong, J. Liu, X. Wang, B. Bai, and H. Dai, “Deep reinforcement learning for efficient data collection in uav-aided internet of things,” *IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, 2020.
- [108] M. Yi, X. Wang, J. Liu, Y. Zhang, and B. Bai, “Deep reinforcement learning for fresh data collection in uav-assisted iot networks,” *IEEE INFOCOM - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 716–721, 2020.
- [109] K. Li, W. Ni, E. Tovar, and M. Guizani, “Deep reinforcement learning for real-time trajectory planning in uav networks,” *International Wireless Communications and Mobile Computing (IWCMC)*, pp. 958–963, 2020.
- [110] L. Liu, K. Xiong, J. Cao, Y. Lu, P. Fan, and K. B. Letaief, “Average aoi minimization in uav-assisted data collection with rf wireless power transfer: A deep reinforcement learning scheme,” *IEEE Internet of Things Journal*, vol. 9, no. 7, pp. 5216–5228, 2022.
- [111] K. K. Nguyen, T. Q. Duong, T. Do-Duy, H. Claussen, and L. Hanzo, “3d uav trajectory and data collection optimisation via deep reinforcement learning,” *IEEE Transactions on Communications*, pp. 1–1, 2022.
- [112] M. Samir, C. Assi, S. Sharafeddine, D. Ebrahimi, and A. Ghrayeb, “Age of information aware trajectory planning of uavs in intelligent transportation systems: A deep learning approach,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 12 382–12 395, 2020.
- [113] O. Bouhamed, H. Ghazzai, H. Besbes, and Y. Massoud, “A uav-assisted data collection for wireless sensor networks: Autonomous navigation and scheduling,” *IEEE Access*, vol. 8, pp. 110 446–110 460, 2020.
- [114] W. Fan, K. Luo, S. Yu, Z. Zhou, and X. Chen, “Aoi-driven fresh situation awareness by uav swarm: Collaborative drl-based energy-efficient trajectory control and data processing,” *IEEE/CIC International Conference on Communications in China (ICCC)*, pp. 841–846, 2020.
- [115] M. Sun, X. Xu, X. Qin, and P. Zhang, “Aoi-energy-aware uav-assisted data collection for iot networks: A deep reinforcement learning method,” *IEEE Internet of Things Journal*, vol. 8, no. 24, pp. 17 275–17 289, 2021.
- [116] C. H. Liu, C. Piao, and J. Tang, “Energy-efficient uav crowdsensing with multiple charging stations by deep learning,” *IEEE INFOCOM - IEEE Conference on Computer Communications*, pp. 199–208, 2020.
- [117] K.-S. Hwang and Y.-J. Chen, “An adaptive state aggregation approach to q-learning with real-valued action function,” *IEEE International Conference on Systems, Man and Cybernetics*, pp. 164–170, 2010.
- [118] Y. Li, S. Zhang, F. Ye, T. Jiang, and Y. Li, “A uav path planning method based on deep reinforcement learning,” *IEEE USNC-CNC-URSI North American Radio Science Meeting (Joint with AP-S Symposium)*, pp. 93–94, 2020.
- [119] Y. Yu, J. Tang, J. Huang, X. Zhang, D. K. C. So, and K.-K. Wong, “Multi-objective optimization for uav-assisted wireless powered iot networks based on extended ddpg algorithm,” *IEEE Transactions on Communications*, vol. 69, no. 9, pp. 6361–6374, 2021.
- [120] X. Liu, Y. Liu, N. Zhang, W. Wu, and A. Liu, “Optimizing trajectory of unmanned aerial vehicles for efficient data acquisition: A matrix completion approach,” *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1829–1840, 2019.
- [121] L. Shen, N. Wang, Z. Zhu, Y. Fan, X. Ji, and X. Mu, “Uav-enabled data collection for mmTc networks: Aem modeling and energy-efficient trajectory design,” *IEEE International Conference on Communications (ICC)*, pp. 1–6, 2020.
- [122] J. Joseph, M. Radmanesh, M. N. Sadat, R. Dai, and M. Kumar, “Uav path planning for data ferrying with communication constraints,” *IEEE 17th Annual Consumer Communications Networking Conference (CCNC)*, pp. 1–9, 2020.
- [123] C. Lin, G. Han, X. Qi, J. Du, T. Xu, and M. Martinez-Garcia, “Energy-optimal data collection for unmanned aerial vehicle-aided industrial wireless sensor network-based agricultural monitoring system: A clustering compressed sampling approach,” *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 4411–4420,

- 2021.
- [124] L. Shi and S. Xu, "Uav path planning with qos constraint in device-to-device 5g networks using particle swarm optimization," *IEEE Access*, vol. 8, pp. 137 884–137 896, 2020.
- [125] Z. Wang, R. Liu, Q. Liu, J. S. Thompson, and M. Kadoch, "Energy-efficient data collection and device positioning in uav-assisted iot," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1122–1139, 2020.
- [126] V. K. Chawra and G. P. Gupta, "Multiple uav path-planning for data collection in cluster-based wireless sensor network," *First International Conference on Power, Control and Computing Technologies (ICPC2T)*, pp. 194–198, 2020.
- [127] B. Kong, H. Huang, and X. Jia, "Path planning for sensor data collection by using uavs," *14th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)*, pp. 199–205, 2018.
- [128] M. Dorigo and L. M. Gambardella, "Ant colonies for the traveling salesman problem," *Biosystems*, vol. 43, no. 2, pp. 73–81, 1997.
- [129] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Icnn95-international Conference on Neural Networks*, 2002.
- [130] S. Das and P. N. Suganthan, "Differential evolution: A survey of the state-of-the-art," *IEEE Transactions on Evolutionary Computation*, vol. 15, no. 1, pp. 4–31, 2011.
- [131] O. Bozorg-Haddad, M. Solgi, and H. Loiciga, *Shuffled Frog-Leaping Algorithm*, 2017.
- [132] W. Chen, S. Zhao, R. Zhang, Y. Chen, and L. Yang, "Uav-assisted data collection with nonorthogonal multiple access," *IEEE Internet of Things Journal*, vol. 8, no. 1, pp. 501–511, 2021.
- [133] S. Sotheara, N. Aomi, T. Ando, L. Jiang, N. Shiratori, and S. Shimamoto, "Effective data gathering protocol in wsn-uav employing priority-based contention window adjustment scheme," *IEEE Globecom Workshops (GC Wkshps)*, pp. 1475–1480, 2014.
- [134] S. K. Gupta and P. Sinha, "Overview of wireless sensor network: a survey," *Telos*, vol. 3, no. 15 μ W, p. 38mW, 2014.
- [135] Rashmi, Sharan, Sinha, Yiqiao, Wei, Seung-Hoon, and Hwang, "A survey on lpwa technology: Lora and nb-iot - sciencedirect," *ICT Express*, vol. 3, no. 1, pp. 14–21, 2017.
- [136] M. Ayyash, H. Elgala, A. Khreishah, V. Jungnickel, T. Little, S. Shao, M. Rahaim, D. Schulz, J. Hilt, and R. Freund, "Coexistence of wifi and lifi toward 5g: concepts, opportunities, and challenges," *IEEE Communications Magazine*, vol. 54, no. 2, pp. 64–71, 2016.
- [137] D.-T. Ho and S. Shimamoto, "Highly reliable communication protocol for wsn-uav system employing tdma and pfs scheme," *IEEE GLOBECOM Workshops (GC Wkshps)*, pp. 1320–1324, 2011.
- [138] D.-T. Ho, J. Park, and S. Shimamoto, "Performance evaluation of the pfsc based mac protocol for wsn employing uav in rician fading," *IEEE Wireless Communications and Networking Conference*, pp. 55–60, 2011.
- [139] X. Zhu, C. Jiang, L. Kuang, N. Ge, and J. Lu, "Non-orthogonal multiple access based integrated terrestrial-satellite networks," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 10, pp. 2253–2267, 2017.
- [140] Y. Liu, Z. Qin, Y. Cai, Y. Gao, G. Y. Li, and A. Nallanathan, "Uav communications based on non-orthogonal multiple access," *IEEE Wireless Communications*, vol. 26, no. 1, pp. 52–57, 2019.
- [141] W. Wang, N. Zhao, L. Chen, X. Liu, Y. Chen, and D. Niyato, "Uav-assisted time-efficient data collection via uplink noma," *IEEE Transactions on Communications*, vol. 69, no. 11, pp. 7851–7863, 2021.
- [142] X. Mu, Y. Liu, L. Guo, J. Lin, and H. V. Poor, "Intelligent reflecting surface enhanced multi-uav noma networks," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 10, pp. 3051–3066, 2021.
- [143] X. Lin, J. Bergman, F. Gunnarsson, O. Liberg, S. M. Razavi, H. S. Razaghi, H. Rydn, and Y. Sui, "Positioning for the internet of things: A 3gpp perspective," *IEEE Communications Magazine*, vol. 55, no. 12, pp. 179–185, 2017.
- [144] C. Xu, D. Huang, and F. Kong, "Small uav passive target localization approach and accuracy analysis," *Chinese Journal of Scientific Instrument*, no. 05, pp. 1115–1122, 2015.
- [145] D. I. Han, J. H. Kim, C. O. Min, S. J. Jo, J. H. Kim, and D. W. Lee, "Development of unmanned aerial vehicle (uav) system with waypoint tracking and vision-based reconnaissance," *International Journal of Control Automation & Systems*, vol. 8, no. 5, pp. 1091–1099, 2010.
- [146] W. Xu, G. Wang, and M. Chen, "Node localization of wireless sensor networks based on SR-CKF assisted by unmanned aerial vehicles," *CAAI Transactions on Intelligent Systems*, 2019.
- [147] F. Li, P. Han, and T. Luo, "Adaptive area location algorithm combining with packet lost rate and RSSI in wireless sensor networks," *Journal on Communications*, vol. 30, no. 9, pp. 15–23, 2009.
- [148] C. You and R. Zhang, "3d trajectory optimization in rician fading for uav-enabled data harvesting," *IEEE Transactions on Wireless Communications*, vol. 18, no. 6, pp. 3192–3207, 2019.
- [149] R. Han, J. Wang, L. Bai, J. Liu, and J. Choi, "Age of information and performance analysis for uav-aided iot systems," *IEEE Internet of Things Journal*, vol. 8, no. 19, pp. 14 447–14 457, 2021.
- [150] G. Zaho, B. Liu, and C. Gao, "Moving horizon estimation of uav with random parameter uncertainty and data missing," *Systems Engineering and Electronics*, vol. 041, no. 012, pp. 2849–2854, 2019.
- [151] P. Wang, P. Yao, and Y. Nie, "Distributed uav formation cooperative control with measurement noise and data packet loss," *4th China Conference on Command and*

Control.