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Energy-Constrained UAV Data Acquisition in Wireless Sensor Networks with the Age of Information

Jinxuan Xiong, Zhimin Li, Hongzhi Li, Lin Tang and Shaohong Zhong *

School of Computer and Information Engineering, Central South University of Forestry and Technology, Changsha 410004, China
* Correspondence: shaohzhong@csuft.edu.cn; Tel.: +86-133-0848-6466

Abstract: This paper considers a wireless sensor network (WSN) assisted by the unmanned aerial vehicle (UAV) in the Internet of Things (IoT). The UAV departs from the data center to the ground node to collect sensor node data as a relay. Under the constraints of battery energy, the UAV will travel to and from the data center repeatedly and transmit the collected sensor node data. The freshness of the node data received by the data center is measured by the Age of Information (AoI) as a performance metric. A genetic algorithm is used to plan the flight trajectory of the UAV. To ensure the data's integrity and accuracy in a single sensor node, the UAV continuously collects sensor node data when the distance from the sensor node is less than the minimum acquisition distance. Through simulation experiments, we analyzed the influence of changing acquisition distance, the initial battery capacity, acquisition success probability, and transmission power on the peak age of information and the average age of information.

Keywords: wireless sensor network; UAV relay; age of information

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1. Introduction

1.1. Background

With the recent development of the Internet of Things, collecting information on wireless sensor networks requires many data nodes. In wireless sensor networks, the data collected by sensor nodes need to be sent to a data control center for analysis. Collecting and updating data in a timely manner and performing node data analysis are crucial. In real-time applications, outdated data information will badly impact the analysis and research of the whole system. Therefore, it is very important to ensure the timeliness of information to meet the real-time transmission requirements of the system. Network deployment costs for remote areas with complex buildings or ecological environments are relatively high, and manual data collection is also complex. In these places, sensor nodes must be deployed to monitor various processes in real-time. The high mobility and flexibility of unmanned aerial vehicles (UAVs) can help wireless sensor networks collect data and quickly transmit it back to a data center for analysis [1].

Timely and adequate data also plays a vital role in data analysis. To more effectively evaluate the freshness of collected data, this paper introduces the concept of age of information (AoI) to measure data freshness [2]. The AoI represents the time difference between the generation time of data and the current time. The concept of the information age is mainly oriented towards real-time application scenarios that require high timeliness of the collected data, and is used to describe the timeliness or freshness of the data collected by the system. Compared with traditional metrics such as throughput and delay, the AoI can more accurately describe the freshness of information at the receiver. The minimization of AoI plays a crucial role in real-time and accurate data analysis.

1.2. Related Work

The battery energy of a UAV is mainly used for the flight and hovering of the UAV and supplying power to other devices. In [3], S. Zhang et al. designed an energy-saving data acquisition strategy based on sensor node wake-up scheduling and the UAV trajectory design to address the energy consumption problem in data acquisition in wireless sensor networks. They constructed a weighted energy consumption minimization problem for UAV and SNs. Currently, most small rotor UAVs operate on battery power, and the limited battery energy has become the main limiting factor for UAVs in various application scenarios [4]. It is significant to optimize the total energy consumption of the UAV and extend the lifetime of the network for the UAV as a relay communication network [5]. It is crucial to extend UAVs' working time while ensuring their communication performance to develop UAV-assisted wireless sensor network communication technology.

In the scenario where the UAV acts as a relay between sensor nodes and a data analysis center in wireless sensor networks, some have studied the design scheme to minimize the AoI of the system. When there is only one sensor node and one target node, A. Cao et al. proposed a communication strategy. They optimized the flight trajectory of UAVs to minimize the peak AoI of the network [6]. In [7], M. A. Abd-Elmagid et al. proposed an age optimal strategy to study the joint optimization of flight trajectory and status update packet scheduling for battery-constrained UAVs collecting data in wireless sensor networks. They proposed a deep reinforcement learning algorithm to obtain an optimal strategy that minimizes the sum-AoI. Y. Luo et al. studied a UAV trajectory planning problem for minimizing the information age over a sensor network defined on a square grid graph [8]. An HPA algorithm for graphs with at least one Hamiltonian path and a tree search algorithm were developed to study the time-average network AoI. In [9], Tong. P et al. proposed using a data collection node to collect data from a group of sensor nodes and the UAV as a relay assistant to collect data from the data collection point and transmit it to the scene model of the data center. They jointly optimized the sensor cluster and UAV flight trajectory to minimize the maximum AoI of all sensor nodes. In [10], Jia Z et al. proposed a solution framework based on dynamic planning methods, using the concept of age to study the path planning and data collection problems of UAVs. They considered the selection of data collection modes, energy consumption of each node, and age evolution of collected information. With further research and development of UAV applications in wireless sensor networks, using algorithms to plan collaborative data transmission between multiple UAVs has become increasingly attractive [11]. In [12], X. Gao et al. studied the data collection problem and the information freshness of sensor nodes in multiple UAV-assisted wireless sensor networks. Under the limited endurance of UAVs, an improved ant colony algorithm was used to optimize the flight trajectory of the UAV. C. Liu et al. studied the process of multiple unmanned aerial vehicles taking off from and returning to the data center to collect data. They designed a centralized information sharing mechanism to avoid repeated collection of information [13]. Improving the energy efficiency of UAVs, reducing their total energy consumption, and extending the overall survival time of the network play an essential role in optimizing UAV communication.

The flight path scheme of a UAV has an important impact on the data collection of wireless sensor networks. It will change the transmission distance between sensor nodes and the UAV, affecting the energy consumed by the UAV when collecting sensor node data. Moreover, the UAV's flight path and speed also determine the collection delay. Proper UAV flight path planning and flight mode planning can be selected based on application scenarios and mission objectives. In this paper, considering the large number and wide distribution of ground sensor nodes, we used a genetic algorithm to plan the flight path of a UAV. Under energy constraints, we studied how to make the UAV collect as much data as possible. We specified the minimum initial acquisition distance, and the UAV started to collect sensor data when the distance from the ground sensor node was less than the acquisition distance. In order to ensure the integrity and accuracy of the data collected by the UAV, the UAV repeatedly collected the sensor node's data during its flight. Finally, the information age of the data packets in sensor nodes collected by the UAV was analyzed through simulation experiments. The main contributions of this work are summarized as follows:

(a) Under the energy constraint of the UAV, we studied how to plan its flight path to achieve the best transmission effect, which was achieved by minimizing the information age of a single node and the information age of the entire network node.

(b) We used a genetic algorithm to plan the flight path of the UAV. In the process of UAV flight path planning, each path from the starting point to the end point was represented as an individual in the genetic algorithm, and each path contained in it was represented as a chromosome.

(c) We primarily analyzed and calculated the AoI of the ground sensor node data collected by the UAV based on the planned flight path as a reference for network performance. We considered the peak AoI of a single sensor node and the average AoI of the entire wireless sensor network under different acquisition success rates, acquisition distances, and transmission powers.

The remainder of this article is organized as follows: Section 2 introduces the system model and its application scenarios, and the data acquisition model and energy consumption model for the UAV are proposed. Section 3 presents the genetic algorithm process used for the UAV motion planning, the information age model of a single node, and the derivation and calculation process of peak information age and average information age in this paper. Section 4 presents the simulation experiments conducted to study the information freshness of the above sensor network systems under different parameters. Section 5 summarizes the work.

2. System Model

Consider a wireless sensor network, as shown in Figure 1. The system consists of a data center, a UAV, and N sensor nodes. This scenario assumes that in some unexpected situations such as natural disasters, ground sensors are deployed in this environment to monitor and collect data. In this scenario, due to the limitations of the natural environment, the data center is remote from the wireless sensor networks. In addition, the collected data needs to be updated to the data center in a timely manner for analysis as a basis for guiding and judging the next step. Therefore, the use of UAVs as relays to assist in data transmission is necessary in this wireless sensor network scenario in order to achieve high-quality and timely data transmission.

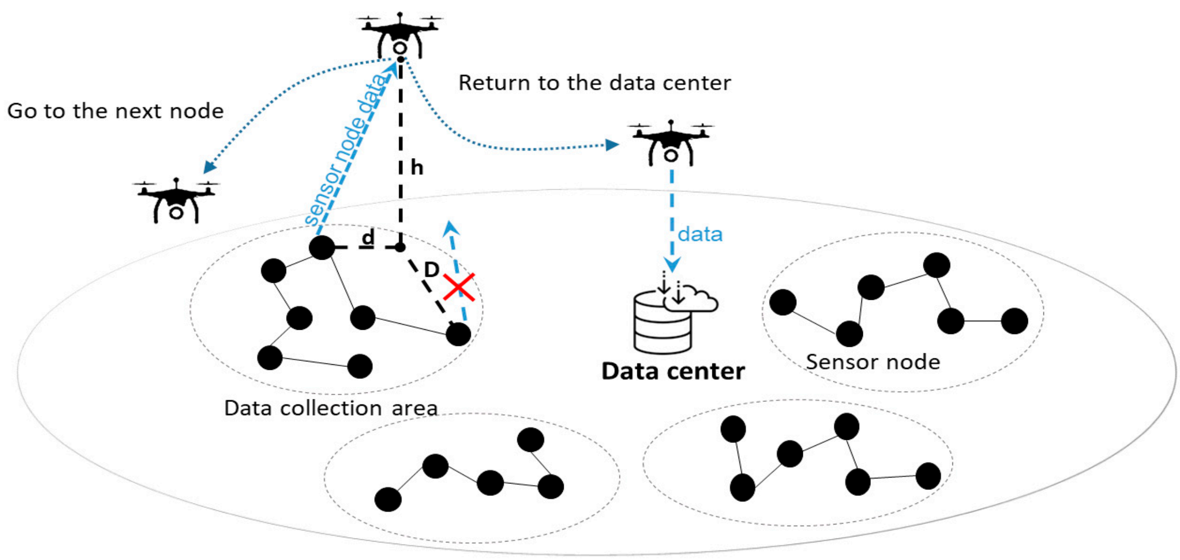

Figure 1. The system model.

Considering the energy constraints of the UAV, we plan its flight path as it collects the data from sensor nodes during its flight. When the power of the UAV is insufficient to support its flight to the next node and return to the data center, the UAV will fly back to the data center directly to transfer the collected data and charge or replace its battery. The UAV will then take off again until all the data from the node cluster are collected. Suppose that each sensor node has data that needs to be collected by the UAV, and there is a certain distance between two sensor nodes. When the UAV collects the data from the next node, it will not be affected by the previous one.

We assume that when the distance between the UAV and the ground sensor node is less than the acquisition distance, the UAV starts to collect node data. At this time, the position of the UAV is $L(t) = (x_t,\ y_t,\ z_t)$. To better adapt to the deployment environment of sensor nodes and save the flight energy of the UAV, we set the flight height $h(t)$ of the UAV to meet the following requirements:

$$h_{\min} \ \leq \ h_{(t)} \ \leq \ h_{\max} \tag{1}$$

2.1. Data Collection Model

The UAV must collect the node's data when flying over each sensor node. To ensure the integrity and accuracy of the data in the node, the UAV will cycle to collect the data in the node when flying over the sensor node. It is assumed that the UAV can complete data collection in the node within time slot t. The UAV continuously listens to the position information of the ground sensor node during the flight. When it is judged that the distance between the UAV and the node is less than the acquisition distance, the UAV starts to collect data from the sensor node. During the flight, the UAV will calculate the distance between itself and the sensor node while collecting data. When the distance between the UAV and the sensor node is larger than the acquisition distance, the UAV will not be able to collect data. It will calculate whether it has sufficient energy to support its flight to the next sensor node and back to the data center. If the battery energy is insufficient, it will choose to return to the data center. Otherwise, it continues to the next sensor node to collect data. The model of the UAV collecting single sensor node data is shown in Figure 2.

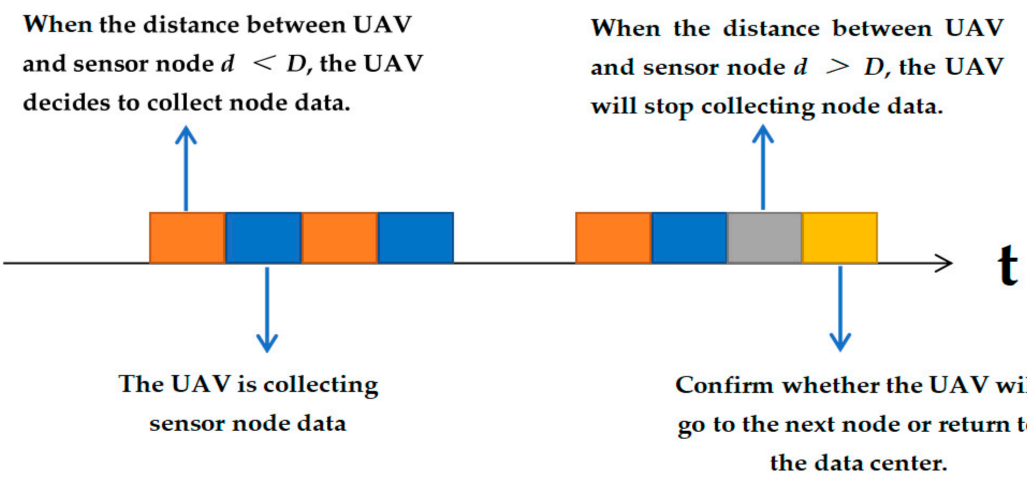

Figure 2. Data collection diagram.

When the distance between the UAV and the ground sensor node is less than the acquisition distance, the UAV immediately establishes communication with the node. At the same time, it is assumed that the UAV flies at a fixed altitude h during the node data collection flight.

According to the Shannon formula [14], during node data collection, the data rate between the UAV and sensor can be expressed as:

$$R_c = Blog_2(1 + \frac{\beta}{h^2\sigma^2}P) \tag{2}$$

where B is the available bandwidth for communication, P is the transmission power of the ground sensor node, β is the power gain of the reference channel over a distance of 1 micrometer and σ^2 is the power of the channel noise. According to the data acquisition probability model in [15], when the UAV collects the data in the sensor node for the *k-th* time, the probability of successful acquisition of the UAV is expressed as:

$$g_n^k(t) = e^{-\xi d_{n_t}} \tag{3}$$

where ξ refers to the parameters for evaluating the sensing performance and d_{n_t} represents the distance between the UAV and the sensor node at time slot t. When unsuccessful data is collected, it will cause severe delay. Therefore, the UAV needs to collect the data in the sensor node circularly to ensure that the collected data is successful. Additionally, f_i^c indicates the number of times the UAV collected data for the *k-th* time when collecting the data of node N_i. The probability of successful acquisition is expressed as:

$$G_n^k = 1 - \left(1 - g_n^k(t)\right)^{f_i^c} \tag{4}$$

To ensure the quality of data collected by the UAV, we set a minimum probability threshold, g_{th} for successful data collection. Then, the probability of successful data acquisition by the UAV should be:

$$g_n^{\mathrm{k}}(t) \geq g_{th} \tag{5}$$

2.2. Energy Consumption Model

For wireless sensor networks, the different flight trajectories of UAVs will affect the freshness of information in the whole network. The change in UAV flight trajectories will also affect the number and order of ground sensor nodes collected by the UAVs after each flight. This paper considers the mode that UAVs can return to many times under the constraint of UAV energy. Frequent return of the UAV after collecting ground sensor node data can effectively reduce the overall AoI of the system. A genetic algorithm is used to optimize the flight path of the UAV to minimize the flight time for the UAV to complete the acquisition task.

The UAV takes off from the data center and goes to the ground node group to collect data. The UAV has hover and flight modes when communicating with the ground node. To save flight time, the UAV uses flight mode when collecting the ground node data. We assume that the UAV will fly at a constant speed of V_f during flight time, maintain a constant speed of V_c during node data acquisition, and maintain $V_f > V_c$. Then, the flight time of the UAV between two sensor nodes i and j can be expressed as:

$$T_{i,j} = T_{i,j}^1 + T_{i,j}^2 = \frac{L_{i,j} - D}{V_f} + \frac{D}{V_c} \tag{6}$$

where $L_{i,j}$ represents the horizontal Euclidean distance between nodes i and j, and $T_{i,\,j}^1$ and $T_{i,\,j}^2$ represent the time spent by the UAV in flight and hover states during the flight from node i to node j, respectively.

Each time the UAV takes off from the data center, it needs to return several times and finish by returning to the starting point. We define a figure as $C = (\Gamma(n+1), X)$, where $\Gamma(n+1) = \{\Gamma(n), 0\}$ represents the data center and X represents the collection of edges. That is, the two adjacent sensor nodes that the UAV flies over are represented as:

$$X = \{(i,j) | \forall i \in \Gamma(n), j \in \Gamma(n+1), i \neq j\} \tag{7}$$

The energy consumption of the UAV corresponding to any side is expressed as:

$$E_{i,j} = \begin{cases} P_1 \frac{L_{i,j}-D}{V_f} = P_1 T_{i,j}^1 & \text{if } j = 0,\ (i,j) \in X \\ P_1 \frac{L_{i,j}-D}{V_f} + P_2 \frac{D}{V_c} = P_1 T_{i,j}^1 + P_2 T_{i,j}^2 & \text{if } j \neq 0,\ (i,j) \in X \end{cases} \tag{8}$$

Among them, P_1 and P_2 represent the power of the UAV when it is in flight state and hover state. For a specific environment, the energy consumed by the UAV is the same when collecting sensor node data. Meanwhile, the overall energy consumption E can be expressed as:

$$E = \sum_{0}^{N} E_{i,j}, (i \neq j) \tag{9}$$

When the remaining energy of the UAV is insufficient to support its flight to the next node for transmission, it returns to the center.

2.3. UAV Trajectory Optimization

The UAV takes off from the data center and sends a signal to activate the ground sensor node. Upon receiving the activation signal, the dormant sensor node will enter the active state and wait for the UAV to fly over and transmit data. The UAV adds the sensor node that has completed data collection to the sensor node queue of the flight path $\Gamma(n), \Gamma(n) = \{1, 2, \ldots, n, n \subset N\}$. The sensor node queue that has not completed the acquisition is expressed as $V\{1, 2, \ldots, n, n \subset N\}$. After the UAV obtains the location information and the number of sensor nodes that can collect data, it uses a genetic algorithm to plan the subsequent flight path, avoid obstacles as much as possible, establish a better communication path with the ground sensor nodes, and minimize the flight path of the UAV. The genetic algorithm (GA) is mainly used to solve the research object with the idea of biological evolution. We used a genetic algorithm to solve the UAV flight path planning problem. The flight path R can be expressed as:

$$R = [\tau_{k,1}, \tau_{k,2}, \ldots, \tau_{k,n}](n \subset N) \tag{10}$$

where k represents the takeoff time of the UAV after completing data acquisition for all the sensor nodes.

In the UAV flight path planning process, each path from the starting point to the endpoint is represented as an individual in the genetic algorithm. Each segment of the path contained in the flight R is $\tau_{k,n}$, which is represented as a chromosome. There are many flight trajectories of UAVs, and the set of all individuals is represented as a population.

3. The UAV Flight Algorithm and AoI Analysis

3.1. The UAV Genetic Algorithm

3.1.1. Initialize the Population

At the initial stage of the genetic algorithm population, the individuals in the population have diversity and randomness. The number of ground sensor nodes in this application scenario model is large, and the deployment scale is extensive so the flight path of the UAV has randomness and diversity. When the UAV takes off from the data center for the first time and goes to the sensor node cluster, because the sensor node range is extensive, the UAV cannot perceive all the sensor nodes on the ground. The UAV randomly selects different sensor nodes as the destination to plan the phased UAV flight path.

We assume that the flight path of each UAV R corresponds to the order in which the UAV collects sensor nodes, and $L_{i,j}$ represents the distance between two sensor nodes, and the energy consumed by two UAVs flying over two sensor nodes i, j is $E_{i,j}$. At the same time, we assume that the initial energy of the UAV is E_i. The UAV flight path can be described as:

$$\begin{gathered} \min \sum_{i,j}^{\mathrm{N}} L_{i,j} \\ s.t. \sum E_{i,j} < E_i \end{gathered} \tag{11}$$

Combined with a genetic algorithm, a matrix P is given to represent the population:

$$P = \begin{bmatrix} R_1 \\ R_2 \\ \ldots \\ R_m \end{bmatrix} \tag{12}$$

3.1.2. Individual Fitness Calculation

The fitness function is used to quantify the attributes of each individual in the population. Fitness can be considered as the quality of the path. The genetic algorithm aims to find the individual with the maximum fitness. The flight energy consumption of a UAV between two nodes is expressed as:

$$E_{i,j} = \mu L_{i,j} \tag{13}$$

where μ Represents the energy consumption coefficient, and $L_{i,j}$ represents the distance between two sensor nodes N_i and N_j.

To understand Algorithm 1, the following examples are given: Suppose that the m-th individual in population P is R_m, where $R_m = [\tau_{m,1},\ \tau_{m,2}, \ldots, \tau_{m,n}](n \subset N)$. The UAV takes off from the data center (starting node 0) to the first sensor node. We execute Equation (13) to calculate the energy consumption of the UAV between two nodes $E_{0,1}$. If $E_{0,1}$ is less than the initial energy E_i of the UAV, then the UAV continues to fly to the first sensor node. Otherwise, it will return to the data center. The below steps are executed in the order of sensor nodes until the UAV returns to the data center with insufficient energy.

Algorithm 1: UAV flight trajectory and fitness calculation

```
Initialize fitness matrix G and trajectory matrix R_m
Initialize UAV energy E = E_i
for k = 1, M do
    Initialize Total distance of UAV D = 0
    Initialize Number of acquisition nodes n = 0
    Initialize R_m represents the trajectory of the UAV
    R_m. append(τ_m,0)
    While True do
        If n == 0 do
            E_0,I = μL_0,i, d = L_0,i
        else do
            E_i−1,I = μL_i−1,i
        if E_i > E + μL_0,i do
            E = E_i − E_0,i, S = S + d
            R_m. append(τ_m,i)
            i = I + 1, n = 1
        else do
            D = D + L_i−1,i, n = 0
        R_m. append(τ_m,0)
    G. append(-S)
Return F, Tr
```

3.1.3. Crossover and Variation

The operations of crossover and mutation are used to produce more new individuals in the genetic algorithm.

The overlapping operation selects two individuals from population P randomly, $R_a = [\tau_{a,1},\ \tau_{a,2}, \ldots, \tau_{a,n}]$ and $R_b = [\tau_{b,1},\ \tau_{b,2}, \ldots, \tau_{b,n}]$, and then randomly selects one of the paths $\tau_{a,t},\ \tau_{b,t}, (t \subset [1, n])$, and exchanges them to get two new individuals.

The variation operation selects individuals for mutation according to the variation probability Y [16] and randomly generates a coefficient each time η, $\eta \subset [0, 1]$. When $\eta < Y$, one individual R_k is randomly selected. Each selected individual $R_k = [\tau_{k,1},\ \tau_{k,2}, \ldots, \tau_{k,n}]$ undergoes the following steps: randomly select two paths in individual $\tau_{k,a}$, $\tau_{k,b}$ to exchange. Then, do k ← k + 1 and repeat the above steps until k > m.

3.1.4. Delete

The purpose of deleting is to eliminate redundant nodes in the optimized path. This operation can effectively prevent redundant nodes from occurring and shorten the flight path length. The main idea can be described as follows: when the path is obtained, each node is traversed from the end of the path. If node N can be easily connected to the starting point, then the node between the starting point and the node N is redundant. The deletion operation is used to delete these redundant nodes and recalculate the fitness function of the path.

3.1.5. Select Elite Individuals

The central idea of a genetic algorithm is that the better the individual is, the better the offspring will be. With this idea, excellent individuals reproduce each time, so that the ordinary population can evolve into the elite population until the termination condition is reached. According to the Roulette Algorithm (RA) [17,18], the probability of an individual e being selected is expressed by Equation (14):

$$\phi(e) = \frac{G_e}{\sum\limits_{i=1}^{m} G_i} \tag{14}$$

where G is the fitness matrix obtained by Algorithm 1, and a new matrix $\rlap{/}p$ will be established by selecting *C-degree* individuals from P with probability *φ(e)*. Then, the Sensitivity Strategy (ES) [19,20] is used to select the individual with the maximum. A new population $\dot{P}$ is formed by splicing $\rlap{/}p$ to retain the best individual in the selection operation.

3.2. AoI Analysis

This section primarily focuses on analyzing and calculating the AoI of the ground sensor node data collected by the UAV. We mainly consider the AoI of a single sensor node, as well as the average and peak AoI of the entire wireless sensor network, under different acquisition success rates and different acquisition distances. To ensure the freshness of the data collected by UAV in the data center, this paper mainly considers minimizing the total AoI of N tasks.

3.2.1. AoI Expression Calculation

The age of information of the data packet in the sensor node N_i is defined as the expectation of the time when the data center receives the last data transmission from the UAV. When the UAV collects sensor node data, it will repeatedly collect data from each sensor node. Therefore, we calculate the information age of the data packet when a single node circularly collects data.

We assume that the time T_i^b is when the UAV starts to collect the data in sensor node N_i, the time T_i^d is when the UAV starts to transmit the data of sensor node N_i to the data center, and the transmission of a data packet is completed in t_i^w. Additionally, t_n^c indicates that the UAV can complete a single acquisition process of data within a certain node within a time slot t, and the default value for one unit time slot is 1 s. Accordingly, the success rate of each acquisition is $g_k^n(t)$. When the acquisition is successful, the corresponding information age can be expressed as:

$$A_i(t)|_s = (T_i^d + t_i^w t_n^c) - T_i^b - f_i^c t_n^c \tag{15}$$

The probability of acquisition failure is $1 - g_k^n(t)$, and the corresponding information age is expressed as:

$$A_i(t)\Big|_f = A_i(t-1) + 1 \tag{16}$$

The information age of a single sensor node in time slot t can be expressed as:

$$A_i(t) = \begin{cases} g_n^{\mathrm{k}}(t) A_i(t)|_s + (1 - g_n^k(t)) A_i(t)|_f, & \forall t = T_i^d + t_i^w t_n^c \\ A_i(t-1) + 1, & otherwise \end{cases} \tag{17}$$

Then, $A_i\ (0) = 0,\ \vee\, i\ \subset\ N.$

3.2.2. AoI for a Single Sensor Node

The minimized information age of a single sensor node problem can be expressed as:

$$\begin{aligned} P_1 :\ & \min A_i \\ s.t.&(16),(17) \end{aligned} \tag{18}$$

The time interval of Equation (15) can be expressed as:

$$\begin{aligned} U_{(i)} &= (T_i^d + t_i^w t_n^c) - T_i^b - f_i^c t_n^c \\ &= T_i^b + f_i^c t_n^c + T_{i,0}^f - \tfrac{D}{V_c} \\ &= T_i^b + f_i^c t_n^c + T_{i,j}^f + T_{j,j+1}^f + \cdots + T_{j,0}^f - \tfrac{D}{V_c} \end{aligned} \tag{19}$$

When $j = 0$,

$$U_{(i)} = T_i^b + f_i^c t_n^c + T_{i,0}^f - \frac{D}{V_c}$$

Then Equation (15) can be expressed as:

$$A_i(t)|_s = \begin{cases} \sum\limits_{i,j} T_{i,j}^f + T_i^b + f_i^c t_n^c - \frac{D}{V_c}, & j \neq 0 \\ T_i^b + f_i^c t_n^c + T_{i,0}^f - \frac{D}{V_c}, & j = 0 \end{cases} \tag{20}$$

When $\forall\, i \in\ \Gamma(n),\ j \in\ \Gamma(n+1),\ i\ \neq\ j.$

The information age of a single sensor node at time slot t can be expressed as:

$$A_i(t) = \begin{cases} g_n^k(t) f_i^c t_n^c + (1 - g_n^k(t)) A_i(t)|_f + \sum\limits_{i,j} T_{i,j}^f - \frac{D}{V_c},\ \vee\, t = T_i^d + t_i^w t_n^c \\ A_i(t-1) + 1, otherwise \end{cases} \tag{21}$$

If the probability of successful sensor data acquisition by UAV is close to one, the information age of a single sensor node can be expressed as:

$$A_i = T_i^c + \Delta_{(i)} + (T_i^c - T_1^c) + f_n^i t_i^w - \frac{D}{V_c} \tag{22}$$

3.2.3. AoI in the Wireless Sensor Network

The minimized information age in the wireless sensor network under the constraint of UAV energy can be expressed as:

$$\begin{aligned} P_2 :\ & \min \sum_{i=1}^{j} A_i, j \in n \\ s.t.&E \leq E_i \end{aligned} \tag{23}$$

The sequence diagram of the sensor node group collected by the UAV after flying out of the data center is shown in Figure 3.

According to Figure 3, Equation (22) can be calculated as:

$$\begin{aligned} \sum_{i=1}^{j} A_i &= [T_1^c + \Delta_{(1)} + f_n^i t_i^w - \tfrac{D}{V_c}] + [T_2^c + \Delta_{(2)} + 2 f_n^i t_i^w - \tfrac{D}{V_c}] + \\ &\quad \cdots + [T_{\mathrm{j}}^c + \Delta_{(j)} + j f_n^i t_i^w - \tfrac{D}{V_c}] \\ &= T_1^c + T_2^c + \cdots + T_j^c + \Delta_{(1)} + \Delta_{(2)} + \cdots + \Delta_{(j)} \\ &\quad + (1 + 2 + \cdots + j) f_n^i t_i^w - \tfrac{jD}{V_c} \\ &= \sum_i^j T_i^c + \sum_i^j \Delta_{(i)} + \tfrac{j(j+1) f_n^i t_i^w}{2} - \tfrac{jD}{V_c} \end{aligned} \tag{24}$$

Then, $\forall\, i \in \Gamma(n),\ j \in \Gamma(n+1),\ i\ \neq\ j,\ \sum_i^j \triangle(i)$ can be expressed as the flight time of the UAV. In this section, a genetic algorithm is used to plan the flight path of a UAV, reduce the flight time, and meet the following criteria:

$$\Delta_{(1)} > \Delta_{(2)} > \cdots > \Delta_{(j)} \tag{25}$$

According to the flight trajectory of the UAV, the expected average age of the network can be expressed as:

$$\widetilde{A} = \frac{1}{j}\sum_{i=1}^{j} A_i \quad = \frac{1}{j}[\sum_{i}^{j} T_i^c + \sum_{i}^{j}\Delta_{(i)} + \frac{j(j+1)f_n^i t_i^w}{2} - \frac{jD}{V_c}] \\ = \frac{1}{j}\sum_{i}^{j} T_i^c + \frac{1}{j}\sum_{i}^{j}\Delta_{(i)} + \frac{(j+1)f_n^i t_i^w}{2} - \frac{D}{V_c} \tag{26}$$

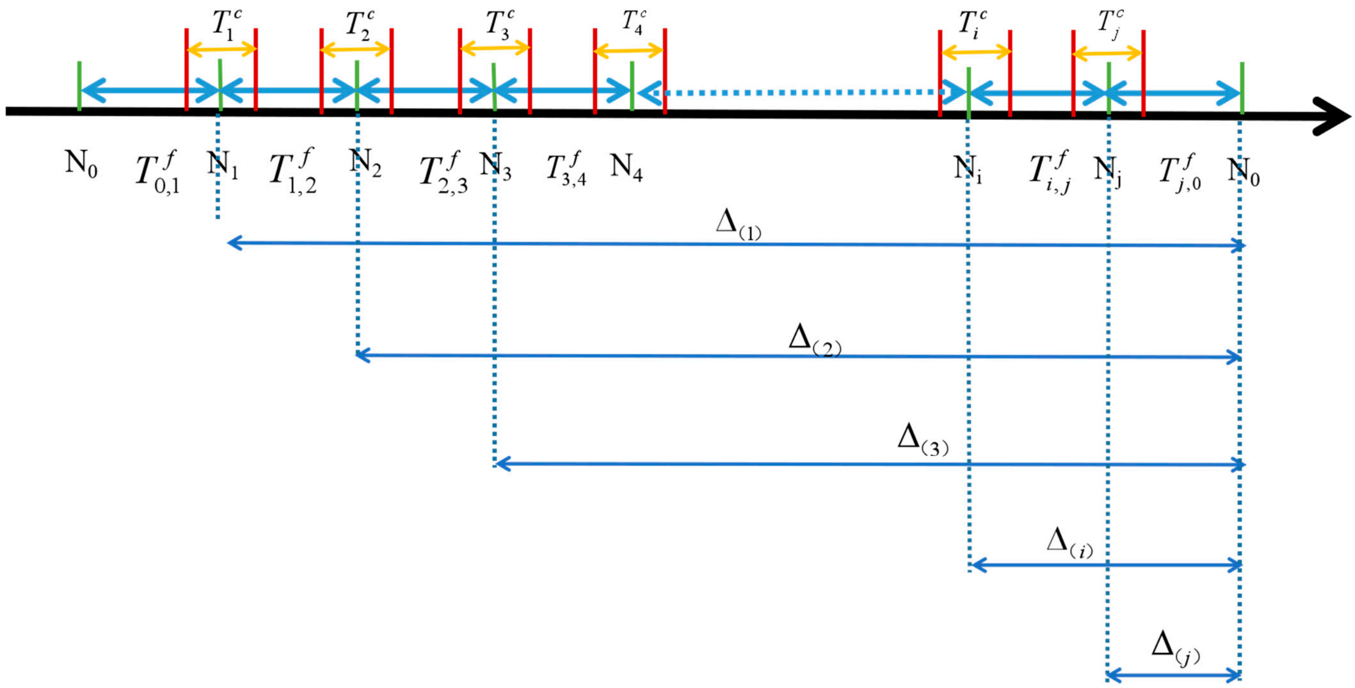

Figure 3. Sequence diagram of a data collection node by the UAV.

In this section, it is assumed that when the data nodes in the sensors collected by the UAV are transmitted to the data center, the total time consumed is far less than the time spent flying to the data center after the last sensor node collected by the UAV, that is:

$$\sum_{i=1}^{j} t_i^w f_n^i << \Delta_{(j)} \tag{27}$$

According to Equations (21), (24), and (26), as well as the flight path and sequence diagram of the UAV, the peak age information of the network in this section can be expressed as the information age of the first sensor node data collected after the UAV flies out, that is:

$$A_P \quad = (T_i^d + t_i^w) - (T_i^b + t_i^c) \\ = \Delta_{(1)} + t_i^w + (f_i^c - 1)t_n^c - \frac{D}{V_c} \tag{28}$$

4. Simulation Results

In this section, we conducted simulation experiments to study the effects of the acquisition distance when the UAV starts to collect information and the battery level of the UAV on the information age, as well as the impact of the change in acquisition success rate and the UAV's information transmission power on the information acquisition process. As a classic breadth-first search path planning algorithm, the Dijkstra algorithm uses a greedy algorithm strategy to find the shortest path from one vertex to the rest of the vertices. We used the Genetic algorithm proposed in this paper and the Dijkstra algorithm [21,22] to plan the scheduling of the UAV, and analyzed the freshness of information at nodes, which is reflected in the peak and average age of information. The experimental parameters are shown in Table 1 below.

Table 1. The simulated parameters.

Parameter	Value
Fixed flying altitude h	100 m
Bandwidth B	1 MHz
Channel gain at a reference distance of 1 m	−60 dB
The power of channel noise σ^2	−100 dBm
The duration of each slot t	1 s
The UAV speed during flight time V_f	10 m/s
The UAV speed during hover time V_c	2 m/s
The UAV data acquisition distance D	5 m, 10 m
The data collection success rate G	[0.6, 1]
The transmission power P	[0, 1] W

Figure 4 shows the peak AoI and average AoI changes of the system as the energy level of the UAV increases at different acquisition distances: $D = 5$ m and $D = 10$ m. Due to the energy constraints of the UAV, a low energy level is not sufficient to support long-term work, and the UAV can only travel between the nearest node and the data center. At this time, the peak and average AoI values are small, with the same trend of change. As the energy level of the UAV increases, the time of each departure flight increases, allowing the UAV to collect information from multiple nodes during each round of flight. This results in an increase in AoI. When $D = 5$ m, the UAV has a smaller acquisition distance and needs to fly closer to the node to start collecting node information. As a result, the time required is longer, resulting in an increase in the information age compared to when $D = 10$ m.

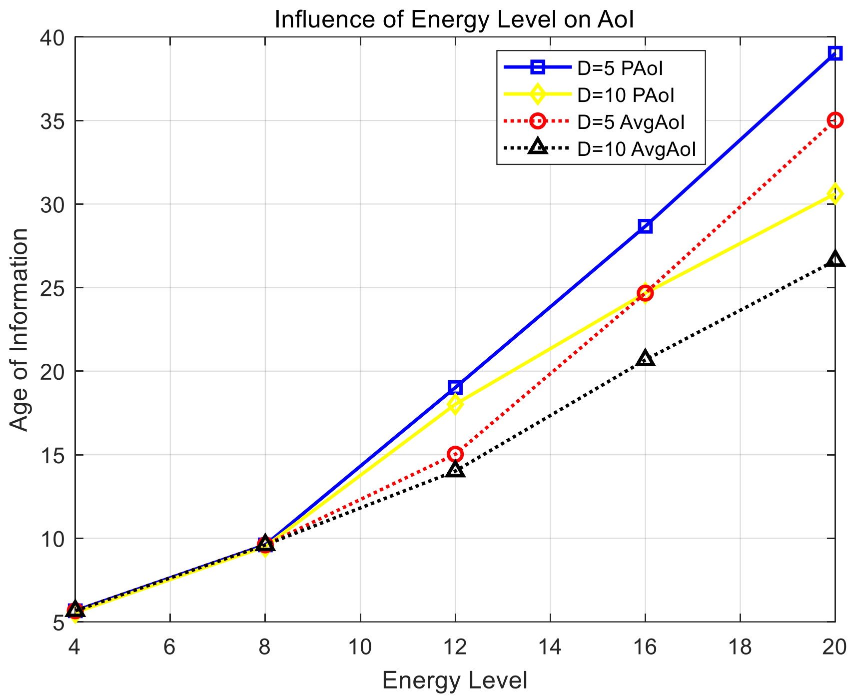

Figure 4. Influence of Energy Level on AoI.

Figure 5 shows the trend of the peak and average age of information of the system under different acquisition success rates. The genetic algorithm proposed in this paper and the Dijkstra algorithm are used for comparison. As the acquisition success rate gradually increases, the peak age of information in the system gradually decreases. The average age of information in the system gradually decreases as the acquisition probability increases, and gradually stabilizes when the acquisition success rate approaches 1. Compared to the shortest path algorithm, the peak and average information ages of the genetic algorithms are reduced, achieving a smaller information age and better results. In summary, a higher success rate of the UAV acquisition of sensor data results in a smaller peak and average information age of the system.

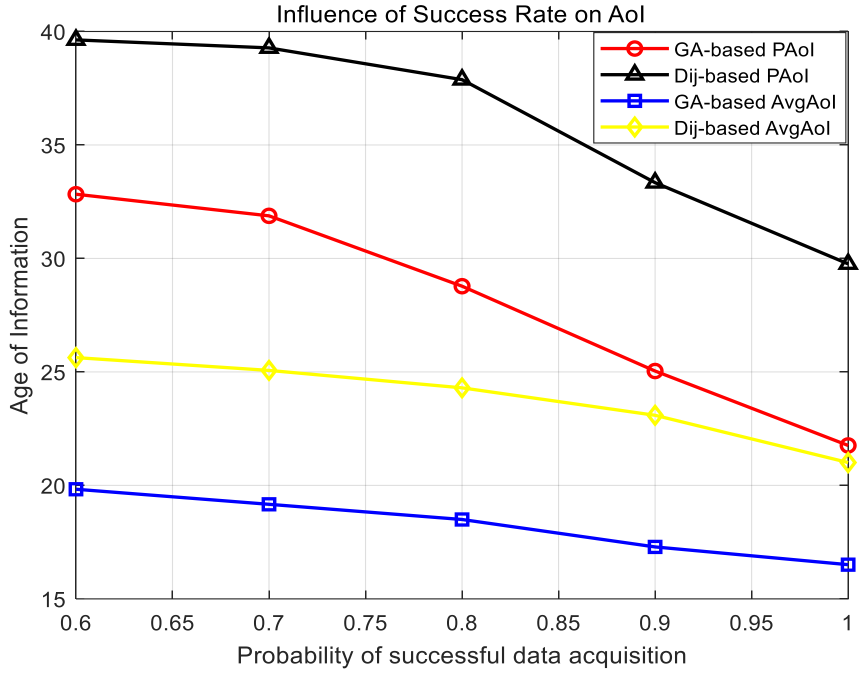

Figure 5. Influence of the data acquisition success rate on AoI.

Figure 6 shows the trends in peak system information age and average information age as the transmission power increases from 0.2 *W* to 1.0 *W*. The genetic algorithm proposed in this paper is compared with the Dijkstra algorithm. As the transmission power gradually increases, the peak and average age of information in the system gradually decrease and eventually stabilize. Using the genetic algorithm yields a lower system information age than using the shortest path algorithm. When the information age is lower, the system information is fresher; therefore, the genetic algorithm has better performance.

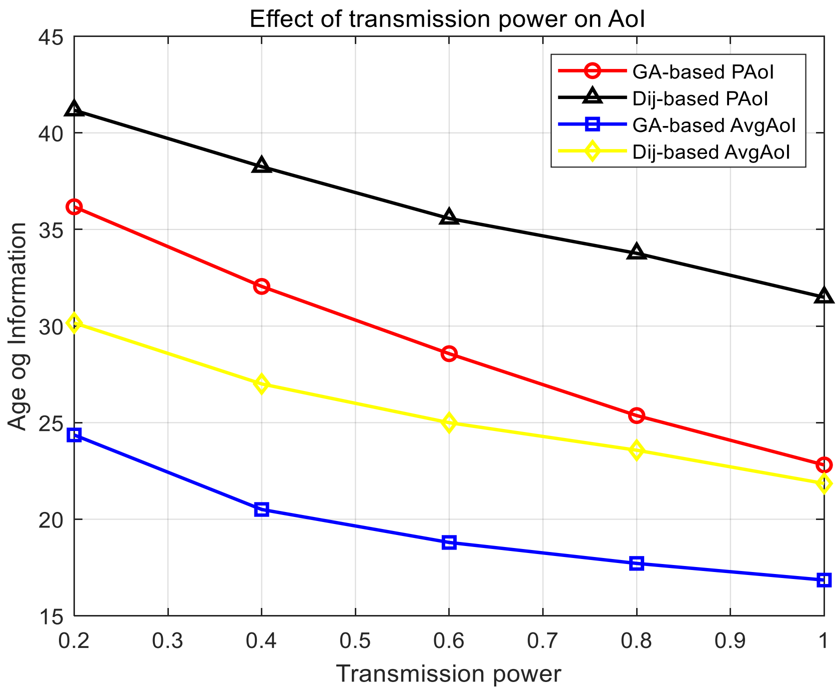

Figure 6. Influence of the UAV transmission power on AoI.

5. Conclusions

In this paper, we studied a UAV-aided data acquisition and transmission model for wireless sensor networks in the field of the Internet of Things. In the case of limited energy, we used a genetic algorithm to plan the UAV's flight path. We sought to minimize the peak information age of a single node and the average information age of the entire node group. The mathematical expressions of the average AoI and the peak AoI of the network system model used in this paper were obtained through calculation. The influence of the UAV acquisition distance and information acquisition success rate on the AoI was studied, as well as the change in the acquisition success rate and the UAV information transmission power on the information acquisition process.

The proposed method has a reference value for the Internet of Things wireless sensor network with a wide range, many sensors, and a high requirement for information freshness. In future work, we will also study artificial intelligence algorithms to plan the path of a UAV in order to further optimize its flight path reduce its flight energy consumption to increase its endurance.

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