IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 3, 2020, accepted August 10, 2020, date of publication August 14, 2020, date of current version August 26, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3016779

Revenue Optimization of a UAV-Fog Collaborative Framework for Remote Data Collection Services

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This work was supported in part by the National Natural Science Foundation of China under Grant 61303043 and Grant 61802030, in part by the International Cooperative Project for Double First-Class, Changsha University of Science and Technology (CSUST) under Grant 2018IC24, and in part by the Researchers Supporting Project from King Saud University, Riyadh, Saudi Arabia, under Grant RSP-2020/102.

ABSTRACT Unmanned aerial vehicles (UAVs) can provide remote data collection services with quality of service guarantees. The typical application fields include geographic information systems, such as topological survey and natural disasters and hazards monitoring. In the bad geographic environment, wireless communication performance of UAVs cannot be guaranteed. Therefore, the efficiency of remote data collection cannot be guaranteed. This paper proposes a collaborative framework of UAVs and fog computing for remote data collection. Our goal is to maximize the revenue of UAVs with the support of fog computing, so we need to find the optimal computation resources allocation and task assignment scheme. This is a mixed integer nonlinear programming problem. The block coordinate descent method is used to solve this problem, which allows the original problem to be divided into the optimal task assignment sub-problem and the optimal computation resource allocation sub-problem. The greedy algorithm, heuristic algorithm and brute force algorithm are proposed to solve the optimal task assignment sub-problem. The convex optimization analysis method is used to solve the optimal resource allocation sub-problem. The genetic algorithm is used as a benchmark to compare with the heuristic-based block coordinate descent algorithm. The numerical simulation and network simulator based-simulation results show that the proposed UAV-Fog collaborative data collection problem can be efficiently solved by the block coordinate descent algorithm based on the heuristic strategy.

INDEX TERMS Unmanned aerial vehicles, geographic information system, fog computing, remote data collection.

I. INTRODUCTION

A. BACKGROUND AND PROBLEM STATEMENT

Unmanned aerial vehicles (UAVs) with sensor devices can perform remote data collection tasks in complex geographical environment due to their high mobility, therefore they can be used as a new technology for remote sensing and surveying tasks [1], [2] or as a supplement and alternative to the traditional wireless sensor networks [3]–[5]. For example, in [2], UAVs were introduced and applied to collect geographic data in Sweden. In [6], UAVs were used to inspect power lines in China. In [7], forest data were collected by UAVs in the USA. The research results of these practical works show that UAVs can achieve better remote data collection performance, and UAV-enabled remote data collection is a trend in remote sensing technology. Some efforts have been devoted to optimizing the operating parameters of data collection UAVs, including optimizing energy consumption [3], flight time [4] and trajectory [3], [4]. In these papers, UAVs collect data and send them directly to a ground base station (GBS) through wireless networks; therefore, the quality of the data collection service depends on the quality of the wireless communication. However, broadband wireless networks are not available in all places. When the data collection work is carried out in a remote region, the network conditions are poor and the broadband wireless network is not covered. Therefore,

The associate editor coordinating the review of this manuscript and approving it for publication was Moayad Aloqaily.

the delivery after data collection needs to be carried out through the Delay Tolerant Network (DTN) [1], which will make the efficiency of remote data collection low. A UAV can also fly to the communication range of the ground base station to transmit data, but the energy consumption of the flight will increase, and the data collection cost will increase too. To achieve a better balance between data collection efficiency and cost, this paper proposes a remote data collection service framework that combines UAV and fog computing.

B. RELATED WORK

Fog computing is devoted to providing computation and communication resources for Internet of Things (IoT) users in the proximate area of IoT devices [8], [9]. Fog computing is similar to multi-access edge computing (MEC), which is treated as one of the key technologies towards 5G by European Telecommunications Standards Institute (ETSI) [10]–[12]. Fog computing is expected to play an important role in the industrial IoT and cyber-physical systems [13], such as smart industry [14] and smart agricultural technology [15] Without loss of generality, we use "fog nodes" to represent the nodes with communication and computing resources near IoT devices [16]. Because the nodes of edge computing and fog computing are limited by their geographical location, UAV assisted edge computing is proposed to expand the ability of edge computing [17]–[21]. In [18], agents (UAVs) are introduced to the task offloading, and a new task offloading framework based on agents (UAVs) is proposed. UAV and edge cloud execute the offloaded tasks together. In [19], Hu *et al.* studied the architecture of UAV-assisted edge computing (UMEC). A UAV hovering in an area can be used as a computing server or as a relay to help the user device compute its tasks by further offloading the computing tasks to the access point. In [20], Sahil Garg *et al.* proposed a data-driven traffic optimization model, in which the UAV shares information with edge computing devices, and the UAV acts as a relay node between the vehicle and the edge node, thus reducing the data processing delay. In [21], a UAV not only serves as an MEC server, but also powers IoT devices via Wireless Power Transfer (WPT) technology. All of the above works regard UAVs as MEC nodes with strong communication and computation abilities. In contrast, in the remote sensing and surveying data collection work, after the UAVs collect the data, they need to be transferred back to the ground base station for storage and processing. For example, in geographic information collection, the obtained data need to be sent back to the ground base station for 3D modelling via stereophotogrammetry [2]. Therefore, the previous methods of combining UAVs with edge computing or UAV-enabled MEC cannot be directly used for UAV-enabled remote data collection services.

In this paper, we propose a fog computing supported UAV-enabled remote data collection service framework, abbreviated as UAV-Fog Collaborative Data Collection (UFDC). The main contributions of this paper are as follows:

1. For the first time, a framework of remote data collection based on the cooperation of UAVs and fog computing is proposed, and a formal model is established to describe the problem of maximizing the revenue of UAV cluster under the constraints of time delay and resources. This is a mixed-integer nonlinear programming (MINLP) problem.

2. The block coordinate descent method is used to solve the optimization problems described above. The original problem can be divided into two sub-problems. The greedy algorithm, heuristic algorithm and brute force algorithm are proposed to solve the task assignment sub-problem of UAVs. Using the KKT condition analysis method of convex optimization, the analytic solution of computation resource allocation sub-problem of fog node is obtained.

3. The model and algorithm are verified by numerical simulation and network simulator based simulation. It is verified that the block coordinate descent method based on the heuristic algorithm can obtain the best cluster revenue when the algorithm execution time is small.

The rest of this paper is organized as follows: in the second section, the UFDC system model is introduced, and the formulated description of the problem of maximizing the UAV cluster revenue is described. In the third section, the optimization methods of this problem are presented. In the fourth section, the numerical results are introduced. In the last section, the conclusions are drawn.

The main notations used in this paper are listed in Table 1.

TABLE 1. Notations.

Symbol	Definition
U	UAV
F	Fog node
n	The amount of UAVs
m	The amount of fog nodes
H	Height of a UAV
D_i	Data size of the task carried by UAV_i
C_i	CPU cycles of the task carried by UAV_i
f_j^{max}	The maximum resources that the jth fog node can allocate
L	Distance from the UAV to the base station
R	The reward a UAV can get for the task
γ	Cost parameter of flight time of UAVs
V	Flight velocity of a UAV
k_{ij}	Task assignment 0-1 decision variable. It is 1 when the task of the i-th UAV is assigned to the j-th fog node, otherwise it is 0.
T_{ij}^f	Flight time from UAVi to fog node Fj
t_{ij}^H	Hover time of a UAV
f_{ij}	Computation resources allocated by fog node j to UAV i
P	Constant power consumption of a UAV
q	Unit price of one CPU cycle of a fog node
r_{ij}	Data transmission rate between UAV i and fog node j
d_{ij}	Flight distance of UAV i from data collection point to fog node j
h_{ij}	Channel power gain
σ^2	noise power
β_0	Channel power gain at a reference distance of 1 meter

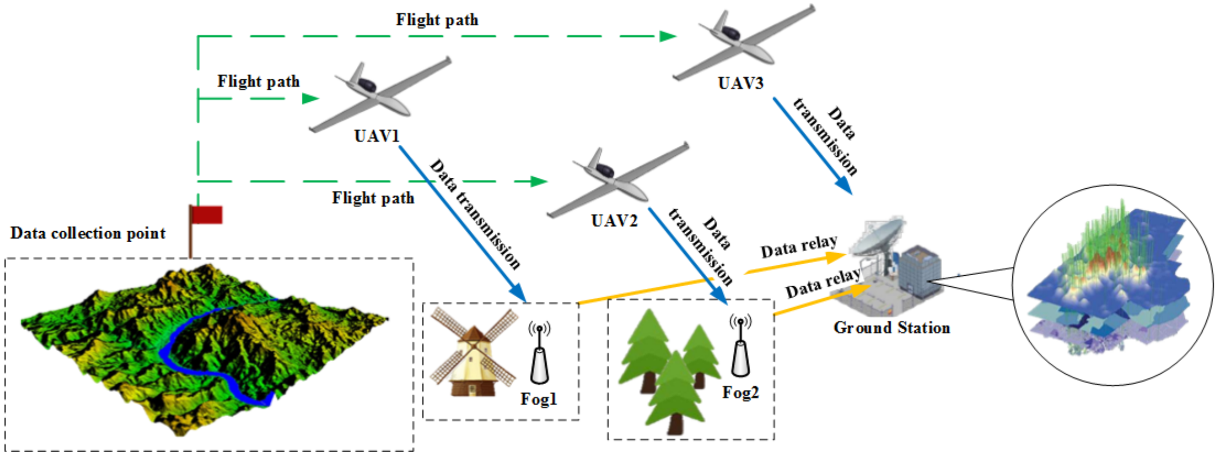

FIGURE 1. An example scenario to illustrate the system framework of UAV-Fog collaborative data collection.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. DESCRIPTION OF FRAMEWORK

In the scenario proposed in this paper, because the data collection point is located in a remote area, the broadband wireless network does not cover the area, therefore, after the UAV collects the data, it needs to fly back to the ground base station to transmit the data, which brings the flight time delay and costs. The operator of the data collection service can choose to rent the resources of a fog computing node to preprocess, store and forward the collected data. A fog computing node has a certain amount of communication and computing resources. A fog computing node can receive the IoT data collected by UAVs with low latency and preprocess the data. Because a fog node has a storage device, it can also temporarily store data, and then asynchronously send the data to the remote ground base station. Consider a scenario as shown in Fig. 1, where there are three UAVs, two fog nodes and a ground station. Here, UAV1 offloads the collected geographic information data to node fog1 for preprocessing, UAV2 offloads the collected geographic information data to the node fog2 for preprocessing, and UAV3 offloads the collected geographic information data to the ground base station. Because the fog node asynchronously sends the data to the ground base station, UAV1 and UAV2 do not need to wait for the ground base station to receive the data. UAV1 and UAV2 can immediately return to the collection point to continue to collect data. In this way, compared with UAV3, UAV1 and UAV2 can reduce the time of returning data and improve the efficiency of remote data collection.

The formal description of the UFDC proposed in this paper is as follows. There are n UAVs in the system, which are expressed as $U_i, i = 1, 2, 3 \ldots, n$. Each UAV's speed is constant, with a speed of V and a fixed flight height of H. The size of the task data collected by each UAV and the number of clock cycles required for preprocessing are D_i, and C_i respectively. The initial coordinates of the UAV are (x_i, y_i), $i = 1, 2, 3, \ldots, n$, and they are distributed near the data collection point. There are m fog nodes, which are expressed as F_j, $j = 1, 2, 3, \ldots, m$. Each fog node has computing resources. The maximum resource of each fog node is $f_j^{\max}$, $j = 1, 2, 3, \ldots$,m, and the position coordinates of each fog node are expressed as (x_j, y_j), $j = 1, 2, 3, \ldots$,m.

B. COMPUTATION AND COMMUNICATION MODEL

1) COMPUTATION MODEL

Without loss of generality, suppose that UAVs are randomly distributed near the data collection point at the beginning. When enough data are collected by UAVs, there are two offloading modes as follows:

a: OFFLOADING AT THE GROUND STATION

When UAV U_i is assigned to offload its task to the GBS, the revenue of the UAV is as follows:

$$Z_{U_i}^G = t(R - (\frac{L}{V} \times \gamma + \beta \times P \times t^H)) \tag{1}$$

L represents the distance from the UAV to the GBS, which is the same and a constant for each UAV when it offloads data to the GBS; γ represents the energy consumption cost parameter of the UAV's flight time; R represents the reward that U_i can obtain for performing the task once; and V represents the flight speed of the UAV. For the convenience of the analysis, we temporarily assume that V is a constant. We will further discuss the case that V is not a constant in the network simulator-based simulation section. β is the cost parameter of the energy consumption of a UAV when hovering. P is the energy consumption of a UAV when hovering. t^H is the hovering duration of a UAV. t is the number of times that a UAV performs data collection tasks in time period I. Without loss of generality, these parameters are identical for all UAVs performing the same data collection task.

b: OFFLOADING AT THE FOG NODES

When UAV U_i is assigned to offload its task to F_j, the revenue of the UAV is as follows:

$$Z_{U_i}^{F_j} = \sum_{j=1}^{m} k_{ij} \times \left[t_{ij} \left(R - \sum_{j=1}^{m} k_{ij} \left(T_{ij}^{f} \times \gamma + \beta \times P \times t_{ij}^{H} + q \times f_{ij} \right) \right) \right] \tag{2}$$

This is subject to the following constraints:

$$\sum_{j=1}^{m} k_{ij} = 1, k_{ij} \in \{0, 1\} \tag{3}$$

$$0 < t_{ij}^{H} \leq T_i^{\max} \tag{4}$$

$$\sum_{i=1}^{n} k_{ij} f_{ij} \leq f_j^{\max}, \quad f_{ij} \geq 0 \tag{5}$$

Constraint (3) indicates that the task of a UAV can only be offloaded to one fog node, constraint (4) indicates that there is a maximum hovering time for a UAV, and constraint (5) indicates that the sum of all computation resources allocated to UAVs from fog node j cannot exceed the maximum computation resources that can be rented from fog node j. T_{ij}^{f} is the time when UAV U_i flies into the communication range of fog node F_j. Then, we have the following:

$$T_{ij}^{f} = \frac{d_{ij}}{V} \tag{6}$$

where d_{ij} is the distance from U_i to F_j:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{7}$$

and t_{ij}^{H} is the hovering time of UAV, t_{ij}^{H} can be expressed as follows:

$$t_{ij}^{H} = t_{ij}^{r} + t_{ij}^{c} \tag{8}$$

where t_{ij}^{r} represents data transmission time of the task, and t_{ij}^{c} represents data computation time of the task. The expressions are as follows:

$$t_{ij}^{r} = \frac{D_i}{r_{ij}} \tag{9}$$

$$t_{ij}^{c} = \frac{C_i}{f_{ij}} \tag{10}$$

where r_{ij} is the data rate between UAV U_i and Fog node F_j. It is calculated using the following formula:

$$r_{ij} = B^{*} \log_2 \left(1 + \frac{p_i^{*} h_{ij}}{\sigma^2} \right) \tag{11}$$

where B is the bandwidth, and σ^2 is the power of noise. h_{ij} is the channel gain power, which can be calculated using the following formula:

$$h_{ij} = \frac{\beta_0}{H^2 + \left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{12}$$

where t_{ij} represents the number of times the UAV performs data collection tasks in time period I.

$$t_{ij} = \frac{I}{2^{*} \frac{d_{ij}}{V} + \frac{D_i}{r_{ij}} + \frac{C_i}{f_{ij}} + S} \tag{13}$$

where S is the constant duration that a UAV spends in data collection.

2) COMMUNICATION MODEL

Because the remote data collection task is carried out in remote areas, a broadband network, such as a 5G cellular network, is not available. Thus, direct ground-to-UAV communications, such as unlicensed spectrum 2.4GHz, are often used for data transmission [23]. The confirmation information of UAV communication with the ground station is very small, so we can ignore the data transmission time on the downlink. The transmission rate of the uplink between a UAV and the ground station or fog node is calculated using (11).

C. ECONOMIC VIABILITY ANALYSIS

Obviously, compared with the traditional model, if the proposed UFDC model is to improve revenues, it should meet the following requirements:

$$Z_{U_i}^{F_j} > Z_{U_i}^{G} \tag{14}$$

Therefore, it is easy to get the following results:

$$q < \frac{R(1-\delta) + \theta(\delta L - d_{ij}) + \beta P(\delta t^{H} - t_{ij}^{H})}{f_{ij}} \tag{15}$$

where $\delta = \frac{t}{t_{ij}} < 1, \theta = \frac{\gamma}{V}$

Here, q is the unit price of one CPU cycle of fog node. Only when q is a very small value, can we improve revenues. According to the current quotation of cloud computing providers, such as that of the Azure cloud computing service of Microsoft,[1] the corresponding unit price of the virtual machine computing resources is approximately \$5.2 $\times 10^{-4}$ per GHz per minute (with supporting storage and network resources) in the pay-as-you-go class of the tariff. Thus, the proposed model can be expected to improve revenues in most cases applying fog computing.

D. PROBLEM FORMULATION

To maximize the revenue of UAVs, it is necessary to optimize the resource and task allocation of the UFDC model. Suppose that the initial locations of the UAVs are near the data collection point. The resource and task allocation optimization problem of the UFDC model can be formulated as follows:

$$MP: \underset{k_{ij}, f_{ij}}{Max} \ Ut = \sum_{i=1}^{n} Z_{U_i}^{F_j} \quad \text{subject to}: (3), (4), (5) \tag{16}$$

[1] https://azure.microsoft.com/en-us/pricing/details/virtual-machines/windows/

The MP problem is a mixed-integer nonlinear programming problem (MINLP), which is an NP-hard problem [24], [25]. It is very hard to figure out the precise optimal solution of this kind of problem. Therefore, we use the block coordinate descent method (BCD) to obtain the approximate solution. As presented in [23], the BCD is widely used to solve the complicated non-convex multivariable joint optimization problems [3], [16], [21], [23]. Although the BCD algorithm cannot guarantee the global optimal solution of the MINLP problem, it can obtain the suboptimal solution via division and iteration and greatly reduce the difficulty of solving the non-convex multivariable joint optimization problem. The performance of the BCD algorithm has been verified in many research works [3], [16], [21], [23]. In the block coordinate descent method, the vector of variables is partitioned into different blocks. In each iteration, the algorithm fixes the values of some variable blocks, and searches in one-dimension along a coordinate direction at the current point to obtain the local optimal value of a function. According to the feature of the main problem **MP**, we can fix k_{ij} to get the computation resource allocation sub-problem and fix f_{ij} to get the task assignment sub-problem.

III. SOLUTIONS

A. COMPUTATION RESOURCE ALLOCATION SUB-PROBLEM

The computation resource allocation sub-problem can be formulated as follows:

$$\begin{aligned} \text{SP1}: \ & \underset{f_{ij}}{Max} \ Ut \ = \sum_{\mathrm{i}=1}^{\mathrm{n}} Z_{U_{\mathrm{i}}}^{F_j} \\ & \text{subject to}: \ (4), (5) \end{aligned} \tag{17}$$

Constraints (4) and (5) are linear, and it is easy to verify that the objective function Ut is a concave function. Hence we can use Lagrange dual function and Karush-Kuhn-Tucker (KKT) [26] conditions to solve SP1. The Lagrange dual function and Lagrange multipliers are expressed as follows:

$$\begin{aligned} L(f, \lambda) = & -\sum_{i=1}^{n} Z_{U_i}^{F_j} + \sum_{a=1}^{m} \lambda_a (\sum_{i=1}^{n} k_{ia} f_{ia} - f_a^{\max}) \\ & - \sum_{b=1}^{m} \lambda_b \sum_{i=1}^{n} k_{ib} f_{ib} + \sum_{c=1}^{n} \lambda_c (t_{cj}^H - T_c^{\max}) \\ & - \sum_{g=1}^{n} \lambda_g t_{gj}^H \end{aligned} \tag{18}$$

where:

$$\begin{aligned} \lambda_a \geq 0, \quad & a = 1, \ldots, m \\ \lambda_b \geq 0, \quad & b = 1, \ldots, m \\ \lambda_c \geq 0, \quad & c = 1, \ldots, n \\ \lambda_g \geq 0, \quad & g = 1, \ldots, n \end{aligned} \tag{19}$$

Since k_{ij} is known, we only need to consider the case of $k_{ij} = 1$ here. When $k_{ij} = 1$, $f_{ij} > 0$ and $t^H > 0$ hold. According to the KKT conditions, we can get the following expressions for the optimal solution:

$$\begin{aligned} \nabla_f L(f*, \lambda*) = & -\nabla \sum_{i=1}^{n} Z_{U_i}^{F_j} + \sum_{a=1}^{m} \lambda_a^* \nabla (\sum_{i=1}^{n} k_{ia} f_{ia}^* - f_a^{\max}) \\ & - \sum_{b=1}^{m} \lambda_b^* \nabla \sum_{i=1}^{n} k_{ib} f_{ib}^* + \sum_{c=1}^{n} \lambda_c^* \nabla (t_{cj}^H - T_c^{\max}) \\ & - \sum_{g=1}^{n} \lambda_g^* \nabla t_{gj}^H = 0 \end{aligned} \tag{20}$$

$$\lambda* \geq 0 \tag{21}$$

$$(\sum_{i=1}^{n} k_{ia} f_{ia}^* - f_a^{\max}) \leq 0, \quad a = 1, \ldots, m \tag{22}$$

$$-\sum_{i=1}^{n} k_{ib} f_{ib}^* \leq 0, \quad b = 1, \ldots, m \tag{23}$$

$$(t_{cj}^H - T_c^{\max}) \leq 0, \quad c = 1, \ldots, n \tag{24}$$

$$-t_{gj}^H \leq 0, \ g = 1, \ldots, n \tag{25}$$

$$\lambda_a^* (\sum_{i=1}^{n} k_{ia} f_{ia}^* - f_a^{\max}) = 0, \quad a = 1, \ldots, m \tag{26}$$

$$\lambda_b^* \sum_{i=1}^{n} k_{ib} f_{ib}^* = 0, \quad b = 1, \ldots, m \tag{27}$$

$$\lambda_c^* (t_{cj}^H - T_c^{\max}) = 0, \quad c = 1, \ldots, n \tag{28}$$

$$\lambda_g^* t_{gj}^H = 0, \quad g = 1, \ldots, n \tag{29}$$

where f^*, λ^* are the optimal decision variables and Lagrange multipliers. ∇ means the partial derivative

Using formula (20) - (29), we can discuss the following cases to get the optimal solution.

1. All Lagrange multipliers $\lambda^* = 0$. In this case, according to (20), the following equation holds:

$$\frac{\partial \sum_{i=1}^{n} Z_{U_i}^{F_j}}{\partial f_{ij}} = \frac{a1 \times f_{ij}^2 + b1 \times f_{ij} + c1}{(\frac{a1}{q} \times f_{ij} + C_i)^2} = 0 \tag{30}$$

We get the optimal solution as follows:

$$\begin{aligned} f_{ij}^* & = \frac{-b1 + \sqrt{b1^2 - 4{*}a1{*}c1}}{2{*}a1} \\ a1 & = q \times (2 \times T_{ij}^f + t_{ij}^r + S) \\ b1 & = 2 \times C_i \times q \\ c1 & = C_i \times [T_{ij}^f \times \gamma - (S + 2 \times T_{ij}^f) \times \beta \times P - R] \end{aligned} \tag{31}$$

This solution must satisfy constraints (22)-(25). Otherwise, this solution will be rejected. Here $f_{ij}^* > 0$ always holds because $c1 < 0$ holds. Therefore, the following constraints should be guaranteed when f_{ij}^* is the optimal solution.

$$\frac{C_i}{f_{ij}^*} + \frac{D_i}{r_{ij}} \leq T_i^{\max} \Rightarrow f_{ij}^* \geq \frac{C_i}{T_i^{\max} - \frac{D_i}{r_{ij}}} \tag{32}$$

$$\sum_{i=1}^{n} f_{ij}^* \leq f_j^{\max} \tag{33}$$

2. $\lambda_b^* \neq 0$ *or* $\lambda_g^* \neq 0$. In this case, $f_{ib}^* = 0$ and $t_{gj}^H = 0$ hold. Nevertheless, we only consider the case of $k_{ij} = 1$, that is, we only optimize the computation resource allocation for UAV U_{i} when its data are offloaded to fog node F_{j}. Therefore, this case will not happen in the context. 3. $\lambda_a^* \neq 0$ and $\lambda_c^* \neq 0$. In this case, according to (26) and (28), the following equations hold:

$$\sum_{i=1}^{n} f_{ij}' = f_j^{\max} \tag{34}$$

$$f_{ij}'' = \frac{C_i}{T_i^{\max} - \frac{D_i}{r_{ij}}} \tag{35}$$

It's hard to guarantee that formula (34) and (35) hold at the same time. Formula (34) and (35) correspond to the upper bound and lower bound of the computation resources that can be allocated to UAVs in a fog node F_j. Since $k_{ij} = 1$, formula (35) is always larger than zero, that is, $T_i^{\max} - D_i/r_{ij} > 0$ holds.

4. Only $\lambda_a^* \neq 0$.

For the consistency of the symbolic expression, here we use λ_j' for λ_a^*. In this case, the following equation must hold according to the KKT conditions:

$$\begin{aligned}
&\nabla_f L(f,\lambda) = 0 \\
&\Rightarrow \frac{a1 \times f_{ij}^2 + b1 \times f_{ij} + c1}{(\frac{a1}{q} \times f_{ij} + C_i)^2} + \lambda_j' = 0 \\
&\Rightarrow \lambda_j' = -\frac{a1 \times f_{ij}^2 + b1 \times f_{ij} + c1}{(\frac{a1}{q} \times f_{ij} + C_i)^2}
\end{aligned} \tag{36}$$

Because $\lambda_j' > 0$, we thus get the following:

$$a1 \times f_{ij}^2 + b1 \times f_{ij} + c1 < 0 \tag{37}$$

As depicted in Fig. 2 (a), if formula (37) holds, the optimal solution should be in the interval of the horizontal coordinate values corresponding to the shadow part in (a), where f_{ij}'' is the lower bound of solution and is expressed as formula (35). The following conditions must be satisfied for the optimal solution:

$$f_{ij}'' \leq f_{ij}^{opt} < f_{ij}^* \tag{38}$$

$$\sum_{i=1}^{n} f_{ij}^{opt} = f_j^{\max} < \sum_{i=1}^{n} f_{ij}^* \tag{39}$$

Formula (39) is inferred from formula (26) (38) and $\lambda_a^* \neq 0$. f_{ij}^{opt} represents the optimal solution. As mentioned at the beginning of this section, the objective function Ut is a concave function and f_{ij}^* is its maximum point. Therefore, in the interval of $[f_{ij}'', f_{ij}^*)$, the function is monotonically increasing. Thus the optimal solution in this case can be found via linear search with the constraint (39).

5. Only $\lambda_c^* \neq 0$

For the consistency of the symbolic expression, here we use λ_i' for λ_c^*. The following formula must hold according to

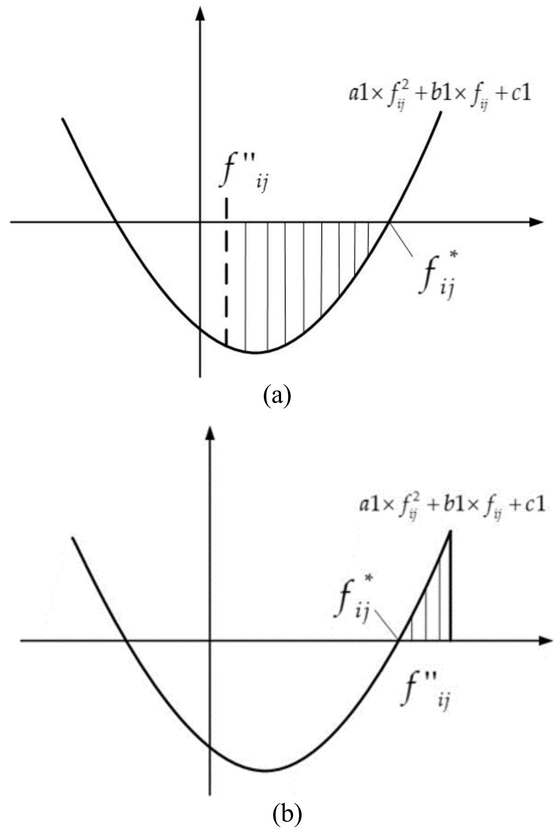

FIGURE 2. Optimal solution to resource allocation in two different cases: (a) Only $\lambda_a^* \neq 0$, and (b) Only $\lambda_c^* \neq 0$.

the KKT condition in this case:

$$\begin{aligned}
&\nabla_f L(f,\lambda) = 0 \\
&\Rightarrow \frac{a1 \times f_{ij}^2 + b1 \times f_{ij} + c1}{(\frac{a1}{q} \times f_{ij} + C_i)^2} - \lambda_i'' \frac{C_i}{f_{ij}^2} = 0 \\
&\Rightarrow \lambda_i'' = \frac{a1 \times f_{ij}^2 + b1 \times f_{ij} + c1}{(\frac{a1}{q} \times f_{ij} + C_i)^2} \times \frac{f_{ij}^2}{C_i}
\end{aligned} \tag{40}$$

Because $\lambda_i'' > 0$, we thus get the following:

$$a1 \times f_{ij}^2 + b1 \times f_{ij} + c1 > 0 \tag{41}$$

As shown in Fig. 2 (b), the solution satisfying (41) is in the interval of the horizontal coordinate values corresponding to the shaded part in the figure. Furthermore, the optimal solution must satisfy the lower bound constraint. Therefore, the following conditions must be satisfied for the optimal solution:

$$f_{ij}^{opt} \geq f_{ij}'' > f_{ij}^* \tag{42}$$

$$\sum_{i=1}^{n} f_{ij}^* < \sum_{i=1}^{n} f''_{ij} \leq \sum_{i=1}^{n} f_{ij}^{opt} \leq f_j^{\max} \tag{43}$$

f_{ij}'' is the lower bound of the solution and is expressed as formula (35). Since the objective function Ut is a concave function and f_{ij}^* is its maximum point, in the interval of $(f_{ij}^{*}, +\infty)$, the function is monotonically decreasing. Thus the optimal solution in this case is f_{ij}''.

B. TASK ASSIGNMENT SUB-PROBLEM

The task assignment sub-problem can be expressed as following formula:

$$\mathrm{SP2}: \underset{k_{ij}}{Max}\ Ut = \sum_{\mathrm{i}=1}^{\mathrm{n}} Z_{U_{\mathrm{i}}}^{F_j} \quad \text{subject to}: (3), (5) \tag{44}$$

In the sub-problem SP2, the computation resource f_{ij} that is allocated to UAV U_i by fog node F_j is fixed. SP2 is a kind of integer programming problem called generalized assignment problem [27], [28], which is NP-hard in the strong sense [27]. We use the brute force algorithm, greedy algorithm and heuristic algorithm [28] to solve this problem.

1) GREEDY ALGORITHM

First, we rank each UAV according to the value density of its task (from high to low), where the value density refers to the revenue that can be achieved per unit of computing resources. The algorithm needs to calculate the value densities of the UAVs on each fog node. Next, starting from the fog node closest to the data collection point, the UAVs are selected for task offloading to the fog node in the order of their unit value density from high to low. When the computation resources of one fog node have been exhausted, the next closest fog node is selected, until all tasks are offloaded. If there are still UAVs left after the computation resources of all fog nodes are allocated, the remaining UAVs are set to fly back to the ground base station for task offloading. The pseudo code of the greedy algorithm is as follows.

Algorithm 1 Greedy Algorithm

Input: $Z_{U_i}^{F_j}, t_{ij}^{H}, f_{ij}, f_j^{\max}, T_i^{\max}, n, m$
Output: k_{ij}, Ut
1: calculate value density $vd_{ij} = Z_{U_i}^{F_j}/f_{ij}$ for each i, j;
2: rank each UAV according to vd_{ij} in non-ascending order;
3: Loop while there are UAVs that are not allocated computation resources and there are fog nodes that have resources left;
4: choose the largest vd_{ij} with $k_{ij} = 0$; if assigning UAV U_i to fog node F_j can satisfy constraint (3) and (5), set $k_{ij} = 1$;
5: End Loop
6: Let the remaining UAVs offload their data to the GBS.

2) HEURISTIC ALGORITHM

The heuristic algorithm proposed by Martello *et al.* [28] needs to calculate the "desirability" of assigning UAV i to fog node j first. Let e_{ij} be the measurement of desirability. The algorithm considers all unassigned UAVs iteratively and finds the UAV U_{i^*} with the largest difference between the largest and the second largest e_{ij}. Then, UAV U_{i^*} is assigned to fog node j with the largest e_{i^*j}. Next, the current solution is improved by locally adjusting the assignment strategy for each UAV. The pseudo code of the heuristic algorithm is in algorithm 2.

In the heuristic algorithm, the desirability measurement is needed. According to the research in [28], good results can be obtained by using the following measurement methods.

1. $e_{ij} = Z_{U_i}^{F_j}$. In this case, the improvement phrase can be skipped.
2. $e_{ij} = Z_{U_i}^{F_j}/f_{ij}$
3. $e_{ij} = -f_{ij}$
4. $e_{ij} = -f_{ij}/f_j^{\max}$

Algorithm 2 Heuristic Algorithm

Input: $Z_{U_i}^{F_j}, t_{ij}^{H}, f_{ij}, f_j^{\max}, T_i^{\max}, n, m$
Output: k_{ij}, Ut
1: calculate desirability e_{ij} for each i, j;
2: Loop while there are UAVs that are not allocated computation resources and there are fog nodes that have resources left;
3: calculate $\Delta_i = e_{ij'} - e_{ij''}$ fory each unassigned U_i, where $e_{ij'}$ is the largest e_{ij} and $e_{ij''}$ is the second largest e_{ij}, and satisfy constraint (5) for each f_{ij}.
4: choose U_{i^*} that has the largest Δ_{i^*}, assign U_{i^*} to the corresponding fog node $F_{j'}$;
5: End Loop
6: If the feasible solution is found in the steps 1-5, Loop
7: for each $k_{ij} = 1$ find another j' so that $Z_{U_i}^{F_{j'}} > Z_{U_i}^{F_j}$ and it would not violate constraint (5) if we let $k_{ij} = 0$ and $k_{ij'} = 1$
8:End Loop

3) BRUTE FORCE ALGORITHM AND COMPLEXITY ANALYSIS

Because it is NP complete to judge whether there is a feasible solution to the generalized assignment problem [27], and problem SP2 in this section is a non-linear optimization problem, there is no suitable approximate algorithm that approaches the optimal solution of the problem, and it is not possible to use the algorithm of the linear integer programming problem. To evaluate the performances of the greedy algorithm and heuristic algorithm, we use the brute force algorithm as the benchmark.

The time complexities of the brute force algorithm, greedy algorithm and heuristic algorithm are $O(m^n)$, $O(nm \log m + nm)$ and $O(nm \log m + n^2)$, respectively. Obviously, if the value of n is close to that of m, the time complexities of the greedy algorithm and heuristic algorithm will be approximately the same. If $n \gg m$, the time complexity of the heuristic algorithm will be higher.

C. BLOCK COORDINATE DESCENT ALGORITHM FOR MAIN PROBLEM

Because the main problem is a MINLP problem, there is no polynomial time global optimization algorithm or approximate optimization algorithm. To solve the main problem **MP**, we use the block coordinate descent method to find the local optimal solution of the main problem. The pseudo code of block coordinate descent algorithm is as follows:

Algorithm 3 Block Coordinate Descent Algorithm

Input: $Z_{U_i}^{F_j}$, t_{ij}^{H}, f_{ij}, $f_j^{\max}$, $T_i^{\max}$, n, m
Output: k_{ij}, Ut
1: set the initial values of $f_{ij}(0)$ for each i, j; set $k_{ij}(0) = 0$ for each i, j;
2: Loop while $|Ut(\tau+1) - Ut(\tau)| > \varepsilon$ and $\tau \leq 1000$, where τ is the number of iterations;
3: solve SP2 with $f_{ij}(\tau)$ fixed to get $k_{ij}(\tau+1)$;
4: solve SP1 with $k_{ij}(\tau+1)$ fixed to get $f_{ij}(\tau+1)$;
5: calculate $Ut(\tau+1)$
6: End Loop

The initial values of $f_{ij}(0)$ can be calculated according to formula (34) or randomly generated in the interval $\left[f_{ij}^{\min}, f_j^{\max}\right]$, where $f_{ij}^{\min}$ is calculated according to formula (34), and $f_j^{\max}$ is the upper bound of the computation resources that can be allocated to the UAV on a fog node. We choose the second way to generate the initial values of $f_{ij}(0)$. Because it is a NP-complete problem to determine whether MP has a feasible solution, the greedy algorithm and heuristic algorithm usually cannot be guaranteed to find a feasible solution. However, because we can choose to offload the UAV tasks to the ground base station, both algorithms can return a feasible solution in the practice. Thus, in the performance comparison, we only consider the cases in which the feasible solution of the problem exists.

IV. NUMERICAL SIMULATION

The values of the simulation parameters in this paper are taken from the configurations of [21], [22], which are listed in Table 2.

TABLE 2. Simulation parameters.

Parameter	Value
L	20km
R	350
γ	0.1
V	20m/sec
β	0.2
P	59.2watt
q	8.5×10^{-6} / sec
B	2.5GHz
σ^2	-60dbm
β_0	-30dbm
H	100m
p_i	37dbm
S	600sec
$T_i^{\max}$	30sec
I	14400sec

Without loss of generality, we let the fog nodes be uniformly distributed in a line from 1km to 5km from the data collection point. The initial location of UAVs is from 50m to 100m from the data collection point. The task data size is randomly distributed from 200GB to 230GB. The task CPU cycles are randomly distributed from 800GHz to 830GHz. The maximum computation resources that can be allocated to UAVs are from 250GHz to 300GHz. There are 5 fog nodes by default.

A. NUMERICAL RESULTS OF THE ALGORITHMS FOR THE TASK ASSIGNMENT SUB-PROBLEM

In this section, we compare the performance of the different algorithms in solving the task assignment sub-problem. In each simulation round with the same parameters, we take the average value of 5 runs for each data point. Fig. 3 shows the revenues of four heuristic algorithms with different desirability measures. It can be observed that under our simulation configurations, the heuristic algorithm adopting the third and the fourth desirability measurements have the best result. Therefore in the next simulation, we use the fourth desirability measurement.

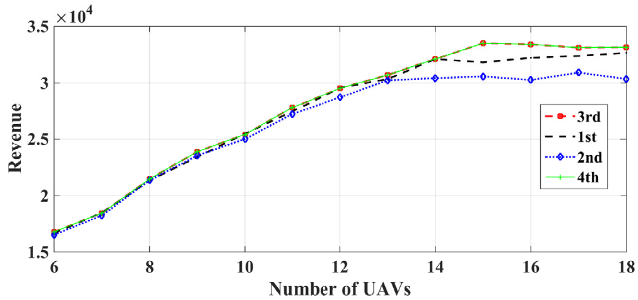

FIGURE 3. The comparison of different desirability measurements of the heuristic algorithm.

Fig. 4 and Fig. 5 show the change in the revenues and running time of the three different algorithms as the number of UAVs increases. As shown in Fig. 4, when the number of UAVs is small, the difference between the three algorithms is very small. When the number of UAVs exceeds 10, the difference becomes more obvious. Since the optimal solution is always obtained by the brute force algorithm, the revenue obtained by the brute force algorithm is larger than that of the other two algorithms. In addition the heuristic algorithm is basically better than the greedy algorithm. As shown in Fig. 5, the running time of the brute force algorithm increases significantly as the number of UAVs increases, while the other two algorithms basically show no change and remain small. Because the time complexity of the brute force algorithm is much greater than those of the other two algorithms, we only compare the performances of the heuristic algorithm and greedy algorithm in the next comparison.

Fig. 6 shows the changes in the revenue obtained by the three different algorithms as the number of fog nodes

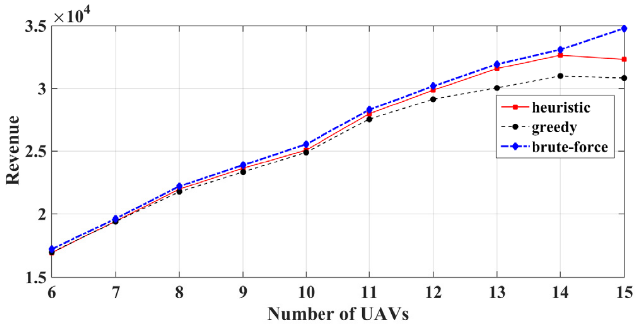

FIGURE 4. The impact of different numbers of UAVs on revenue.

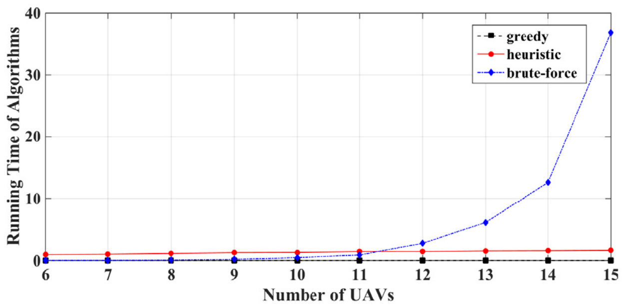

FIGURE 5. The impact of different number of UAVs on the running time.

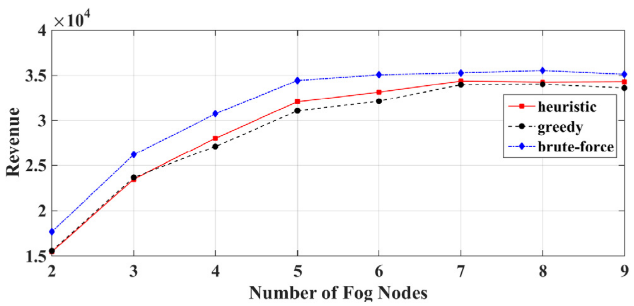

FIGURE 6. The impact of different numbers of fog nodes on revenue.

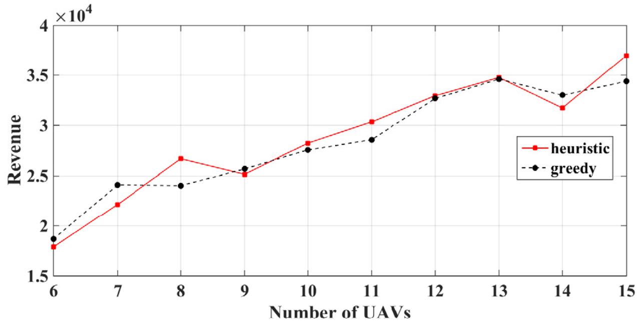

FIGURE 7. The impact of different number of UAVs on revenue(BCD).

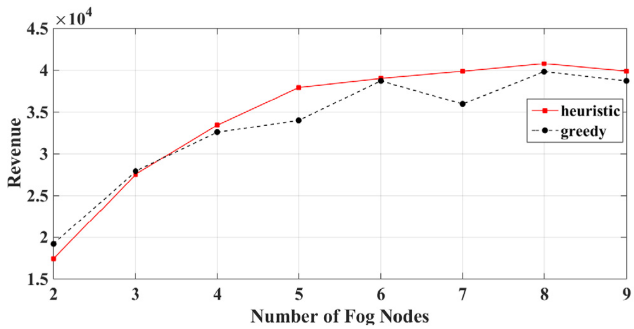

FIGURE 8. The impact of different numbers of fog nodes on revenue(BCD).

increases. It can be seen that as the number of fog nodes increases, the revenue curve of the three algorithms tends to be stable, and the difference between the heuristic algorithm and brute force algorithm is not significant. This result shows that in the case of abundant computation resources, increasing the total number of fog nodes will not improve the overall performance of the system.

B. NUMERICAL RESULTS OF THE BLOCK COORDINATE DESCENT ALGORITHM FOR THE MAIN PROBLEM

Fig.7 and Fig.8 respectively show the changes in the revenues obtained by the block coordinate descent (BCD) algorithm based on the heuristic strategy and the greedy strategy as the numbers of UAVs number and fog nodes increase, respectively.

Compared with the results depicted in Fig. 4 and Fig. 6, Fig.7 and Fig. 8 show that the block coordinate descent algorithm achieves a better result, that is, more revenue is obtained. This result occurs because the block coordinate descent algorithm includes the adjustment of computation resource allocation strategy in each iteration. The adjustment of the computation resources enables the block coordinate descent method to further optimize the solution of the main problem using greedy strategy and heuristic strategy, and it also reduces the gap between the heuristic algorithm and greedy algorithm.

V. NETWORK SIMULATOR BASED SIMULATION

This section presents the simulation based on the opportunistic network simulator ONE [29]. As argued in [30], the network simulator-based simulation can provide an easier way to test applications and protocols than a real network test-bed because the simulator based simulation has some significant advantages, including scalability, flexibility, reproducible scenarios, etc.. According to references [1], [2], [30] and [31], the design of the UAV-fog collaborative remote data collection framework is as follows:

1. The UAVs are equipped with sensors or cameras for data collection tasks and are operated autonomously by onboard computers [2].
2. The UAVs are piloted on the predefined routes, such as the waypoint mobility model [1], [30].

3. The UAVs utilize the UAV-to-ground communication channel to communicate with fog nodes. The communication standard could be Wi-Fi [31] or the unlicensed spectrum 2.4GHz [23].
4. Each fog node has a network interface for the receiving UAVs' data. The data of a UAV can only be offloaded to one of the fog nodes.
5. Each UAV has two kinds of flight modes [32]: the circular flight mode for hovering or stay-at mobility [30] and the straight flight mode for waypoint mobility.
6. Each fog node has limited computation and storage resources for processing the UAVs' data.

According to the above framework design, some simulation environment parameters of the ONE are set as table 3:

TABLE 3. Some simulation parameters of the one.

Parameter	Value
Network Interface	Simple Broadcast Interface
Transmission Rate	10MB/sec
Transmission Range	400m
No. of Message Event Generator	1
No.of Mobile Nodes(UAVs)	15
No.of Stationary Nodes(Fog)	1~6
The buffer size of UAVs	300MB
The buffer size of Fog nodes	2.1GB
Speed of UAVs	[10,15]m/sec
Mobility model	Map based movement (waypoint)
Routing protocol	First contact
Event Intervals	[25,35]sec
Simulation time	21600sec

As depicted in Fig. 9, *b0* is the event generator, which represents the data collection point. *fly18* is a mobile node, which represents a UAV. *Fog12*~*Fog67* are stationary nodes, which represent fog nodes. It should be noted that the flight speed of each UAV varied from 10 to 15 (meters per second) in this section. This configuration is different from the previous assumption in section II that the flight speed is a constant. Zeng *et al.* [32], [33] figured out the closed-form of propulsion energy consumption models for fixed-wing and rotary-wing UAVs in straight and level flight with a constant flight speed. These authors also calculated the optimal speeds for circular flight and straight flight mode. Therefore, to optimize the energy consumption, the flight speed of UAVs should be set as a constant, and it should be changed only when the flight mode is changed. However, it is difficult to keep a UAV flying at a constant speed. It is acceptable that the speed of a UAV fluctuates in a small range. Therefore, the simulation in this section is closer to the practical situation, that is, the flight speed of a UAV is uniformly distributed in a small range. In the optimization procedure, the mathematical expectation of the flight speed can be used for the calculation.

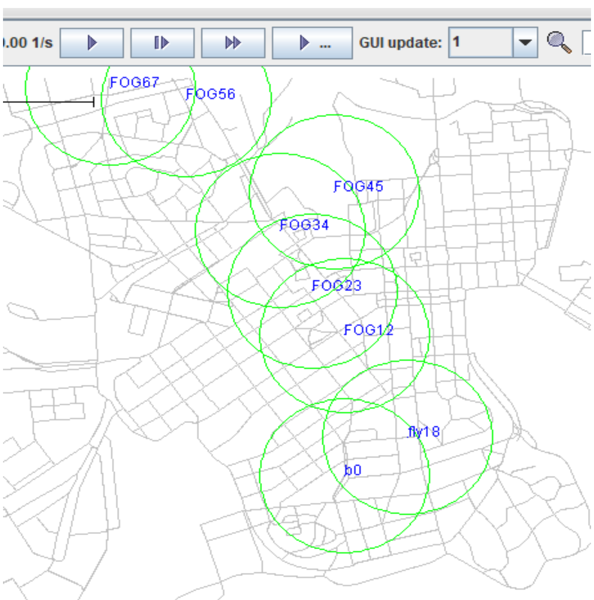

FIGURE 9. The graphic user interface of the ONE simulator.

In this simulation, the performance of the heuristic-based block coordinate descent algorithm (Heu-BCD) is compared with that of the genetic algorithm [34], [35]. As mentioned in the previous section, to the best of our knowledge, there is no previous work that addresses the UFDC problem. The key to solving this problem is to find a compromise between the UAV flight time and data processing time. The UAV itself cannot be used as a computing platform. In the related work, the genetic algorithm is used to solve the service offloading problem of fog computing in a bus network [34] and the energy consumption optimization problem of the UAV swarm [35]. Therefore, this section takes the genetic algorithm as the benchmark. The basic parameters of the genetic algorithm are set as follows: the probability of crossover is 0.9, the mutation probability is 0.05, the size of the population is 1000, and the maximum evolution generation is 1000.

The simulation procedure is as follows:

First, the solutions of two algorithms are calculated in MATLAB. Second, the simulation parameters of ONE are configured according to the obtained solutions. Then the simulation results, such as the UAV flight duration and flight times are obtained by running the simulation. Finally, the simulation results are substituted into the revenue formula (2) to calculate the final revenue value.

The simulation results are shown in Fig. 10. The number of fog nodes varied from 1 to 6. It can be seen that Heu-BCD algorithm achieves better revenues than the genetic algorithm

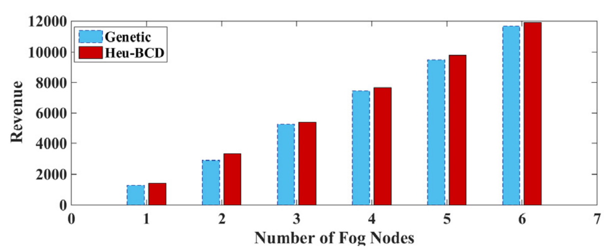

FIGURE 10. The simulation results in the ONE simulator.

at all simulation points. Similar to the results of the numerical simulation, as the number of fog nodes increases, the overall revenue gradually increases, which shows the feasibility of UFDC model in the simulation environment of this paper.

VI. DISCUSSION AND CONCLUSION

According to the results of the numerical simulation and the network simulator based simulation, based on the proposed UAV-fog collaborative remote data collection framework (UFDC) and the corresponding optimization model, the corresponding optimization algorithm can effectively improve the revenue of UAV-enabled remote data collection. In the numerical simulation, the heuristic algorithm performs better than the greedy algorithm. In the simulation based on the ONE simulator, the heuristic-based block coordinate descent algorithm outperforms the genetic algorithm. Different from the previous research work, this paper does not assume that the UAV has enough computing power, but rather it assumes that the UAV needs to send the collected data to the ground base station for processing. One typical applications is the collection of geographic information data. Because the scenario considered in this paper is data collection in remote areas, a large amount of data collected by a UAV cannot be directly sent to the base station, but rather it must be carried by the UAV to the base station and delivered within the receiving range of the base station. Therefore, this paper proposes renting the computation resources of fog nodes to preprocess and forward data. The optimization results mainly depend on the abundance of computation resources relative to the number of UAVs. In the case of reduced computation resources (more UAVs or less fog nodes), the optimization results are poor. When the computation resources are reduced to zero, the model will degenerate into the traditional UAV data collection model in remote areas.

In the future research work, we can combine multiple data transmission models with the UAV-fog computing framework, such as using the UAV ad hoc network or cooperative UAVs to transmit data [17], [31], [35], or we can consider extending the UAV-fog collaborative data collection framework to more application fields, such as electric vehicles and smart grid [36], cooperative fog-based IoT [37], or intelligent transportation [38], [39].

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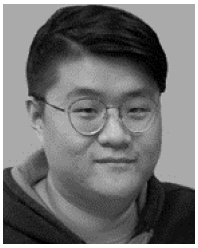

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