Fog Based Computation Offloading for Swarm of Drones

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Abstract-Due to the limited computing resources of swarm of drones, it is difficult to handle computation-intensive tasks locally, hence the cloud based computation offloading is widely adopted. However, for the business which requires low latency and high reliability, the cloud-based solution is not suitable, because of the slow response time caused by long distance data transmission. Therefore, to solve the problem mentioned above, in this paper, we introduce fog computing into swarm of drones (FCSD). Focusing on the latency and reliability sensitive business scenarios, the latency and reliability is constructed as the constraints of the optimization problem. And in order to enhance the practicality of the FCSD system, we formulate the energy consumption of FCSD as the optimization target function, to decrease the energy consumption as far as possible, under the premise of satisfying the latency and reliability requirements of the task. Furthermore, a heuristic algorithm based on genetic algorithm is designed to perform optimal task allocation in FCSD system. The simulation results validate that the proposed fog based computation offloading with the heuristic algorithm can complete the computing task effectively with the minimal energy consumption under the requirements of latency and reliability.

Index Terms—Swarm of drones, fog computing, computation offloading, latency and reliability, genetic algorithm

I. INTRODUCTION

Swarm of drones, which are considered as an intensely promising development direction of Unmanned Aerial Vehicles (UAVs), has made great progress in recent years. Swarm of drones are composed by numerous small and low-cost UAVs, through collaborating with each other, the drones can show strong ability to accomplish the tasks which are difficult for a single large UAV. As a consequence, swarm of drones are widely used for a variety of applications, such as agriculture, smart city, search and rescue, remote sensing, military, etc [1]. For most of these applications, drones are brought to deal with computation-intensive tasks, such as path planning, pattern recognition, etc [2]. However, due to its limited resources (e.g., battery power, computing capability), the single drone is too difficult to handle the complicated task locally [3]. Therefore, to address the computation-intensive tasks mentioned above, some researches considered computation offloading to a cloud server, and then obtain the result from the cloud [4]. In this manner, the capability of swarm of drones is greatly enhanced in a virtual way. And it is suitable for some business (e.g., topographic mapping, resource exploration, environmental monitoring, etc.) which are not sensitive to latency and reliability. But in practice, quite a few computing tasks which the drones need to process, have low latency and high reliability requirements, such as military object recognition, disaster rescue, emergency obstacle avoidance, etc [5] [6]. However, cloud servers are generally located far away from the drones, and long-distance data transmission will lead to high latency, even in some harsh environments, there is no working wireless infrastructure to connect the drones and cloud. Hence, the cloud based computation offloading is not suitable to address the latency and reliability sensitive business.

In order to further enhance the ability of swarm of drones to cope with computation-intensive tasks, specifically focusing on those tasks with low latency and high reliability requirements, we introduce fog computing [7] into swarm of drones. The drones which close to the initiator drone are thought to be fog computing nodes to complete the computing task collaboratively.

Fog computing is a novel computing paradigm which is not intended to replace cloud computing but to compliment it. Recently, there are many researches about fog computing enhancing cloud computing. In [8], authors considered leveraging buses as fog computing servers to provide fog computing services for the mobile users on bus and share the pressure of roadside cloudlets. The authors in [9] proposed combined fog-cloud architecture to reduce the latency of service. In [10], authors formulated a computation offloading game to improve the quality of experience of IoT users in hierarchical fog-cloud computing architecture. But there is no existing research to introduce fog computing into the work of swarm of drones, as a supplementary solution for the computation offloading of cloud computing.

In practice, swarm of drones usually work in harsh environments, and inevitable disturbances (e.g., hardware damage, software breakdown, communication link failure, etc.) will lead to the failure of the task. Hence, besides considering the latency guarantee, a proper reliability-guarantee mechanism is especially needed. However, there are few existing researches about fog (or edge) based computation offloading both considering the latency and reliability guarantee [11]. Therefore, in order to complete the computing task within low latency and high reliability requirements, we construct a

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certain mathematical model for system's latency and reliability during task execution, and take the latency and reliability as the constraints of the optimization problems formulated, thus the computation offloading scheme must be able to meet the requirements of the business on latency and reliability.

A big challenge for swarm of drones utilizing fog computing to deal with computing task is their limitation of battery endurance, hence, under the premise of ensuring the completion of the task within low latency and high reliability requirements, we formulated the energy consumption of whole swarm of drones as the target function of optimization problem, to reduce the overall energy consumption and extend the working time of the swarm of drones as far as possible. Since the formulated problem is NP-hard, we design a heuristic algorithm based on genetic algorithm to solve the problem.

In summary, the main contributions of this paper are as follows:

- To enhance the ability of swarm of drones to handle complicated tasks, we introduce fog computing into swarm of drones (FCSD), as a supplementary solution for the cloud based computation offloading.
- To meet the latency and reliability requirements of the computing tasks, we construct a certain mathematical model for system latency and reliability during task execution.
- To improve the practicality of the FCSD system in practice, the energy consumption of FCSD is constructed as the optimization target function, to reduce the energy consumption so that extend the working time of swarm of drones.
- To solve the NP-hard problem formulated, we design a latency and reliability constrained minimum energy consumption algorithm based on genetic algorithm (LRGA-MIE).

The rest of the paper is organized as follows. The system model and problem formulation are presented in Section II. Section III presents the offloading algorithm proposed. The simulation results and analyses are given in Section IV. Finally, Section V conclude the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In order to enhance the ability of swarm of drones addressing computation-intensive tasks which are sensitive to latency and reliability, the FCSD system is proposed. The architecture of FCSD is shown in Fig. 1.

The drone dr_0 has a computing task $\Psi_0 \triangleq \{D_0, \alpha_0, T_0, R_0\}$, where D_0 denotes the input size of the total task; T_0 and R_0 represent the latency and the reliability constraints, respectively. We define E_0 as the total required amount CPU cycles to complete the task Ψ_0 . The number of CPU cycles E_0 is modeled as $E_0 = \alpha_0 D_0$, where $\alpha_0(\alpha_0 > 0)$ depends on the computational complexity of the task [12]. The drone dr_0 requests nearby drones dr_i that can serve as the fog nodes to complete the task Ψ_0 collaboratively. These drones available nearby, denoted by a set $\mathcal{D} = \{dr_1, dr_2, \dots, dr_p\}$, are equipped with storage and

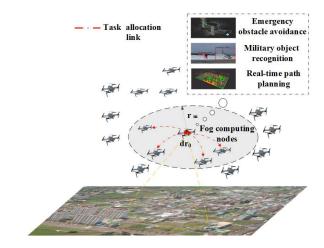


Fig. 1. The computation offloading architecture of FCSD

computation resources. We define f_0 as the CPU frequency of the drone dr_0 . Similarly, the CPU frequency of the drones available nearby, denoted by a set $\mathcal{F} = \{f_1, f_2, \ldots, f_p\}$. The coordinate of the drone dr_0 is (x_0, y_0, z_0) . The $\mathcal{C} = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \cdots, (x_p, y_p, z_p)\}$ are the three-dimensional coordinates of the drones available nearby, respectively.

The distance between the drone $dr_i \in \mathcal{D}$ and the drone dr_0 can be given by

$$g_{0,i} = \left[(x_0 - x_i)^2 + (y_0 - y_i)^2 + (z_0 - z_i)^2 \right]^{\frac{1}{2}}, g_{0,i} \le r, \quad (1)$$

where r is the maximum communication radius of individual drones. According to [8] [13], the uplink rate from dr_0 to dr_i can be given as

$$R^{\rm UL}(0,i) = W^{\rm UL} \log_2\left(1 + \frac{P_{\rm Tx}\left(g_{0,i}^{-\gamma}|h_0|\right)}{N_0}\right),\tag{2}$$

where W^{UL} represents the uplink channel bandwidths between the drone dr_0 and dr_i ; P_{Tx} denotes the transmission power of the drone dr_0 ; γ is the path loss exponent which ranges from $2 \le \gamma \le 5$; h_0 is the complex Gaussian channel coefficient which follows the complex normal distribution CN(0,1); N_0 is the additive white Gaussian noise(AWGN).

The task Ψ_0 would be partition into several subtasks by the drone dr_0 and distributed to multiple drones. In practice, how to partition a task depends on not only application, but also the requirements, which is worth studying further. Therefore, for simplicity, it can be assumed that the task can be divided into any proportion with arbitrary precision, and there is no overlap between any two subtasks [11]. According to the status of the dr_0 and $dr_i \in \mathcal{D}$, the initiator drone dr_0 can make different task offloading and allocation decisions¹. We define ρ ($0 \le \rho \le 1$) as the offloading coefficient, therefore, the part of the task Ψ_0 which need to be executed locally, can be described as $\rho \Psi_0$, and the part of the task which need to be offloaded to the drones available nearby is $(1 - \rho) \Psi_0$. Then, we denote the subtask offloaded to the drone dr_i as

¹In practice, the drone interacts with the surrounding drones to complete the formation, networking, collaborative works, etc., which enables the drone to be aware of the status of the surrounding drones. [14]

 $\lambda_i(1-\rho)\Psi_0$, where $\lambda_i \in [0,1]$, and $\sum_{i=1}^p \lambda_i = 1$. We define $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_p]^T$ as the task allocation vector.

After decision, the drone dr_0 and the drones $dr_i \in \mathcal{D}$ are orchestrated to perform distributed computing to complete the task Ψ_0 collaboratively. These low-cost drones fly slowly and tend to form a relatively stable formation, rather than constantly changing [1]. In the meantime, the transmission latency of the subtask is extremely short when the data size is small. Therefore, we assume that the relative distance and the states of the drones will not change during the task assignment process, and each assigned subtask will be executed immediately on the drone dr_i and dr_0 .

A. Latency Model

The latency of the drone dr_0 processing the subtask $\rho \Psi_0$ is defined as

$$T_{\text{Local}} = \frac{\rho \alpha_0 D_0}{f_0}.$$
(3)

When the drone dr_0 offloading the subtask $\lambda_i(1-\rho)\Psi_0$ to the drone dr_i , the size of the transmitted data will be $\beta\lambda_i(1-\rho)D_0$, where β ($\beta \ge 1$) represents a ratio of the transmitted data size to the original task data size due to transmission overhead [12]. Thus, the transmission latency of the subtask from the drone dr_0 to the drone dr_i is

$$T_i^{\text{UL}} = \frac{\beta \lambda_i (1-\rho) D_0}{R^{\text{UL}}(0,i)}.$$
(4)

And the computation latency of the subtask addressed on the drone dr_i is

$$T_i^{\text{Comp}} = \frac{\alpha_0 \lambda_i (1-\rho) D_0}{f_i}.$$
 (5)

Due to the data size of the result of each subtask is much smaller than the input one, the latency caused by downlink transmission can be neglected [15]. The total execution latency of the subtask completed on the drone dr_i is given by

$$T_i = T_i^{\text{UL}} + T_i^{\text{comp}}$$

= $\frac{\beta \lambda_i (1-\rho) D_0}{R^{\text{UL}}(0,i)} + \frac{\alpha_0 \lambda_i (1-\rho) D_0}{f_i}.$ (6)

Therefore, the total execution latency of the task Ψ_0 can be described as

$$T_{\text{Total}} = \max_{i \in p} \{ T_{\text{Local}}, T_i \}$$

$$= \max_{i \in p} \left\{ \frac{\rho \alpha_0 D_0}{f_0}, \frac{\beta \lambda_i (1-\rho) D_0}{R^{\text{UL}}(0,i)} + \frac{\alpha_0 \lambda_i (1-\rho) D_0}{f_i} \right\}.$$
(7)

To meet the latency requirement of the task Ψ_0 , the total execution latency T_{Total} should meet the constraint $T_{\text{Total}} \leq T_0$.

B. Reliability Model

The swarm of drones usually work in harsh environments, and inevitable disturbances (e.g., hardware damage, software breakdown, communication link failure, etc.) will lead to the failure of the whole task, and always with serious consequence. Therefore, a proper reliability-guarantee capability is especially needed to ensure the successful completion of the mission.

According to the widely accepted reliability model proposed by Shatz [16], the system reliability is that " the product of the probability that each processor is operational during the time of processing the tasks assigned to it, and the probability that each communication link is operational during the period of the data transmission."The failure of the drones and communication links follow a Poisson process [16], further, the failure rates of the drone dr_0 and dr_i are defined as ν_0 and ν_i , respectively, and the failure rate of the communication links between dr_0 and dr_i is defined as $\mu_{0,i}$. Therefore, the computation reliability of the drone dr_0 and dr_i can be represented as $e^{-\nu_i \frac{\rho_0 \rho_0}{f_0}}$ and $e^{-\nu_i \frac{\lambda_i (1-\rho)\alpha_0 D_0}{f_i}}$, respectively. And the communication reliability between dr_0 and dr_i can be represented as $e^{-\mu_{0,i} \frac{\lambda_i (1-\rho)\beta D_0}{R^{\rm OL}(0,i)}}$. The reliability of the subtask which executed locally can be represented as

$$R_{\text{Local}} = e^{-\nu_0 \frac{\rho \alpha_0 D_0}{f_0}}.$$
(8)

Then, the reliability of the subtask which distributed to the drone dr_i can be represented as

$$R_{i} = e^{-\nu_{i} \frac{\lambda_{i}(1-\rho)\alpha_{0}D_{0}}{f_{i}} - \mu_{0,i} \frac{\lambda_{i}(1-\rho)\beta D_{0}}{R^{\mathrm{UL}}(0,i)}}.$$
(9)

Therefore, the reliability of the swarm of drones during the execution time of the task Ψ_0 can be given by

$$R_{\text{Total}} = R_{\text{Local}} \prod_{i=1}^{p} R_{i}$$

$$= e^{-\nu_{0} \frac{\rho \alpha_{0} D_{0}}{f_{0}} + \sum_{i=1}^{p} \left(-\nu_{i} \frac{\lambda_{i} (1-\rho) \alpha_{0} D_{0}}{f_{i}} - \mu_{0,i} \frac{\lambda_{i} (1-\rho) \beta D_{0}}{R^{0} L_{(0,i)}} \right)}.$$
(10)

To meet the reliability requirement of the task Ψ_0 , the total reliability R_{Total} should meet the constraint $R_{\text{Total}} \ge R_0$.

C. Energy Consumption Model

To improve the practicality of the FCSD system, how to minimize the energy consumption, under the premise of ensuring the completion of the task within latency and reliability requirements, must be taken into account. Therefore, a mathematical model that minimizes the energy consumption of FCSD processing a single task is constructed.

1) Computational energy consumption: The computational energy consumption of the drone dr_0 and dr_i can be given by

$$E_{\text{Local}}^{\text{Comp}} = k f_0^{\sigma} T^{\text{Local}}; \tag{11}$$

$$E_i^{\text{Comp}} = k f_i^{\sigma} T_i^{\text{Comp}},\tag{12}$$

respectively, where kf_0^{σ} and kf_i^{σ} are the computation power of the drone dr_0 and dr_i . According to [17], the k > 0 and the $\sigma \ge 2$ (which usually close to 3), are the positive constant. As in [18], the k and the σ can be set as 1.25×10^{-26} and 3, respectively.

Therefore, the total computational energy consumption of the swarm of drones is represented as

$$E_{\text{Total}}^{\text{Comp}} = k f_0^{\sigma} T_{\text{Local}} + \sum_{i=1}^p k f_i^{\sigma} T_i^{\text{Comp}}$$

= $k f_0^{\sigma} \frac{\rho \alpha_0 D_0}{f_0} + \sum_{i=1}^p k f_i^{\sigma} \frac{\alpha_0 \lambda_i (1-\rho) D_0}{f_i}.$ (13)

2) Transmission energy consumption: The transmission energy consumption of the drone dr_0 and the drone dr_i can be given as

$$E_{\text{Local}}^{\text{Trans}} = P_{\text{Tx}} T_i^{\text{UL}}; \tag{14}$$

$$E_{i}^{\text{Trans}} = P_{\text{Rx}} T_{i}^{\text{UL}},\tag{15}$$

respectively, where P_{Tx} and P_{Rx} denote the transmitting and receiving power of the drone dr_0 and dr_i , respectively, which are regarded as constant [18]. Therefore, the total transmission energy consumption of the FCSD system can be given by

$$E_{\text{Total}}^{\text{Trans}} = \sum_{i=1}^{p} E_{\text{Local}}^{\text{Trans}} + \sum_{i=1}^{p} E_{i}^{\text{Trans}}$$

$$= \sum_{i=1}^{p} P_{\text{TR}} \frac{\beta \lambda_{i} (1-\rho) D_{0}}{R^{\text{UL}}(0,i)} + \sum_{i=1}^{p} P_{\text{SR}} \frac{\beta \lambda_{i} (1-\rho) D_{0}}{R^{\text{UL}}(0,i)}.$$
(16)

In summary, the total energy consumption of the swarm of drones can be represented as

$$E_{\text{Total}} = E_{\text{Total}}^{\text{Comp}} + E_{\text{Total}}^{\text{Trans}}$$

$$= k f_0^{\sigma} \frac{\rho \alpha_0 D_0}{f_0} + \sum_{i=1}^p k f_i^{\sigma} \frac{\alpha_0 \lambda_i (1-\rho) D_0}{f_i} + \sum_{i=1}^p P_{\text{Tx}} \frac{\beta \lambda_i (1-\rho) D_0}{R^{\text{UL}}(0,i)} + \sum_{i=1}^p P_{\text{Rx}} \frac{\beta \lambda_i (1-\rho) D_0}{R^{\text{UL}}(0,i)}.$$
(17)

D. Problem Formulation

To sum up, a problem to minimize the energy consumption of FCSD within latency and reliability constraints, is modeled as follows:

$$\mathcal{P}:$$
 $(\rho, \lambda_i) = \arg\min E_{\text{Total}}$ (18)

$$\int \rho + \sum_{i=1}^{p} \lambda_i (1-\rho) = 1$$
(19a)

$$\begin{array}{c|c} \text{Total} \leq I_0 \\ \text{Brand} \geq R_0 \\ \end{array} \tag{19b}$$

$$n_{\text{Total}} \ge n_0$$
 (190)

$$\left(\begin{array}{c} 0 \le \lambda_i, \rho \end{array} \right) \tag{19d}$$

III. LRGA-MIE ALGORITHM

To find the optimal solution of the problem \mathcal{P} , we design a latency and reliability constrained minimum energy consumption algorithm based on the real-code genetic algorithm (LRGA-MIE) [19].

Genetic algorithm (GA) is a kind of widely used heuristic algorithm due to its advantages of better global searching capability, strong robustness, parallel processing capability, etc. In the real-coded GA, each individual $X_i =$ $\{x_{i1}, x_{i2}, \dots, x_{i(p+1)}\}$ in the population represents a possible solution of the optimization problem, which would be initially set to a random value. And then, through the constant evolution of selecting, crossing over and mutating the initial population, an optimal individual is found. Different from the unconstrained optimization problem, the problem \mathcal{P} formulated has several constraints including equality and inequality constraints (i.e., Eq. (19a), (19b), (19c) and (19d)). However, GA cannot solve constrained optimization problem directly. Therefore, we adopt exterior penalty function method [20] to transform the constrained problem into an unconstrained optimization problem.

In the following, the design details of LRGA-MIE algorithm are explained.

The fitness function of LRGA-MIE is reconstructed as follows:

$$f(\boldsymbol{X}) = \begin{cases} E_{\text{Total}}(\boldsymbol{X}) & \boldsymbol{X} \in \boldsymbol{F}; \\ E_{\text{Total}}(\boldsymbol{X}) + h(g) \sum_{j=1}^{p+4} E_j(\boldsymbol{X}) + \xi(\boldsymbol{X},g) & \boldsymbol{X} \in \boldsymbol{S} - \boldsymbol{F}, \end{cases}$$
(20)

where F is the feasible region in the search space S, and S - F denotes the infeasible region. h(g) represents the penalty factor, which is a large number and usually taken a strictly increasing positive sequence that tends to infinity as the number of iterations increases. $E_j(X)$ is the constraint violation value of the infeasible individuals for the *jth* constraint, and $\xi(X, g)$ indicates an additional heuristic value for infeasible individuals in the *gth* generation. $E_j(X)$ and $\xi(X, g)$ can be expressed as

$$E_{j}(\boldsymbol{X}) = \begin{cases} \max(0, -\boldsymbol{X}(j)) & 1 \le j \le p+1; \\ | \boldsymbol{X}(1) + \sum_{i=2}^{p+1} \boldsymbol{X}(i)(1 - \boldsymbol{X}(1)) - 1 | & j = p+2; \\ \max(0, T_{\text{Total}} - T_{0})) & j = p+3; \\ \max(0, R_{0} - T_{\text{Total}})) & j = p+4, \end{cases}$$
(21)

$$\xi(\boldsymbol{X},g) = Wor(g) - \min_{\boldsymbol{X} \in \boldsymbol{S}-\boldsymbol{F}} \left\{ E_{\text{Total}}(\boldsymbol{X}) + h(g) \sum_{j=1}^{p+4} E_j(\boldsymbol{X}) \right\}, \quad (22)$$

respectively, where $E_{\text{Total}}(X)$ represents the fitness value of the *gth* generation feasible individuals. Wor(g) records the feasible individual with the worst fitness through *g* generation evolution, and guarantee that the fitness of the feasible individuals are always better than the infeasible individuals during the course of the iteration. Whose value can be updated by

$$Wor(g) = \max\left\{Wor(g-1), \max_{\boldsymbol{X} \in \boldsymbol{F}} \{E_{\text{Total}}(\boldsymbol{X})\}\right\}.$$
 (23)

In the LRGA-MIE algorithm, each chromosome, namely each individual X_i in the population is designed as a onedimensional real array with p + 1 genes, which should be randomly initialized with real number in the searching space S firstly. Then, the fitness value of each individual would be calculated according to Eq. (20) to evaluate the population. Next, the genetic operators are performed to update the initial population. And the specific genetic operators are given as follows:

Selection: In this paper, 2-tournament selection strategy with elitism preservation² is adopted for its advantages of simplicity and efficiency. Firstly, the individuals with the lowest fitness values (i.e., elitism individuals) are directly retained into the next generation of populations. Then, the remaining individuals are randomly selected in pairs and the individual with lower fitness value will be retained to the next generation.

²Analyzing the convergence and the time complexity of GA is an extremely challenging theoretical issue in the evolutionary computation area, which is beyond the scope of this paper. But it has been proved that the GA with elitism preservation must converge to the global optimal solution [21].

Crossover: Crossover is to passed the original good genes onto the offspring. Where two new children individuals (i.e., X'_1 , X'_2) are generated by a linear combination of the two parent individuals (i.e., X_1 , X_2). The relationship between offspring and parents can be described as

$$\begin{cases} \boldsymbol{X_1'} = \delta \boldsymbol{X_1} + (1 - \delta) \boldsymbol{X_2}; \\ \boldsymbol{X_2'} = \delta \boldsymbol{X_2} + (1 - \delta) \boldsymbol{X_1}, \end{cases}$$
(24)

respectively, where δ is a random number on interval (0, 1).

Mutation: Mutation operation determines the local search capability of the LRGA-MIE and improves the diversity of individuals in the population. In this paper, the non-uniform mutation operator is applied. When the individual $X_i = \{x_{i1}, x_{i2}, \dots, x_{il}, \dots, x_{i(p+1)}\}$ mutates into the new individual $X'_i = \{x_{i1}, x_{i2}, \dots, x'_{il}, \dots, x'_{i(p+1)}\}$, the new gene x'_{il} can be calculated as

$$x_{il}' = \begin{cases} x_{il} + (1 - x_{il})(1 - q^{(1 - g/G)b}) & \text{if } random(0, 1) = 0, \\ x_{il} + x_{il}(1 - q^{(1 - g/G)b}) & \text{if } random(0, 1) = 1. \end{cases}$$
(25)

Where q is a random number in the range of [0, 1] with uniform distribution. g is the current evolution generation, and G represents the maximum evolution generation. b is a system parameter, which determines the degree of dependence of the random number perturbations on the evolution generation g. The value of b is in the range of [2, 5]. random(0, 1) denotes any value of 0 or 1 with equal probability.

To minimize the energy consumption in Eq. (17), the basic steps of LRGA-MIE are shown in Algorithm 1.

The time complexity of LRGA-MIE can be presented by $\mathcal{O}(G * S * (p+1))$, where S represents the population size. According to [22], S and G are linear functions with respect to p+1, hence the time complexity of LRGA-MIE is $\mathcal{O}(p^3)$.

Algorithm 1 LRGA-MIE algorithm	Igorithm	LRGA-MIE	algorithm
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Require: $p, \mu_{0,i}, \nu_i, \nu_0, \mathcal{D}, \mathcal{F}, \Psi_0, G, S$					
p; p ;					
Ensure: BestFitness, BestSolution					
1: Randomly initialize each individual X_i in the Population					
2: globalBestFitness = 0					
3: for Generation:1 to G do					
1 : 1 = 0					
5: for each individual $X_i \in$ Population do					
Calculate the value of $E_i(\mathbf{X})$ using equation (21)					
7: end for					
8: Calculate the value of $\xi(\mathbf{X}, g)$ and $Wor(g)$ using equation (22) and					
(23)					
9: for each individual $X_i \in$ Population do					
10: Calculate the fitness value $f(X_i)$ using equation (20)					
11: if $f(X_i) < \text{localBestFitness then}$					
12: $localBestFitness = f(X_i)$					
13: $localBestSolution = X_i$					
14: end if					
15: end for					
16: if localBestFitness < globalBestFitness then					
17: globalBestFitness = localBestFitness					
18: BestSolution = localBestSolution					
19: end if					
20: Select individuals from the Population;					
21: if rand $< pc$ then					
22: $crosspop = cossover(Population, pc)$					
23: end if					
 24: if rand < pm then 25: mutatepop = mutate(crosspop, pm) 					
26: end if 27: Update the Population: Population = mutatepop					
28: end for 20: nature RestSolution clobalRestEitnes					
29: return BestSolution, globalBestFitnes					

TABLE I					
SYSTEM PARAMETERS OF FCSD					
Parameter	Value	Parameter	Value		
W^{UL}	1 MHz	f_0, f_i	Unif([0.2, 0.9] GHz)		
N_0	-100 dBm	(x_0, y_0, z_0)	(0 m, 0 m, 0 m)		
P_{Tx}	1.258 W	(x_i, y_i, z_i)	randomly in 100 m ³ area		
P_{Rx}	1.181 W	ν_0, ν_i	Unif([0.001, 0.3])		
γ	3	μ_i	Unif([0.001, 0.3])		
h_0	CN(0,1)	f_c	1 GHz		
k	1.25×10^{-26}	W^{c}	2 MHz		
σ	3	μ_c	0.17		
r	$100 m^3$	ν_c	0.00001		
β	1	(x_{c}, y_{c}, z_{c})	(2000 m, 2000 m, 2000 m)		

IV. PERFORMANCE AND EVALUATION

In this section, to testify the performance of the FSCD system with LRGA-MIE algorithm, a set of simulation results are presented. Referring to [8], [18], [23]–[27], the system parameters of FCSD are summarized in TABLE I.

The parameters of the algorithm are set as follows: The maximum number of iterations is 300. The population size (i.e., G) is 100. The crossover and mutation probability (i.e., pc and pm) are set as 0.8 and 0.1, respectively. And the value of Wor(0) is set as 10^5 .

In the following simulations, the parameters of the task Ψ_0 are set as follows, unless otherwise specified or used as variables. D_0 is set as 1 MB. α_0 is set as 1900/8 to represent a computational intensive task [17]. T_0 and R_0 are set as 0.8 s and 0.99, respectively. And we assumed that there are a total of 10 drones available nearby that can serve as fog computing nodes to help dr_0 achieved the computing task Ψ_0 , i.e., p = 10. The numerical results in this section are based on an average value over 3000 Monte Carlo simulations.

A. Latency Performance Comparison of Three Computation Architectures

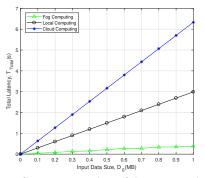


Fig. 2. Latency performance comparison of three computation architecture

Fig. 2 shows the latency performance comparison of three computation architectures, i.e., cloud computing, local computing and fog computing. With the increasing of the input data size, the cloud computing curve is intensely higher than the local computing curve and fog computing curve. The reason is that the transmission latency of cloud computing architecture is growing linearly with the increasing of the input data size, due to the long distance data transmission and limited bandwidth between cloud and the drone dr_0 . Furthermore, the local computing curve is relatively lower than the cloud computing curve. This is because that the drone dr_0 has a certain amount of computing ability. When the computing task is relatively smaller, it is able to handle the task locally in a relatively low computation latency and without transmission

latency. But, when the input data size increased, limited by its computing ability, the local computing manner cannot complete the computing task with lower latency. The fog computing latency, as we can see, is always lower than other two kinds of computing manners, this is because that the transmission latency of fog computing is relatively lower due to the surrounding fog nodes are intensely close, and meantime the computation latency is relatively lower as well, because of it integrates the computational ability of numerous fog nodes. When the input data size of the task Ψ_0 is 0.5 MB, we can observe that the latency performance of fog computing improved by 93.12% and 85.42% compared with the cloud computing and local computing respectively. Therefore, the fog computing based computation offloading is suitable for latency sensitive business of swarm of drones.

B. Reliability Performance Comparison of Different Algorithms

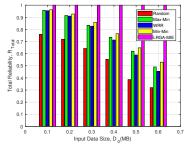


Fig. 3. Reliability performance comparison of different algorithms

In this section, we analyze the high efficiency of the LRGA-MIE algorithm in improving reliability in FCSD by comparing it with the Max-Min [28], Weighted Round Robin (WRR) [29] and Min-Min [30] algorithm, and also the random task assignment. The simulation results are shown in Fig. 3. As we can see, when the input data size is relatively smaller, the Max-Min, WRR, Min-Min and LRGA-MIE algorithms all have good performance, compared to the random task assignment. Specifically, when the input data size is 0.1 MB, the reliability of these algorithms are all higher than 0.95. However, with the increasing of the input data size, the reliability performance of the Max-Min, WRR, Min-Min, LRGA-MIE algorithms decrease in different degree. This is because the increase of input data size will increase the processing latency of some fog nodes and even the entire FCSD system, according to Eq. (7). Furthermore, no matter which fog nodes increase in transmission latency or computation latency, the total reliability of the FCSD system will be decreased, according to Eq. (17). But for LRGA-MIE algorithm, as we can see from the Fig. 3, it has always maintains intensely higher reliability. As the input data size increase from 0.2 MB to 0.6 MB, the reliability of LRGA-MIE only decrease from 0.9997 to 0.9989. And when the input data size is 0.6 MB, we can observe that the reliability of LRGA-MIE is higher than that of Max-Min, WRR, Min-Min algorithm and random task allocation strategy by 0.4674, 0.529, 0.5041 and 0.683, respectively. Therefore, the LRGA-MIE algorithm is better suited for optimizing reliability with global consideration of computation capability, transmission capability and failure rate.

C. Energy Consumption Performance Impact by Latency Constraint and Reliability Constraint

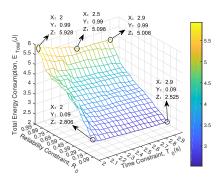


Fig. 4. Energy consumption performance impact by latency constraint and reliability constraint

In this section, we discuss the impact of latency and reliability constraints on total energy consumption of FCSD. The simulation results are shown in Fig. 4. As we can see, when the latency constraint is fixed, the total energy consumption will gradually decrease with the reducing of reliability constraint. Similarly, when the reliability constraint is fixed, the total energy consumption will gradually decrease with the improving of latency constraint. This is because whether the reliability constraint is reduced or the latency constraint is increased, the feasible domain of the optimization problem is extended, and thus more solutions with low energy consumption performance can be obtained. However, we can observe that when the reliability is fixed, e.g., $R_0 = 0.99$, as the latency constraint increases gradually, the energy consumption curve will drop rapidly first, i.e., T_0 ranges from 2 s to 2.5 s, then the rate of decline will slow down and finally the curve will be tend to be gentle, i.e., T_0 ranges from 2.5 s to 2.9 s. It is because that, in this reliability constraint, the computing task Ψ_0 can be completed within 2.5 s. When the latency constraint is greater than 2.5 s, the latency constraint is not the main factor hindering the performance of the system, therefore, the increasing of the latency constraint will not have a significant impact on the energy consumption performance of FCSD.

D. Energy Consumption Performance Comparison of Different Algorithms

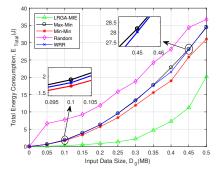


Fig. 5. Energy consumption performance of different algorithms

In this section, we analyze the energy consumption performance of different algorithms in FCSD. The simulation results are shown in Fig. 5. We can observe that the random task assignment has the worst energy consumption performance. When the input data size is relative smaller, although not as good as LRGA-MIE algorithm, the performance of the WRR, Max-Min and Min-Min algorithms are not bad, compared to the random task assignment. However, with the increasing of the input data size, the energy consumption of the Max-Min, Min-Min and WRR algorithms and random task assignment increase rapidly. As we can see, the energy consumption of Max-Min algorithm approaches that of the WRR algorithm, and the Min-Min algorithm is slighter better than the Max-Min and WRR algorithms. But the LRGA-MIE algorithm maintains good performance all along, due to its strong global search ability. It shows that under the premise of ensuring low latency and high reliability requirements of the computing task, the LRGA-MIE algorithm has intensely good performance in reducing the energy consumption in FCSD, and it has strong adaptability and stability to the growth of the input data size. When the input data size is 0.5 MB, the energy consumption performance of the LRGA-MIE algorithm improved by 44.87%, 41.16%, 41.12% and 34.77%, compared with the random task assignment, Max-Min, WRR and Min-Min algorithm, respectively.

V. CONCLUSION

In this paper, to solve the problem that the cloud based computation offloading is not suitable for addressing the latency and reliability sensitive task, we introduced the fog computing based computation offloading into swarm of drones (FCSD). And specifically focusing on the latency and reliability business scenarios and improving the practicality of FCSD, an optimization problem to minimize the energy consumption of FCSD within latency and reliability constraints is constructed. In order to solve the NP-hard problem we formulated, the LRGA-MIE algorithm was proposed. The simulation results demonstrated that the LRGA-MIE can minimize the energy consumption of FCSD, on the basis of completing the computing task within latency and reliability requirements. In future research work, two things are on our agenda. One is to reduce the algorithm complexity of LRGA-MIE to further improve its practicability. The other is to utilize some new technologies (e.g., cognitive radio [31], orbital angular momentum [32], etc.) to solve the problem of spectrum resource shortage when the number of UAV increases rapidly.

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