Joint Drone Association and Content Placement in Cache-Enabled Internet of Drones

Jingjing Yao, *Student Member, IEEE* and Nirwan Ansari, *Fellow, IEEE*

***Abstract*—Internet of drones (IoD), employing drones as the internet of things (IoT) devices, brings flexibility to IoT networks and has been used to provision several applications (e.g., object tracking and traffic surveillance). The explosive growth of users and IoD applications injects massive traffic into IoD networks, hence causing congestions and reducing the quality of service (QoS). In order to improve the QoS, caching at IoD gateways is a promising solution which stores popular IoD data and sends them directly to the users instead of activating drones to transmit the data; this reduces the traffic in IoD networks. In order to fully utilize the storage-limited caches, appropriate content placement decisions should be made to determine which data should be cached. On the other hand, appropriate drone association strategies, which determine the serving IoD gateway for each drone, help distribute the network traffic properly and hence improve the QoS. In our work, we consider a joint optimization of drone association and content placement problem aimed at maximizing the average data transfer rate. This problem is formulated as an integer linear programming (ILP) problem. We then design the Drone Association and Content Placement (DACP) algorithm to solve this problem with low computational complexity. Extensive simulations demonstrate the performance of DACP.**

***Index Terms*—Drone, Internet of Things (IoT), Internet of Drones (IoD), caching, drone association, content placement, quality of service (QoS).**

I. Introduction

The Internet of Things (IoT) connects billions of IoT devices, e.g., sensors and actuators, over a distributed environment to enable various applications, e.g., smart grid, home, city, industry and agriculture [1, 2]. To provision wide-area IoT networks, cellular infrastructure is usually utilized, where base stations (BSs) are deployed to act as the IoT gateways and receive data from IoT devices. Adopting drones, also known as unmanned aerial vehicles (UAVs), as the IoT devices is a promising way to improve the flexibility of IoT networks owing to their high mobility. Internet of Drones (IoD), which refers to the integration of drones and IoT networks, has been applied for object tracking and delivery, traffic surveillance and disaster rescue [3, 4]. An important application of IoD is the sensing service where multiple drones are deployed in the air to collect environmental information (e.g., images and videos) from several points of interest [5, 6]. The collected data are then sent via the IoT gateway to users, who request the data, for further processing (e.g., traffic monitoring).

Although IoD has gained great attention from both the academic and industry owing to its great benefits, it still faces several challenges [7]. Owing to the rapid growth of IoT services and applications, increased amount of traffic is injected into the IoT networks; this may cause network congestion and hence degrade the user quality of service (QoS) [8, 9]. Another challenge is drones' limited on-board battery capacity owing to their size and weight limitations [10]. Frequent sensing data transfers from drones, because of the growing requests from users, speed up the drainage of drones.

Caching at IoD gateways can be considered as a promising approach to reduce the IoD network traffic and reduce drone energy consumption [11]. In cache-enabled IoD networks, each BS is equipped with a storage-limited cache. Popular sensing data can be cached at the caches so that users can obtain requested data directly from the caches instead of activating drones to transmit the data [12]. Therefore, caching not only helps reduce the network traffic from drones to BSs, but also decrease the energy consumption of drones by avoiding frequently data transmission. In order to make the most use of the storage-limited caches, appropriate content placement problem strategy should be designed to determine which data should be cached at different caches. On the other hand, drone association problem determines the serving BS for each drone. Intuitively, a drone should be associated with the nearest BS to reduce the data transmission power and hence the energy consumption. However, if too many drones are assigned to one BS, the BS may be congested, hence reducing the user QoS [13]. Therefore, an appropriate drone association strategy should be designed.

Considering both drone association and caching in IoD networks has not been readily found yet. To fill this gap, in our work, we jointly optimize the drone association and content placement problem in cache-enabled IoD networks for the sensing service with the objective to maximize the user QoS which is characterized as the average IoD data transfer rate.

The rest of the paper is organized as follows. The related works are presented in Section II. Section III describes the system model. The joint optimization of drone association and content placement problem is formulated in Section IV. An algorithm is designed in Section V to address the problem. We evaluate the performance of our designed algorithm in Section VI. Finally, the paper is concluded in Section VII.

II. Related Works

Drone-aided networks have been investigated in several studies. Drone base station (DBS) has been adopted in many works to provide additional wireless coverage and enhance wireless network conditions. The DBS placement problem is a critical issue to be addressed. Zhang *et al.* [14] investigated the 3-D DBS placement problem in an in-band full-duplex cellular network to maximize the whole network's throughput. Their work only considers one DBS. Chen *et al.* [15]

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utilized drones as relays and studied the optimum placement of multiple drones to maximize the system reliability which was measured by power loss and bit error rate.

Gharibi *et al.* [5] first proposed the IoD architecture and designed five conceptual layers for IoD including airspace, node to node, end to end, service and application layer. Koubaa and Qureshi [16] adopted IoD networks and proposed DroneTrack, which is a real-time object tracking system, to follow a moving object. To overcome the energy limitation of drones, Long *et al.* [17] proposed an energy neutral IoD (enIoD) where recharging stations were introduced to energize the drones. The enIoD can be used for packet delivery. Chen and Wang [18] designed a light-weight network coding scheme to enhance the security and privacy of cloud data in IoD networks. They demonstrated that their scheme can reduce up to 10% energy consumption as compared with the traditional hash-based scheme. Wazid *et al.* [19] discussed IoD authentication models to give data access to authorized users. They also surveyed related security protocols and identified some challenges in IoD networks. Fan and Ansari [20] proposed a traffic load balancing scheme for the drone-assisted IoT networks to minimize the wireless network latency. However, the above works consider neither drone association problem nor caching in IoD networks.

Caching has been applied to IoT networks to reduce energy consumption of IoT devices and network traffic. Niyato *et al.* [21] proposed to use cache for IoT sensing service. The cache can be located at the IoT gateway and its data can be retrieved by users. They introduced a threshold adaptation algorithm to maximize the hit rate of the sensing service. Sun and Ansari [22] applied the cache-enabled IoT networks for smart parking application in smart cities and demonstrated the benefits of caching popular IoT resources. Duan *et al.* [23] investigated a space-reserved cooperative caching scheme where each cache is divided into two parts. One part is used for storing prefetched data from IoT devices and the other is for storing the temporarily buffering data in the wireless transmission queue. Yao and Ansari [11] explored a Stackelberg game in cache-enabled energy harvesting aided IoT networks to improve QoS. However, caching in IoD networks has not been addressed yet.

To the best of our knowledge, joint optimization of drone association and content placement problem in cache-enabled IoD networks has not been reported in the literature yet. We hence try to address this joint problem in our work with the objective to maximize the user QoS.

III. System Model

In our cached-enabled IoD architecture (as shown in Fig. 1), N drones are deployed in the air to provide the IoD sensing service where drones collect the environment information (e.g., images and videos) and then send them to users requesting the data through the mobile core network for further processing (e.g., traffic condition monitoring). We denote i, where $i \in \mathcal{I} = \{1, 2, ..., N\}$, as an index of a drone. For wide area communications, the cellular network is usually utilized as the infrastructure to provision IoD sensing service [24], where M BSs act as the IoT gateway to receive data from the associated drones and send the data to the mobile core network. We denote Boolean variables x_{ij} to indicate whether drone i is associated with BS j ($x_{ij} = 1$ if affirmative). For example, in Fig. 1, drone1 is associated with BS1 while drone2 and drone3 are assigned to BS2. We assume each BS connects to the mobile core network by high speed wired links with capacity B *Mbps*. BS $j \in \mathcal{J} = \{1, 2, ..., M\}$ is equipped with a cache with storage capacity L_j. If the requested data i (i.e., IoD data of drone i) is cached at BS j, data i can be transmitted to the user directly from the cache at BS j. Otherwise, data i should be obtained from drone i to the user relayed by BS j if $x_{ij} = 1$. We denote Boolean variables y_{ij} to indicate whether data i is cached at BS j ($y_{ij} = 1$ if affirmative). Although the localizations of drones and BSs are important to determine the performances of our IoD architecture [25], we only consider static BSs and drones (i.e., hovering in the air) in our work.

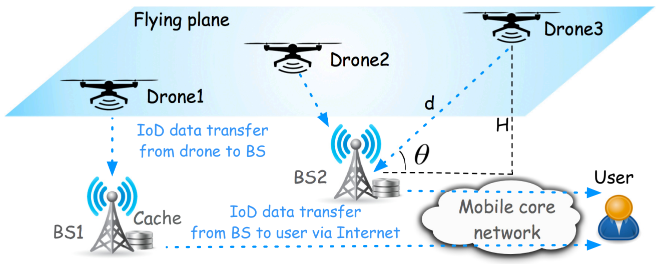

Fig. 1. Sensing service in cache-enabled IoD architecture.

A. Air to Ground Channel

We assume all drones are flying within the flying plane with the height of H. Practically, H can be chosen as the minimum height to avoid all constructions [26]. The wireless channel between a drone and a BS is characterized as the air to ground channel. Since the signals received by a BS may be either line of sight (LoS) or non-line of sight (NLoS), we utilize the widely used probability model [27, 28, 29] to measure the probabilities of LoS and NLoS:

$$P(LoS) = \frac{1}{1 + \alpha \exp(-\beta[\frac{180}{\pi}\theta - \alpha])}, \tag{1}$$

$$P(NLoS) = 1 - P(LoS), \tag{2}$$

where α and β are constants which relate to the environment, e.g., rural and urban; θ is the elevation angle as shown in Fig. 1. The average air to ground path loss can then be calculated as

$$\overline{PL} = P(LoS) \times PL_{LoS} + P(NLoS) \times PL_{NLoS}, \tag{3}$$

where PL_{LoS} and PL_{NLoS} are path losses of LoS and NLoS signals, respectively, which are modeled by the free space propagation loss with additional excessive path loss values [30]:

$$PL_{LoS} = 20 \log_{10}(\frac{4\pi f_c d}{c}) + \xi_{LoS}, \tag{4}$$

$$PL_{NLoS} = 20 \log_{10}(\frac{4\pi f_c d}{c}) + \xi_{NLoS}, \tag{5}$$

where d is the distance between a drone and a BS (as shown in Fig. 1); c is the speed of light; f_c is the carrier frequency; ξ_{LoS} and ξ_{NLoS} are constants that relate to the environment.

Then, the air to ground channel between drone i to BS j is denoted as $G_{ij} = 10^{-\frac{PL}{10}}$. Therefore, the IoD data transmission rate R_{ij} from drone i to BS j can be calculated as

$$R_{ij} = W \log_2(1 + \frac{p_i G_{ij}}{N_0 W}), \tag{6}$$

where W denotes the system bandwidth; p_i denotes the transmission power of drone i; N_0 is the noise power spectrum density.

B. QoS Model

We characterize the QoS model as the average IoD data transfer rate [11]. When the IoD data of drone i is requested, the user can obtain these data by two possible data transfer methods. If data i is not cached in any of the BSs, i.e., $\sum_{j=1}^{M} y_{ij} = 0$, the data has to be transmitted from drone i. Since drone i is associated with BS j if $x_{ij} = 1$, the transmission rate of drone i can be calculated as $r_i = \sum_{j=1}^{M} R_{ij} x_{ij}$. Note that the IoD data transmission to the user goes through two hops (i.e., from drone to BS and from BS to the user). The data transfer rate to the user is $\min\{r_i, B\} = r_i$ since we assume the BS backhaul link capacity is larger than that of the air to ground channel. On the other hand, if data i is cached in any of the caches, i.e., $\sum_{j=1}^{M} y_{ij} = 1$, the data is transmitted directly from the cache and hence the data transfer rate is B. Therefore, the average data transfer rate is calculated as

$$\begin{aligned}\bar{V} &= \sum_{i=1}^{N} \lambda_i [B \sum_{j=1}^{M} y_{ij} + (1 - \sum_{j=1}^{M} y_{ij}) \sum_{j=1}^{M} R_{ij} x_{ij}] \\ &= \sum_{i=1}^{N} \lambda_i [B \sum_{j=1}^{M} y_{ij} + \sum_{j=1}^{M} R_{ij} x_{ij} - \sum_{j=1}^{M} y_{ij} \sum_{j=1}^{M} R_{ij} x_{ij}],\end{aligned} \tag{7}$$

where λ_i is the probability that data i are requested and $\sum_{j=1}^{M} y_{ij} \sum_{j=1}^{M} R_{ij} x_{ij} = (y_{i1} + y_{i2} + ... + y_{1M})(R_{i1}x_{i1} + R_{i2}x_{i2} + ... + R_{iM}x_{iM}) = R_{i1}x_{i1}y_{i1} + R_{i1}x_{i1}y_{i2} + ... + R_{i1}x_{i1}y_{iM} + R_{i2}x_{i2}y_{i1} + R_{i2}x_{i2}y_{i2} + ... + R_{i2}x_{i2}y_{iM} + ... + R_{iM}x_{iM}y_{i1} + R_{iM}x_{iM}y_{i2} + ... + R_{iM}x_{iM}y_{iM} = \sum_{j=1}^{M} \sum_{k=1}^{M} R_{ij} x_{ij} y_{ik}$. Hence, Eq. (7) can be converted to

$$\begin{aligned}\bar{V} = &\sum_{i=1}^{N} \sum_{j=1}^{M} B \lambda_i y_{ij} + \sum_{i=1}^{N} \sum_{j=1}^{M} \lambda_i R_{ij} x_{ij} \\ &- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{M} \lambda_i R_{ij} x_{ij} y_{ik}.\end{aligned} \tag{8}$$

IV. Problem Formulation

For the IoD sensing service, the IoD data (e.g., images or videos) collected by drones are sent to the user through the mobile core network for further processing. We formulate the joint optimization problem of drone association and content placement problem for the IoD sensing service in this section. In order to improve the QoS, we try to maximize the average IoD data transfer rate [31]. Hence, our problem is formulated as

$$\begin{aligned}\textbf{P0:} \ \max_{\boldsymbol{x}, \boldsymbol{y}} \ &\sum_{i=1}^{N} \sum_{j=1}^{M} B \lambda_i y_{ij} + \sum_{i=1}^{N} \sum_{j=1}^{M} \lambda_i R_{ij} x_{ij} \\ &- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{M} \lambda_i R_{ij} x_{ij} y_{ik}\end{aligned} \tag{9}$$

$$\text{s.t.} \quad \sum_{j=1}^{M} x_{ij} = 1, \quad \forall i \in \mathcal{I}, \tag{10}$$

$$y_{ij} \le x_{ij}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, \tag{11}$$

$$\sum_{i=1}^{N} l_i y_{ij} \le L_j, \quad \forall j \in \mathcal{J}, \tag{12}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, \tag{13}$$

$$y_{ij} \in \{0, 1\}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}. \tag{14}$$

Eq. (9) is the objective function which aims to maximize the average data transfer rate. Eq. (10) indicates that a drone can only be associated with one BS. Eq. (11) implies that a drone's data can only be cached at its associated BS. Eq. (12) imposes that all data cached in each BS should not surpass its storage capacity. Eqs. (13) and (14) indicate that x_{ij} and y_{ij} are binary variables.

Problem **P0** is a non-linear integer programming problem owing to the products of $x_{ij} y_{ik}$ in Eq. (9); this feature makes it intractable [32]. We hence introduce another Boolean variable $z_{ijk} \in \{0, 1\}$ to enable $z_{ijk} = x_{ij} y_{ik}$. To make the objective function linear, the following constraints should be added to problem **P0**: 1) $z_{ijk} \le x_{ij}$; 2) $z_{ijk} \le y_{ik}$; 3) $z_{ijk} \ge x_{ij} + y_{ik} - 1$ [33]. Hence, problem **P0** can be transformed into an integer linear programming (ILP) problem **P1**:

$$\begin{aligned}\textbf{P1:} \ \max_{\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}} \ &\sum_{i=1}^{N} \sum_{j=1}^{M} B \lambda_i y_{ij} + \sum_{i=1}^{N} \sum_{j=1}^{M} \lambda_i R_{ij} x_{ij} \\ &- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{M} \lambda_i R_{ij} z_{ijk}\end{aligned} \tag{15}$$

$$\text{s.t.} \quad (10) - (14),$$

$$z_{ijk} \le x_{ij}, \ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{J}, \tag{16}$$

$$z_{ijk} \le y_{ik}, \ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{J}, \tag{17}$$

$$z_{ijk} \ge x_{ij} + y_{ik} - 1, \ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{J}, \tag{18}$$

$$z_{ijk} \in \{0, 1\}, \ \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{J}. \tag{19}$$

Note that the ILP problem **P1** is still difficult to solve and its optimal solution can be obtained by branch-and-bound algorithm or exhaustive search at the expense of high computational complexity. We hence design a heuristic algorithm to attain the suboptimal solution in the next section and utilize its optimal solution by CPLEX for comparison in simulations.

V. Problem Solution

In this section, we present our proposed Drone Association and Content Placement (DACP) algorithm to solve problem **P0**. Note that caching in IoD networks can greatly improve the data transfer rate because the requested data can be directly transmitted from the caches and the backhaul data rate B can be achieved. Therefore, the IoD data should be cached as many as possible. Based on this intuition, the basic idea of DACP is to first solve the content placement problem and then the drone association problem using the results from the first one.

A. Content Placement Problem

The content placement problem determines which IoD data are cached at the caches of BSs. The content placement problem is then formulated as

$$\textbf{P2:}\ \max_{\boldsymbol{y}} \sum_{i=1}^{N} \lambda_i (\sum_{j=1}^{M} y_{ij}) \tag{20}$$

$$\text{s.t.} \quad (12), (14),$$

$$\sum_{j=1}^{M} y_{ij} \leq 1, \quad \forall i \in \mathcal{I}. \tag{21}$$

In the objective function in Eq. (20), λ_i reflects the popularity of different IoD data. Hence, Eq. (20) indicates that popular IoD data should be cached as many as possible. Note that each drone can only be associated with one BS (as shown in Eq. (10)), each IoD data, therefore, can only be stored at one cache; this is reflected in Eq. (21). Problem **P2** falls into the 0-1 multiple knapsack problem [34]. In the 0-1 multiple knapsack algorithm, N items with different weights and prices are determined to put in M weight-limited knapsacks. Its objective is to maximize the total prices of items in all knapsacks. In problem **P2**, the IoD data and cache can be considered as the item and knapsack, respectively. λ_i and l_i are the price and weight of item i and L_j is the weight capacity of knapsack j.

B. Drone Association Problem

The drone association problem determines the associated BS for each drone. We formulate the drone association problem as

$$\textbf{P3:}\ \max_{\boldsymbol{x}} \sum_{i=1}^{N} \sum_{j=1}^{M} (1 - \sum_{k=1}^{M} y_{ik}^{*}) \lambda_i R_{ij} x_{ij} \tag{22}$$

$$\text{s.t.} \quad (10), (13),$$

$$x_{ij} \geq y_{ij}^{*}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}. \tag{23}$$

We obtain the results of problem **P2**, denoted as y_{ij}^{*}, by solving the 0-1 multiple knapsack problem. Eq. (22) can hence be obtained by substituting y_{ij}^{*} into Eq. (9). Eq. (23) is equivalent to Eq. (11). We can deduce from Eq. (22) that, if IoD data i is cached (i.e., $1 - \sum_{k=1}^{M} y_{ik}^{*} = 0$), x_{ij} does not contribute to the objective function. In that case, $x_{ij} = y_{ij}^{*}, \ \forall j \in \mathcal{J}$ because data from drone i can only be cached at the BS with which it is associated. Therefore, to solve problem **P3**, we only need to consider the IoD data which are not cached at any caches (i.e., $\sum_{k=1}^{M} y_{ik}^{*} = 0$). For each drone i whose data are uncached, it can only be associated with one BS. In order to maximize Eq. (22), it is preferable to associate each uncached drone i to the BS with the maximum R_{ij}, i.e., $j = \arg\max_{j \in \mathcal{J}} \{R_{ij}\}$.

We summarize DACP in Alg. 1. Line 1 calculates the content placement solution of problem **P2**. The loop in Lines 3-10 calculates the drone association solution for each drone. Lines 4-5 determines the drone association solution if the data are cached. Lines 7-8 associate the drone with the BS which achieves the largest data rate.

Algorithm 1: DACP

Input : $N, M, B, l_i, L_j, R_{ij}, \lambda_i$
Output: Average data transfer rate $\bar{V}$

1 Calculate y_{ij}^{*} by solving 0-1 multiple knapsack problem **P2** ;
2 Initialize $x_{ij}^{*} = 0$;
3 **for** *each* $i \in \mathcal{I}$ **do**
4   **if** $\sum_{k=1}^{M} y_{ik}^{*} = 1$ *(data i are cached)* **then**
5         $x_{ij}^{*} = y_{ij}^{*}, \ \forall j \in \mathcal{J}$;
6   **else**
7   Calculate $j^{*} = \arg\max_{j \in \mathcal{J}} \{R_{ij}\}$;
8   Associate drone i with BS j^{*}, i.e., $x_{ij^{*}}^{*} = 1$;
9   **end**
10 **end**
11 Calculate $\bar{V}$ according to Eq. (7) with x_{ij}^{*} and y_{ij}^{*} ;
12 **return** $\bar{V}$;

VI. Performance Evaluation

Table I. Summary of simulation parameters.

Parameter	Value
Area	1000 *m* $\times$ 1000 *m*
Number of drones N	50
Number of BSs M	5
Drone flying height H	500 *m*
System bandwidth W	10 *MHz*
Drone wireless transmission power p	3 *W*
Noise power density N_0	-174 *dBm/Hz*
BS backhaul date rate B	500 *Mbps*
Data size of drones l	1.0 *Mb* 2.0 *Mb*
Cache storage capacity L	5 *Mb*

Simulations are set up to evaluate the performances of our proposed algorithm DACP in this section. The optimal solution of the ILP problem **P1** obtained by CPLEX, denoted as ‘Optimal’, is utilized as the contrast algorithm. We also combine the existing works as another contrast algorithm (denoted as ‘Bench’), which first solves the drone association problem where each drone is associated with the nearest BS

[35], and then the content placement problem where data with more popularity are preferentially cached until the cache storage is full [11].

In our simulation, we consider a 1000 m $\times$ 1000 m area, where there are $N = 50$ drones and $M = 5$ BSs. The drones and BSs are all uniformly distributed in this area. We assume that all drones fly within a flying plane with the height of 500 m. The environment-related parameters α and β in Eq. (1) is 9.6 and 0.28, respectively. The speed of light c is 3×10^8 *m/s* and the carrier frequency f_c is 2 *GHz*. ξ_{LoS} and ξ_{NLoS} are 1 *dB* and 20 *dB*, respectively. Note that the above ground to air channel parameters are consistent with [27]. The system bandwidth W is 10 *MHz*, the drone wireless transmission power p_i is 3 *W*, and the noise power density $N_0 = -174$ *dBm/Hz*. The backhaul data rate of each BS $B = 500$ *Mbps*. The data length of each drone is randomly chosen from 1.0 *Mb* to 2.0 *Mb*. The caching storage capacity of each cache is 5 Mb. For the popularity of each IoD data, we utilize the widely used Zipf distribution [36] in which the probability of requesting data i is $\lambda_i = \frac{i^{-\delta}}{\sum_{k=1}^{N} k^{-\delta}}$, where δ is the popularity skewness parameter which implies the differences among different λ_i. A large δ implies that a small portion of data are requested by most users. Contrarily, if $\delta = 0$, users request data from all drones with equal probability.

Fig. 2 evaluates the performance of DACP with different numbers of drones ranging from 20 to 80. We can observe from Fig. 2 that the average data rates from all three algorithms decrease as the number of drones increases because more drones imply that fewer drones' data can be cached at the limited caching storages and hence the average data rates are reduced. Our proposed DACP performs very close to the optimal solution of ILP. Bench first optimizes the drone association problem and then decides the content placement decisions according to the drone association solution, and so the caching storages may not be fully utilized. Therefore, in Fig. 2, DACP performs better than Bench.

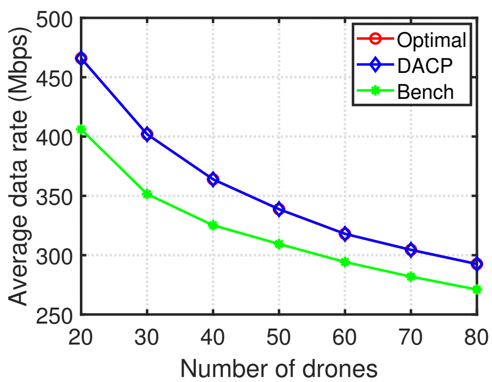

Fig. 2. Average data rate vs number of drones.

Fig. 3 compares the performances of Optimal, DACP and Bench with different numbers of BSs ranging from 3 to 9. The average data rates of all three algorithms go up as the number of BSs increases, because a larger number of BSs introduces more caching storages and more data can be cached, hence increasing the average data rates. DACP always performs better than Bench for the similar reason as shown in Fig. 2. DACP achieves the average data rate very close to Optimal's.

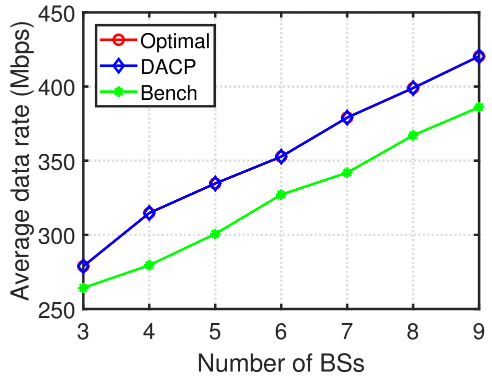

Fig. 3. Average data rate vs number of BSs.

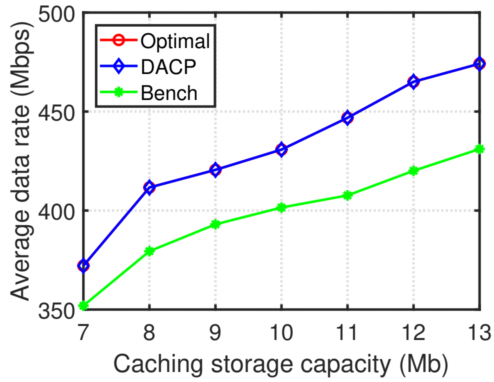

Fig. 4. Average data rate vs caching storage capacity.

Fig. 4 depicts the average data rates of different algorithms with different caching storage capacities. Note that a larger caching storage capacity allows more IoD data to be cached and hence increases the average data rate. Therefore, the trends of all three algorithms in Fig. 4 go up with the caching storage capacity. Similar to Fig. 2 and Fig. 3, DACP performs very close to Optimal and better than Bench.

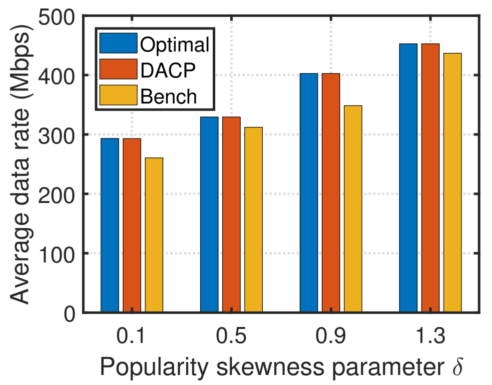

Fig. 5. Average data rate vs popularity skewness parameter.

We also investigate the impacts of different popularity skewness parameters on the performance of the three algorithms in Fig. 5. A larger popularity skewness parameter means that more users request a small part of all data. In an extreme case, all users request the data from one drone i. By caching the only data i at the storage-limited caches, all users can be served and the average data rate can be as high as the backhaul data rate B. Therefore, a larger skewness parameter leads to a higher average data rate, as shown in Fig. 5. We can also observe that DACP achieves similar average data rate to Optimal's and higher than Bench's.

VII. Conclusion

We have proposed a cache-enabled IoD architecture for the sensing service, where each BS is equipped with a cache that stores popular IoD data in order to improve the QoS (i.e., average data transfer rate). In this architecture, we have investigated the joint optimization of drone association and content placement problem to maximize the average data transfer rate constrained by the caching storage limitation. An ILP model has been formulated to address this joint optimization problem. In order to reduce the computational complexity of ILP, we have proposed DACP which first optimizes the content placement problem and then the drone association problem. Simulation results have demonstrated that DACP achieves similar results to the optimal solutions of ILP and performs better than the existing algorithms.

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