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An Energy-Efficient Edge Offloading Scheme for UAV-Assisted Internet of Things

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***Abstract*—As the ever-increasing capacities of internet of things (IoT), unmanned aerial vehicle (UAV)-assisted IoT becomes a promising paradigm for improving network connectivity, extending the coverage of network and computing offloading. However, due to the limitation of battery lifetime and computing capacities of UAVs, the offloading scheme for UAVs presents a new challenge in IoT. Therefore, in this paper, an energy-efficient edge offloading scheme is proposed to improve the offloading efficiency of UAVs. Firstly, based on the data transmission delay of UAVs and computing delay of edge nodes, the matching scheme is designed to obtain the optimal matching between UAVs and edge nodes. Secondly, the energy-efficient offloading scheme for UAVs and edge nodes is modeled as a bargaining game. Then, the offloading strategy based on incentive algorithm is developed to improve the offloading efficiency. Finally, the simulation results demonstrate that the proposed offloading scheme can significantly promote the effectiveness of offloading compared with the conventional schemes.**

***Index Terms*—Internet of things (IoT), unmanned aerial vehicles (UAVs), computing offloading, bargaining game.**

I. Introduction

As the emerging development of internet of things (IoT), the use of unmanned aerial vehicles (UAVs) has been expected to enhance the performance of existing networks in terms of connectivity, coverage and flexibility [1]–[3]. Compared with the conventional manned vehicles, the UAVs have the advantages for disaster surveillance, environment detection and emergence missions without personnel involved. Moreover, UAVs can assist base stations to offload data to support the rapidly increasing data services due to its mobility and flexibility. Recently, the performance optimization for offloading scheme in UAV-assisted IoT has been discussed from academia and industry [4].

In parallel, the UAV-assisted applications have increasingly emerged in the field of wireless communications [5]. For instance, one typical UAV-assisted application is emergency communication. UAVs have the capabilities to assist ground networks to collect, process and deliver data in disaster scenario. Another significant UAV-assisted application is cooperation sensing. A swarm of UAVs can communicate with each other cooperatively to carry out complex missions and transmit sensing data to base stations. Moreover, in the application of relay station. UAVs can be deployed flexibly in flying ad-hoc networks to act as relay stations to assist communication service with the ground devices.

Despite the advancement capabilities of UAVs, the limited computing power and energy supply present the challenges of data processing [6]. There are mainly three limitations on the resources for UAVs. a) Energy efficiency: due to the limited onboard battery for UAV, the flying and hovering durations are short and incapable of providing long term communications. b) Computing capacity: the intensive computing on UAVs results in high delay due to its limited computing resources. c) Offloading choice: offloading to cloud servers suffers from the high transmission delay and consumption, and reduces the quality of experience (QoE) of UAVs. Therefore, how to design an efficient offloading scheme for UAVs becomes the critical issue in IoT.

To address the above issues caused by the limited resources for UAVs, this paper proposes an energy-efficient edge offloading scheme for UAV-assisted IoT, which includes the following sub-schemes: 1) Matching scheme, considering the limited computing resources, the matching scheme is designed based on the preference lists of UAVs and edge nodes to select the optimal partners. 2) Offloading scheme, based on the computing, transmission and delay overheads, the offloading decision is determined by the UAV to improve its QoE. 3) Incentive scheme, the transaction process for offloading between UAV and edge node is modeled as the bargaining game, where the optimal strategy can significantly improve the offloading efficiency.

The remainder of this paper is organized as follows. Section II reviews the related work. Section III presents the system model. Section IV introduces the energy-efficient edge offloading scheme. Performance evaluations are shown in Section V, and Section VI closes this paper with conclusion and future work.

II. Related Work

There have been an increasing number of studies on offloading scheme in IoT. Misra *et al*. [7] presented a greedy heuristic-based approach to solve the multi-hop task offloading problem and reduce the average delay and energy consumption. Ning *et al*. [8] modeled the computation offloading problem as the integer linear programming problem and proposed a heuristic resource allocation algorithm to obtain the optimal offloading strategy. Min *et al*. [9] developed an offloading scheme based on reinforcement learning to determine the

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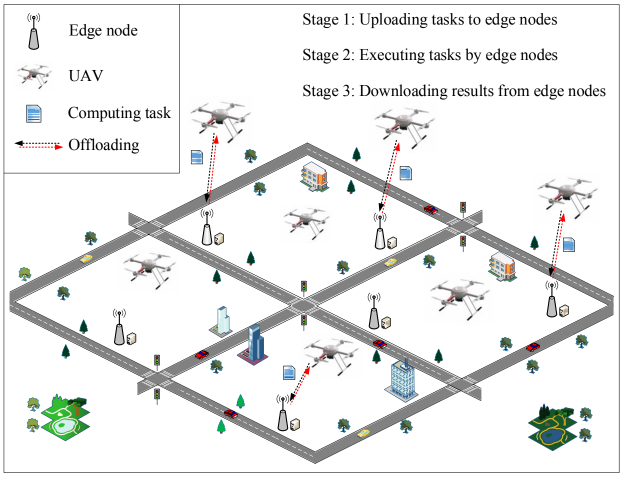

Fig. 1. Offloading framework for UAV-assisted IoT.

optimal edge device and the offloading rate of IoT devices. An iterative searching-based task offloading scheme was presented by Guo *et al*. [10] to jointly optimize the task offloading and transmission power allocation. Zhao *et al*. [11] developed a collaborative computation offloading scheme to optimize the computation offloading decision for automobiles in vehicular networks. However, the offloading scheme between UAVs and edge nodes in IoT is still not discussed effectively in most of the existing works.

III. System Model

A. UAV Model

UAVs: We consider a number of UAVs sensing and performing computing tasks in IoT. The set of UAVs is denoted by $\mathcal{U} = \{u_1, u_2, \ldots, u_k\}$, and the hovering location of UAV u is represented by $l_u = (x_u, y_u, z_u)$. Each UAV can execute at most one task at a time and it should be finished within a period time. Due to the limited onboard battery, UAVs have restricted computing capacities [12]. Let $\overline{\sigma_u}^{\max}$ and $\overline{\sigma_u}$ denote the maximum available computing resource and the occupied computing resource of UAV u, respectively. Thus, the abundant idle computing resource of UAV u can be calculated by

$$\sigma_u = \overline{\sigma_u}^{\max} - \overline{\sigma_u}. \tag{1}$$

Edge nodes: The edge nodes with computing capacities can be used to execute a large number of computing tasks. The set of edge nodes in IoT is denoted by $\mathcal{N} = \{n_1, n_2, \ldots, n_k\}$, and the location of edge node n is indicated by $\overline{l_n} = (\overline{x_n}, \overline{y_n}, \overline{z_n})$. Let $\overline{\sigma_n}^{\max}$ and $\overline{\sigma_n}$ indicate the maximum available computing resource and the occupied computing resource of edge node n, respectively. Thus, the abundant idle computing resource of edge node n can be calculated by

$$\sigma_n = \overline{\sigma_n}^{\max} - \overline{\sigma_n}. \tag{2}$$

B. Communication Model

The communication link can be connected between UAV and edge node when executing task offloading. Then, the tasks are offloaded by UAVs to edge nodes through wireless communication links. However, due to the mutual interference among wireless links, the data transmission rate is affected by other UAVs. Considering the transmission distance and the path-loss of wireless link, the signal-to-interference-plus-noise ratio when communicating between UAV u and edge node n can be calculated by

$$\varsigma_{u,n} = \frac{p_u {g_{u,n}}^{-\delta_{u,n}}}{\varphi_0 + \sum_{i \in \mathcal{U}, i \neq u} p_i {g_{i,n}}^{-\delta_{i,n}}}, \tag{3}$$

where p_u denotes the transmission power of UAV u. $g_{u,n}$ is the distance of wireless link between UAV u and edge node n, which can be calculated by $g_{u,n} = \sqrt{(x_u - \overline{x_n})^2 + (y_u - \overline{y_n})^2 + (z_u - \overline{z_n})^2}$. $\delta_{u,n}$ indicates the path-loss exponent of wireless link. φ_0 is the background noise power. Thus, the available data transmission rate between UAV u and edge node n can be calculated by

$$r_{u,n} = w \log_2 \left(1 + \varsigma_{u,n}\right), \tag{4}$$

where w is the wireless link bandwidth.

C. Offloading Model

When the UAV's computing resource is insufficient, the computing tasks will be offloaded to edge nodes. The set of computing tasks in IoT is denoted by $\mathcal{M} = \{m_1, m_2, \ldots, m_k\}$. Each UAV can dynamically adjust the offloading proportion for task computing. Let ρ_u indicate the offloading proportion of UAV u to edge node and $\rho_u \in [0, 1]$. The size of input bits for offloading computing and local computing can be calculated by

$${\omega_m}^O = b_m \rho_u, \tag{5}$$

$${\varpi_m}^L = b_m \left(1 - \rho_u\right), \tag{6}$$

where b_m is the size of computing task m. Each UAV can coordinate the offloading computing (i.e., ${\omega_m}^O$) and local computing (i.e., ${\varpi_m}^L$) to finish the task. As shown in Fig. 1, the offloading computing process consists of three phases: a) uploading data to edge node through the wireless link, b) executing the offloading task by edge node, c) downloading the results from edge node to UAV.

IV. Energy-Efficient Edge Offloading Scheme

A. Matching Scheme for UAVs and Edge Nodes

When executing offloading for UAVs, they will select the optimal edge nodes to offload its computing tasks. The selection process among UAVs and edge nodes can be modeled as a matching scheme. The matching scheme is described as a triple $\Phi = \{\mathcal{U}, \mathcal{N}, \mathcal{P}\}$. The players are the sets of $\mathcal{U}$ and $\mathcal{N}$ (i.e., UAVs and edge nodes). Here, $\mathcal{U} \cap \mathcal{N} = \emptyset$. $\mathcal{P}$ is the set of preference lists for UAVs and edge nodes. Each player in set $\mathcal{U}(\mathcal{N})$ has a preference for each player in set $\mathcal{N}(\mathcal{U})$. Therefore, the one-to-one matching construction Φ is defined as follows:

$\Phi(u) = n, \forall u \in \mathcal{U}, n \in \mathcal{N}$ indicates that UAV u is matched with edge node n. Otherwise, $\Phi(u) = u, \forall u \in \mathcal{U}$ means that UAV u has not been matched with any edge nodes.

To implement the matching, each UAV constructs its preference list by ranking edge nodes according to the preference value [13]. For UAV u, the preference is inversely proportional to the computing delay of edge node, which is denoted by

$$P(u)|_{\Phi(u)=n} = \frac{1}{{\tau_n}^O}, \tag{7}$$

where ${\tau_n}^O$ denotes the computing delay of edge node n, which can be calculated by

$$\tau_n{}^O = \frac{b_m \rho_u}{{\sigma_n}^{\max} - \overline{\sigma_n}}. \tag{8}$$

From (8), the low computing delay of edge node will be matched by UAV with high priority. For edge node n, the preference is inversely proportional to the data transmission delay of UAV, which is denoted by

$$P(n)|_{\Phi(n)=u} = \frac{1}{{\tau_u}^L}, \tag{9}$$

where ${\tau_u}^L$ represents the data transmission delay of UAV u, which can be calculated by

$${\tau_u}^L = \frac{b_m \rho_u}{r_{u,n}}. \tag{10}$$

From (10), we can obtain that the low transmission delay of UAV will be matched by edge node with high priority.

Let $\succ$ denote the preference relation for UAV and edge node. If $P(u)|_{\Phi(u)=n} > P(u)|_{\Phi(u)=n'}$, $n \succ n^{'}$, which means that UAV u prefers edge node n to edge node $n^{'}$. Moreover, if $P(n)|_{\Phi(n)=u} > P(n)|_{\Phi(n)=u'}$, $u \succ u^{'}$, which indicates that edge node n prefers UAV u to UAV $u^{'}$. We set the preferences of UAVs and edge nodes by a descending order based on $P(u)|_{\Phi(u)=n}$ and $P(n)|_{\Phi(n)=u}$. Therefore, the set of preference lists can be obtained by $\mathcal{P} = \left\{ P(u)|_{\Phi(u)=n}; P(n)|_{\Phi(n)=u} \right\}, \forall u \in \mathcal{U}, n \in \mathcal{N}$. The optimal matching rule is defined as follows.

Matching rule: a) For UAV $u \in \mathcal{U}$, it proposes to match its most preferred edge node in its preference list $P(u)|_{\Phi(u)=n}$. b) For edge node $n \in \mathcal{N}$, it proposes to match its most preferred UAV in its preference list $P(n)|_{\Phi(n)=u}$.

B. Offloading Strategy for UAVs and Edge Nodes

After UAVs match with the optimal edge nodes, the computing, transmission and delay overheads are evaluated to obtain the optimal offloading strategy.

Computing overhead. There are two different computing types: local computing and offloading computing. The computing overhead can be calculated by

$${\theta_1}^{over} = \alpha {e_m}^L + (1-\alpha) {e_m}^O, \tag{11}$$

where $\alpha \in [0,1]$ is the weighting parameter. Let ${\varrho_u}^L$ and ${\varrho_n}^O$ denote the unit energy consumption of one cycle for UAV u and edge node n, respectively. Thus, the energy consumption of local computing and offloading computing can be calculated by ${e_m}^L = b_m(1-\rho_u)\sigma_u {\varrho_u}^L$ and ${e_m}^O = b_m \rho_u \sigma_n {\varrho_n}^O$, respectively.

Transmission overhead. The energy consumption of data transmission is used to evaluate the transmission overhead, which can be calculated by

$${\theta_2}^{over} = b_m \rho_u \mu^O, \tag{12}$$

where μ^O denotes the unit power consumption of transmission.

Delay overhead. There are three different delays for offloading computing: local delay, transmission delay and offloading delay. The delay overhead can be calculated by

$${\theta_3}^{over} = \nu_1 {t_m}^L + \nu_2 {t_m}^T + \nu_3 {t_m}^O, \tag{13}$$

where $\nu_i\,(i=1,2,3)$ are the weighting parameters and $\nu_1 + \nu_2 + \nu_3 = 1$. The local computing delay and offloading computing delay can be calculated by ${t_m}^L = \frac{b_m(1-\rho_u)}{\sigma_u} \times {z_u}^L$ and ${t_m}^O = \frac{b_m \rho_u}{\sigma_n} \times {z_n}^O$, respectively. ${z_u}^L$ and ${z_n}^O$ denote the number of processor cycles for processing one bit of UAV u and edge node n, respectively. The transmission delay can be calculated by the offloading size and the data transmission rate, i.e., ${t_m}^T = \frac{b_m(1-\rho_u)}{r_{u,n}}$.

When UAVs offload its computing tasks to edge nodes, the process of offloading service for UAVs and edge nodes is modeled as a bargaining game. The valuation (i.e., reserve price) of offloading service for UAV u is related to its satisfaction. We can calculated by

$$\mathcal{V}_u(\rho_u) = \lambda_u \log_2\left(1 + \frac{\overline{{t_m}^L}}{{t_m}^L} + \frac{\overline{{t_m}^T}}{{t_m}^T} + \frac{\overline{{t_m}^O}}{{t_m}^O}\right), \tag{14}$$

where λ_u is the adjustment parameter. $\overline{{t_m}^L}$, $\overline{{t_m}^T}$ and $\overline{{t_m}^O}$ are the maximum local computing delay, maximum transmission delay and maximum offloading computing delay, respectively.

The valuation (i.e., reserve price) of offloading service for edge node n is proportional to its energy consumption and inversely proportional to the offloading computing delay. We can calculate by

$$\mathcal{V}_n(\rho_u) = \xi_n {e_m}^O + \zeta_n \frac{1}{{t_m}^O}, \tag{15}$$

where ξ_n and ζ_n are the adjustment parameters. Based on the valuation of UAV n and edge node n (i.e., $\mathcal{V}_u(\rho_u)$, $\mathcal{V}_n(\rho_u)$), we have the following three cases: 1) $\mathcal{V}_u(\rho_u) < \mathcal{V}_n(\rho_u)$. The UAV u and edge node n fail to reach an agreement for offloading service. The transaction will be cancelled. 2) $\mathcal{V}_u(\rho_u) = \mathcal{V}_n(\rho_u)$. The UAV u and edge node n reach an agreement for offloading service. The reserve price $\mathcal{V}_u(\rho_u)$ is paid to edge node n. 3) $\mathcal{V}_u(\rho_u) > \mathcal{V}_n(\rho_u)$. The difference of the reserve price between UAV u and edge node n can be calculated by $\mathcal{C}_m = \mathcal{V}_u(\rho_u) - \mathcal{V}_n(\rho_u)$, which can be regarded as a cake for offloading service. Each participant pursues the maximum utility from the cake. Therefore, the utilities of UAV u and edge node n can be calculated by

$$\mathcal{U}_u(\mathcal{C}_m) = \gamma_{u,m}\mathcal{C}_m = \gamma_{u,m}\left(\mathcal{V}_u(\rho_u) - \mathcal{V}_n(\rho_u)\right), \tag{16}$$

$$\mathcal{U}_n(\mathcal{C}_m) = \gamma_{n,m}\mathcal{C}_m = \gamma_{n,m}\left(\mathcal{V}_u(\rho_u) - \mathcal{V}_n(\rho_u)\right), \tag{17}$$

where $\gamma_{u,m}, \gamma_{n,m} \in [0,1]$ are the offers of UAV u and edge node n for the cake, respectively. We have $\gamma_{u,m} + \gamma_{n,m} = 1$.

C. Optimal Offloading Strategy Based on Bargaining Game

In the bargaining game, UAVs and edge nodes provide their offers in turn to determine the optimal partition (i.e., ${\gamma_{u,m}}^*, {\gamma_{n,m}}^*$) of the cake. Here, the discount factor $\varepsilon \left(0 \le \varepsilon \le 1\right)$ is developed to indicate the patience degree of players in the bargaining game. The players (i.e., UAV u and edge node n) will accept the offer provided by another player as soon as possible to obtain more utilities. For UAV u, the discount factor is related to the offloading computing delay, which can be calculated by

$$\varepsilon_u = \frac{1}{\left(1+\psi_n\right)^{\upsilon_u}}, \tag{18}$$

where υ_u denotes the coefficient of patience degree for UAV u. $\psi_n = {t_m}^O$ indicates the offloading computing delay of edge node n.

For edge node n, the discount factor is associated with the data transmission delay, which can be calculated by

$$\varepsilon_n = \frac{1}{\left(1+\psi_u\right)^{\upsilon_n}}, \tag{19}$$

where υ_n denotes the coefficient of patience degree for edge node n. $\psi_u = {t_m}^T$ is the data transmission delay of UAV u.

Based on the discount factors, the utilities of UAV u and edge node n in the round k can be calculated by

$$\mathcal{U}_u(\mathcal{C}_m)^k = {\varepsilon_u}^{k-1}{\gamma_{u,m}}^k\mathcal{C}_m, \tag{20}$$

$$\mathcal{U}_n(\mathcal{C}_m)^k = {\varepsilon_n}^{k-1}{\gamma_{n,m}}^k\mathcal{C}_m. \tag{21}$$

From (20) and (21), we can find that both UAV u and edge node n should reach an agreement as soon as possible in the bargaining game to gain more utilities. The offloading strategy based on incentive algorithm is shown in Algorithm 1.

Theorem 1. There exists the Nash equilibrium in the proposed bargaining game. When the edge node n first provides its offer, the optimal partition is given by ${\gamma_{n,m}}^* = \frac{1-\varepsilon_u}{1-\varepsilon_u\varepsilon_n}$. When the UAV u first provides its offer, the optimal partition is given by ${\gamma_{u,m}}^* = \frac{1-\varepsilon_n}{1-\varepsilon_u\varepsilon_n}$.

Algorithm 1 : Offloading Strategy Based on Incentive Algorithm

```
Input: b_m, e_m^O, e_m^L, t_m^O, t_m^T, υ_u, υ_n, λ_u, ξ_n, ζ_n;
Output: ρ_u, γ_{u,m}^*, γ_{n,m}^*;
Initialization: UAV u matches with edge node n based
    on matching scheme;
for u ∈ U, n ∈ N do
  if V_u(ρ_u) > V_n(ρ_u) then
    Calculate the difference of the reserve prices C_m;
    if Edge node n first provides its offer then
      γ_{n,m}^* = (1-ε_u)/(1-ε_u ε_n);
    else
      if UAV u first provides its offer then
        γ_{u,m}^* = (1-ε_n)/(1-ε_u ε_n);
      end if
    end if
  else
    if V_u(ρ_u) = V_n(ρ_u) then
      The reserve price V_u(ρ_u) is paid to edge node n
        by UAV u;
    end if
  else
    if V_u(ρ_u) < V_n(ρ_u) then
      The transaction between UAV u and edge node n
        is cancelled;
    end if
  end if
end for
```

TABLE I
SIMULATION PARAMETERS

Parameters	Values
φ_0	-100dBm
w	10kHz
${z_u}^L, {z_n}^O$	1,0.2
${\varrho_u}^L, {\varrho_n}^O$	4,1
μ^O	1
λ_u	2
ξ_n, ζ_n	0.8,0.2
α	0.5

V. Performance Evaluations

A. Simulation Setup

In the simulations, the number of UAVs in the IoT is set to be 20. The flying range of UAVs is set to 1000 m^2. The number of edge nodes in the IoT is set as 20. The size of input bits for computing is 3 Gbps. The transmission power of UAV is selected from the interval $[152, 190]\,\mathrm{mW}$. The offloading proportion of UAV follows the uniform distribution within $[0, 1]$. The abundant idle computing resource of edge node is chose from $[0.5, 10]\,\mathrm{GHz}$. The abundant idle computing resource of UAV is set to be $1\mathrm{GHz}$. Other parameters in the simulations are given in TABLE I [14].

The performance of the proposed offloading scheme is compared with the conventional schemes, which are the distributed computation offloading strategy (DCOS) [15], the offloading computing scheme (OCS), respectively. In the OCS, the computing task is totally offloaded to edge node.

B. Results and Analysis

Fig. 2 shows the changes of average overhead with different number of UAVs. It can be seen that the proposed scheme can achieve the lowest overhead compared with other schemes. The reasons for these are as follows: on one hand, the optimal matching scheme between UAVs and edge nodes are obtained to reduce the computing, transmission and delay overheads. On the other hand, the optimal offloading strategy for UAVs is determined based on the bargaining game, which improves the offloading efficiency. Thus, the average overhead in the proposed scheme is lower than that of other schemes.

Fig. 3 shows the changes of utilities of UAVs with different number of UAVs. As can be seen that the proposed scheme can obtain the higher utility for UAVs than other schemes. It is because that the optimal transaction between UAVs and edge nodes is determined by the bargaining game. The average

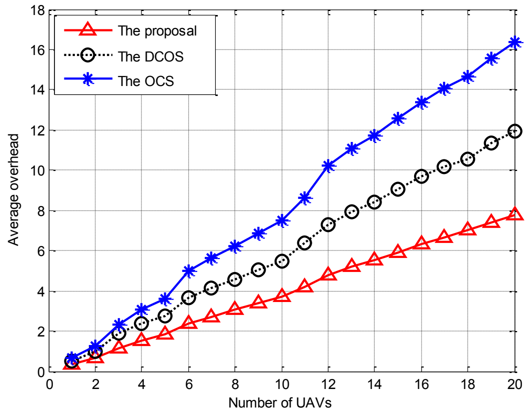

Fig. 2. The changes of average overhead with different number of UAVs.

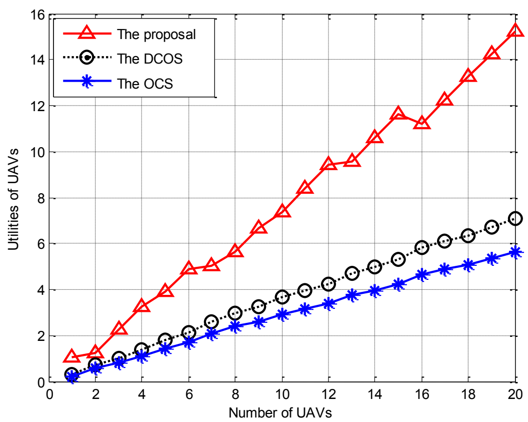

Fig. 3. The changes of utilities of UAVs with different number of UAVs.

amount of offloading computing increases as the increase of the number of UAVs, which brings the high utility to UAVs.

VI. Conclusion and Future Work

In this paper, we have proposed an energy-efficient edge offloading scheme for UAV-assisted IoT to improve the offloading efficiency. Firstly, the offloading model has been developed to obtain the offloading proportion for task computing. Secondly, based on the computing delay of edge node and data transmission delay of UAV, the matching scheme between UAVs and edge nodes has been designed to choose the optimal partners. Thirdly, to improve the offloading efficiency, the transaction process between UAV and edge node has been modeled as the bargaining game, where each participant can obtain the maximum utility from the game. Finally, simulation results have been shown that the proposed scheme can significantly improve the offloading efficiency. As for the future work, we plan to take the security into account to improve the reliability of offloading in IoT.

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