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A UAV migration-based decision-making scheme for on-demand service in 6G network



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KEYWORDS

6G; UAV migration; Migration cost; On-demand service **Abstract** In the context of the 6th generation (6G) network, UAV-aided networking is emerging as a promising solution to burst traffic offloading and on-demand service coverage. Given the dynamic networking environment, a UAV migration scheme needs to be as flexible, efficient, and adaptive as possible. To address this issue, a UAV migration-based decision-making scheme is put forward to make a tradeoff between migration costs and the satisfaction of service requirements. In the scheme, a UAV adaptive migration strategy (UAMS) is adopted to improve the migration efficiency. Meanwhile, the corresponding signaling interaction process is designed according to different UAV migration scenarios. The experimental results show that the proposed approach makes a significant improvement in the performance of the whole system and takes obvious advantage over traditional solutions.

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1. Introduction

The 6th generation mobile network (6G) has gradually become the networking direction of deployment in various countries, and is expected to realize the interconnection of all things [1-3]. The huge amount of access also leads to the gradual expansion of the network service scope and the sharp increase of network traffic in 6G [4]. It is difficult for traditional ground base stations (BS) to meet the needs of sudden hot traffic demands in local areas. The air-ground cooperative communication network assisted by multi-UAVs has become an effective solution to large traffic offloading and communication blind spot coverage in emergencies [5].

In high-density communication user scenarios, UAVs can be deployed as temporary base stations or the UAV can act as an aerial base station or access node to assist wireless communication [6]. In the framework of space-air-ground-sea integrated network, the utilization of UAVs plays an important role in global three-dimensional depth coverage. UAVs can also be equipped with communication equipment as highly mobile end users responsible for data acquisition in the internet of things (IoT) environment [7]. In a word, UAV communication technology is regarded as a critical component of 6G mobile networks.

As mentioned in [8], the 6G networking designs may make the transition from the stationary terrestrial infrastructure model to aerial mobile connectivity. However, the dynamic

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development of UAV communication technology is still in the initial stage, and 6G has a brand new technological development compared with 5G, so there are still many challenges for the UAV-aided 6G mobile networking to explore and study in depth. First, the high mobility and flexible deployment of UAVs make auxiliary networking and mobility management difficult [9]. Moreover, due to the limited energy and computing capacity of UAV, it is necessary to design a mobility control method that takes into account both UAV service capability and energy consumption [10]. Therefore, at least three problems should be considered for UAV dynamic migration scheme to best cater to the instantaneous wireless traffic in a territory.

- How to decide which UAV and where it should be migrated. One of the greatest challenges is to identify the out-migration UAV and the in-migration area that the out-migration UAV will be redeployed.
- The number of UAVs for migrating and the total migration costs need to be considered. Repositioning all UAVs improves service load balancing, but it also increases computing overhead and reduces energy efficiency. A well-designed UAV migration mechanism must be performed to balance migration costs and load balancing.
- The impact of UAV migration on network topology and signaling interaction should also be taken into account. In order to reduce signaling overhead, inter-region UAV migration should be avoided when executing the migration plan.

To address the impact of migration costs on migration efficiency in the context of UAV migration, we propose a UAV adaptive migration strategy (UAMS) scheme. In UAMS scheme, the objective is how to select a UAV with low migration cost as out-migration UAV as well as which area with higher services demand is decided as in-migration area. The main contributions of this work are as follows:

- A UAV migration-based decision-making scheme is built, which can reduce the impact of UAV migration on system overhead in the context of 6G network service burst.
- On the basis of the optimal migration efficiency conditions, the UAV migration problem is formulated as a set of the migration actions, and UAMS algorithm is adopted for reducing migration cost and system signaling overhead.
- According to different UAV migration strategies, corresponding signaling interaction processes are designed and given.

The remainder of the work is organized as follows. Section 2 gives the related works. Section 3 presents the system model and the problem formulation. Section 4 develops the UAV migration-based decision-making scheme. Section 5 gives simulation results, followed by Sect. 6 to conclude the paper.

2. Related works

The three-dimensional (3D) deployment of a single UAV is relatively simple and usually a single objective optimization problem. The authors in [11] proposed the optimal deployment scheme to maximize the number of covered users. Zhang M et al. [12] proposed to decoupage the 3D position into the vertical and horizontal deployment problems of the UAV, and modeled the deployment problem as the placement of minimum closed circle. The uthors in [13] discussed how an efficient UAV 3D placement algorithm would support efforts to maximize the total number of user equipment whilst utilizing the minimum required power. Zeng y et al. [14] studied the energy-efficient UAV mobile communication via trajectory optimization by taking into account the flight energy consumption, and a theoretical model on the UAV's propulsion energy consumption was derived.

As described in [15], optimal positioning of multi-UAV was one of the most critical challenges and must be addressed in dense beyond 5G (B5G) and 6G deployment scenarios. Most of works in the context of the application of B5G/6Genabled UAVs as BSs can be expressed as direct functions of localization and optimal positioning efficacy. For example, the authors in [16] realized an optimal drone positioning mechanism to address the requirement for transmission power minimization, and divided the multi-objective optimization problem into two different sub-problems. Considering the high dynamics and self-organization characteristics of UAV-aided networking, the authors in [17] proposed an alliance-based 6G UAV task-driven network model.

In view of the flexible deployment of multi-UAVs, ondemand coverage services can be provided for users when regional communication services need fluctuate greatly [18– 20]. Some works have addressed the problem of dynamic deployment and repositioning of UAVs, however few works have considered the UAV movement cost and the system overhead of network reconfiguration. The objective of this paper is to minimize the UAV migration cost while ensuring service capability. To solve the optimization problem, the UAMS scheme is adopted. In UAMS scheme, the multi-objective optimization problem is transformed into UAV migration problem under different local control centers (LSC). When the UAVs move within the control range of the LSC, the intra-LSC moving strategy is adopted, otherwise, the inter-LSC migration strategy is performed, as shown in Fig. 1.

3. System model and problem formulation

3.1. System Description

In this paper, we consider a downlink wireless network that consists of M macro base stations (MBSs) and N UAVs $U = \{u_1, u_2, \dots, u_N\}$. Let $R = \{\Re_1, \Re_2, \dots, \Re_j, \dots, \Re_M\}$ denote the set of coverage areas, and \Re_j is the area covered by *j*-th MBS. Assume that all UAVs and users' equipment work in the single antenna mode. The variables defined in equations are summarized in Table 1.

In general, the energy consumption of UAV is composed of the communication-related energy and propulsion energy [14]. The propulsion energy, which is also treated as mechanical energy consumption (MEC), is required for ensuring that the UAV remains hovering as well as for supporting its mobility [21]. The communication-related energy, usually much smaller than MEC and thus ignored here, is due to the radiation, signal processing and other circuitry. This paper focuses on the migration flight stage of UAVs, ignoring its takeoff and landing processes. Assume that all UAVs work at a fixed height,



Fig. 1 Adaptive on-demand migration coverage under multi-UAVs cooperative networking.

Table 1	Summary of the variables.
Variable	Description
U, u_i	The set of N UAVs, <i>i</i> -th UAV
$\mathfrak{R}_j,\mathfrak{R}$	Area covered by <i>j</i> -th MBS, areas set
$U_{\mathfrak{R}_i}$	The set of UAVs in area \Re_i
$d_{u_i \Re_i}$	Migration distance of u_i migrating from \Re_i to \Re_j
c_1, c_2	Two constant aerodynamic parameters
t,v	Migration time and speed of u_i migrating to \Re_j
$E_{u_{ii}}$	Mechanical energy consumption of u_i migrating to \Re_j
Г	Load distribution factor of UAVs
l_{μ_i}, \overline{l}	Service load of the <i>i</i> -th UAV, average load of N UAVs
$f_{u_iA_i}$	UAV arrangement index
α,β	Balance factor between energy consumption and
	system load
$_i, Q$	Three-dimensional (3D) position coordinate of $UAVu_i$,
	3D positions set
$C_{\mathfrak{R}_j}, C_{\max}$	Service demand in area, maximum service capacity of
	UAV
O_{\Re}	Areas set for UAV out-migration
u^*	The UAV for migrating

which can be the lowest height for UAVs to avoid collision in practice. For steady straight-and-level migrating flight with constant speed v, the MEC of UAV u_i for migrating to area \Re_i can be represented as

$$E_{u_i A_j} = \left(c_1 v^3 + \frac{c_2}{v}\right) t \tag{1}$$

where c_1 and c_2 are two aerodynamic parameters, and which are related to air density, UAV's weight and wing area, etc.

As expressed in [22], when the UAV migrates from one area to next, it will not fly with the maximum speed since there is a tradeoff between the flight speed and the energy consumption. When the flight speed v is determined, the migration time t is related to the migration distance. Thus, the MEC can be also represented as

$$E_{u_iA_j} = c_1 v^2 d_{u_i\mathfrak{R}_j} + c_2 d_{u_i\mathfrak{R}_j} \tag{2}$$

The expression in (2) shows that for level migration with a fixed altitude, the *i*-th UAV's migration energy cost mainly depends on the velocity v and migration distance $d_{u_i \Re_i}$.

Note that when the UAVs with heavy load are migrated, the system load in the area will be unbalanced. Thus, the selection of migrating UAVs should concern the system load balancing problem. In this paper, the UAVs' load variance is used as the system load balance factor Γ , and Γ is given by

$$\Gamma = \frac{1}{N} \sum_{i=1}^{N} \left(l_{u_i} - \bar{l} \right)^2 \tag{3}$$

where l_{u_j} is the service load of the UAV u_i , and l is the average load of N UAVs.

3.2. Problem formulation

In the air-ground heterogeneous cooperative 6G network, the UAVs' coverage areas will change dynamically with the change of service demand distribution. Thus, on-demand and immediate covering is a key metric to be considered when modeling UAV migration. Considering load balancing and users' service requirement distribution, a flexible UAV migration model should be constructed for on-demand coverage. In this case, making the load more balanced while ensuring less UAV migration cost is the key indicator. Therefore, the UAV migration modeling problem can be formulated as

$$\min_{\mathcal{Q}} \left(\alpha \Gamma + \beta \sum_{i=1}^{N} \sum_{\Re_{j} \in R} E_{u_{i} \Re_{j}} f_{u_{i} \Re_{j}} \right)$$
(4)

where $Q = (1, 2, \dots, i, \dots, N)$ is the location set of N UAVs, and *i* is the three-dimensional (3D) position coordinate of the UAV*u_i*, $f_{u_iA_j}$ is the UAV arrangement index, indicating whether UAV *u_i* is selected to cover area*A_j*, and thus it is expressed as

$$f_{u_i \Re_j} = \begin{cases} 1 \ u_i \ is \ selected \ to \ cover \ \Re_j \\ 0 \ otherwise \end{cases}$$
(5)

4. Uav Migration-Based Decision- making scheme

It is obvious that the optimization problem above is a complex nonlinear programming problem, and it is difficult to find the optimal solution by solving the mathematical model. To solve this problem, a low complexity strategy is proposed in the following subsection. In addition, signaling design for UAVs migration will also be presented.

4.1. UAV adaptive migration strategy

The purpose of UAV migration strategy is to migrate some the lightly loaded UAVs to the higher loaded areas with less migration costs. We formulate the UAV migration problem as a series of migration actions and present quadruple $\langle U_{\Re_i}, u_i, U_{\Re_j} \rangle$ to characterize migration action. Where U_{\Re_i} and U_{\Re_j} denote the set of UAVs in area \Re_i and \Re_j , respectively. When \Re_j is selected as the in-migration area that requires UAVs to migrate into for coverage, our focus is which area should be selected as out-migration \Re_i and how to choose the UAV u_i as migrating UAV u^* . Notice that when $\Re_i = \Re_j$, the UAV moves in the same area and the CP connection to LSC remains unchanged, which is regarded as UAV migrating intra-LSC. On the other hand, when $\Re_i \neq \Re_j$, the UAVs migrate from one area to another, which is viewed as UAV migrating inter-LSC.

• UAV Migrating Intra-LSC Strategy

The number of UAVs required by \Re_j is related to the service demand in the area. Assume that all UAVs have the same maximum service capacity C_{\max} , and C_{\Re_j} denotes the service demand for UAV-aided communication in area \Re_j . The shortage degree of UAVs required by area \Re_j can be expressed as

$$s_{\mathfrak{R}_i} = \left\lceil C_{\mathfrak{R}_i} / C_{\max} \right\rceil - \left| U_{\mathfrak{R}_i} \right| \tag{6}$$

where $\lceil \cdot \rceil$ means ceiling function, + represents the number of UAVs in set U_{\Re_i} , and C_{\max} is equal to $\beta \times \eta$, where β is the total bandwidth of UAV and η is the average spectral efficiency of the system.

If $s_{\Re_j} \ge 0$, intra-LSC migration action will be performed. UAVs move within area \Re_j and the CP connections to LSC remain unchanged, which reduce the system signaling overhead. Steps of intra-LSC migration action are elaborated as follows:

Step 1: Obtain the users' distribution in area \Re_j and determine the coverage center point (x_{\Re_j}, y_{\Re_j}) .

Step 2: Choose a UAV u_i with the smallest load in area \Re_j .

Step 3: Move UAV u_i to the point (x_{\Re_j}, y_{\Re_j}) .

Step 4: Use the method in Ref. [11] to optimize the altitude h_{\Re_j} , and locate the 3D position $(x_{\Re_j}, y_{\Re_j}, h_{\Re_j})$ as migration position for the UAV u_i .

• UAV Migrating Inter-LSC Strategy

When the shortage degrees_{\Re_i} < 0, inter-LSC migration action will be performed. Each area \Re_i calculates its shortage degrees_{\Re_i}, ifs_{\Re_i} > 0, the area \Re_i is added into out-migration areas setO_{\Re}. In order to improve the migration efficiency, a UAV migration algorithm based on greedy method is proposed. The algorithm iteratively selects the local optimal migration action according to the migration cost and load balance. The algorithm process is as follows:

Step 1: Choose area \mathfrak{R}_i greedy from out-migration areas set $O_{\mathfrak{R}}$.

Step 2: Use Eq. (1) to calculate the migration cost $E_{u_{ij}}$ of each UAV u_i in \Re_i .

Step 3: selected a u_i as the migration UAV u^* based on the following equation:

$$u^* = \operatorname{argmin}_{u_i \in U_{\mathfrak{R}_i}} \left\{ \Gamma^* E_{u_i A_j} \right\}$$
(7)

where Γ^* is the system load distribution factor after UAV migration.

Step 4: Add migration action $\langle U_{\Re_i}, u^*, U_{\Re_j} \rangle$ to migration list, and then execute it.

Step 5: Repeat steps 1–4 until the demand for communication services is relatively balanced.

4.2. UAV migration signaling process

In order to realize the handover without user awareness, the continuity of interaction process and signaling operation should be maintained during the movement of the UAV. The following focuses on the function and signaling design of the core network and access network with different UAV migration strategies.

• Signaling Design for UAVs Migrating Intra-LSC

The signaling process of UAV migrating intra-LSC is shown in Fig. 2. The LSC periodically detects the users' activity and sends the UAV a movement command in time according to the change of service requirements. At the same time, a service configuration command is sent to the UAVs that do not need to move. The migrating releases the DP connection with its service users. After the service decision is made, an optimal UAV is selected to serve the users covered by the migrating UAV. On the other hand, the migrating establishes a DP connection with the new users. It can be seen that in the whole signaling process, the CP of the migrating UAV is always controlled by the LSC.





Fig. 2 Signaling for UAVs migrating intra-LSC.

• Signaling Design for UAVs Migrating Inter-LSC

While the target service users is within the range of LSC2, the migrating UAV is under the control of LSC1. In this condition, NSC is needed to execute multi-LSCs coordination, as shown in Fig. 3. LSC2 sends collaboration request information to NSC, when it detects that the amount of user service requests in its area is too large. After receiving the cooperation information, LSC1 sends a movement command to the migrating UAV. The migrating UAV releases the DP connection to its service users, and then the data service is provided by other UAV controlled by LSC1, which is the same as the signaling process of UAVs migrating intra-LSC in Fig. 2. After that, the migrating UAV sends radio resource control (RRC) connection request to LSC2. And then, the migrating UAV establishes DP connection with the users within the area of LSC2 after receiving confirmation information.

5. Simulation analysis

5.1. Simulation settings

In this section, MATLAB simulation tool is used to conduct system-level simulation for UAV dynamic cooperation network. The 1Km*1Km simulation region is divided into two sub-regions by 2 MBSs, and each MBS is used as a LSC. In each sub-region, 2 small BSs with coverage radius of 250 m are used as the base coverage and 6 UAVs are used for dynamic UAV-aided communication. It is assumed that 1000 users are randomly and uniformly distributed initially, and users access the service fairly. The minimum user quality of service (QoS) rate is 0.1Mbps ~ 0.5Mbps. The system bandwidth is 10 MHz and the carrier frequency is 3.5 GHz. Assume that, the UAV is deployed on the same frequency as the SBS. For simplicity, MBS only serves as the control center and does not receive service access from users. The UAVs fly at a fixed altitude of 100 m, and the operation time is T = 100 s. Furthermore, the two constant aerodynamic parameters of the UAVs are set as $c_1 = 0.000926$ and $c_2 = 2250$. Unless otherwise stated, the parameter values used in the simulation experiment refer to Table 2. The following experiments only analyze the performance indicators of UAV.

5.2. Performance evaluation

The proposed scheme UAMS is compared with UAV fixed deployment scheme (FDS) and the proactive hotpots coverage scheme (PHCS) [25]. In FDS, the UAVs are uniformly and fixedly deployed in the simulation region. In PHCS, the authors determined the proactive coverage area within the unit period, whereby the UAVs were assigned to cover the corresponding areas based on first-best-effort and second-patching algorithm. PHCS can also be seen as a semi-dynamic UAV deployment scheme.

We first consider service delay time of UAV with different user moving speed in time period T. For UAMS, the delay time is mainly related to the UAV migration time and the signaling interaction time of migration process. Since the signaling interaction time is much less than the migration time, the average migration time of UAV is taken as the service delay time in this situation. The delay caused by the users moving out of the coverage area of the UAV is regarded as the service



Fig. 3 Signaling for UAVs migration inter-LSC.

Table 2 Simulation parameters.			
Parameter	Value		
Frequency	3.5 GHz		
System bandwidth	10 MHz		
SBS transmission power	46dbm/36dbm/30dBm		
UAV transmission power	100 m		
Path loss model	BS:140.7 + 37.6 $\log_{10}(d)$		
	UAV: ATG path loss model [23]		
Maximum number of UAV service users	50		
UAV flying speed	30 m/s		
User moving model	Random Way Point model [24]		
User moving speed	[0.2 m/s-1.4 m/s]		
Maximum number of UAV service users UAV flying speed User moving model User moving speed	50 30 m/s Random Way Point model [24] [0.2 m/s-1.4 m/s]		

delay time in scheme FDS. Assume that FDS redeploys all the UAVs every 100 s to adapt to the change of users' position, and thus the redeployment time of UAVs is the service delay time.

Fig. 4 shows the comparison of UAVs' service delay time of the proposed scheme with FDS and PHCS with different user moving speed. It is observed that the proposed UAMS achieve better service delay time performance than PHCS and FDS, which demonstrates the adaptive UAV migration method can effectively reduce the UAV flight time and signaling interaction time. Besides, the service delay time of UAMS and FDS increases with user moving speed. In contrast, the service delay time of PHCS has little correlation with user moving speed. The reason is that the UAVs are assigned to cover the determined proactive coverage area (PCA), so the delay time is related to the number of PCAs and the redeployment time of the UAVs.



Fig. 4 UAVs' service delay time versus user moving speed.

Fig. 5 shows the comparison of UAVs' average load rate of the proposed scheme with FDS and PHCS with different user moving speed. As shown in Fig. 5, the load rate of FDS fluctuates greatly with the increase of user moving speed, while PHCS and UAMS have been little affected. This is because that the UAVs in FDS cannot follow the users very well, while UAMS can automatically relocate the UAVs to adapt to service requirements caused by users' movement.

Fig. 6 presents the spectrum efficiency gain of the three schemes in different user aggregation conditions. The coefficient of variation (CoV) is used as the index of user aggregation. The larger the value of CoV, the higher the degree of user aggregation [26]. As seen in the figure, with the higher value of CoV, the spectrum efficiency gain (SEG) of FDS decreases, while the SEGs of UAMS and PHCS increase.



Fig. 5 UAVs' average load rate versus user moving speed.



Fig. 6 Spectrum efficiency gain versus user aggregation.

Another important finding is that UAMS and PHCS demonstrate very similar performance which is better than the performance of FDS. This result can be explained by the fact that the users can get better coverage service by dynamically adjusting the positions of UAVs. The UAVs are deployed without repositioning in FDS, which leads to fewer users covered by some UAVs when more users are gathering, resulting in lower average spectral efficiency. It is also found that the proposed UAMS has better spectral efficiency compared with PHCS. This may be due to the rapid change in network structure caused by the redeployment of all UAVs in PHCS, consequently decreasing the value of average spectral efficiency gain.

Fig. 7 shows the communication energy efficiency (CEE) and mechanical energy efficiency (MEE) of UAV in different user aggregation conditions. The calculation methods of CEE and MEE refer to [21]. As seen in the figure, the CEEs of the UAMS and PHCS are very close to each other, and they are much more efficient than that of FDS. It can be due to decreasing the average distance between the UAVs and the users in UAMS and PHCS, consequently reducing the value of average CEE. It is also found that the MEE of FDS decreases with the increase of CoV < 3 value. This result can be explained by the fact the fixed UAVs in FDS serve users during the operation time, when the user aggregation degree increases, the probability of some users not being covered increases. In contrast, the performance of UAMS increases with the higher value of CoV, because the smaller user aggregation range reduces the migration cost of UAVs.

6. Conclusion

In this paper, the primary objective is to make an efficient UAV migration scheme for on-demand service requirements. For this purpose, the UAV migration cost and the system load distribution are measured firstly. Further, the UAV migration problem is modeled as a migration efficiency optimization problem. To solve the problem, a low complexity UAV migration algorithm is proposed. And then, the signaling design of



Fig. 7 CEE and MEE of the three schemes versus user aggregation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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