Computer Networks 185 (2021) 107660

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Towards intelligent virtual resource allocation in UAVs-assisted 5G networks

Haotong Cao [a,c], Yue Hu [b], Longxiang Yang [a,*]

[a] Jiangsu Key Laboratory of Wireless Communications, Nanjing University of Posts and Telecommunications, Nanjing 210003, PR China
[b] Department of Key Accounts, China Mobile Group Jiangsu Co., Ltd., Nanjing 210029, PR China
[c] Department of Computing, The Hong Kong Polytechnic University, Hong Kong, PR China

ARTICLE INFO

Keywords:
5G networks
UAV
Intelligent virtual resource allocation
Virtual network embedding

ABSTRACT

With the aim of providing novel services and applications having high data rate and low latency, the 5G networks are designed. Thus, it is essential to manage and schedule the physical resources efficiently in 5G era. Virtualization technologies are seen as the most potential enabling approaches towards 5G networks. The known key issue is the virtual resource allocation, called as virtual network embedding (VNE). However, previous researchers simply focus on allocating resources in an inflexible way. As unmanned aerial vehicles (UAVs) communication plays an important role in 5G, we need to add UAVs into the 5G networks in order to expand the coverage and agility of services. In this paper, we investigate the issue of intelligent virtual resource allocation in UAVs-assisted 5G networks. Especially, we propose one intelligent virtual resource allocation algorithm, labeled as *Intell-UAV-5G*. When receiving one network service, our *Intell-UAV-5G* implements the network service in an intelligent manner. Though virtualized UAV moves, our *Intell-UAV-5G* is able to predict all possible connecting access nodes and continue the network service intelligently. Meanwhile, our *Intell-UAV-5G* can minimize the time of service interruption. Thus guaranteeing the service quality. We also conduct the experiment to highlight the *Intell-UAV-5G* efficiency. The mostly-similar algorithms are derived for performance comparison. Performance metrics are carefully recorded and discussed.

1. Introduction

Both academia and industry have reached the consensus that the 5G networks [1–4] are designed for providing massive network elements connection and fulfilling explosive data growth. Meanwhile, more novel network services and applications [5], having high data rate and low latency, emerge in 5G era. Therefore, it is necessary to manage and schedule the physical network resources efficiently. Considering the heterogeneity nature of dedicated hardware, it is a great burden [6] for telecommunication service providers (TSPs) to invest and upgrade these hardware continuously. Therefore, virtualization technologies (e.g. network virtualization, NV [1], network function virtualization, NFV [4]) are seen as the most potential approach towards the upgrading tendency of 5G. By conducting virtualization, underlying physical resources (e.g. radio, computing, storage, bandwidth) can be abstracted into virtual resources easily. TSPs can manage, schedule and allocate their owned virtualized physical resources easily.

In order to implement 5G network services and load virtualized network elements to their full capacities, TSPs need to be equipped with abundant algorithms, having the function of allocating virtual resources efficiently. In the literature, it attracts significant research attention. In both academia and industry, the resource allocation problem can be called as virtual network embedding (VNE) [7]. There exist abundant technical publications in the literature [7–10]. These publications enables to help following researchers to start the VNE research quickly. However, existing technical publications [7–28] allocate the virtual resources in an inflexible way. For instance, once one network service is allocated and implemented, no intelligent scheme exists in order to adjust the allocation results. In addition, all nodes of virtual network services are assumed to be static throughout their lifespan. None considered the embedding and allocation in case certain node moves. Though a few publications (e.g. [27,28]) discussed the node mobility, none mentioned which concrete network scenario [27] can be applied. However, ‘the last one mile’ in resource allocation aspect is very important. That is to say, the node mobility cannot be ignored in real networking research. In addition, existing publications (e.g. [28]) did not evaluate their proposed algorithms in a continuous time event. The evaluation scheme further limits their contributions.

Therefore, we research the intelligent virtual resource allocation, on the basis of 5G networks. We also consider the mobile virtual node so as to research the node mobility effect on the virtual resource allocation results. Instead of discussing about node mobility in an abstracted

* Corresponding author.
E-mail address: yanglx@njupt.edu.cn (L. Yang).

https://doi.org/10.1016/j.comnet.2020.107660
Received 31 August 2020; Received in revised form 25 October 2020; Accepted 27 October 2020
Available online 5 November 2020

manner, we consider the concrete mobile network scenario. Unmanned aerial vehicles (UAVs) research [29–32] has emerged in recent years. As UAV will play an important role in 5G era [29], we incorporate mobile UAVs into the 5G networks in order to expanding the coverage and angle of novel network services.

In this paper, we conduct a research on the virtual resource allocation in UAVs-assisted 5G networks. The formal problem model for UAVs-assisted 5G networks is involved. Another novel profit model, quantifying the effect of UAV mobility, is presented, too. With respect to the novel profit model, the penalty of virtual network service interruption is considered. Then, we propose an intelligent virtual resource allocation algorithm, labeled as *Intell-UAV-5G*. Our *Intell-UAV-5G* consists of two sub-algorithms: *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*. With respect to the *Intell-UAV-5G-Active* algorithm, it enables to predict all possible connecting access nodes and continue the implement virtual service quickly when the service interruption happens. With respect to the *Intell-UAV-5G-Reactive* algorithm, it can re-allocate and re-embed the virtual network immediately when the service interruption happens. In order to highlight our *Intell-UAV-5G*, we conduct the experiment evaluation. Experiment results demonstrate that *Intell-UAV-5G* outperforms the selected derived algorithms, in terms of income and virtual service acceptance. For example, the virtual service acceptance ratio advantage of *Intell-UAV-5G* is beyond 14% (10 000 time unit point).

(1) The new formal problem model for UAVs-assisted 5G networks is presented in this paper (Section 3). Previous problem models for solving virtual resource allocation were developed from the fixed core networks and computer networks. No researcher [7,9,10] had not considered integrating the UAVs into the virtual resource allocation problem model yet;

(2) Another novel profit model is proposed in Section 3. Besides of quantifying revenue and cost, the novel profit model enables to quantify the penalty. The quantified penalty results from the UAVs mobility. Previous profit models [7,9,10] did not consider quantifying the penalty. Not to mention quantifying the UAV mobility and service interruption;

(3) An intelligent virtual resource allocation algorithm is proposed in this paper (Section 4). The intelligent resource allocation algorithm is labeled as *Intell-UAV-5G*. The *Intell-UAV-5G* consists of two sub-algorithms. One sub-algorithm is *Intell-UAV-5G-Active*. The *Intell-UAV-5G-Active* enables to predict all possible connecting access nodes and continue the implement virtual service quickly when the service interruption happens. The other sub-algorithm is *Intell-UAV-5G-Reactive*, enabling to conduct the re-allocation and assignments when the service interruption happens;

(4) A comprehensive experiment is conducted in Section 5. The experiment work aims at validating *Intell-UAV-5G* efficiency. We select the mostly-similar resource allocation algorithms to make up the experiment simulation part. Experiments results are carefully recorded, plotted and discussed.

The rest of this paper is well organized: Related work is presented in Section 2. Problem model and profit model for UAVs-assisted 5G networks are both presented in Section 3. The intelligent algorithm *Intell-UAV-5G* is detailed in Section 4, including its two sub-algorithms. Experiment work and result discussion are presented in Section 5. In the end, we conclude this paper and outlook the future work.

2. Related work

Serving as the dominant issue in 5G networks, it is vital to efficiently allocate virtual resources. Efficient and optimal resource allocations per user contribute to implementing various network services and applications smoothly. In 5G networks, virtual resources required to be allocated are usually abstracted into the resource attributes of nodes and links. Multiple nodes and links form up the virtual network service. Therefore, the type of virtual resource allocation is called as VNE. Existing survey papers [7–11] have well categorized and discuss the algorithms, aiming at allocating virtual resources efficiently.

For instance, Dietrich et al. [12] solved the virtual resource allocation per network service from the TSP sides. By exposing limited TSP network resource information, Dietrich et al. can deploy virtual network service smoothly by sacrificing the acceptance ratio performance. In Ref. [13], Cao et al. explored to allocate virtual resources by considering the whole network attributes and resource information. Though achieving efficient resource allocation, the whole TSP network information must be fully known ahead. This is not feasible in the real networking environment. While in Ref. [14], the hot blockchain method is adopted by Cao et al. so as to ensure the security of virtual resource allocation. In Ref. [15], Gong et al. researched the efficient virtual resource allocation via considering location and one-step allocation method. Zhang et al. [16] studied the virtual resource allocation in multi-layer optical network. Thus limiting the contribution. It can be used in optical networks. While in Ref. [17], Cao et al. introduced the idea of adjustment to solve virtual resource allocation. Though ensuring the acceptance ratio and QoS per virtual service, it is simply adopted in static computer networks. In Ref. [18], Han et al. tried to allocate virtual resource in fiber-wireless access network. Thus being limited within the access network area. Wang et al. [19] researched the secure virtual resource allocation against covert channel attacks. It is a narrow topic in security area. While in Ref. [20], Yuan et al. considered topology attributes so as to allocate resources in data center networks. Kaur et al. [21] researched the resource allocation in V2G environment. The game theoretical approach was adopted to deal with resource allocation. In Refs. [22] and [24], Liang et al. researched the resource allocation in wireless cellular networks supporting virtualization. The known alternating direction method of multipliers (ADMM) algorithm was adopted to do the distributed virtual resource allocation (radio spectrum). In addition, the cellular content caching was also considered in [24]. However, the node ability was not considered in [24]. Hu et al. [23] proposed one novel virtual resource allocation framework for fixed networks supporting NFV technology. However, the focus of this paper was not proposing allocation algorithms. While in Ref. [25], Yu et al. studied the resource allocation and provision in NFV-enabled networks. The goal of Ref. [25] is to ensure the time-sensitive service. However, Yu et al. continued to focus on static services and nodes. Thus not being able to be promoted to real application. In Ref. [26], Kumar et al. considered the multi-layer resource allocation in IoV environment. Different from previous publications, Kumar et al. aimed at ensuring the quality of healthcare services. However, the attribute of mobility of end nodes were not taken into account.

Though abundant algorithm publications [12–26] were proposed to deal with virtual resource allocation, they have two main problems. The first problem is that most of these algorithms are static. That is to say, end nodes of virtual service are static. While in the 5G networks, end nodes are usually mobile. Thus, we need to consider the case where the implemented service must be continued when certain one virtual node are out of coverage. In the literature, few publications [27,28] exist. In Ref. [27], Guan et al. researched the virtual resource allocation in dynamic metro/access networks. However, one key problem exists: only considering the access resource allocation. The proposed algorithm consumes too much time. Thus being evaluated in the discrete event. While in Ref. [28], the node mobility effect was added in the resource allocation. However, the authors simply adopted the mathematical programming tool to allocate virtual resources. This means that the proposed algorithm [28] could not be used in continuous time event. The second problem is the implemented services in these publications are all one-dimensional. As we know, the network service must be multi-dimensional [29] in 5G era. In the last one mile, the connectivity must be flexible. Thus, UAVs are introduced, serving as the supplement of fixed 5G networks [30].

Different from previous studies [7–28], we research and solve both existing problems in this paper. We not only consider the node mobility

Table 1
Main mathematical symbols for physical network and virtual network service.

Dada center nodes	DC^P
Optical switching nodes	OS^P
Random access nodes	RA^P
Physical links	L^P
Virtual network service	G^V
Virtual data center nodes	VDC^V
Virtual UAVs	$VUAV^V$
Starting time of G^V	$start(G^V)$
Starting service time of G^V	$starser(G^V)$
Expiring time of G^V	$expiry(G^V)$

in virtual resource allocation research for 5G, but also adding the UAVs so as to provide the agile and multi-dimensional services. In order to remove the high time complexity, we propose the intelligent *Intell-UAV-5G*. The *Intell-UAV-5G* promises to run each virtual resource allocation within polynomial time. The *Intell-UAV-5G* consists of two sub-algorithms. One sub-algorithm is *Intell-UAV-5G-Active*. The *Intell-UAV-5G-Active* enables to predict all possible connecting access nodes and continue the implement virtual service quickly when the service interruption happens. The other sub-algorithm is *Intell-UAV-5G-Reactive*, enabling to conduct the re-allocation and assignments when the service interruption happens. In addition, we construct one novel profit model for UAVs-assisted 5G networks. Different from previous revenue models [7–11], we introduce and formulate the penalty function. From the lifecycle of each virtual service, we formulate the total profit by serving the virtual service. In addition, our profit model leaves extra space for adding more new elements. In future and complex 5G scenario, more elements consuming the revenue can be added. To validate the proposed algorithm, we do the comprehensive experiment work. We also derive two counterpart algorithms for comparison. We record and discuss the experiment results in detail.

3. Formal problem model and profit model

3.1. Formal problem model for UAVs-assisted 5G networks

In UAVs-assisted 5G networks, UAVs has the function of exchanging data and traffic flow with their connected data centers through a heterogeneous underlying physical network. The heterogeneous physical network usually consists of three parts: data center part, switching part, and random access part. Refer to Fig. 1. In the bottom of Fig. 1, we plot one underlying physical network. Within the data center part, it mainly consists of multiple data centers. With respect to the switching part, it involves multiple optical switching nodes. While in the random access part, it is made up of multiple random access nodes. Physical fiber links are deployed to connect these three parts (see Table 1).

The whole underlying UAVs-assisted 5G networks can be modeled by the weighted undirected graph $G^P = (N^P, L^P)$, where N^P and L^P represent the set of all physical nodes and physical links, respectively. With respect to the N^P set, it consists of three different kinds of physical nodes: data center nodes DC^P, optical switching nodes OS^P, and random access nodes RA^P. With respect to each data center node $dc^P \in DC^P$, it has a storage capacity $sto(dc^P)$. With respect to each random access node $ra^P \in RA^P$, it has radio channel resource $rad(ra^P)$ and a radius coverage $cov(ra^P)$. Within the coverage $cov(ra^P)$, UAV can be connected to the access node $rad(ra^P)$. Take note that multiple UAVs within the same coverage of ra^P can share the same ra^P. We do not take the inner channel interference [31] into account in this paper. With respect to each physical link $l^P \in L^P$, it has bandwidth resource $band(l^P)$. In addition, we define $Path^P$, denoting the set of loop-free physical paths in G^P.

With respect to the resource requiring to be allocated, they are usually abstracted into the resource attributes of virtual nodes and virtual links. These virtual nodes and links can be represented by a virtual network service. The virtual network service in UAVs-assisted 5G networks environment can be modeled by the undirected weighted graph $G^V = (N^V, L^V)$, where N^V and L^V represent the set of virtual nodes and virtual links, respectively. With respect to the N^V set, it is made up of two parts: virtual data center nodes part VDC^V and virtual UAVs part $VUAV^V$. With respect to each virtual data center node $vdc^V \in VDC^V$, it has a demand of virtual storage $sto(vdc^V)$. With respect to each virtual UAV node $vUAV^V \in VUAV^V$, it has requested radio channel resource $vUAV(ra^V)$ and required location $(X(vUAV^V), Y(vUAV^V))$. With respect to each virtual link in $l^V \in L^V$, it has required bandwidth $band(l^V)$. In addition, the virtual network service $G^V = (N^V, L^V)$ in UAVs-assisted 5G networks has its own time attributes: starting time $start(G^V)$, starting service time $starser(G^V)$, expiring time $expiry(G^V)$, maximum allowed interruption time $MaxInter(G^V)$, interruption time point $Inter(G^V)$, interruption ending time point $InterEnd(G^V)$.

In this paper, the virtual network service in UAVs-assisted 5G networks is represented as a line topology or a star topology. With respect to the line topology, it refers to a virtual UAV connecting a virtual data center. With respect to the star topology, it represents two different UAVs connecting a virtual data center. For better understanding, VN 1 and VN 2 are line topology and star topology in the upper part of Fig. 1, respectively. Other topologies are not taken into account in this paper. We need to take note that virtual data center nodes per virtual network service must be embedded onto data center nodes in UAVs-assisted 5G network, fulfilling storage resources. Virtual UAVs per virtual network service must be embedded onto random access nodes in UAVs-assisted 5G networks, fulfilling radio channel resources. With respect to each virtual link, it must be embedded onto one physical path, fulfilling bandwidth resource demand. In addition, both end nodes of the virtual link must be assigned to suitable data center node and random access node. Based on these, the virtual resource allocation of G^V is done. With respect to both VNs embedding and resource allocation results, they are plotted in Fig. 1.

3.2. Profit model for UAVs-assisted 5G networks

In this subsection, we formulate the profit model for UAVs-assisted 5G networks that is totally different from previous profit model [7–11]. For a better understanding, we take certain one virtual network service G^V as an example.

With allocating enough virtual resources to G^V successfully, it starts to serve the end user of G^V. The end user begins to pay for being served G^V. Hence, we can start to earn the income of G^V from end user. Its starting service time is $starser(G^V)$ while its expiring time is $expiry(G^V)$. Therefore, the total amount of income of G^V can be formulated in Expression 1.

$$\boldsymbol{Income}\left(G^V\right) = T^{G^V} \cdot \boldsymbol{Income}\left(G_t^V\right) \tag{1}$$

where T^{G^V} represents the service time of G^V (Expression 2). With respect to $\boldsymbol{Income}\left(G_t^V\right)$, it represents the income of G^V per unit time (Expression 3).

$$T^{G^V} = expiry(G^V) - starser(G^V) \tag{2}$$

$$\begin{aligned}\boldsymbol{Income}\left(G_t^V\right) = {} & \alpha(Income)\cdot \sum_{vdc^V \in VDC^V} \mathbf{sto}(vdc^V) \\ & + \beta(Income)\cdot \sum_{vra^V \in RA^V} \mathbf{rUAV}(ra^V) \\ & + \gamma(Income)\cdot \sum_{l^V \in L^V} \mathbf{band}(l^V)\end{aligned} \tag{3}$$

where $\alpha(Income)$, $\beta(Income)$, and $\gamma(Income)$ are weighting factors, aiming at balancing different virtual resources. These weighting factors also can been as the unit price of allocated resources.

Besides of considering the income of G^V, we must consider the cost of accommodating the virtual service G^V. Similar to its income formulation, the cost of G^V is formulated in Expression 4.

$$\boldsymbol{Cost}\left(G^V\right) = T^{G^V} \cdot \boldsymbol{Cost}\left(G_t^V\right) \tag{4}$$

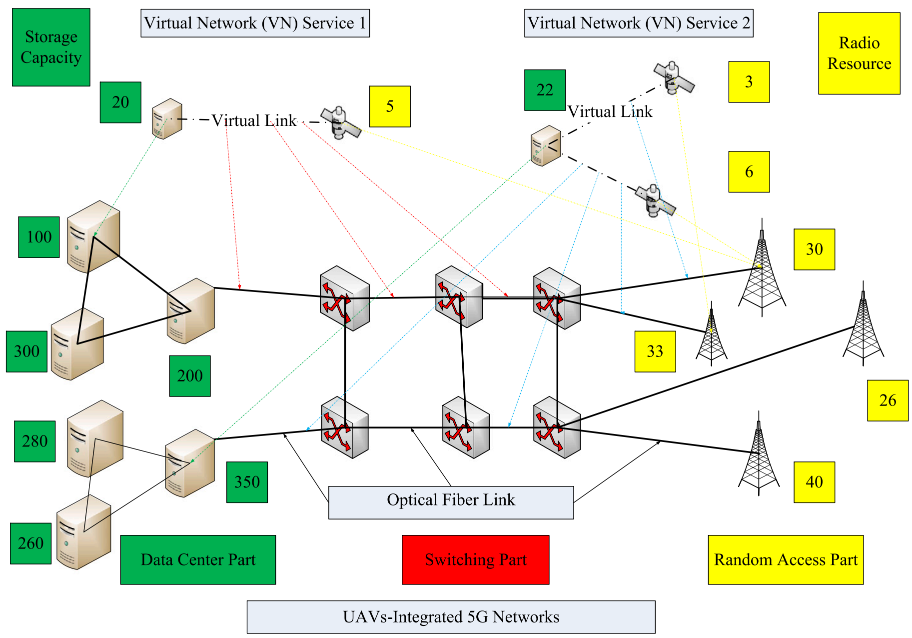

Fig. 1. Example of virtual resource allocation in UAVs-assisted 5G networks.

where T^{G^V} represents the service time of G^V (Expression 2). With respect to $\boldsymbol{Cost}\left(G_r^V\right)$, it represents the cost of accommodating G^V per unit time (Expression 5).

$$\begin{aligned}\boldsymbol{Cost}\left(G_r^V\right) = {}& \alpha(cost)\cdot\sum_{vdc^V\in VDC^V}\mathbf{sto}(vdc^V)\\ &+\beta(cost)\cdot\sum_{vra^V\in RA^V}\mathbf{rUAV}(ra^V)\\ &+\gamma(cost)\cdot\sum_{l^V\in L^V}\sum_{path^P\in Path^P} Num_{l^V}^{path^P}\cdot\mathbf{band}(l^V)\end{aligned}\tag{5}$$

where $Num_{l^V}^{path^P}$ records the number of physical links in the selected physical path that accommodates the virtual link l^V. $\alpha(Cost)$, $\beta(Cost)$, and $\gamma(Cost)$ are weighting factors, aiming at balancing different virtual resources.

Besides of G^V cost, we need to consider the extra cost for the virtual network service interruption [11]. For instance, when the UAV loses connection with its connected access physical node. The virtual service will be interrupted. To make up for the served end user, the TSP will be responsible for the service interruption and pay for the penalty. Hence, it is essential of formulate the penalty function so as to quantify the G^V service interruption. As introduced in above subsection, the interruption time $Inter(G^V)$ must not be larger than the maximum allowed interruption time $MaxInter(G^V)$. Consequently, we formulate the penalty function in Expression 6. Take note that previous profit or benefit models [7–11] had not considered quantifying the penalty yet. This penalty formulation can be seen as another highlight of this paper.

$$\boldsymbol{Penalty}\left(G^V\right) = Inter(G^V)\cdot\boldsymbol{Penalty}\left(G_r^V\right)\tag{6}$$

where $\boldsymbol{Penalty}\left(G_r^V\right)$ represents the penalty function in unit time (Expression 7).

$$\begin{aligned}\boldsymbol{Penalty}\left(G_r^V\right) = {}& \alpha\cdot\sum_{vdc^V\in VDC^V}\mathbf{sto}(vdc^V)\\ &+\alpha\cdot\sum_{vra^V\in RA^V}\mathbf{rUAV}(ra^V)+\alpha\cdot\sum_{l^V\in L^V}\mathbf{band}(l^V)\end{aligned}\tag{7}$$

where α is a small constant which is much smaller than the weights in Expression 3.

In conclusion, the profit of accommodating one virtual network service G^V during its lifespan can be calculated:

$$\begin{aligned}\boldsymbol{Profit}\left(G^V\right) = {}& \boldsymbol{Income}\left(G^V\right)-\boldsymbol{Cost}\left(G^V\right)\\ &-\boldsymbol{Penalty}\left(G^V\right)\end{aligned}\tag{8}$$

With respect to the following virtual network services, the above profit model for G^V can be adopted to record their profits during their lifetime.

4. Intelligent virtual resource allocation algorithm

This section consists of four sub-sections. We firstly adopt the programming method in order to calculate the exact and optimal allocation solution per virtual network. Then, we will detail our intelligent algorithm *Intell-UAV-5G*. The *Intell-UAV-5G* algorithm consists of two sub-algorithms: *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*. In the next two subsections, *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* are presented in both Sections 4.2 and 4.3, respectively. While in the last sub-section, we discuss the time complexity and conclude this section.

4.1. Programming method for optimal resource allocation

In the area of virtual resource allocation, the programming method is widely accepted as the approach towards exact and optimal solution [10]. Thus, we adopt the integer programming model (ILP) method to model the virtual resource for UAVs-5G networks.

In the first place, we define two kinds of binary variables. The first type of binary variables is X, indicating the relationship between virtual (UAV, data center) nodes and physical (random access, data center) nodes. The other type of binary variables is Y, indicating the relationship between virtual links between physical paths.

In the second place, it is the objective function. In this paper, we aim at minimizing the consumed physical resources for accommodating one virtual network service. This is in accordance with the goal of TSP. Minimizing the consumed resources enables to leave more space for accommodating more virtual networks. Thus improving the profit in the long run. We formulate the objective function in Expression 9.

$$\begin{aligned}Obj:\quad \boldsymbol{Cost}\left(G^V\right) = {}& \alpha(cost)\cdot\sum_{vdc^V\in VDC^V}\mathbf{sto}(vdc^V)\\ &+\beta(cost)\cdot\sum_{vra^V\in RA^V}\mathbf{rUAV}(ra^V)\end{aligned}$$

$$+\gamma(cost)\cdot\sum_{l^V\in L^V}\sum_{path^P\in Path^P}Num_{l^V}^{path^P}\cdot\mathbf{band}(l^V) \quad (9)$$

where $Num_{l^V}^{path^P}$ records the number of physical links in the selected physical path that accommodates the virtual link l^V. $\alpha(Cost)$, $\beta(Cost)$, and $\gamma(Cost)$ are weighting factors, aiming at balancing different types of virtual resources.

Thirdly, it is the constraints that must be fulfilled while we try to accommodate the G^V, ranging from Expression 10 to Expression 18.

$$\forall vdc^V\in VDC^V,\quad \sum_{dc^P}X_{dc^P}^{vdc^V}=1 \quad (10)$$

$$\forall vUAV^V\in VUAV^V,\quad \sum_{ra^P}X_{ra^P}^{vdc^V}=1 \quad (11)$$

where Expression 10 aims at ensuring each virtual DC node in the virtual network embedding onto only one physical DC node. With respect to Expression 11, it aims at ensuring that each virtual UAV in the virtual network is embedded onto only one physical random access node.

$$\forall dc^P\in DC^P,\quad \sum_{vdc^V}X_{dc^P}^{vdc^V}\le 1 \quad (12)$$

$$\forall ra^P\in RA^P,\quad \sum_{vUAV^V}X_{ra^P}^{vdc^V}\le 1 \quad (13)$$

where Expression 12 and Expression 13 aim at ensuring that at least one virtual (DC or UAV) is embedded onto one physical (DC or random access) node while doing the resource allocation. Ranging from Expression 10 to 13, we vividly show the relationship between each virtual node and each physical node.

$$\forall l^V\in L^V,\exists path^P\in Path^P,\quad \sum_{path^P}(Y_{path^P}^{l^V})=1 \quad (14)$$

where Expression 14 indicates that there must exist one isolated physical path $path^P$ for accommodating the virtual link l^V. Take note that two end nodes of virtual link l^V are embedded onto corresponding physical nodes ahead.

$$\forall dc^P\in DC^P,\quad \sum_{vdc^V}X_{dc^P}^{vdc^V}\cdot sto(vdc^P)\le sto(dc^P) \quad (15)$$

$$\forall ra^P\in RA^P,\quad \sum_{vUAV^V}X_{ra^P}^{vdc^V}\cdot vUAV(ra^V)\le rad(ra^P) \quad (16)$$

$$\boldsymbol{EuclideanDistance}(vUAV^V,ra^P)=\sqrt{\left(X(vUAV^V)-X(ra^P)\right)^2+\left(Y(vUAV^V)-X(ra^P)\right)^2}\le cov(ra^P) \quad (17)$$

where Expression 15 and Expression 16 indicate that the embedded DC node and random access node must reserve enough storage and radio resources for accommodating virtual DC node and virtual UAV node. With respect to Expression 17, it indicates that the distance between the connected random node and virtual UAV must be within the maximum allowed distance.

$$\forall l^V\in L^V,\exists path^P\in Path^P,\quad \sum_{path^P}Y_{path^P}^{l^V}\cdot band(l^V)\le band(path^P) \quad (18)$$

where Expression indicates that the accommodated physical path $path^P$ must have available bandwidth resource to allocate to the embedded virtual link l^V.

With formulating the programming model, we can use the professional software tool, such as GPLK [33], CPLEX [34], to calculate the resource allocation solution of virtual network service at certain time point. However, the fact that the programming model method has the flaw of high complexity. The complexity of ILP model is usually up

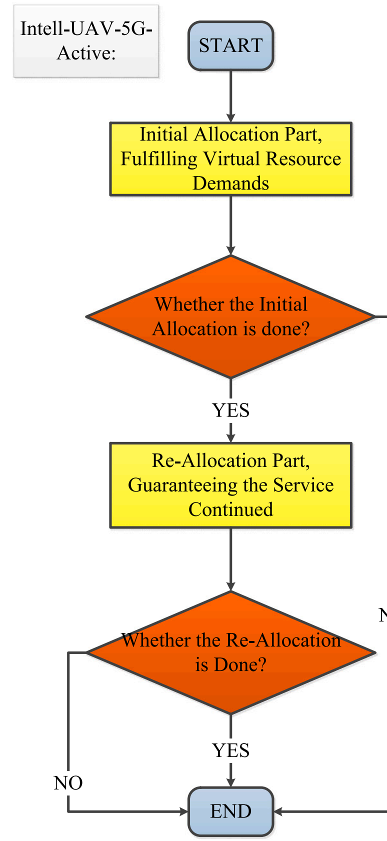

Fig. 2. Flow chart of *Intell-UAV-5G-active* sub-algorithm.

to the exponential level [32,33]. When the network scale is large, no matter physical or virtual, the number of binary variables increases. Thus further increasing the time complexity.

Though programming model method promises to achieve the optimal resource allocation, we will come into the trouble that the UAV flies into the coverage of another access point while we are calculating the previous access point. Instead, we need to propose the intelligent resource allocation algorithm. Our proposed intelligent *Intell-UAV-5G* algorithm not only provides a feasible resource allocation solution in polynomial time, but also reacts or backups the resource allocation ahead. Therefore, our *Intell-UAV-5G* is derived into two sub-algorithms: *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*.

4.2. *Intell-UAV-5G-Active sub-algorithm*

The *Intell-UAV-5G-Active* sub-algorithm consists of two parts: **Initial Resource Allocation Part** and **Resource Re-Allocation Part**. See Fig. 2. We plot the flow chart of *Intell-UAV-5G-Active*. The *Intell-UAV-5G-Active* aims at predicting all possible connecting access nodes and continue the implemented service intelligently.

Initial Resource Allocation Part:

At first, we will calculate all physical nodes' sorting values of G^P, by adopting the greedy method [5](Expression 19). Then, we will define three node sets ($Set(DC^P)$, $Set(OS^P)$, and $Set(RA^P)$) for storing different kinds of physical nodes (DC^P, OS^P, and RA^P). In each node set, physical nodes are sorted in a decreasing order.

$$\boldsymbol{Value}\left(n^P\right)=\alpha(resource)\cdot\sum_{mn^P\in N^P}\mathbf{band}(mn^P) \quad (19)$$

where n^P can be one physical DC node or switch node or random access node. $\alpha(resource)$ represents the amount of storage (DC) or radio (random access node). Each switch node is assumed to have 100 unit resources in this paper. mn^P represents one direct physical link, having end nodes of m^P and n^P. Expression 19 has the function of calculating the product of physical node n^P resource and the bandwidth sum of its adjacent links

Afterwards, we will start to complete the resource allocation and mapping of virtual data center node vdc^V. In this paper, we consider its virtual storage demand. Hence, we will select the most appropriate physical data node from $Set(DC^P)$. The greedy method is adopted to deal with the virtual data venter node vdc^V. When the storage demand of vdc^V is fulfilled by the most appropriate physical data center, the resource allocation and mapping of virtual data center vdc^V node are done.

Next, it is the resource allocation and mapping of virtual mobile UAV node $vUAV^V$. In this paper, virtual radio channel resource $vUAV(ra^V)$ and required location $(X(vUAV^V), Y(vUAV^V))$ constraints are considered. In order to select the appropriate access node for connecting $vUAV^V$, we adopt the greedy method. We will select the most appropriate access node ra^P from $Set(RA^P)$, fulfilling virtual UAV radio resource and location demands. Especially, the distance between the virtual UAV $vUAV^V$ and mapped access node ra^P $(X(ra^P), Y(ra^P))$ must be within the radius coverage $cov(ra^P)$ (Expression 20).

$$\begin{aligned}&\boldsymbol{EuclideanDistance}(vUAV^V, ra^P) =\\&\sqrt{\left(X(vUAV^V) - X(ra^P)\right)^2 + \left(Y(vUAV^V) - X(ra^P)\right)^2}\\&\le cov(ra^P)\end{aligned} \tag{20}$$

With completing the virtual data center mapping and UAV node mapping successfully, we will continue to map the virtual link l^V. With respect to the virtual link resource allocation and embedding of l^V, we adopt the universal shortest path approach to find the suitable physical path between mapped data center node and access node. We need to take note that the physical path having the minimum number of intermediate optical switching nodes will be selected. In addition, the selected path must reserve enough bandwidth resource for accommodating l^V. If the shortest physical path is not suitable, we will find the second shortest path. We will stop until the suitable path is found. Otherwise, we will reject the G^V.

Above all procedures are the initial allocation of our *Intell-UAV-5G-Active*. We name this part as *Intell-UAV-5G-Active-Ini*. Derived from previous publication [34], the *Intell-UAV-5G-Active-Ini* can complete the allocation within polynomial time.

Resource Re-Allocation Part:

Though completing the initial resource allocation and mapping of virtual network, the virtualized UAV will fly within its lifespan. The virtualized UAV will fly from one position to another position. To get rid of virtual network service interruption and ensure continuous data transmission, we need to make the virtual network service continued. Hence, we propose the re-allocation part, named as *Intell-UAV-5G-Active-Re*. The *Intell-UAV-5G-Active-Re* aims at predicting the UAV possible connecting access nodes and driving the virtual service re-allocation. In this paper, we set the UAV flying trajectory in a straight line. The flying speed is fixed and defined to be $speed$.

With respect to our *Intell-UAV-5G-Active-Re*, it consists of two following sub-parts:

(1) *Predict Virtualized UAV Possible Connecting Access Nodes*: We still take the allocated and mapped G^V as the example. As presented in above subsection, it has a virtual UAV node $vUAV^V$, mapped onto the access node ra^P. We firstly calculate the Euclidean Distances between $vUAV^V$ with remaining random access nodes in $Set(RA^P)$, by adopting Expression 9. Then, we define another set $DisSet(vUAV^V)$ for storing these distance values. In addition, we introduce one time unit t_0. Next, we will the product of $speed$ and t_0. Consequently, we can regard the mapped $vUAV^V$ as a circle center. The circle has a radius of $(speed * t_0)$. Afterwards, we will let all values in $DisSet(vUAV^V)$ set minus $(speed * t_0)$. We will select four lowest values and their corresponding access nodes. In addition, we will add the value of $[\boldsymbol{EuclideanDistance}(vUAV^V, ra^P) - (speed * t_0)]$. Therefore, these five access nodes will be the possible connecting access nodes of $vUAV^V$ in the next time unit. We will store these five access nodes in a new defined Possible Connected Access Node Set $PCASet(vUAV^V)$. With respect to the pseudo codes of this sub-part, we present them in Algorithm 1.

Algorithm 1 The Method of Finding UAV Possible Connecting Access Nodes

Input: UAV speed $speed$, a time unit t_0
Output: Possible Connected Access Node Set $PCASet(vUAV^V)$
1: Define one value set $DisSet(vUAV^V)$, having no element.
2: Define an integer k, $k = 0$.
3: Excluding the ra^P form $Set(RA^P)$ set.
4: Define an integer ϵ, its value is $|Set(RA^P)|$.
5: **while** $\epsilon \le \delta$ **do**
6: $\quad k = k + 1$;
7: $\quad \boldsymbol{EuclideanDistance}(vUAV^V, ra_k^P) = \boldsymbol{EuclideanDistance}(vUAV^V, ra_k^P) - (speed * t_0)$;
8: $\quad$ Add the value of $\boldsymbol{EuclideanDistance}(vUAV^V, ra_k^P)$ into $DisSet(vUAV^V)$ set;
9: **end while**
10: Select the four lowest value form $DisSet(vUAV^V)$ set and their corresponding access nodes.
11: Add the ra^P and store five access nodes into Possible Connected Access Node Set. $PCASet(vUAV^V)$
12: Output the $PCASet(vUAV^V)$.

(2) *Ensure Implemented Virtual Service Continued*: With achieving the Possible Connected Access Node Set $PCASet(vUAV^V)$ successfully, we will determine which concrete access node connects the virtual UAV node in the next time unit. If the value of $\boldsymbol{EuclideanDistance}(vUAV^V, ra^P)$ is the lowest among all five access nodes, we will select the virtual UAV to connected to ra^P. Consequently, the allocated resources will remain. No further change is required. If the value of certain $\boldsymbol{EuclideanDistance}(vUAV^V, ra_k^P)$ is the lowest, we will need to update and re-allocate virtual radio channel resource to the virtual UAV node in the next time unit. We will map the virtual UAV onto the appropriate access node ra_k^P. In addition, the virtual UAV will lose connection with previous access node ra^P. We need to take note that ra_k^P must reserve enough radio resource. Otherwise, we will select the other suitable access node from remaining access nodes in $PCASet(vUAV^V)$ set.

Above two sub-parts will repeat in the next time unit. We will monitor the possible connecting access nodes for the virtual UAV until the virtual service G^V expires. We aim at ensuring each implemented virtual network service continued. Derived from Ref. [33] and Ref. [34], above two sub-parts of *Intell-UAV-5G-Active* can be completed within polynomial time.

4.3. Intell-UAV-5G-Reactive sub-algorithm

The *Intell-UAV-5G-Reactive* has the function of recovering the implemented service immediately when the service interruption happens. The *Intell-UAV-5G-Reactive* consists of two parts: **Initial Resource Allocation Part** and **Reactive Re-Allocation Part**. With respect to its flow chart, we plot Fig. 3.

With respect to the **Initial Resource Allocation Part**, its details are same to the details in above sub-section. With respect to the **Reactive Re-Allocation Part**, it can be seen as another **Initial Resource Allocation Part**. It works when the virtual UAV moves to lose the connection with its previous connected random access physical point. For saving space, we do not repeat the details again.

As discussed in above sub-section, **Initial Resource Allocation Part** can be completed within polynomial time [34]. With respect to the **Reactive Re-Allocation Part**, its complexity is approaching that of **Initial Resource Allocation Part**. Therefore, **Reactive Re-Allocation Part** is another polynomial-time procedure [34].

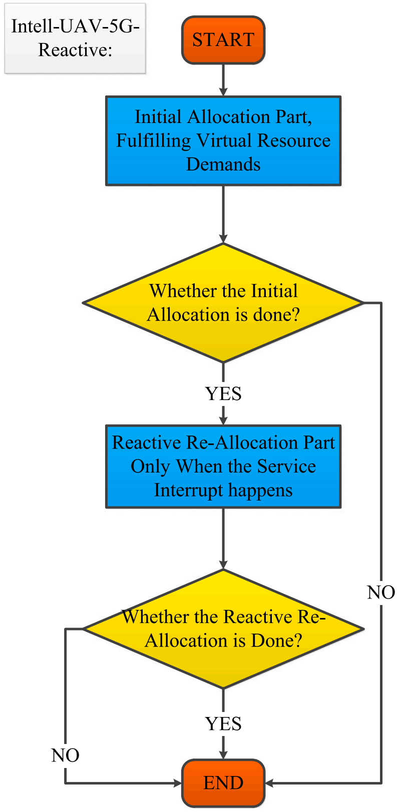

Fig. 3. Flow chart of *Intell-UAV-5G-Reactive* sub-algorithm.

4.4. Complexity discussion of intelligent intell-UAV-5G

As presented in Sections 4.2 and 4.3, we discussed the details of *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*. With respect to *Intell-UAV-5G-Active*, its complexity consists of initial allocation part and re-allocation part. While in each part, its complexity is at the polynomial level. Thus, our intelligent *Intell-UAV-5G-Active* is a polynomial-time algorithm. When serving one given virtual network and allocating its resources, *Intell-UAV-5G-Active* will not incur too much time.

With respect to the complexity of *Intell-UAV-5G-Reactive*, it is lower than that of *Intell-UAV-5G-Active*. It is owing to the fact that *Intell-UAV-5G-Reactive* works when the virtual UAV comes into interruption. *Intell-UAV-5G-Active* always works, no matter service continued or interrupted. Thus, the intelligent *Intell-UAV-5G-Reactive* sub-algorithm is another polynomial-time algorithm.

Based on above discussion, our *Intell-UAV-5G* is an intelligent algorithm, without involving too much time.

4.5. Discussion of balance between the intelligence and the exact

As presented in above subsections, the ideal situation is that the exact algorithm can serve as the intelligent and convenient algorithm for allocating and re-allocating virtual resource demands per virtual network service.

However, one key technical flaw exists in the exact algorithm category. The key flaw is the high algorithm complexity of the exact algorithm. Since the exact algorithm is based on the programming model approach, its searchable solution space is too large. It is hard to find the most intelligent and efficient solution within limited time. Thus, it will consume too much time to find the initial resource allocation assignment. If the virtual service interruption happens, it will incur much extra time to re-allocate the resource allocation assignment. This cannot be adopted to the real dynamic networking environment. It lies in the fact that demands and topology of future network service vary from time to time. It is of importance to realize the resource allocation in the intelligent way.

Therefore, it is necessary to do the initial resource and re-allocation in the intelligent manner. Meanwhile, the consumed time of allocating virtual resources must be minimized. The allocation quality must be guaranteed, too. It is necessary to achieve the balance between the intelligence and the exact.

5. Experiment evaluation

5.1. Experiment settings

In this section, we plan to highlight our *Intell-UAV-5G* by conducting the experiments. With respect to the scale of underlying physical network, it has 100 physical nodes, including 5 data center nodes, 6 optical switching nodes, and 89 access nodes. All physical nodes are uniformly distributed in a two-dimensional plane of 5000*5000. Each pair of physical nodes, within its node type, has a connectivity possibility of 0.5. With respect to the storage of each data center node, it is an integer following the uniform distribution between 300 and 500. With respect to the radio channel resource of each access node, it is an integer uniformly distributed between 10 and 15. In addition, each access node has a coverage radius of 500. With respect to each substrate link, connecting underlying physical nodes, its bandwidth is an integer, uniformly between 200 and 300.

With respect to each virtual network service, its topology is fixed, as described in Section 2. Each virtual network topology can be line or star. With respect to each virtual data center node, its required storage is an integer uniformly between 20 and 30. With respect to each virtualized UAV node, its required radio resource is an integer, uniformly distributed between 2 and 5. With respect to each virtual link, it has a bandwidth demand, uniformly distributed between 10 and 30. Each virtual network service has a maximum allowed interruption time of 3 time units. In addition, virtual network services arrive following the Poisson distribution. The virtual network arrival rate is set 5 every 100 time units. An exponentially distributed lifetime, having an average value of 10 time units, is defined for each virtual network. The experiment runs up to 10 000 time units. With respect to weights in Expression 3, they are all set to be 1. With respect to weights in Expression 5, they are all set to be 0.3. With respect to weights in Expression 7, they are all set to be 0.1. We detail these parameters so as to be easily re-produced by following researchers [35–37].

Since no related algorithm has been proposed in the literature [11], we derive our *Intell-UAV-5G* into two extra versions. With respect to the first version, it is labeled as *UAV-5G-Ver1*. The *UAV-5G-Ver1* conducts the virtual resource allocation without considering UAV mobility. With respect to the second version, it is *UAV-5G-Ver2*. The *UAV-5G-Ver2* conducts the allocation of virtual network service with considering the UAV mobility. Thus, four algorithms in total make up our experiment.

5.2. Experiment discussion

In this subsection, we plot and discuss the experiment results. Figs. 4–6 and TSP income results, virtual network acceptance ratio, and TSP penalty results, respectively.

In Fig. 4, we plot the income results of all selected four algorithms. Derived from Fig. 4, we can draw the apparent conclusion that our intelligent *Intell-UAV-5G* algorithm (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) achieves more allocation income than the two remaining virtual resource allocation algorithms (*UAV-5G-Ver1* and *UAV-5G-Ver2*). The better performed algorithm is the *UAV-5G-Ver2* that considers the UAV mobility. Hence, we mainly talk about the performance gap between our *Intell-UAV-5G* and *UAV-5G-Ver2*. Throughout the experiment time, we can achieve two discoveries. With respect to the first discovery, it is that the income gap between our *Intell-UAV-5G*

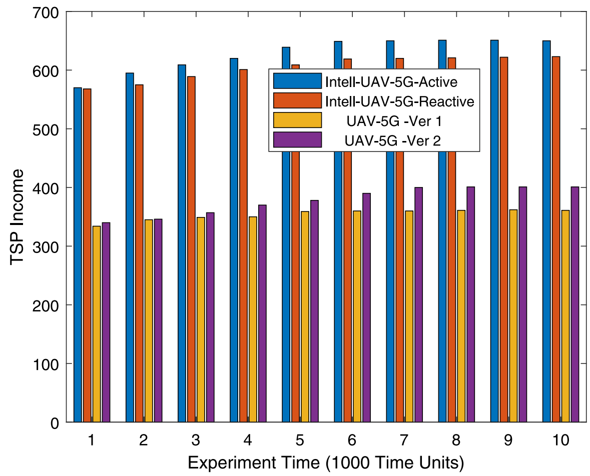

Fig. 4. Income results of TSP.

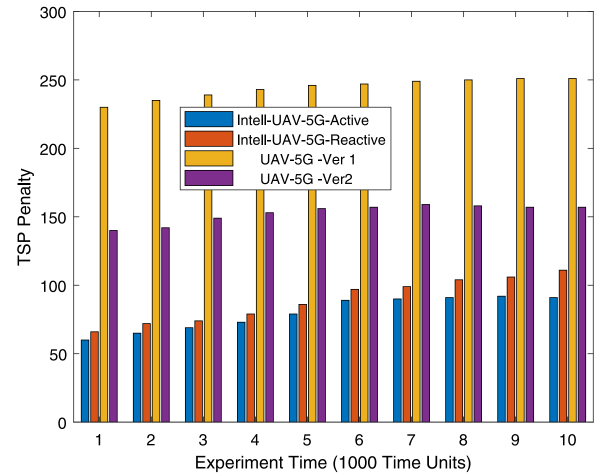

Fig. 6. Penalty results of TSP.

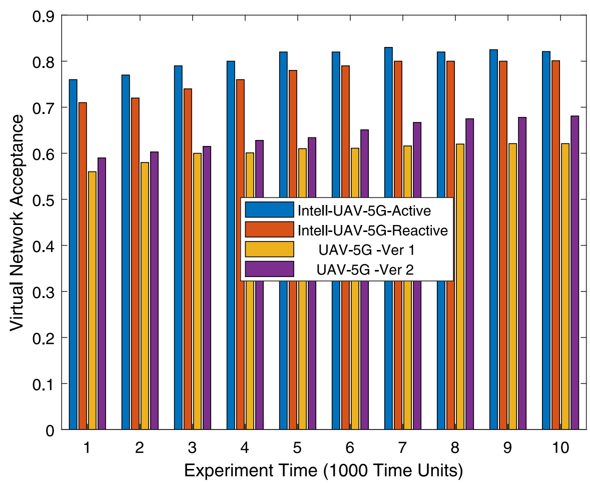

Fig. 5. Virtual network service acceptance of TSP.

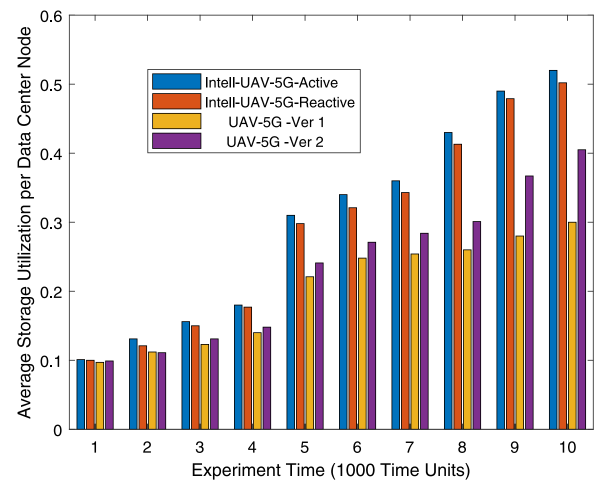

Fig. 7. Average storage resource utilization results.

and *UAV-5G-Ver2* is becoming larger in the first stage of experiment. The reason for this income gap is that our *Intell-UAV-5G*, especially our *Intell-UAV-5G-Active*, considers and predicts the UAV movement ahead. Hence, our *Intell-UAV-5G* has a higher probability to accommodate more virtual network services and ensure implemented services run. In contrast, *UAV-5G-Ver2* simply considers the mobile UAV in the first time where the resource allocation is conducted. Therefore, the service interruption will happen when the UAV flies out of the coverage of previous connected access point. Correspondingly, more penalties are incurred. The income gap becomes larger in the early stage. That is to say, our intelligent algorithm can flexibly allocate resources and continue the services, comparing with the existing rigidity. With experiment time extending, the performance gap will achieve a stable state. The cause of this stable gap is the fact that new arriving and expiring virtual network services and new released resources will achieve the balance.

With respect to the virtual service acceptance ratio results, we plot Fig. 5. Apparently, our *Intell-UAV-5G* (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) achieves the highest acceptance throughout the whole experiment. The performance advantage is in accordance with the income advantage in Fig. 4. That is to say, our intelligent algorithm contributes to accommodating more network services. Virtual network acceptance ratio metric can reveal the profit metric directly. If accommodating more and more requested virtual services, it means that more physical resources are allocated successfully. Thus, more end users are served successfully. These users will pay more income to TSP. Thus, profit of TSP will be increasing. Till 10 000 time unit point, the virtual service acceptance ratio of our *Intell-UAV-5G* (*Intell-UAV-5G-Active*) is approaching 0.821. The better performed *UAV-5G-Ver2* algorithm is close to 0.681. Apparently, our *Intell-UAV-5G* has an apparent advantage of around 14%.

In Fig. 6, it is the penalty results of TSP, recording the amount of punishments for virtual service interruption. We can easily find the fact that *UAV-5G-Ver1* incurs the largest amount of penalty among all three algorithms. The *UAV-5G-Ver1* does not contain the re-allocation part, just aiming at completing initial virtual resource allocation and mapping. With respect to the *UAV-5G-Ver1*, it achieves the second highest penalty results. Though considering the UAV mobility, it ignores dealing with the service interruption. In Fig. 6, our *Intell-UAV-5G* (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) incurs the least amount of penalties. This is in accordance of the results in Fig. 5. Since our *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* can recover the service in an intelligent manner, our *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* avoids paying extra penalties. Our *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* considers the re-allocation, no matter active ore reactive. That is to say, the results in Fig. 5 prove our *Intell-UAV-5G* efficiency indirectly. In general, our *Intell-UAV-5G* is an intelligent algorithm, not only providing efficient resource allocation assignments, but also recovering the implemented services quickly.

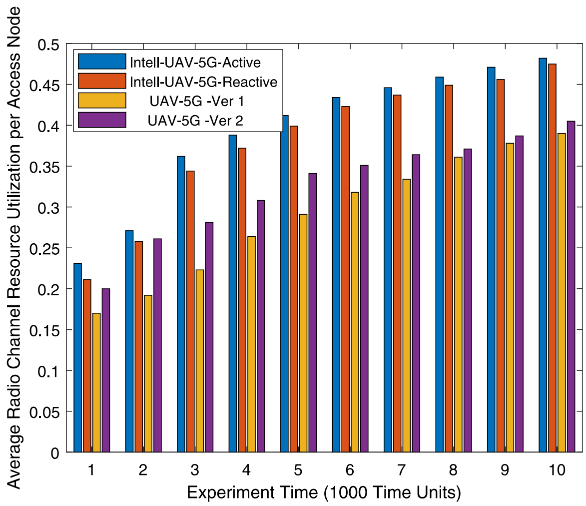

Fig. 8. Average radio channel utilization results.

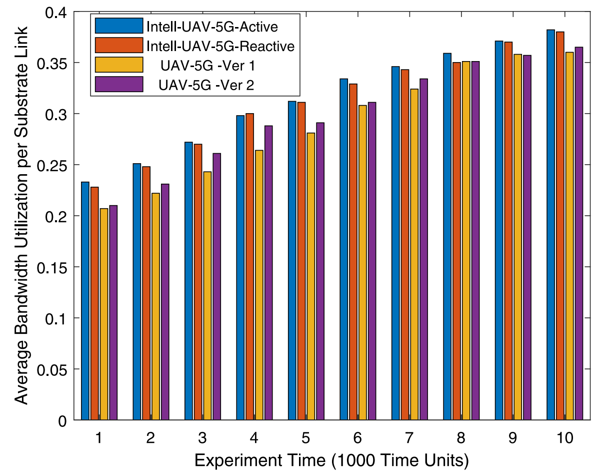

Fig. 9. Average bandwidth utilization results.

Besides of discussing the profit related metrics, we need to measure the resource consumption results. We aim at having a full knowledge of our intelligent *Intell-UAV-5G*. From Figs. 7 to 9, we plot the resource consumption results (storage resource utilization, radio channel resource utilization, and substrate link bandwidth utilization). We will discuss the results in the following paragraphs.

In Fig. 7, we plot the average storage resource utilization results of all four algorithms. Apparently, we can draw two apparent conclusions. With respect to the first conclusion, it is that our *Intell-UAV-5G* algorithm (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) consumes the largest amount of storage resources among three algorithms. As discussed in Fig. 5, our *Intell-UAV-5G* achieves the highest acceptance results. Therefore, our *Intell-UAV-5G* will consume more substrate resources than remaining two algorithms (*UAV-5G-Ver1* and *UAV-5G-Ver2*). With respect to the second conclusion, it is the storage resource gap is becoming larger, with experiment extending. Since our intelligent *Intell-UAV-5G* predicts all possible access substrate nodes and guarantee re-allocation quality, more virtual services can be accommodated. Consequently, the storage resources can be utilized efficiently. With respect to two compared algorithms (*UAV-5G-Ver1* and *UAV-5G-Ver2*), the quality of re-allocation cannot be guaranteed. Thus leading to lower acceptance. In the end, the lower storage utilization will be achieved.

In Fig. 8, we plot the average radio channel utilization results of all four algorithms. Similar to the results discussion of Fig. 7, we can draw two apparent conclusions. The first conclusion is that our *Intell-UAV-5G* (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) consumes more radio resources than remaining two algorithms. The reason for this conclusion has been talked in above paragraph. Since *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* achieve higher acceptance ratio, more access nodes will be occupied. Therefore, *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive* will consume more amount of radio resources than the two algorithms.

The second conclusion is that it is necessary to conduct the re-allocation when the mobile UAV node moves out of the range of previous connected access substrate node. Derived from Fig. 8, *UAV-5G-Ver1*, ignoring UAV mobility and re-allocation, achieves the lowest radio resource utilization. If considering re-allocation, the radio resource utilization will be improved. With respect to the *UAV-5G-Ver2*, considering UAV mobility while ignoring re-allocation, achieves the second lowest radio resources. The results show us that predicting ahead or react to service interruption is very essential. In order to allocate resources efficiently and continue the implemented services, it is important to intelligently consider mobility.

In Fig. 9, we plot the average link bandwidth utilization of all four algorithms. Though our *Intell-UAV-5G* (*Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*) continues to achieve the highest bandwidth utilization, the gap advantage is not apparent than the node resource consumption results. It is owing to the link mapping strategy. The link mapping and bandwidth resource strategy of all four algorithms are similar. Thus having similar behaviors. Since our *Intell-UAV-5G* accepts more requested virtual services, our *Intell-UAV-5G* has the highest link bandwidth resource utilization.

6. Conclusion work

In order to expand the service coverage of 5G networks and implement the resource allocation in an intelligent manner, we research the virtual resource allocation problem in virtualized UAVs-assisted 5G networks. An intelligent algorithm *Intell-UAV-5G* is proposed in this paper.

The Problem model and profit model for UAVs-5G networks are firstly constructed. We also introduce the penalty function in the profit model which is the first attempt in VNE research area. Then, the *Intell-UAV-5G* algorithm is detailed. The *Intell-UAV-5G* consists of two sub-algorithms: *Intell-UAV-5G-Active* and *Intell-UAV-5G-Reactive*, enabling to predict all possible connecting access nodes of virtual UAV and continue the implemented network services. To demonstrate our *Intell-UAV-5G*, we record, plot and discuss the experiment results. For example, our *Intell-UAV-5G* has an apparent virtual service acceptance ratio advantage of around 14% than the derived algorithms.

In the next research stage, we will try to research the trajectory effect on the quality of virtual resource allocation [38–40] in the first place. In this paper, we simply consider the straight trajectory [41]. Thus requiring studying a more complex trajectory. Secondly, we will introduce the third dimension (3-D) [42]. Considering the 3-D nature [43,44], the virtual resource allocation algorithms have the potential to be promoted to real application. Thirdly, we will incorporate the detailed wireless resources (spectrum, power) to be allocated. Heterogeneous resources [45,46] require to be allocated in 5G era.

CRediT authorship contribution statement

Haotong Cao: Software, Validation, Writing - review & editing. **Yue Hu:** Investigation, Editing. **Longxiang Yang:** Resources, Project administration, Supervision.

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.

Acknowledgments

Some preliminary results [47] were partly presented in 2020 IEEE International Conference on Communications (IEEE ICC 2020), June 7–11, 2020, Dublin, Ireland. The authors would like to thank the associate editor and assigned reviewers for their excellent work and constructive comments, which improved the paper quality. The paper was partly supported by National Key Research and Development Program of China under Grant 2018YFC1314903, National Natural Science Foundation of China under Grant 61372124 and 61427801, and 62071246.

References

[1] J.G. Andrews, et al., What will 5G be? IEEE J. Sel. Areas Commun. 32 (6) (2014) 1065–1082.
[2] S. Garg, A. Singh, S. Batra, N. Kumar, L. Yang, UAV-empowered edge computing environment for cyber-threat detection in smart vehicles, IEEE Netw. 32 (3) (2018) 42–51.
[3] M. Maier, M. Chowdhury, B. Rimal, D. Van, The tactile internet: Vision, recent progress, and open challenges, IEEE Commun. Mag. 54 (5) (2016) 138–145.
[4] Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2015-2020, white paper, Cisco, 2016.
[5] A. Jindal, G. Aujla, N. Kumar, SURVIVOR: A blockchain based edge-as-a-service framework for secure energy trading in SDN-enabled vehicle-to-grid environment, 153 (2019) 36–48.
[6] G.S. Aujla, R. Chaudhary, N. Kumar, J. Rodrigues, A. Vinel, Data offloading in 5G-enabled software-defined vehicular networks: A stackelberg-game-based approach, IEEE Commun. Mag. 55 (8) (2017) 100–108.
[7] H. Cao, H. Hu, Z. Qu, L. Yang, Heuristic solution of virtual network embedding: A survey, China Commun. 15 (3) (2018) 186–219.
[8] R. Mijumbi, J. Serrat, J. Gorricho, N. Bouten, F. Turck, R. Boutaba, Network function virtualization: State-of-the-art and research challenges, IEEE Commun. Surv. Tutor. 18 (1) (2016) 236–262.
[9] E.J. Davalos, B. Baran, A survey on algorithmic aspects of virtual optical network embedding for cloud networks, IEEE Access 6 (1) (2018) 20893–20906.
[10] H. Cao, S. Wu, Y. Hu, Y. Li, L. Yang, A survey of embedding algorithms for virtual network embedding, China Commun. 16 (12) (2019) 1–33.
[11] H. Cao, L. Yang, Z. Liu, M. Wu, Exact solutions of VNE: A survey, China Commun. 13 (6) (2016) 48–62.
[12] D. Dietrich, A. Rizk, P. Papadimitriou, Multi-provider virtual network embedding with limited information disclosure, IEEE Trans. Netw. Serv. Manage. 12 (2) (2015) 188–201.
[13] H. Cao, L. Yang, H. Zhu, Novel node-ranking approach and multiple topology attributes-based embedding algorithm for single-domain virtual network embedding, IEEE Internet Things J. 5 (1) (2018) 108–120.
[14] H. Cao, Y. Hu, Q. Wang, S. Wu, L. Yang, A blockchain-based virtual network embedding algorithm for secure software-defined networking, in: Proc. IEEE INFOCOM WKSHPS, 2020, pp. 1–6.
[15] L. Gong, H. Jiang, Y. Wang, Z. Zhu, Novel location constrained virtual network embedding (LC-VNE) algorithms towards integrated node and link mapping, IEEE/ACM Trans. Netw. 24 (6) (2016) 3648–3661.
[16] J. Zhang, Y. Ji, M. Song, H. Li, R. Gu, Y. Zhao, J. Zhang, Dynamic virtual network embedding over multilayer optical networks, J. Opt. Commun. Netw. 7 (9) (2015) 918–927.
[17] H. Cao, S. Wu, G.S. Aujla, Q. Wang, L. Yang, H. Zhu, Dynamic embedding and quality of service-driven adjustment for cloud networks, IEEE Trans. Ind. Inform. 16 (2) (2020) 1406–1416.
[18] P. Han, Y. Liu, L. Guo, Qos satisfaction aware and network reconfiguration enabled resource allocation for virtual network embedding in fiber-wireless access network, Comput. Netw. 143 (2018) 30–48.
[19] Z. Wang, J. Wu, Z. Guo, G. Cheng, H. Hu, Secure virtual network embedding to mitigate the risk of covert channel attacks, in: 2016 IEEE INFOCOM WKSHPS, 2016, pp. 1–2.
[20] Y. Yuan, C. Wang, S. Peng, K. Sood, Topology-oriented virtual network embedding approach for data centers, IEEE Access 7 (2019) 2429–2438.
[21] K. Kaur, A. Dua, A. Jindal, N. Kumar, M. Singh, A. Vinel, A novel resource reservation scheme for mobile PHEVs in V2G environment using game theoretical approach, IEEE Trans. Veh. Technol. 64 (12) (2015) 5653–5666.
[22] C. Liang, F.R. Yu, Distributed resource allocation in virtualized wireless cellular networks based on ADMM, in: 2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), 2015, pp. 360–365.
[23] Y. Hu, S. Lou, S. Wu, L. Yang, Service function chain embedding framework for NFV-enabled IoT application, in: 2020 IEEE/CIC International Conference on Communications in China (ICCC Workshops), 2020, pp. 80–84.
[24] C. Liang, F.R. Yu, H. Yao, Z. Han, Virtual resource allocation in information-centric wireless networks with virtualization, IEEE Trans. Veh. Technol. 65 (12) (2016) 9902–9914.
[25] H. Yu, J. Yang, C. Fung, Fine-grained cloud resource provisioning for virtual network function, IEEE Trans. Netw. Serv. Manage. 17 (3) (2020) 1363–1376.
[26] N. Kumar, K. Kaur, A. Jindal, J. Rodrigues, Providing healthcare services on-the-fly using multi-player cooperation game theory in Internet of Vehicles (IoV) environment, Digit. Commun. Netw. 1 (3) (2015) 191–203.
[27] Y. Guan, Y. Zong, Y. Liu, L. Guo, Z. Ning, J. Rodrigues, Virtual network embedding supporting user mobility in 5G metro/access networks, in: 2019 IEEE Int. Conf. Commun. (ICC), 2019, pp. 1–7.
[28] G. Chchlidakis, V. Friderkos, Mobility aware virtual network embedding, in: 2015 IEEE Conference on Communications (ICC), 2015, pp. 1–6.
[29] N. Motlagh, M. Bagaa, T. Taleb, UAV-based IoT platform: A crowd surveillance use case, IEEE Commun. Mag. 55 (2) (2017) 128–134.
[30] R. Bali, N. Kumar, Secure clustering for efficient data dissemination in vehicular cyber–physical systems, Future Gener. Comput. Syst. 56 (2016) 476–492.
[31] J. Li, F.R. Yu, G. Deng, C. Luo, Z. Ming, Q. Yan, Industrial internet: A survey on the enabling technologies, applications and challenges, IEEE Commun. Surv. Tutor. 19 (3) (2017) 1504–1526.
[32] R. Chaudhary, N. Kumar, S. Zeadally, Network service chaining in fog and cloud computing for the 5G environment: Data management and security challenges, IEEE Commun. Mag. 55 (11) (2017) 114–122.
[33] T.H. Cormen, C. Stein, R. Rivest, C. Leiserson, Introduction to Algorithms, second ed., McGraw-Hill Higher Education, 2001.
[34] M. Newman, Networks: An Introduction, Oxford University Press, Oxford, UK, 2010.
[35] H. Cao, S. Hu, L. Yang, New functions added to ALEVIN for evaluating virtual network embedding, in: 2016 IEEE Internation Conference on Computer and Communications, 2016, pp. 2411–2414.
[36] E. Zegura, K. Calvert, S. Bhattacharjee, How to model an internetwork, in: Proc. IEEE INFOCOM, 1996, pp. 594–602.
[37] [Online], Simulation Platform for Scotfield Cao, 2018, Available: http://pan.baidu.com/s/1gekPZrl.
[38] H. Cao, S. Wu, Y. Hu, R. Mann, Y. Li, L. Yang, H. Zhu, An efficient energy cost and mapping revenue strategy for inter-domain NFV-enabled networks, IEEE Internet Things J. 7 (7) (2020) 5723–5736.
[39] Y. Zeng, R. Zhang, T.J. Lim, Throughput maximization for uavenabled mobile relaying systems, IEEE Trans. Commun. 64 (12) (2016) 4983–4996.
[40] S. Garg, K. Kaur, N. Kumar, J. Rodrigues, Hybrid deep-learning-based anomaly detection scheme for suspicious flow detection in SDN: A social multimedia perspective, IEEE Trans. Multimedia 21 (3) (2019) 566–578.
[41] Q. Wu, Y. Zeng, R. Zhang, Joint trajectory and communication design for multi-uav enabled wireless networks, IEEE Trans. Wirel. Commun. 17 (3) (2018) 2109–2121.
[42] H. Cao, S. Wu, Y. Guo, H. Zhu, L. Yang, Mapping strategy for virtual networks in one stage, IET Commun. 13 (14) (2019) 2207–2215.
[43] M. Alzenad, A. El-Keyi, F. Lagum, H. Yanikomeroglu, 3-d placement of an unmanned aerial vehicle base station (uav-bs) for energyefficient maximal coverage, IEEE Wirel. Commun. Lett. 6 (4) (2017) 434–437.
[44] H. Cao, Y. Zhu, G. Zheng, L. Yang, A novel optimal mapping algorithm with less computational complexity for virtual network embedding, IEEE Trans. Netw. Serv. Manage. 15 (1) (2018) 356–371.
[45] D. He, M. Ma, S. Zeadally, N. Kumar, K. Liang, Certificateless public key authenticated encryption with keyword search for industrial internet of things, IEEE Trans. Ind. Inform. 14 (8) (2017) 3618–3627.
[46] H. Cao, A. Xiao, Y. Hu, P. Zhang, S. Wu, L. Yang, On virtual resource allocation of heterogeneous networks in virtualization environment: A service oriented perspective, IEEE Trans. Netw. Sci. Eng. 7 (4) (2020) 1–13.
[47] H. Cao, S. Wu, Y. Hu, G. Aujla, L. Yang, Virtual resource allocation for tactile and flexible services in UAVs-integrated 5G networks, in: 2020 IEEE Int. Conf. Commun., 2020, pp. 1–6.

Haotong Cao received the B.S. Degree in Communication Engineering from Nanjing University of Posts and Telecommunications (NJUPT) in 2015. He received the Ph.D. Degree in Communication and Information Systems from NJUPT, China, in 2020. He was a visiting scholar of Loughborough University, U.K. in 2017. He is now the Postdoc in The Hong Kong Polytechnic University, P.R. China. He has served as the TPC member of multiple IEEE conferences, such as IEEE INFOCOM, IEEE ICC, IEEE Globecom. He is also serving as the reviewer of multiple academic journals, such as IEEE/ACM Transactions on Networking, (Elsevier) Computer Networks, IEEE Transactions on Network and Service Management, and IEEE Transactions on Network Science and Engineering. He has published multiple IEEE Trans./Journal/Magazine papers since 2016. His research interests include wireless communication theory, resource allocation in wired and wireless networks. He was awarded the Postgraduate National Scholarship of China in 2018.

Yue Hu received the B.S. Degree in Network Engineering from Nanjing University of Posts and Telecommunications in 2013, the M.S. Degree in Electronic and Communication Engineering from Nanjing University of Posts and Telecommunications, Nanjing, China, in 2016, and the M.S. Degree in Communication Engineering from Melbourne University, Melbourne, Australia, in 2015. She is currently working in China Mobile Communications Group Jiangsu Co., Ltd. Her research interests include Internet of Things technology.

Longxiang Yang is currently with the College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications (NJUPT), Nanjing, China. He is a Full Professor and Doctoral Supervisor of NJUPT. He is also the head of College of Telecommunications and Information Engineering, NJUPT. He has fulfilled multiple National Natural Science Foundation projects of China. He has authored and co-authored over 200 technical papers published in various journals and conferences. His research interests include cooperative communication, network coding, wireless communication theory, 5G mobile communication systems, ubiquitous networks and Internet of things.