A Contract Theory-based Incentive Mechanism for UAV-enabled VR-based Services in 5G and Beyond

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***Abstract*—The proliferation of novel infotainment services such as Virtual Reality(VR)-based services has fundamentally changed the existing mobile networks. These bandwidth-hungry services expanded at a tremendously rapid pace, thus, generating a burden of data traffic in the mobile networks. To cope with this issue, one can use Multi-access Edge Computing (MEC) to bring the resource to the edge. By doing so, we can release the burden of the core network by taking the communication, computation, and caching resources nearby the end-users (UEs). Nevertheless, due to the vast adoption of VR-enabled devices, MEC resources might be insufficient in peak times or dense settings. To overcome these challenges, we propose a system model where the service provider (SP) might rent Unmanned Area Vehicles (UAVs) from UAV service providers (USPs) to serve as micro-based stations (UBSs) that expand the service area and improve the spectrum efficiency. In which, UAV can pre-cached certain sets of VR-based contents and serve UEs via air-to-ground (A2G) communication. Furthermore, future intelligent devices are capable of 5G and B5G communication interfaces, and thus, they can communicate with UAVs via A2G links. By doing so, we can significantly reduce a considerable amount of data traffic in mobile networks. In order to successfully enable such kinds of services, an attractive incentive mechanism is required. Therefore, we propose a contract theory-based incentive mechanism for UAV-assisted MEC in VR-based infotainment services, in which the MEC offers an amount reward to a UAV for serving as a UBS in a specific location for certain time slots. We then derive an optimal contract-based scheme with individual rationality and incentive compatibility conditions. The numerical findings show that our proposed approach outperforms the Linear Pricing (LP) technique and is close to the optimal solution in terms of social welfare. Additionally, our proposed scheme significantly enhanced the fairness of utility for UAVs in asymmetric information problems.**

***Index Terms*—Augmented reality, Virtual reality, contract theory, computational caching.**

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Manuscript received ; revised.

I. Introduction

Metaverse is an extension of the Internet to realize the virtual world through augmented and virtual reality (AR/VR) [1]. Being a fundamental element of the metaverse, AR/VR has been studied widely. In particular, AR/VR over wireless has gained the significant interest of researchers in both academia and industry. High-definition visuals, sounds, sensory data, and animations of AR/VR disparate quality of service (QoS) in correlation to the traditional networks, thus posing different communication, computing, and storage challenges. The various applications of AR/VR require low latency and high resource allocation, which creates a bottleneck at the air interface of wireless networks. Multi-access edge computing (MEC) has contributed well to address this bottleneck by reducing the transmission and processing latency significantly. In a three-tier architecture of MEC networks, the cloud server, the base stations, and edge servers collaborate for VR content delivery. However, the fixed locations of MEC edge servers limit the resource management for VR-based contents delivery. Moreover, the redundant deployment of MEC edge servers is efficient only during peak traffic hours and remains unused otherwise.

To address this issue, replacing fixed MEC edge servers with flying Unmanned Area Vehicle (UAV) edge servers is a better alternative. Undoubtedly, the salient features of automation, flexibility, and better signal-to-noise ratio (SNR) make the UAV-based MEC network more efficient for VR-based contents delivery. Many research works have studied the deployment of UAVs as MEC servers in wireless networks. However, UAV-based MEC networks for VR content delivery need further investigation.

An example of a VR-based service is an on-demand 360-degree video over mobile networks [2]. This is an essential feature of VR-based services that provide UEs with partial or fully immersive virtual environments on head-mounted devices (HMD) such as VR gear or commodity phones. Typically, VR-based contents are stored in high-definition videos such as 8K, 4K, etc., to enhance the quality of experience (QoE) [3]–[5]. Therefore, it requires a massive amount of bandwidth for transmitting the VR-based contents in the network [4]. Consequently, serving VR-based contents via only cellular links at the MEC is a crucial challenge. Intelligibly, a promising solution for serving VR-based contents in mobile networks is employing alternative communication technology such as D2D communication or A2G communication. However, D2D communication might not be suitable in this scenario, where the mobility of users will significantly affect the performance of D2D links. Therefore, we propose the solution of A2G communication, where the SP might rent a UAV from USP to serve as a UBS at a desired location for some time slots. In such a case, the SP offers an amount of reward to the USP. Then, the USP might choose to accept or reject the request of the SP. If the request is accepted, the USP must deploy UAV according to the requirements of the SP, i.e., the location, and set of contents to be cached. As a result, a considerable amount of data traffic can be offloaded via A2G links. However, an attractive incentive mechanism is required that motivate the USP to participate in this model.

There are various approaches for designing this kind of incentive mechanisms such as auction theory, Stackelberg game, and bargaining game [6]. Nevertheless, most of these solution approaches are the iterative mechanism that requires a long convergence time and various information exchange among players. To tackle these challenges, we employed the contract theory to design an attractive incentive mechanism for UAV-assisted MEC in VR-based services. In this solution approach, the SP offers some rewards to the USP for providing its UAVs. The reward can be defined as monetary or free mobile data and proportionally with the amount of effort that the UAV participates in the system [7]. Moreover, in the designed approach, the SP only has information related to the VR-based contents, e.g., content popularity, projection type popularity, and certain network conditions such as user request rate. This information is not available on the USP side. On the other hand, the USP only has information related to UAVs, such as energy, cache storage capacity, and ability to serve as UBS. This information determines which type a UAV might belong to; and thus, it is a critical condition to optimize the UAV utility in the contract theory model. In such a case, this imbalance of information between the SP and USP posed an information asymmetry problem that created an unfairness in incentive mechanism design. There is a need to tackle this challenge, but the aforementioned solution approaches could not solve it. Therefore, in this paper, we proposed a solution approach that guarantees the fairness of the utility for UAVs with the information asymmetry problem. Our key contribution can be summarized as follows:

- We present a system model that allows UAV pre-cache a set of VR-based contents and serve in the required location by the base station (BS) for some duration via air-to-ground (A2G) communication.
- We propose an incentive mechanism that maximizes the social welfare to benefit both the BS and the UAV's service provider (USP). However, obtaining solutions for the formulated problem is intractable due to the large constraints and the information asymmetry problem, e.g., content popularity, user request rate, and UAV types.
- We reduce the size of constraints by employing contract theory and constraint reduction via a series of lemmas. Moreover, we tackle the information asymmetric via two conditions, e.g., Individual Rationality (IR) and Incentive Compatible (IC).
- Finally, we derive an optimal contract scheme w.r.t. IR and IC constraints. Furthermore, we present intensive numerical results to validate our proposal.

The rest of this paper is organized as follows: We covered the related works in Section II. The system model describes in Section III. Sections IV present our problem formulation and proposed solution approach. Simulation results are presented in Section V. Finally, Section VI concludes the paper.

II. Related works

A. MEC for AR/VR Applications

Recently, the provisioning of low latency content to AR/VR applications by enabling MEC has been studied. The authors in [8] presented a survey on enabled industrial verticals in 5G. The authors discussed the contributions of MEC-enabled networks in various AR/VR applications to demonstrate the severity of AR/VR task demands as a significant bottleneck. In [9], the authors mentioned several requirements and challenges for cellular-connected wireless VR such as VR interaction latency cannot exceed 100(ms), etc. Similarly, the work in [10] surveyed various aspects of the wireless VR in B5G with the internet of intelligence such as resource allocation problems and resource utilization assurance. The common challenge of VR-based service over the wireless network is data traffic with a stringent latency requirement. Typically, VR-based contents represents in a high-definition which requires a massive amount of bandwidth to deliver over the network. Therefore, in [11] the author proposed a predicting scheme for VR video streaming in mobile networks, where a part of the VR-based content in Field-of-View (FoV) will be transmitted in the highest quality, while the remaining parts of the content will be delivered in a lower quality or blur. The authors in [12] proposed a MEC-enabled small-cell network for VR video applications. In the proposed architecture, horizontal and vertical collaboration among multiple MEC servers is performed to reduce end-to-end latency in VR. The authors in [13] proposed MEC-assisted VR video streaming on Terahertz communication. With the aim to reduce the energy consumption in Terahertz, the transmit power and rendering offloading of VR are optimized using deep reinforcement learning. Similarly, panoramic VR video streaming on millimeter wave communication was proposed in [14]. The MEC-enabled networks contribute well to providing bandwidth and energy efficiency. The authors in [15] proposed a proactive caching for 360-degree video streaming. To meet the field-of-view (FOV) prediction, caching, computation, and coding requirements of 360-degree VR, a MEC-enabled network is exploited. The authors in [16] studied communication, cashing, and computation (3C) in a VR environment. A collaboration among MEC and users to cache and offload FOV was proposed.

The works mentioned above demonstrate the efficiency of MEC-enabled networks for VR applications. However, these works do not utilize the UAV-based MEC networks in their frameworks.

B. UAV-Assisted MEC Networks

UAVs are replacing the static MEC servers to exploit their flexibility, automation, and ease of deployment at the desired locations. For instance, the authors in [17] and [18] proposed using UAVs as a MEC server to deliver better channel quality. Then, they formulated an energy minimization optimization problem to optimize UAV beamforming, processing, and trajectory, which was solved by an iterative algorithm. The authors in [19] involved NOMA in the UAV-MEC network environment. They studied the security aspects of a flying eavesdropper and proposed a secure communication scheme. The authors in [20] performed the resource allocation in a MEC network with multiple UAVs. They then proposed a multi-agent federated reinforcement learning algorithm to design a semi-distributed framework for resource allocation. The authors in [21] proposed an energy harvesting network for IoT devices by UAVs. In the proposed UAV-MEC network, the UAVs were further used to offload the IoT data for processing. A similar approach to offload IoT data to a UAV-enabled MEC network was proposed in [22]. Then, a successive convex optimization-based algorithm was proposed to optimize the UAV position, computation resources, communication resources, and task-splitting decisions. The authors in [23] studied a hierarchical infrastructure of UAVs consisting of a centralized UAV and multiple bottom UAVs for the maritime communication network. They proposed a deep reinforcement learning scheme to optimize the UAV trajectory and resource allocation. In [24], the authors proposed a multi-agent deep reinforcement learning (MADRL)-based approach for task offloading and resource allocation that aims to minimize the overall network computation cost in multi-UAV enabled IoT edge network. Another solution approach to reduce data traffic in the network has been proposed in [25]. In which, the author designed a solution approach based on DRL regarding human-centric features, random way-point user mobility model for UAV content caching, and placement in mobile edge network.

However, the works mentioned earlier studied the UAV-enabled MEC servers and did not consider VR applications in their formulations.

Very few works have studied the UAV-assisted MEC networks for VR applications. The authors in [26] exploited UAVs' communication and computing resources to achieve low end-to-end latency for VR users. The joint optimization problem of UAV locations and resource allocation was solved by decomposing into subproblems which are solved sequentially. A similar approach to UAV-based MEC networks for VR content delivery was proposed in [27]. The problem of UAVs' association, caching, computation, and location was formulated and solved through successive convex optimization.

In contrast to the related works, we propose UAV-based MEC-enabled networks for VR content delivery to meet the research gap among the works mentioned above.

C. Contract Theory

Contract theory is the one of special applications in game theory, which studies how a principal develops agreements with asymmetric information to encourage agents to contribute to specific tasks [28]. For instance, a contract theory-based inventive mechanism for contents sharing via D2D communication is proposed in [29]. Similarly, the study in [30] employed contract theory for the cache storage renting model between the content provider (CP) and network operator (NO). Additionally, the problem of lightweight satellite resource allocation based on contract theory has in considered in [31]. Similarly, the work in [32] study the problem of secure spectrum sharing for the Internet of Vehicles (IoVs). Moreover, to encourage reliable federated learning has been considered in [33]. In [34], the authors proposed on-device computational caching for AR-based services via D2D communication. As a result, the above work indicates the benefits of employing contract theory in the real-world.

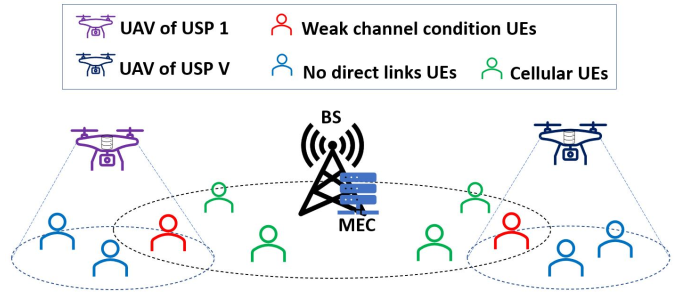


Fig. 1: System Model

III. System model

In this paper, we consider a network model (shown in Fig. 1) that includes a single BS equipped with MEC[1] capability, a set $\mathcal{N}$ of N users that clustered in L groups based on its geographical location, denoted as $\Omega_l = \{1, 2, \dots, N_l\}, l \in L$, where N_l is the number of users in cluster l, $\Omega_l \cap \Omega_{l'} = \emptyset, \forall l, l' \in L$. We also consider a set of K VR-based contents (VRCs) denoted as $\mathcal{K} = \{1, 2, \dots, K\}$ that the BS can serve in its service area. We assume that the network is dense; and thus, UEs in any cluster $l \in L$ have no direct communication links or weak channel conditions with the BS. Hence, the service provider (SP) might have to deploy an extra access point or physical base station to expand its service area. However, these solutions are costly and not economically friendly for the SP. Therefore, we propose a novel system model that SP might rent a UAV from USP[2] to deploy as a micro-base-station (UBS). We let $\mathcal{V}$ denote the set of V USPs, $\mathcal{V} = \{1, 2, \dots, V\}$.

On the other hand, we assumed that UEs are experiencing 360-video streaming which is one of the essential features of VR-based services. The VR-based content can be supported by Head Mounted Devices (HMDs), Oculus Rift, Samsung GearVR or Sony PlayStation VR, or commodity phones [35]. According to the user equipment, we have various projection types of VRC such as equirectangular projection (ERP), cube-map projection (CMP), adjusted cube map projection (ACP), adjusted equal-area projection (AEP), Equi-angular projection (EAC) [36], [37]. Let $\mathcal{M}$ be the set of M projection types in the system, $\mathcal{M} \triangleq \{0, 1, 2, \dots, M\}$. For instance, $m = 0$ represents the sphere format of VRC, and $m = 1$ represents for ERP format. For simplicity, we denote (k, m) as VRC k

[1]We use the term "SP", "BS" and "MEC" interchangeably.
[2]We use the term "USP" and "UAV" interchangeably.

at projection type m, and $S_{(k,m)}$ (in MB) denotes the size of the VRC (k, m).

Typically, UE sends a request for VRC (k, m) to the BS, and if (k, m) is available at the BS storage, it can be served directly via cellular links. If (k, m) is missing, the BS might upgrade from $(k, 0)$ to (k, m) via EEOA-ERP and EEOA-CMP schemes [38]. Otherwise, the BS has to fetch (k, m) from the content provider (CP) via backhaul links. In dense settings, the user request rate is huge; and thus, the probability that the requests dropped by UEs is the highest due to the limitation on physical resources such as computing capacity, cache storage, or communication resources. To cope with these challenges, one can use on-device caching that allows users to share the cache contents via D2D communication [34]. By doing so, we can increase the number of cached contents in the networks and the spectrum efficiency by reusing the spectrum from the cellular user to D2D users. It is a promising solution, but tills have some limitations, such as a user's cache storage and the device's power being constrained. Additionally, user availability varies in the service region; for example, user mobility reduces the availability of cached content. Therefore, we propose a system model in which the SP might employ some UAVs to increase the number of UBS's in the systems, which can reduce the requests served by the BS. In such a scenario, UAVs need to pre-cache some of the VRCs in set $\mathcal{K}$ and fly to location l required by the BS, then hover there for some duration J. For example, UEs may use VR-based services during a 1 outdoor event near the BS. As a result, there may be an overloading problem with the BS's communication and computation capabilities due to the rapid increase in the number of active UEs in the service area. The BS must therefore rent a set of UAVs to serve as UBSs for $J = 1$ hour. In this paper, we discretize the requirement duration J equally into a set $\mathcal{T}$ of T time slots with the period of each time slot t being $j = J/T, t \in T$. By doing so, it can increase service quality, expand service area coverage, and improve spectrum efficiency by utilizing the A2G communication technique.

Recently, UAV-assisted MEC has been investigated in various works on the communication network, such as task offloading [39]–[41], and data offloading [42]–[44]. The UAV can serve as a base station or mobile-micro computing server for task offloading and as a relay node for data offloading. In our model, a UAV must pre-cache some of the VRCs before flying to a predetermined point provided by the BS. If a request from a UE is hit, it indicates that the requested VRC is already cached in the UAV's storage during the period the UAV is actively operating. The UAV immediately serves the request via A2G links. In this case, the UAV serves as a BS. On the other hand, if the requested VRC is missed, it means the VRC is not cached in UAV's storage, then the UAV needs to forward the request to the BS to fetch the VRC. In this case, the UAV serves as a relay node. Moreover, we assume that the SP does not own UAVs; and thus, to deploy a UAV in a designed location, the SP needs to rent from the USPs. In such a case, an attractive incentive mechanism is required to motivate the USP to cooperate with the SP for the UAV-assisted MEC model. This incentive mechanism is needed to maximize the utility of both the SP and USPs. Therefore, we propose an incentive mechanism based on the *Contract theory* [45] to solve the UAV-assisted MEC problem. By employing contract theory, we can deal with the problem of the *information asymmetry*, which results in the USP not knowing the user request rate and content popularity and the SP not knowing which UAVs are actively using the system during T time slots. The following sub-sections will present communication, computational, caching, and contract to model.

A. Communication model

This subsection presents our communication models, including communication between UAVs and UEs and between UAVs and BSs. Similar to our previous work in [46], we consider A2G and the 5G-based communication technologies in this work. A2G communication is a technique that supports the communication between UAVs and ground devices or BSs. This communication technique is significantly different from the terrestrial communication channel [47]. Moreover, we assume that the communication between the BS and CP via a wired or wireless backhaul link with a fixed W_{CP} (Mpbs) bandwidth. Firstly, we model the communication between UAVs and UEs.

1) UAV to UE communication via A2G: In this case, the communication takes place between the UAV and the UE. In which, the Line-of-Sight (LoS) $\mathrm{PL}^{n,v}_{LoS}[t]$ and Non-Line-of-Sight (NLoS) path-loss $\mathrm{PL}^{n,v}_{NLoS}[t]$ of UE $n \in N$ associated with UAV $v \in V$ at time slot t is given, respectively by:

$$\begin{aligned} \mathrm{PL}^{n,v}_{LoS}[t] &= 2\vartheta \log\left(\frac{4\pi d_{nv}[t] f^c}{c}\right) + \eta_{LoS}, \\ \mathrm{PL}^{nv}_{NLoS}[t] &= 2\vartheta \log\left(\frac{4\pi d_{nv}[t] f^c}{c}\right) + \eta_{NLoS}, \end{aligned} \tag{1}$$

where η_{LoS}, and η_{NLoS} are average added losses for LoS and NLoS link, respectively. ϑ is the path-loss exponent, i.e., $\vartheta \geq 2$. f^c is the carrier frequency, c is the speed of light, and $d_{nv}[t]$ is the instantaneous distance between UAV v and UE n at time slot t. Let $\{x_n[t], y_n[t], z_n[t]\}$ and $\{x_v[t], y_v[t], z_v[t]\}$ be the coordinates of UE n and UAV v, respectively. The relative distance between UAV v and UE n is given by:

$$d_{nv}[t] = \sqrt{(x_n[t] - x_v[t])^2 + (y_n[t] - y_v[t])^2 + (z_n[t] - z_v[t])^2}. \tag{2}$$

Moreover, the probability of the LoS component depends on the environment and elevation angle between the UAV and ground device [46], [47]. Thereby, the probability of the LoS component between UAV v and UE n is given by:

$$\mathrm{Pr}^{nv}_{LoS} = \frac{1}{1 + C \exp\left[D\left(\frac{180}{\pi}\tan^{-1}\frac{h_v[t]}{d_{nv}[t]} - C\right)\right]}, \tag{3}$$

where C and D are constant coefficients which depends on the environment, $h_v[t] = z_v[t]$ is the hovering altitude of UAV v at time slot t. Intuitively, the NLoS component probability is given by:

$$\mathrm{Pr}^{nv}_{NLoS} = 1 - \mathrm{Pr}^{nv}_{LoS}. \tag{4}$$

Therefore, the average path-loss of UE n associated with UAV v at time slot t is given by:

$$\overline{\text{PL}}_{nv}[t] = \text{Pr}_{LoS}^{nv}\text{PL}_{LoS}^{nv}[t] + \text{Pr}_{NLoS}^{nv}\text{PL}_{NLoS}^{nv}[t], \quad \forall t \in T, \forall n \in N, \forall v \in V.$$

Moreover, according the work in [46], [48], the channel gain between user n and UAV v at time slot t is given by:

$$G_{nv}[t] = 10^{-\overline{\text{PL}}_{n,v}[t]/10}, \forall n \in N, v \in V. \tag{5}$$

Consequently, the instantaneous achievable downlink transmission data rate of UE n associated with UAV v at time slot t is given by:

$$R_{nv}[t] = B_v[t] \log_2 \left(1 + \frac{P_{nv}[t]G_{nv}[t]}{I_0}\right), \quad \forall t \in T, \forall n \in N, v \in V,$$

where $B_v[t]$ is the system bandwidth available at UAV v, $P_{nv}[t]$ is the transmit power of UAV v, I_0 is the Gaussian noise power. We assume that UAVs are using orthogonal frequency; and thus, there is no co-tier interference among UAVs [46]–[48]. Furthermore, we assume that UAV is capable with a higher battery capacity compared to the user equipment, thus, it can enhance the SINR for weak channel condition UEs via beam-forming technique [47].

2) UAV to BS communication via A2G: In this case, the communication that takes place between the UAV and BS for the case of the requested VRC is missing on the UAV's side. We consider the wireless links between UAV v and BS as LoS links [47], [48]. Moreover, the UAV is capable of a higher battery capacity compared to the user equipment, and thus, the SINR between the BS and UAV can be stronger than the user equipment by increasing the transmit power levels [47]. Let $R_{v0}[t]$ be the achievable data rate of UAV v and the BS at time slot t. $R_{v0}[t]$ can be modeled as follows:

$$R_{v0}[t] = B_0[t] \log_2 \left(1 + \frac{P_{v0}[t]G_{v0}[t]}{I_0}\right), \forall t \in T, \forall v \in V, \tag{6}$$

where $B_0[t]$ is the system bandwidth between UAV v and the BS, $P_{v0}[t]$ is the transmit power of the BS, $G_{v0}[t]$ is the channel gain between UAV v and the BS which has been define in [46], as follows:

$$G_{v0}[t] = 10^{-(\Psi_{v0} + \Upsilon_{LoS})/10}, \forall v \in V, \tag{7}$$

where Υ_{LoS} is the additional attenuation factor for LoS link, and Ψ_{v0} is the path-loss component between UAV v and BS, given by:

$$\Psi_{v0}[t] = 20 \log_{10}(d_{v0}[t]) + 20 \log_{10}(f_c) + 10 \log_{10}(\frac{2\pi}{c})^2, \tag{8}$$

where f_c is the carrier frequency, $d_{v0}[t]$ is the distance between UAV v and the BS, c is the speed of light. Next, we define the computation and caching model.

B. Computational and Caching Model

Due to the limited cache storage, the BS might not be capable of caching all of VRCs. Therefore, it needs to carefully consider the problem of cache decisions to maximize the cache utility. This is an interesting problem and has been done in many existing works [49]–[51]. These can be considered as input data for our work. Based on the cache decision, the BS might offer a UAV to cache those VRCs. Therefore, we focus more on the problem of UAV deployment and the economic model for UAV-assisted MEC.

1) Caching Model: Caching at the edge has been considered in various works [52]–[55], in which MEC might cache a subset of contents in its storage. If there is a request for infotainment content, the BS will check whether the request is cached. If the requested content has been cached, the request will be served immediately without being forwarded to the CP. By doing so, the traffic in the backhaul network will be significantly reduced proportionally to the number of requests served at the BS. The more cached contents, the larger amount of data traffic in the backhaul network is reduced, and vice versa. However, due to the limitation of cache storage, BS might not cache all of the available contents; and thus, it needs to carefully choose which contents to cache based on certain parameters such as the popularity of the content to increase the utility of caching strategy. Therefore, it is indispensable to consider the popularity of content in any caching model. Similar to our work in [34], [49], we employ the Zipf distribution to calculate the popularity of contents. The Zipf distribution has been widely used in many applications such as ranking, population, etc. Hence, the popularity of content $k \in K$ is modeled as follows:

$$p_k = \frac{1/k^\alpha}{\sum_{i=1}^{K} 1/i^\alpha}, \tag{9}$$

where α is a corresponding parameter of the Zipf distribution, in which the value of p_k is directly proportional to the value of α, e.g., the higher value of α, the larger value of p_k. Similarly, we can model the popularity of VRC projection type $m \in M$ as follows:

$$p_m = \frac{1/m^\alpha}{\sum_{i=1}^{M} 1/i^\alpha}. \tag{10}$$

Let $\delta_{(k,m)}[t]$ be the utility of the BS when is cached VRC (k, m) at time slot t.

$$\delta_{(k,m)}[t] = \text{Pr}_{(k,m)}[t] S_{(k,m)}, \forall k \in K, \forall m \in M, \tag{11}$$

where $\text{Pr}_{(k,m)}[t]$ denotes the probability that VRC (k, m) is being requested at least once in a single time slot t. This probability can be estimated via *the at least once rule*, as follows:

$$\begin{aligned} &\text{Pr}_{(k,m)}[t] = \text{Pr}_k[t]\text{Pr}_m[t], \forall k \in K, \forall m \in M, \forall t \in T, \\ &\text{Pr}_k[t] = \text{Pr}(X_k = 1|\lambda) = 1 - (1 - p_k)^{\lambda - 1}, \forall k \in K, \\ &\text{Pr}_m[t] = \text{Pr}(X_m = 1|\lambda) = 1 - (1 - p_m)^{\lambda - 1}, \forall m \in m, \end{aligned} \tag{12}$$

where X_k, and X_m are random variables that represent event VRC k at projection type m being requested at least once in any given time slot, respectively, and λ is the user request rate (number of requests per time slot) that is assumed to follow the Poison distribution.

Typically, the problem of cache decision-making can be modeled as follows:

PCD :

$$\begin{aligned} \max_{a} \ & \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{m=1}^{M} \Pr_{(k,m)}[t]\log_2(S_{(k,m)})a_{(k,m)} \\ \text{s.t.} \ & \sum_{k=1}^{K}\sum_{m=1}^{M} S_{(k,m)}a_{(k,m)} \le S_{BS}, \end{aligned} \tag{13}$$

where $a_{(k,m)}$ is the decision variable where the BS caches the VRC (k,m) or not, e.g., $a_{(k,m)}=1$ means that the BS will cache the VRC (k,m), otherwise $a_{(k,m)}=0$, and S_{BS} is the cache capacity of the BS. The problem in (13) can be solved via various approaches such as ADMM [49] and Deep Reinforcement Leaning [56]. Let Ω_K be the optimal solution of (13), where $\Omega_K \triangleq \{(k,m), k\in K, m\in M\}$ and $\Omega_K \subset \mathcal{K}$. Next, we present our computation model.

2) Computation model: A computation model is needed in case of request VRCs are missing. In such a case, the BS might transform, or upgrade VRC from one to the requested format, i.e., transform from $(k,0)$ VRC k in sphere format to $(k,1)$ VRC k in the ERP format. Let $S_{(k,0)\to(k,m)}$ be the size of the task that use to transform VRC $(k,0)$ to VRC (k,m), $C_{(k,0)\to(k,m)}$ be the number of CPU cycles per second to process a bit of VRC $(k,0)\to(k,m)$, $f_{(k,0)\to(k,m)}$ be the number of CPU cycles that is allocated to process VRC $(k,0) \to (k,m)$. Let $\zeta_{(k,0)\to(k,m)}[t]$ be the energy consumption, and $\xi_{(k,0)\to(k,m)}[t]$ be the computation latency of the BS in order to transform $(k,0)\to(k,m)$ at time slot t, respectively. $\zeta_{(k,0)\to(k,m)}[t]$ can be modeled as follows:

$$\begin{gathered} \zeta_{(k,0)\to(k,m)}[t] = \kappa(f_{(k,0)\to(k,m)})^2(1-a_{(k,m)}), \\ \forall k\in K, \forall m\in M, \forall t\in T, \end{gathered}$$

where $\kappa = 5\times 10^{-27}$ is the power consumption constant which depends on the CPU architecture [46]. Similarly, the computational latency is given by:

$$\begin{gathered} \zeta_{(k,0)\to(k,m)}[t] = \frac{S_{(k,0)\to(k,m)}C_{(k,0)\to(k,m)}}{f_{(k,0)\to(k,m)}}(1-a_{(k,m)}), \\ \forall k\in K, \forall m\in M, \forall t\in T. \end{gathered}$$

Next, we present the utility of caching and computing at the edge.

3) Utility of caching and computing at the edge: The utility of a caching model can be evaluated in many ways, such as minimizing latency, energy consumption, or maximizing bandwidth saving, the cost for fetching content, hit rate [52]–[55], [57]. For instance, to fetch content from the CP, the SP must pay a certain cost for data traffic in the network. Let C_0 be the cost of fetching the VRC from the CP through the backhaul link per unit of data. The expected utility in terms of cost saving in a given time slot t is given by:

$$\begin{aligned} & U(cost)[t] = \\ & \quad \sum_{k=1}^{K}\sum_{m=1}^{M} \Pr_{(k,m)}[t]S_{(k,m)}(C_0 - C_{(k,m)}[t])(1-a_{(k,m)}), \end{aligned} \tag{14}$$

where $C_{(k,m)}$ is the cost of the BS for caching VRC (k,m). Similarly, the expected bandwidth saving from backhaul links depends on the size of the contents and which can be formulated as

$$U(save)[t] = \sum_{k=1}^{K}\sum_{m=1}^{M} \Pr_{(k,m)}[t]S_{(k,m)}a_{(k,m)}. \tag{15}$$

On the other hand, caching and computing might be evaluated via energy consumption or latency [49]. In which the energy consumed by UAVs for serving VR-based services as a UBS is a benefit for the BS. Let $E_v[t]$ be the energy consumption of UAV v in time slot t for participating in our model. $E_v[t]$ can be modeled as follows:

$$E_v[t] = E_v^{hov}[t] + E_v^{cache}[t] + E_v^{tx}[t], \tag{16}$$

where $E_v^{hov}[t]$ is the energy consumption for hovering, $E_v^{cache}[t]$ is cache maintaining, and $E_v^{tx}[t]$ is energy consumption for transmitting. $E_v^{tx}[t]$ can be modeled as follows:

$$E_v^{tx}[t] = \sum_{(k,m)\in\Omega_v[t]} P_{nv}[t]\frac{S_{(k,m)}}{R_{nv}[t]}, \tag{17}$$

where $\Omega_v[t]$ is the set of request the VRC at UAV v in time slot t. Let E_v^{total} be the energy consumption of UAV v for serving as the UBS for a total number of time slots $\triangle t$. E_v^{total} can be formulated as follows:

$$E_v^{total} = E_v^{in} + E_v^{out} + \sum_{t=1}^{\triangle t} E_v[t], \forall v\in V, \tag{18}$$

where E_v^{in} is the energy consumption for flying to the location requires by the BS, and E_v^{out} is the energy consumption of UAV v to fly back the base of the USP. Based on the aforementioned equations and theoretical analysis, we can see that the cost function of the UAV is concave w.r.t. the size of VRC $S_{(k,m)}$. Generally, we can define the cost function of VRC (k,m) in any given time slot t as follows

$$f_v(k,m)[t] = \begin{cases} (C_0 - C_{(k,m)}[t])S_{(k,m)}, & \text{Cost saving,} \\ (P_{(\cdot)}[t]/R_{(\cdot)}[t])S_{(k,m)}, & \text{Energy consumption,} \\ (1/R_{(\cdot)}[t])S_{((k,m)}, & \text{Latency.} \end{cases} \tag{19}$$

Without loss generality, the cost function of UAV v can be rewritten by any concave, non-decreasing w.r.t. the size of VRC $S_{(k,m)}$. Moreover, based on the works in [34], [45], [58], we employed the logarithm function as our cost function, where we can guarantee the properties of the utility function without violating the *law of small number* in a probabilistic model. Intuitively, $f_v(k,m)[t]$ can be rewritten as follows:

$$\begin{gathered} f_v(k,m)[t] = \Xi_{(k,m)}[t]\log_2(S_{(k,m)}), \\ \forall t\in T, \forall k\in K, m\in M, \end{gathered} \tag{20}$$

where $\Xi_{(k,m)}[t]$ is a control parameter related to power consumption, latency, cost, and bandwidth in time slot t. Then, the expected utility for the BS in terms of UAV v is cached VRC (k,m) is given by:

$$\begin{gathered} f_{BS}(v,k,m)[t] \triangleq \Pr_{(k,m)}[t]f_v(k,m)[t], \\ \forall k\in K, \forall m\in M. \end{gathered} \tag{21}$$

Consequently, the total utility of caching model for the BS at time slot t can be formulated as follows:

$$f_{BS}(\Omega_K)[t] = \sum_{v\in V} \sum_{(k,m)\in\Omega_K} f_{BS}(v,k,m)[t]. \quad (22)$$

Furthermore, we assume that the BS expects a UAV serves as a UBS in a predetermined location for maximum T time slots. Thus, the probability of τ number request VRC over T time slots can be formulated as follows.

$$\Pr(X=\tau|\lambda_l) = \frac{(\lambda_l T)^\tau e^{-(\lambda_l T)}}{\tau!}, \forall k \in K, \forall m \in M, \quad (23)$$

where $\tau!$ is the fractional of τ, λ_l is the user request rate at location l. On the other hand, let $\triangle t$ be the total number of time slots that UAV v can participate in the system. Based on the Taylor series and the Homogeneous Poison Point Process (HPPP), we can formulate the cost function of UAV v for caching the set of Ω_K VRCs that is equivalent to the utility function of the BS for renting UAV v over $\triangle t$ time slots as follows:

$$f_v(\Omega_K) = f_{BS}(v,\triangle t) = (\lambda_l \triangle t) \sum_{(k,m)\in\Omega_K} f_v(k,m)[t], \forall v \in V. \quad (24)$$

It must be noted that, in practical settings, the BS is unaware of the number of time slots a UAV will serve as a UBS. It means that $\triangle t \neq T$. Therefore, the cost function of the UAV which is the utility function of the BS in (24), is conjecture. Therefore, an attractive incentive scheme is required to motivate the USP to deploy UAVs to serve as the UBS. In the next section, we propose a solution contract theory-based incentive mechanism that aims to motivate the USP to deploy UAVs as long as possible such that the utility in the contract of both the USP and the SP is maximized.

IV. Contract Model and Proposed Solution

To motivate USP to cooperate with BS, we present an incentive mechanism based on contract theory. We maximize the payoff for both SP and USP, commonly known as *social welfare*. In this paper, BS is considered the principal, and UAV is considered an agent. In any contract model, the principal will offer a contract bundle $[E(\cdot), R(\cdot)]$ to the agent, where $E(\cdot)$ is the amount of effort that the agent needs to spend to receive an amount of reward $R(\cdot)$. The agent chooses declines or a proper contract bundle to maximize its payoff. Firstly, we design the agent type that is a significant parameter for the agent's feasible contract model and payoff.

A. UAV Types

In this paper, we consider a scenario that a UAV is willing to serve as a UBS at a desired location offered by the SP. Therefore, we assume that UAV is served at a fixed location; and thus, the total number of time slots for serving at a UBS of UAV is the main parameter to estimate its effort and reward. Therefore, we consider the UAV's type is the number of time slots $\triangle t = t - t_0, t_0 = 0$ that are serving at location l. For instance, If the number of time slot that UAV v can serve at location l is $\triangle t = 8$, it means that UAV v belong to type-8, or the type of UAV v is $\theta_{v,\triangle t} = 8$. Moreover, if more than one UAV have the same number of active time slots $\triangle t$, we can say that they have the same type-$\triangle t$ and can be classified in a group type-$\triangle t$. Based on the cost function of UAV in (24), the cost function for UAV associated with the number of active time slots $\triangle t$ can be rewritten as follows:

TABLE I: Summary of the key notations.

Notation	Definition
$\mathcal{N}$	Set of UEs.
$\mathcal{K}$	Set of VRCs.
$\mathcal{M}$	Set of projection types.
Ω_l	Set of UEs at location l.
$\mathcal{V}$	Set of UAVs.
κ	Coefficient of power consumption of the processor.
LoS	Line-of-sight.
$NLoS$	Non-Line-of-sight.
PL	Pathloss.
Pr	Probability.
$X_{(\cdot)}$	Random variable of $(\cdot)$.
R_{nv}	Achievable data rate of UE n associated with UAV v.
(k,m)	VRC k at projection type m, $m \in M, k \in K$.
p_k, p_m	popularity of (k,m).
C, D	Terrains parameter.
η_{LoS}, η_{NLoS}	Additional losses for LoS and NLoS link.
ϑ	Pathloss exponent.
α	The parameter of Zipf distribution.
λ	The parameter of the Poison distribution.
$\boldsymbol{\theta}$	Set of UA types.
θ_t	UAV type associated with t.
$E(\theta)$	Cost function of type θ.
$R(\theta)$	Reward function type θ.
$[E(\cdot), R(\cdot)]$	The contract bundle form.
$R(\cdot)$	The rewards function.
$U_v(\theta)$	Utility function of UAV v associated with contract bundle type θ.
$U_{BS}(\cdot)$	Utility function of the BS associated with contract bundle type θ .

$$\begin{aligned} f_v(\Omega_K) &= \triangle t \lambda_l \sum_{(k,m)\in\Omega_K} f_v(k,m) \\ &= \theta_{v,\triangle t}\lambda_l \sum_{(k,m)\in\Omega_K} f_v(k,m) = E_v(\theta_{v,\triangle t}), \end{aligned} \quad (25)$$

where $\theta_{v,\triangle t} = \triangle t$, and $E(v, \theta_{\triangle t})$ is the cost function of UAV v to serve at location l for $\triangle t$ time slots. The BS needs to solve a contract model for a single location l and single UAV v, but the solution pertains to the rest of the system. Therefore, for simplicity we denote θ_t represents for $\theta_{v,\triangle t}$, $E(\theta_t)$ represents for $E_v(\theta_{v,\triangle t})$, and λ represents for λ_l.

Definition 1. *The type of UAV strictly depends on the number of active time slots $\triangle t$ that will be served as a UBS. If the UAV is serving for less time slot, it will be associated with a lower type, and vice versa.*

It means that, if there are two UAVs v_1 and v_2 are serving as a UBS for a total number of time slots $\triangle t_1$ and $\triangle t_2$, respectively, such that $\triangle t_1 < \triangle t_2$, and thus, $\theta_{t_1} < \theta_{t_2}$. We assume that the SP expects a UAV is serving as a UBS for maximum T time slots; and thus, the set of the type of UAVs can give as follows:

$$\boldsymbol{\theta} \triangleq [0, 1, \ldots, t, \ldots, T], \quad (26)$$

where $\theta_t \in \boldsymbol{\theta}$ can be represented in seconds, hours, etc. Based on this information, the SP designs a proper contract according to each type of UAVs.

It must be noted that we consider the number of time slots that a UAV participated in in the proposed system model as the main feature to identify its types that belong to a single-dimensional type. However, our proposed solution approach remains consistent in the case of multi-dimensional UAV types by employing dimension reduction via the weighted sum method [59], [60].

B. The Utility of the UAV

Given any contract bundle $[E(\cdot), R(\cdot)]$, the utility of UAV v associated with type-t (θ_t) is given by:

$$U_v(\theta_t) = \theta_t \nu\left(R(\theta_t)\right) - \rho E(\theta_t), \tag{27}$$

where ρ is an additional effort [7] put into by the UAV in order to generate an amount of caching utility model $E(\theta_t)$. ρ can be an amount of energy that the UAV hovers during t time slots, cache maintenance, etc. And, $\nu(\cdot)$ is *the self evaluation function* [45]. $\nu(\cdot)$ must be a strictly concave, increasing function and satisfy the following conditions:

$$\nu(0) = 0; \frac{\partial \nu\left(R(\theta_t)\right)}{\partial R(\theta_t)} > 0; \ \frac{\partial^2 \nu\left(R(\theta_t)\right)}{\partial R(\theta_t)^2} < 0. \tag{28}$$

Moreover, the UAV must know exactly its type to choose a proper contract bundle that maximizes its payoff represented in (27).

C. The Utility of the BS

The utility of the BS can be calculated by the expected utility of cached VRCs Ω_K of the UAV and serving as the UBS for a number of time slots $\triangle t$ in a predetermined location (e.g., $E(\theta_{\theta_t})$) minus for the cost for utilizing UAV's resources (e.g., $R(\theta_t)$). Generally, we can say that the BS offers an amount of reward $R(\theta_t)$ to the USP, in order to deploy the UAV to serve as UBS for some duration $\triangle t$. Therefore, the utility of BS in the contract model at type θ_t can be given by:

$$U_{BS}(\theta_t) = E(\theta_t) - \gamma R(\theta_t), \tag{29}$$

where γ is the cost that the BS needs to pay for a unit of payoff $U(\theta_t)$. However, there are T types of UAV, which means that BS is unaware of which is the exact type of UAV. Consequently, based on our previous work in [34], and the works in [7], the BS might play a role that uniformly distributed the probability of a UAV belonging to some type t. Let $\Pr(X_v = \theta_t)$ denote the probability that UAV v is belong to type t. The expected utility of the BS can be modeled as follows:

$$U_{BS} = \sum_{t=1}^{T} \Pr(X_v = \theta_t) U_{BS}(\theta_t). \tag{30}$$

Typically, when the principal has complete information about UAV types, it will play a role that only maximizes its payoffs. However, in this model, we have to deal with the problem of information asymmetry. Therefore, we design a game that balances the payoff of both sides, which is named maximizing social welfare. This will be presented in the next subsection.

D. Social welfare model

In social welfare maximization, we have to maximize the sum of utility on both sides, such as the BS and UAVs. In this work, we assume that a UAV is chosen to serve at only one location and belongs to only one type-t (θ_t). For simplicity, we assume that the unit cost per unit or effort that the BS needs to pay for UAV $\rho = 1$, and $\sum_{t=1}^{T} \Pr(X_v = \theta_t) = 1$.

Definition 2. *A feasible contract bundle $[E(\theta), R(\theta)]$ is called maximum social welfare if and only if the sum of the payoffs of principal and agents for the choice of this bundle is maximal.*

Hence, the social welfare of the contract model can be defined as follows:

$$\begin{aligned} \Pi &= \sum_{t=1}^{T} \Pr(X_v = \theta_t) \left(U_{BS}(\theta_t) + U_v(\theta_t)\right), \\ &= \sum_{t=1}^{T} \Pr(X_v = \theta_t) \left(\theta_t \nu(R(\theta_t)) - \gamma R(\theta_t)\right). \end{aligned} \tag{31}$$

Basically, the BS is unaware of information of $\Pr(X_v = \theta_t)$ such as probability density function. Meanwhile, the UAV is unaware of information about user request rate and content popularity. Therefore, we can not employ any existing conventional optimization approach to solve this problem. However, in this work, to tackle this challenge, we employ contract theory and leverage the information asymmetry problem into a set of constraints such as IC, and IR constraints. It is named the feasibility conditions of the contract model. Next, we describe the feasibility conditions of the contract model.

E. Contract Feasible Conditions

In this paper, we assume that the set of users in each location is disjoint, and the set of contents offered by the BS to UAVs is identically independent. In such a case, we can analyze the solution for a single location and apply it to a vast system model (i.e., multiple locations). For any contract model, two conditions, such as the Individual Rationality (IR) condition and Incentive Compatibility (IC) [45] must be guaranteed to hold the feasibility of the contract. These conditions are defined as follows:

Definition 3. Individual Rationality (IR): *The utility of a UAV, when participating in any contract bundle, must be non-negative.*

$$\theta_t \nu(R(\theta_t)) - E(\theta_t) \geq 0, \forall t \in T, \forall \theta_t \in \theta. \tag{32}$$

This condition aims to ensure the payoff of any UAVs participating in the contract model. The amount of reward $R(\cdot)$ that a UAV received from the BS must compensate with the amount of effort or cost $E(\cdot)$ for any UAV participating in the contract model. If a UAV declines the offers of the BS, we can say that the BS and UAV sign a contract bundle $[E(0), R(0)]$. On the other hand, a UAV must choose a valid contract according to its type. By doing so, UAVs might have the highest payoffs. This can be defined as the following:

Definition 4. Incentive Compatible (IC): *The utility of a UAV achieves the highest value if and only if it chooses the right contract bundle designed for its type.*

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(E(\theta_{t'})) - R(\theta_{t'}), t \neq t', t, t' \in T. \tag{33}$$

Moreover, the amount of reward that a UAV can receive must be monotonicity. Generally, we can say that the more effort UAV put in, the higher rewards must be achieved. Based on the definitions above and conditions, the optimization problem of incentive mechanism based on contract theory is defined as follows:

$$\max_{(E,R)} \sum_{t=1}^{T} \big(\theta_t\nu(R(\theta_t)) - \gamma R(\theta_t)\big) \tag{34a}$$

s.t.

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq 0, \tag{34b}$$

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(R(\theta_{t'})) - E(\theta_{t'}), \tag{34c}$$

$$R(0) < R(\theta_1) < \ldots < R(\theta_t) < \ldots < R(\theta_T), \tag{34d}$$

$$t \neq t', t, t' \in T,$$

where constraints (34b) and (34c) represents for IR and IC conditions, respectively. The monotonicity condition is shown in constraint (34d). As shown in problem (34), we can see that the size of constraint (34b) is $O(T \times (T-1))$, and the size of constraint (34c) is $O(T)$. As a result, obtaining a solution for such a problem is time-consuming and intractable. Therefore, we use constraint reduction techniques like IR constraints reduction, and incentive compatible constraint reduction to reduce the number of constraints to a minimum size while still ensuring the feasibility condition for the original problem.

To begin with, we reduce the size of IR constraints as follows:

Lemma 1. *Given any feasible contract bundle, the IR constraints are always held if and only if the utility of UAV at type-*1 *(*$\theta_t = 1$*) is held.*

Proof: Based on Definition 3, and 4, we can see that:

$$\begin{aligned}
\theta_t\nu(R(\theta_t)) - E(\theta_t) &\geq \theta_{t-1}\nu(R(\theta_{t-1})) - E(\theta_{t-1}),\\
\theta_{t-1}\nu(R(\theta_{t-1})) - E(\theta_{t-1}) &\geq \theta_{t-2}\nu(R(\theta_{t-2})) - E(\theta_{t-2}),\\
\theta_{t-2}\nu(R(\theta_{t-2})) - E(\theta_{t-2}) &\geq \theta_{t-3}\nu(R(\theta_{t-3})) - E(\theta_{t-3}),\\
&\ldots,\\
\theta_1\nu(R(\theta_1)) - E(\theta_1) &\geq \theta_0\nu(R(\theta_0)) - E(\theta_0) = 0.
\end{aligned} \tag{35}$$

Consequently, we can see that if $\theta_1\nu(R(\theta_1)) - E(\theta_1) \geq 0$ the entire of the IR constraints always hold. ■

Lemma 2. Incentive Compatible Constraints Reduction: *For any feasible contract bundle type-t (*θ_t*), the IC constraints are always held if and only if the following conditions are held.*

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(R(\theta_{t+1})) - E(\theta_{t+1}), \tag{36a}$$

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(R(\theta_{t-1})) - E(\theta_{t-1}), \tag{36b}$$

$$\forall t \in T.$$

Proof: Let a and b are two positive number such that $a, b \in T$, and $a < b$. Based on Definition 4, we can the following:

$$\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_b)) - E(\theta_b), \tag{37a}$$

$$\theta_b\nu(R(\theta_b)) - E(\theta_b) \geq \theta_a\nu(R(\theta_a)) - E(\theta_a). \tag{37b}$$

Since, $\nu(\cdot)$ is concave, increasing function (28), and thus, the equality occur if and only if $a = b$. Therefore, we omit the trivial case $a = b$. Intuitively, we consider a case that $a < b$, after some manipulations, we can achieve the following:

$$\nu(R(\theta_a))(\theta_a - \theta_b) > \nu(R(\theta_b))(\theta_a - \theta_b). \tag{38}$$

Then, we can see that $\nu(R(\theta_a)) < \nu(R(\theta_b))$ due to $(\theta_a - \theta_b) < 0$. Furthermore, by using the idea of authors in [34], [7], we can see it expressed as follows:

$$\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_{a-1})) - E(\theta_{a-1}), \tag{39a}$$

$$\theta_a\nu(R(\theta_{a-1})) - E(\theta_{a-1}) \geq \theta_a\nu(R(\theta_{a-2})) - E(\theta_{a-2}), \tag{39b}$$

$$\ldots$$

$$\theta_a\nu(R(\theta_2)) - E(\theta_2) \geq \theta_a\nu(R(\theta_1)) - E(\theta_1). \tag{39c}$$

Intuitively, we can have:

$$\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_1)) - E(\theta_1). \tag{40}$$

Similarly, we can have:

$$\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_{a+1})) - E(\theta_{a+1}), \tag{41a}$$

$$\theta_a\nu(R(\theta_{a+1})) - E(\theta_{a+1}) \geq \theta_a\nu(R(\theta_{a+2})) - E(\theta_{a+2}), \tag{41b}$$

$$\ldots$$

$$\theta_a\nu(R(\theta_{T-1})) - E(\theta_{T-1}) \geq \theta_a\nu(R(\theta_T)) - E(\theta_T). \tag{41c}$$

Then,

$$\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_T)) - E(\theta_T). \tag{42}$$

From (40), and (42), we can see that if $\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_{a+1})) - E(\theta_{a+1})$, and $\theta_a\nu(R(\theta_a)) - E(\theta_a) \geq \theta_a\nu(R(\theta_{a-1})) - E(\theta_{a-1})$ are held, the IC constraints always hold. Consequently, we complete the proof for Incentive Compatible Constraints Reduction. ■

In summary, we reduce the size of IC constraints from $O(T \times (T-1))$ to $O(2 \times T)$, and the size of IR constraints from $O(T)$ to $O(1)$. Thus, we rewrite the original problem stated in (34) by the following:

$$\max_{(E,R)} \sum_{t=1}^{T} \big(\theta_t\nu(R(\theta_t)) - \gamma R(\theta_t)\big) \tag{43a}$$

s.t.

$$\theta_1\nu(R(\theta_1)) - E(\theta_1) \geq 0, \tag{43b}$$

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(R(\theta_{t-1})) - E(\theta_{t-1}), \tag{43c}$$

$$\theta_t\nu(R(\theta_t)) - E(\theta_t) \geq \theta_t\nu(R(\theta_{t+1})) - E(\theta_{t+1}), \tag{43d}$$

$$R(0) < R(\theta_1) < \ldots < R(\theta_t) < \ldots < R(\theta_T), \tag{43e}$$

$$\forall t \in T,$$

Since the size of constraints has been reduced and the monotonicity constraint always held. Hence, we can bind the

Algorithm 1 Optimal Incentive Mechanism-based Contract Theory for UAV-assisted MEC in 5BG

Input: $K, N, V, V, L, \Xi, \lambda, \alpha, \mathbf{p}, \theta$
Output: $\big(E(\cdot), R(\cdot)\big)$
Initialization;
Obtaining optimal solution for contract:
The BS solve problem (43);
Offers contract bundle to USP;
for Each USP $v \in V$ **do**
  Finding a proper location of the USP nearby location of the BS
  if The USP has available UAV **then**
    Offer an optimal contract bundles from (43), $(E(\theta_t), R(\theta_t))$;
    Waiting to receive decision of the USP either reject or accept;
  end if
end for
Contract Execution:
if A USP accept a bundle contract type-θ_t **then**
  USP must deploy a UAV at the location offered by BS during the next t time slots;
  if A request is hit **then**
    The UAV serves the request via A2G;
  else
    The UAV forwards the request to the BS;
  end if
end if
return

constraint (43e) into the feasible set as a projection function to quantify the feasibility of our solution. Moreover, our formulated problem in (43) remains in a strong convexity, where the objective function is linear and constraints are either linear or closed-convex sets. Thus, according to [61], there always exists a stationary solution or global optimal solution for such kind of problem. Therefore, we employed CVXPY [62] as a solver to obtain the optimal solution in this work.

Furthermore, the detail of our proposed framework is presented in Algorithm 1. In which, we have reduced the complexity to solve the problem (34) from $O(T^3)$ to $O(T\log(T)$ [61] in problem (43).

Moreover, if the environment is dynamic and the parameter varies during the contracting time, it will fall into the category of Ex-Ante Contracting [45]. In such a scenario, there is a need to re-execute our proposed Algorithm 1 according to the parameters changed in the network.

V. Numerical Results

A. Simulation setup

In this paper, we choose a network model that has $L = 10$ number of clusters, where the *K-means* algorithm can be employed to cluster UEs based on their geographic location. And, the number of users N_l in each cluster is randomly in range $[100 \sim 150]$, number of VR content $K = 100$, number of projection type $M = 5$. We assume that UAVs

TABLE II: Simulation parameters.

Parameter	Value
Total number of VR content (K)	100 contents
White-noise (I_0)	-174 dBm/Hz [7]
System bandwidth	3 GHz [47]
Number of UAV type (T)	100
Terrain parameters C and D	11.95 and 0.136 [47]
Additional pathloss η_{LoS} and η_{NLoS}	2 and 20 dB[47]
Transmission power P_0 and P_v	10 W and 50 mW[47]
Moving energy consumption E_v^{in}, E_v^{in}	1.0 $\sim$ 5.0 mAh/m[47]
Hovering energy consumption of UAV E_v^{hov}	20.0 mAh[47]
Cache maintenance energy E_v^{cache}	6.25×10^{-12} W/bit [57]
System bandwidth W_v	3 MHz [46]
Bandwidth of each RB(W_b)	180 kHz [34]
The Zipf's parameter (α)	$\{1.0, 2.0, 5.0\}$
The Poisson's parameter (λ)	$\{0.3, 0.6, 0.9\}$

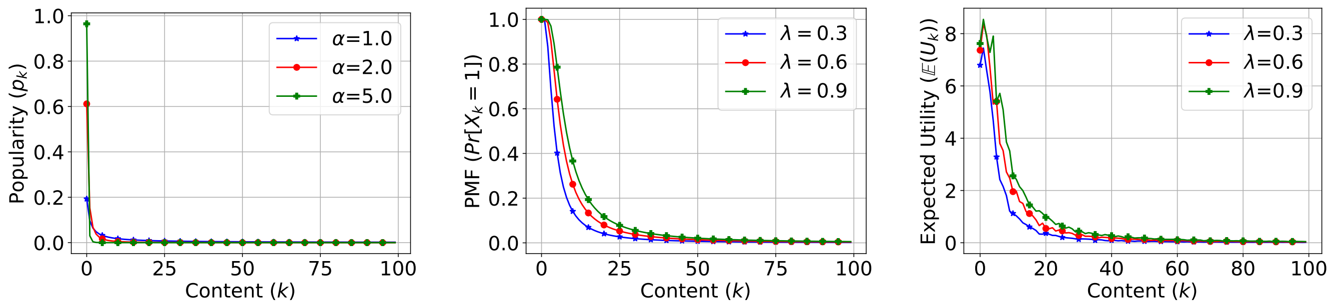
have compatible caching and power capability to participate in this model or that the USP plays an honor role in providing compatible UAVs. Moreover, we assume that the BS requires maximum $T = 100$ time slots which is equivalent to the number of UAV's types $T = 101$ (include $t = 0$), the *self-evaluation* is considered as a logarithm function which satisfies the conditions state in (28). In this work, we assume that the centroid of each cluster is the location to deploy UAV, and the hovering height h_v can be obtained via the work in [47]. The other parameters used in our numerical results are stated in Table II.

Furthermore, we have no such kind of real data set for this model; thus, we use synthesis data that is generated by the Poison distribution, the at least once rule, the Zipf distribution, and the homogeneous Poisson point process for our numerical results. Moreover, we use Python3 [63], and CVXPY [62] as our simulation tools and the base platform to conduct numerical results with specification as follows: Intel core $\text{i}5-4690$ 3.5 (GHz), 16(GB) of memory. The numerical results are computed by taking an average of 100 runs per result to show the validity of our proposed approach.

It must be noted that our performance metric is based on the works in [34], [45] and, [58], where we take into account the performance benchmark of contract theory such as the *information asymmetry problem* and *no information asymmetry problem*. Moreover, *linear pricing* is the based performance benchmark to evaluate the efficiency of any contract-based solution approach [45].

B. Impact of stochastic parameters to the proposed system model

To begin with, we show the popularity of VR content in our network according to the Zipf parameter $\alpha = \{1.0, 2.0, 3.0\}$. As shown in Fig. 2a, we can see that depending on α, the popularity of VR content varies and is almost approximately zero for some content with a lower rank. In Fig. 2b, we use them at least once rule to calculate the probability mass function (PMF) of our synthesis data. In which, the probability of content k is being requested at least once in a single time slot with user request rate λ and popularity p_k, e.g., $\Pr(X_k = 1|\lambda, p_k)$. We can see that content that has higher popularity will have a higher chance of being requested in the next time slot. For instance, given $\alpha = 2.0$, $\lambda = 0.3$ (30%



(a) (b) (c)

Fig. 2: Impact of popularity, user request rate to the caching model: (a) Popularity according to α, (b): Probability Mass Function (PMF) of at least one request w.r.t user request rate λ, and (c) Expected utility versus user request rate and popularity.

of the number of users in a cluster), content $k = 1$ have $\Pr(X_1 = 1|\lambda = 0.3, p_1 = 0.6) = 1.0$ mean while content $k = 5$ only have $\Pr(X_5 = 1.0|\lambda = 0.3, p_5 = 0.3) = 0.4$. In Fig. 2c, we demonstrate the expected utility for individual cache content in the network according to $\alpha = 2$. It shows that the expected utility is direct proportionally to the popularity and user request rate and significantly related to the size of contents. It means that is concrete with our formulated utility function in (20). We can see that some of the content have a very less chance of being requested but have a higher utility than the other content that fluctuates point in the figure. For instance $\mathbb{E}(U_3) = 8.1$ and $\mathbb{E}(U_2) = 7.2$ mean while $p_2 = 0.7$ greater than $p_3 = 0.56$, and $\Pr(X_2 = 1) = 0.87$ greater than $\Pr(X_3 = 1) = 0.705$.

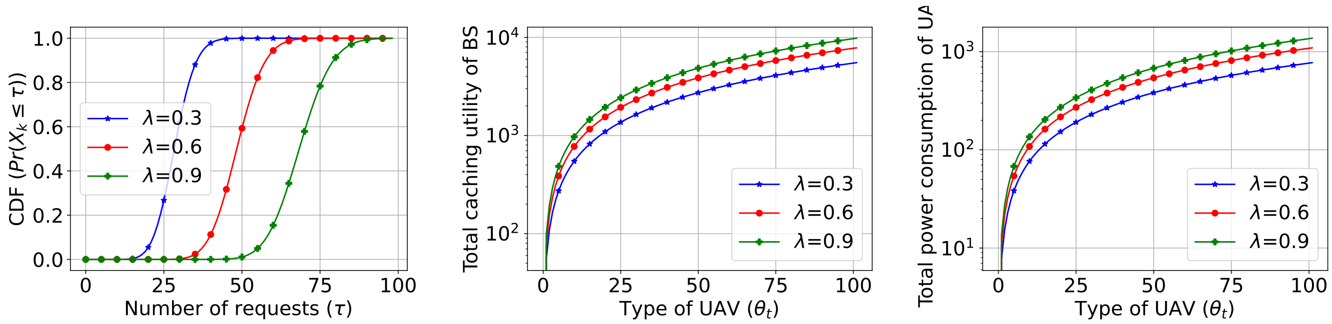
In Fig. 3a, we present the cumulative distribution function (CDF) of the number of requests for VRC given T time slots and user request rates $\lambda = \{0.3, 0.6, 0.9\}$. In which we have a probability of number quest for VRC less than 50 times with $\lambda = 0.3$ is approximate to 1. Meanwhile, when $\lambda = 0.9$ the number of VRC requests during T time slot is mostly approximate to 100 requests with the probability $\Pr(X <= 100) = 0.9$. In Fig. 2c, we analyze the effect of user request rate λ, popularity α, and UAV types θ_t into the total expected utility caching model for the BS. We can see that the higher type of UAVs, the more benefits the BS can achieve. For instance, expected utility of type-100 is approximate to 10^4 with $\lambda = 0.9$, and the expected utility for caching in case of $\theta_t = 100$ with $\lambda = 0.6$ is 6×10^3. On the other hand, given $\lambda = 0.3$, we can see that the expected utility of the BS at type $\theta_t = 25$ is 2×10^3, meanwhile when $\theta_t = 50$, the utility of caching is 5×10^3. Similarly, we have shown the total power consumption of a UAV that is participating in our model in Fig. 3c. The higher type of UAV (θ_t), the more power consumed and vice versa. For instance, $\theta_t = 25$, the total power consumption of an UAV is 2×10^3 (mW), and $\theta_t = 50$ the total power consumption is 6×10^3 (mW). It means that the BS needs to design a contract that guarantees the monotonicity condition in (34d).

C. Optimum Contract solutions

In Fig. 4, we present the performance of our proposed approach, which is a contract theory-based incentive mechanism and compared to the other two conventional methods, which are *No information asymmetry* (NIA), and *Linear Pricing* (LP). These two approaches are typically considered benchmark schemes used in various works in [7], [34], [58]. Note that in NIA, the BS is assumed to have complete information on UAVs that is UAV types (θ_t). It means that BS can design a selfish contract bundle to maximize its payoffs. On the other hand, LP is an approach that the BS that defines a price for a single time slot t and applies system-wise. Fig. 4a shows that our approach guarantees the utility of the BS is strictly non-negative which is only equal to zero at contract type $\theta_t = 0$. Our proposed approach is to achieve a close performance of NIA, which is the maximum utility for the BS. On the other side, the utility of a UAV in NIA is approximately zero due to the BS always designing a scheme that maximizes utility for itself only. Moreover, we can see that our proposed solution approach can guarantee the utility of the UAV is better than NIA and LP that, as shown in Fig. 4b. In Fig. 4c, we have shown the performance of our proposed scheme via social welfare maximization. As shown in the figure, our proposed scheme achieved the same performance as NIA in terms of social welfare maximization while outperforming the LP scheme. According to the results, our proposed scheme not only maximizes social welfare but also maximizes the utility of UAVs.

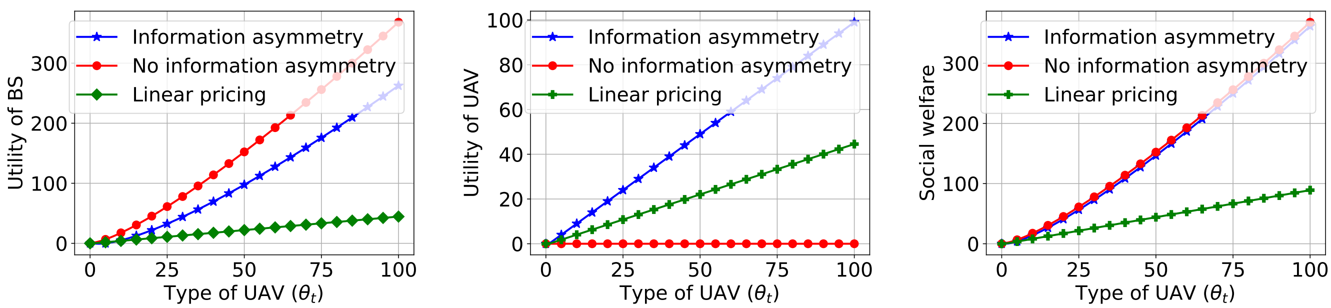
D. Feasibility conditions

In Fig. 4, we can see that the IR constraints (34b) always hold for any UAV type (θ_t). For instance, in Fig. 4a, the utility of BS at type $\theta_t = 50$ is 150, and $\theta_t = 75$ is 250. Similarly, in Fig. 4b, the UAV utility at type $\theta_t = 25$ is 22, and $\theta_t = 75$ is 68. Furthermore, in Fig. 5, we have validate the IC constraint by showing 3 example of $\theta_t = \{30.0, 60.0, 90.0\}$ for a better visualization. We can claim that our proposed approach guarantees the IC conditions based on the numerical results. The UAV achieves maximum utility if and only if it chooses a proper contract according to the UAV type. For instance, if the number of time slots that the UAV can participate is 30, as shown in the figure, we can see that the utility of type-30 $\theta_t = 30$ is the highest at $t = 30$. Similarly for $\theta_{=60}$ and $\theta_t = 90$ is highest at $t = 60$ and $t = 90$, respectively.



(a) (b) (c)

Fig. 3: Stochastic model versus UAV's type: (a) Cumulative Distribution Function (CDF) of the number of requests for a single time slot according to user request rate, (b): Expected caching utility of the BS versus the type of UAVs, and (c) Total power consumption of UAVs versus its type.



(a) (b) (c)

Fig. 4: Performance of proposed framework: (a) Utility of the BS versus UAV types, (b): Utility of UAV versus its type, and (c) Social welfare.

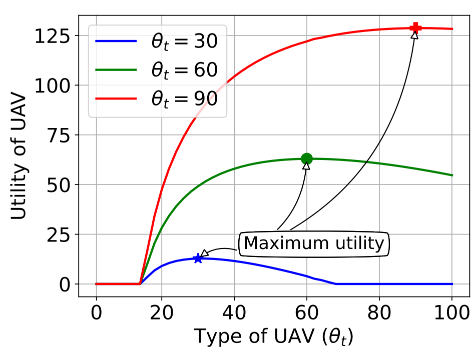


Fig. 5: Feasibility of IC constraints.

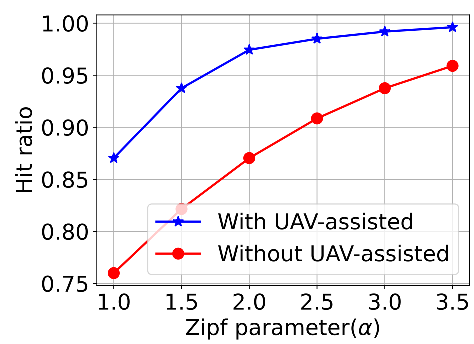


Fig. 6: Impact of proposal model onto the caching model.

E. Impact of UAV caching model

We analyze the impact of the UAV caching model by taking to account our proposed approach and without the UAV caching model. In which, we evaluate the hit ratio on cached VRCs, we fix the user request rate $\lambda = 0.3$ and vary the Zipf parameter $\alpha = \{1.0 \sim 3.5\}$. The total number of UEs in a cluster is $N_l = 20$, and the number of VRC in Ω_K, $|\Omega_K| = 100$. As shown in Fig. 6, our proposal has improved the hit ratio by an average 25% compared to the case that without UAV-assisted MEC.

F. Optimality of contract theory-based solution approach

In this paper, our solution approach is a game theoretic-based approach; thus, the Nash Equilibrium (NE) is considered as the optimal solution [6]. Therefore, we simply integrate the IR and IC conditions into the solution of problem $U_{BS}(\theta_t) = U_v(\theta_t), \forall v \in V, \forall t \in T$. We can easily see that the utility function of BS is linear in (29), and the utility function of UAV is logarithm in (27); thus, exclude the trivial solution at $U_{BS}(0) = U_v(0) = 0$ it always exists a solution for the NE that is visualized in Fig. 7.

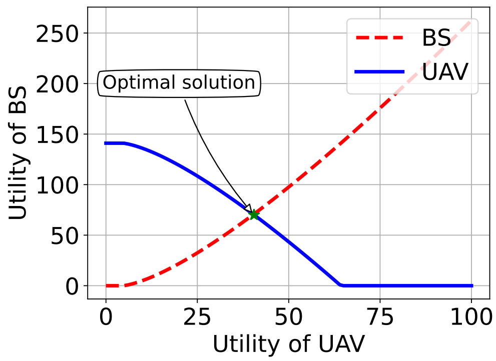


Fig. 7: Optimal solution of contract bundle.

VI. Conclusion

In this paper, we investigated the problem of UAV-assisted MEC on VR-based services in B5G. We designed an attractive incentive mechanism based on contract theory, and we derided an optimal contract design solution under the problem of information asymmetry. By taking comprehensive numerical results, we have shown that the performance of our proposed approach can enhance the social welfare and utility of both BS and UAVs. Moreover, our proposed approach is suitable for A2G communication in B5G. By employing our model, we can increase the network's spectrum efficiency and caching utility. Furthermore, we can improve the quality of VR-based services by utilizing a UAV as a UBS to bring more computation, communication, and caching nearby the end-users.

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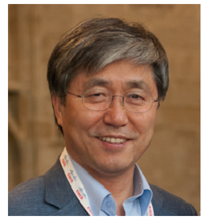

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