

Ruin Theory for Energy-Efficient Resource Allocation in UAV-Assisted Cellular Networks

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Abstract—Unmanned aerial vehicles (UAVs) can provide an effective solution for improving the coverage, capacity, and the overall performance of terrestrial wireless cellular networks. In particular, UAV-assisted cellular networks can meet the stringent performance requirements of the fifth generation new radio (5G NR) applications. In this article, the problem of energy-efficient resource allocation in UAV-assisted cellular networks is studied under the reliability and latency constraints of 5G NR applications. The framework of ruin theory is employed to allow solar-powered UAVs to capture the dynamics of harvested and consumed energies. First, the surplus power of every UAV is modeled, and then it is used to compute the probability of ruin of the UAVs. The probability of ruin denotes the vulnerability of draining out the power of a UAV. Next, the probability of ruin is used for efficient user association with each UAV. Then, power allocation for 5G NR applications is performed to maximize the achievable network rate using the water-filling approach. Simulation results demonstrate that the proposed ruin-based scheme can enhance the flight duration up to 61% and the number of served users in a UAV flight by up to 58%, compared to a baseline SINR-based scheme.

Index Terms—5G new radio (5G NR), user association, energy efficiency, power allocation, ruin theory, surplus process, unmanned aerial vehicles, URLLC.

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I. INTRODUCTION

THE use of *unmanned aerial vehicles (UAVs)* can enable a wide range of smart city applications, ranging from drone delivery to surveillance and monitoring [1]–[3]. Recently, the use of UAVs has greatly increased in wireless-networking applications to provide coverage and capacity enhancement to the ground wireless networks [4]. The flexibility, autonomy, and ease of deployment of UAVs render them suitable to be a part of the future wireless networks. In wireless networking applications, UAVs can have various roles that range from flying base stations (BSs) ([3]) to backhaul nodes ([5]) and users of the cellular network ([3], [6], [7]). Therefore, by leveraging line-of-sight (LoS) communication at high altitudes as well as the dynamic placement of UAVs at desired locations and within a required time [8], the use of UAVs as flying BSs can play a significant role in boosting the capacity of cellular networks [9]. For example, in [10], the authors proposed an UAV-assisted heterogeneous cellular network (HetNet) to meet the communication demands in emergencies for public safety. The authors in [11] used optimal transport theory to enable UAVs to provide communication services to ground users while optimizing their flight time. Moreover, the authors of [12] proposed an efficient UAV BSs in coexistence with a terrestrial network. In particular, when wireless connectivity is needed in difficult and costly deployment locations, UAVs can provide low-cost and low-power alternatives and complement conventional small cell BSs (SBSs). For instance, a joint positioning and user association problem was introduced in [13], where UAVs were used as a replacement for terrestrial SBSs. The authors in [14] used circle packing theory to efficiently deploy multiple UAVs that provide maximum coverage for users. The authors in [15] proposed the deployment of UAVs to power the sensors in an IoT network. The authors in [16] proposed a 3D point process-based UAV deployment where the UAVs with multiple antennas provide downlink coverage to the ground users. The authors in [17] proposed a 3D deployment scheme for the UAVs while guaranteeing the safety distance between UAVs in mmWave network. Moreover, UAVs are a very promising solution to the problem of connectivity in occasionally crowded areas, such as stadiums or open-air shows. Owing to these benefits of UAVs in wireless communications, it is envisioned that future wireless cellular networks [4] will be *UAV-assisted* because they can complement their terrestrial infrastructure with flying UAV

BSs. Meanwhile, to design efficient UAV-assisted cellular networks, it is necessary to address various challenges that range from network modeling to optimization and resource management [3].

The use of UAVs is particularly meaningful for delivering 5G new radio (NR) applications [18]. Enhanced mobile broadband (eMBB) users require high data rates for 3D movies, gaming and AR/VR services. UAVs can promise such high data rates by exploiting the LoS communication [19]. Since UAVs have already been used for data collection from Internet of Things (IoT) networks [20], they can perform well for massive machine type communication (mMTC). Moreover, to meet the reliability and latency demands of ultra-reliable and low-latency communication (URLLC) applications, the LoS communication, and optimal positioning features of UAVs can be promising. Recently, the use of UAVs has been proposed in delay-sensitive and mission critical applications [21]–[23]. The authors in [21] proposed a dynamic trajectory control algorithm to optimize the delay and throughput in the UAV-aided networks. In [22], the authors developed a URLLC channel model to ensure the delay-sensitive delivery of critical control information from the ground station to the UAV. The authors in [23] used a URLLC-enabled UAV to develop a relay system for the delay-sensitive and ultra-reliable communication. The authors in [24] used UAV as a relaying node between the controller and robot when there is no LoS link available between them. The location and power of the UAV is optimized to meet the URLLC reliability requirements. The authors in [25] studied the use of ultra-reliable low latency communications for controlling UAVs and allowing them to avoid collisions. The authors in [26] discussed the URLLC communication for IoT networks while analyzing the security challenges in IoT. However, most of these prior works focused on the use of UAVs to incorporate mMTC or URLLC services, rather than consolidating all of the 5G services. Therefore, we propose the UAV-assisted cellular networks to serve the cellular users while incorporating eMBB, URLLC and mMTC services of 5G NR.

User association and power allocation schemes for the UAV-based networks have been proposed in the literature, e.g., in [27]–[29] and [30]. For instance, the authors in [27] proposed sum power minimization scheme to optimize user association and power allocation in mobile edge computing network (MEC). The authors used an iterative algorithm to solve the formulated problem by decomposing it into three subproblems. The authors in [28] proposed a joint user association and power control scheme for UAV-enabled cellular networks. The authors applied matching-based scheme to form coalition game among the UAVs. The authors in [29] proposed a machine learning based resource allocation scheme for multi-UAV network. The authors in [30] proposed to jointly solve the user association and power allocation problem in UAV-enabled MEC networks using successive convex approximation scheme.

A. Energy Efficiency in UAV-Assisted Cellular Networks

The efficient utilization of the limited onboard energy of a UAV to serve cellular users is a significant challenge. Many

energy-efficient solutions for UAV communication networks have been proposed to address this problem [31]–[36]. For instance, the authors in [31] developed a non-cooperative game to optimize the beaconing periods among competing drones. In this way, the energy consumption in individual drones is optimized in a distributed manner. The authors in [32] proposed a spectrum and energy-efficient scheme for UAV-enabled relay network, in which the UAV path is optimized by allocating the communication time slots between source and destination nodes. In [33], the authors proposed an energy-aware power allocation scheme in the UAV-assisted edge networks while utilizing the internet of vehicles for the computation offloading. The authors in [34] developed a UAV placement scheme to maximize the served users while consuming the minimum transmit power. The authors in [35] designed a UAV communication scheme to optimize the UAV trajectory while minimizing the energy consumption during the UAV flight. The authors in [36] proposed an energy efficiency scheme in downlink (DL) and uplink (UL) decoupled access network. The authors in [37] proposed a downlink energy transfer from the UAVs to the ground IoT devices, and the uplink information transfer from IoT devices to the UAVs.

In order to improve energy efficiency in UAV-assisted wireless networks, it is possible to harness the possibility of *energy harvesting* (particularly using renewable sources such as solar energy), a technical challenge that has not been considered in the aforementioned works [30]–[35]. By employing energy harvesting, the same UAVs can be used to serve the cellular users for a comparatively longer duration to increase the air time of UAV. In this regard, there exist very few studies [38]–[41] that discussed UAVs with energy-harvesting capabilities for wireless networking. In [38], the authors studied the problem of energy management in heterogeneous networks that integrate solar-powered drones. In particular, the approach in [39] is used to optimize the trips of the drones at specific locations so as to minimize the total energy consumption in the network. The authors in [40] addressed the problem of energy limitations in drones by developing a wireless power recharging system which is on renewable energy harvesting. In [41], a comprehensive analysis of the energy harvesting was performed for UAVs from the solar and wind sources. The problem of signal-to-noise-ratio outage minimization for the ground users was formulated to optimize the transmit power and flight duration of UAVs. However, since all the aforementioned works assume energy harvesting in UAV networks that are deployed to assist traditional wireless networks, the study of UAV-enabled networks to satisfy the requirements of heterogeneous user traffic remains largely overlooked. In practice, it is imperative to consider the coexistence between UAV networks with an underlaid next-generation cellular infrastructure incorporating eMBB, URLLC and mMTC services.

B. Contributions

The main contribution of this article is a novel energy-efficient user association and power allocation framework for optimizing energy-constrained UAV-assisted

cellular networks and meet 5G NR performance requirements. To accomplish this goal, we first formulate a joint user association and power allocation problem to achieve the maximum rate for enhanced mobile broadband (eMBB) users in the network under the constraints of URLLC quality-of-service (QoS) requirements and limited power of BSs. Using the framework of *ruin theory* [42], [43], we solve the user association problem by modeling the surplus power in every UAV BS (UBS) [44]. Here, surplus power is defined as the total residual power for a given UAV at any time instant. In particular, we determine the so-called *probability of ruin* of the surplus power in each UBS and then use it for user association with UBSs. The adoption of ruin theory to model the surplus power in the UAVs helps to efficiently capture two opposing power flows that include: (a) the periodic power harvested in the form of regular premiums, and (b) the power allocated to the associated cellular users in the form of claims. In this regard, conventional stochastic optimization cannot properly capture the dynamics of these opposing powers in UAVs. For instance, [35] presented an energy efficient trajectory design scheme for the UAVs. However, they do not consider the energy harvesting in their energy model. The authors in [45] studied the battery dynamics of the UAVs to capture the charging and discharging flows of battery power. In contrast to these schemes, ruin theory captures the charging and discharging flows of powers as well as the randomness in the transmission power of the UAVs. After obtaining the energy-efficient association of the cellular users with a particular BS based on the probability of ruin, the power allocation to the associated users is performed under 5G NR constraints.

In summary, our key contributions include the following:

- To maximize the data rate of eMBB users while satisfying the latency and reliability constraints of URLLC users, we formulate a joint energy-efficient, user association, and power allocation problem. The formulated problem is difficult to solve because the problem is *mixed integer non-linear programming (MINLP)*. Therefore, we propose a novel ruin-based user association and water-filling algorithm for the power allocation to the associated eMBB users.
- First, we model the surplus power in a UBS as function of three components: (a) the initial power in the UAVs at the time of dispatch, (b) the regular harvested power was obtained in the form of premiums from the solar panels mounted on the UAVs, and (c) the transmission power from UAVs to the cellular users. From the surplus process, we determine the probability of ruin which is further used for the user association.
- After user association, we develop a new power allocation algorithm to allocate downlink power to the associated cellular users. Power allocation to the URLLC users is initially performed under a reliability constraint and, then, the water-filling scheme is used to allocate power to eMBB users.
- Simulation results demonstrate that UAV-assisted cellular networks perform well to satisfy the stringent 5G NR requirements. Moreover, we show that the proposed ruin-based user association serves up to 58% more

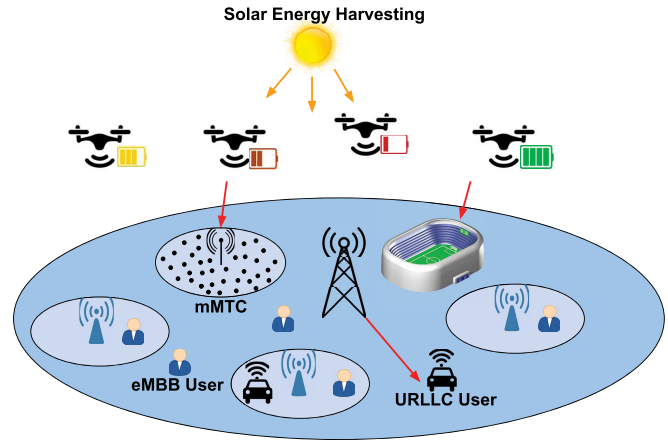


Fig. 1. System model of UAV-assisted cellular network.

number of users during a UAV flight compared to a benchmark SINR-based scheme.

To the best of our knowledge, this is the first study that applies ruin theory to model the surplus power in UBSs for optimizing user association in UAV-assisted cellular networks.

The rest of this article is organized as follows. Section II presents the system model and problem formulation. In Section III, we develop a ruin theoretic framework to model the surplus UAV power which is used for the user association. In Section III-D, the proposed water-filling based power allocation algorithm is developed; and numerical evaluation of the proposed framework are discussed in Section IV. Conclusions are drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a UAV-assisted cellular network that comprises of a single macro BS (MBS), a set \mathcal{S} of S SBSs, and a set \mathcal{U} of U UBSs for the downlink communication. These BSs can be compositely denoted by $\mathcal{T} = \{0\} \cup \mathcal{S} \cup \mathcal{U}$, where $\{0\}$ denotes the index of the MBS. Every UAV has a limited power storage capacity to store ρ_0 power at the start of a flight. Moreover, there is a solar *energy-harvesting module* mounted on every UAV. The UAVs are deployed above the ground cellular network at the corresponding locations denoted by $\mathbf{r}_u = (x_u, y_u, h_u)$, for every UAV $u \in \mathcal{U}$ [22]. We consider the following three types of users in 5G NR environment: (a) a set \mathcal{K}_e of K_e eMBB users, (b) a set \mathcal{K}_u of K_u URLLC users, and (c) a set \mathcal{K}_m of K_m mMTC users. The data obtained from all the IoT nodes of mMTC network is multiplexed in a single frame. The data demand from this single frame is equal to one regular eMBB user demand. Therefore, without loss of generality, we remark that there is only one mMTC user denoted by index $\{0\}$ in the network. All these cellular users are compositely denoted by $\mathcal{K} = \{0\} \cup \mathcal{K}_e \cup \mathcal{K}_u$, where $\{0\}$ denotes the index of the mMTC user.

We study the network for a short duration of time, and the network topology is considered static during this period. For the sake of exposition, we consider that the UAVs $u \in \mathcal{U}$ are deployed at key locations \mathbf{r}_u in which the cellular demand is highest. This assumption is aligned with the main use-case

of UAVs as BSs that service hotspot areas for a temporary duration. We assume that determining the optimal locations follows known algorithms such as in [14].

A. Transmission Model

Due to the different propagation environments, the channel gain of the UBSs differs from the ground SBSs and the MBS. In particular, the channel gain is given by: $h_{jk} = 10^{-\delta_{jk}/10}$ and is a function of the corresponding pathloss δ_{jk} . The path-loss δ_{uk} between UAVs and ground users is composed of LoS path-loss, δ_{uk}^{LoS} and non-LoS path-loss, $\delta_{uk}^{\text{NLoS}}$, respectively given as follows:

$$\delta_{uk}^{\text{LoS}} = 20 \log \left(\frac{4\pi d_{uk} f}{c} \right) + L_{\text{LoS}}, \quad (1)$$

$$\delta_{uk}^{\text{NLoS}} = 20 \log \left(\frac{4\pi d_{uk} f}{c} \right) + L_{\text{NLoS}}, \quad (2)$$

where f is the carrier frequency, and d_{uk} denotes the distance between UAV u and cellular user k . Moreover, L_{LoS} and L_{NLoS} are the average added losses for LoS and NLoS communication, respectively. The probability of existing a LoS link between UAVs and ground users is given as follows [46]:

$$\Pr_{uk}^{\text{LoS}} = \frac{1}{1 + a \exp[b(\frac{180}{\pi} \tan^{-1} \frac{h_u}{d_{uk}}) - a]}, \quad (3)$$

where h_u is the height of the UAV u , and a and b are environment constants, respectively. The probability of non-LoS link between UAVs and ground users is given as follows:

$$\Pr_{uk}^{\text{NLoS}} = 1 - \Pr_{uk}^{\text{LoS}}. \quad (4)$$

Hence, the average path-loss between UAVs and ground users is given as follows:

$$\delta_{uk} = \Pr_{uk}^{\text{LoS}} \delta_{uk}^{\text{LoS}} + \Pr_{uk}^{\text{NLoS}} \delta_{uk}^{\text{NLoS}}. \quad (5)$$

Path-loss δ_{jk} , for the terrestrial BSs $j \in \{\{0\} \cup \mathcal{S}\}$ is given by the following [47], [48]:

$$\delta_{jk} = 15.3 + 37.6 \log(d_{jk}), \quad (6)$$

where d_{jk} denotes the distance between BS j and cellular user k .

The signal-to-interference-plus-noise ratio (SINR), which is denoted by γ_{ij} from the BS j to the cellular user k is given by the following:

$$\gamma_{jk} = \frac{P_{jk} h_{jk}}{\sum_{j' \in \mathcal{J} \setminus \{j\}} P_{j'k} h_{j'k} + \sigma_{jk}^2 \omega_{jk}}, \quad (7)$$

where P_{jk} denotes the downlink transmission power from BS $j \in \mathcal{J}$ to the user $k \in \mathcal{K}$, h_{jk} denotes the channel gain, and σ_{jk}^2 denotes the noise power spectrum density at user k [26]. Note that $P_{j'k}$ denotes the interference power from the neighboring BS j' to the user k and is equal to $P_{j'k''}$, where k'' is another user that uses the same frequency band as user k . ω_{jk} denotes the bandwidth allocated to the communication link between the BS $j \in \mathcal{J}$ and cellular user $k \in \mathcal{K}$. Each BS $j \in \mathcal{J}$ is assigned a portion of the licensed bandwidth denoted by W_j . This bandwidth W_j is further divided equally

among the various cellular users associated with BS j .¹ A bandwidth $\omega_{jk} = \frac{W_j}{\sum_{k \in \mathcal{K}} x_{jk}}$ is allocated to the communication link between the BS $j \in \mathcal{J}$ and cellular user $k \in \mathcal{K}$, where $\sum_{k \in \mathcal{K}} x_{jk}$ denotes the total number of associated users with the BS j . x_{jk} denotes the association variable given as:

$$x_{jk} = \begin{cases} 1, & \text{if user } k \in \mathcal{K} \text{ is associated with BS } j \in \mathcal{J}, \\ 0, & \text{otherwise.} \end{cases}$$

The achievable rate of a cellular user k associated with the BS j is given by the following:

$$R_{jk} = x_{jk} \omega_{jk} \log(1 + \gamma_{jk}), \quad (8)$$

B. 5G NR Traffic Classification Model

As previously explained, the set of cellular users \mathcal{K} in the network can be classified into two main categories based on the 5G NR traffic classification as $\mathcal{K} = \mathcal{K}_u \cup \mathcal{K}_e$ while $\mathcal{K}_u \cap \mathcal{K}_e = \emptyset$, where \mathcal{K}_u denotes the set of URLLC users and \mathcal{K}_e denotes the set of eMBB users. This means that any user k can be classified into one of these two network user groups \mathcal{K}_u or \mathcal{K}_e . The data obtained from all the IoT nodes of mMTC network is multiplexed in a single subframe 1 ms. Thus, we consider the communication for the mMTC traffic which is multiplexed into a single subframe and is dedicated fixed bandwidth of ω_{j0} as shown in Fig. 2. Additionally, we consider the downlink communication for the URLLC and eMBB traffic. It can be observed from Fig. 2 that the arrival of URLLC traffic reduces the achievable rate of the eMBB users because eMBB traffic could be stopped during URLLC transmission. The achievable eMBB rate after serving $\sum_{k' \in \mathcal{K}_u} x_{jk'}$ URLLC requests is given as follows:

$$D_{jk}(x_{jk}, P_{jk}) = \left(T - t \sum_{k' \in \mathcal{K}_u} x_{jk'} \right) R_{jk}, \quad \forall k \in \mathcal{K}_e, \quad (9)$$

where T and t denote the eMBB and URLLC TTIs respectively as shown in Fig. 2. D_{jk} represents the amount of data which can be communicated from BS j to the eMBB user k during time T while simultaneously serving $\sum_{k' \in \mathcal{K}_u} x_{jk'}$ URLLC users.

C. Problem Formulation

We can now formulate an optimization problem to maximize the network rate for eMBB users subject to the URLLC reliability and latency constraints, the power level constraints of each BS $j \in \mathcal{J}$, and the unique association of the cellular users with each BS, as follows:

$$\max_{\mathbf{x}, \mathbf{P}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D_{jk}(x_{jk}, P_{jk}), \quad (10)$$

$$\sum_{k \in \mathcal{K}} P_{jk} \leq \rho_j, \quad \forall j \in \mathcal{J}, \quad (10a)$$

$$\Pr(\gamma_{jk'} \geq \zeta) \geq (1 - \epsilon), \quad \forall j \in \mathcal{J}, \quad \forall k' \in \mathcal{K}_u, \quad (10b)$$

¹Note that the proposed resource allocation scheme can be efficiently used for the multiple antennas on separate instances for each channel resource.

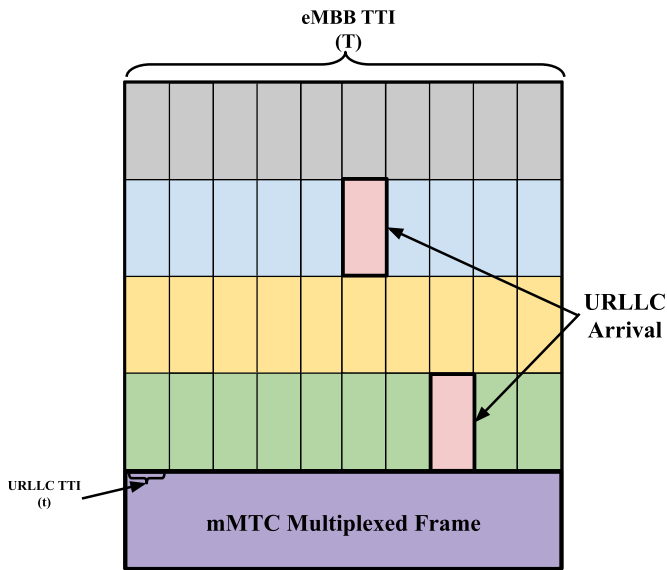


Fig. 2. The frame structure of 5G NR traffic for the coexistence of eMBB, URLLC, and mMTC. mMTC is allocated a dedicated bandwidth. eMBB traffic is pre-scheduled for eMBB TTI duration, T in each frame. URLLC traffic is scheduled instantaneously for URLLC TTI duration, t .

$$\sum_{k' \in \mathcal{K}_u} x_{jk'} = \lambda_u, \quad \forall j \in \mathcal{J}, \quad (10c)$$

$$\sum_{j \in \mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K}, \quad (10d)$$

$$0 \leq P_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}, \quad (10e)$$

$$x_{jk} \in \{0, 1\}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}. \quad (10f)$$

The objective is to maximize the eMBB users' sum-rate in the network. Based on the maximum power level ρ_j of each BS j , the constraint in (10a) limits the total power allocation to all the associated users. (10b) ensures ultra-reliability by maintaining a sufficient SINR level for the URLLC users above the threshold ζ with $1-\epsilon$ confidence level. (10c) ensures low latency for URLLC users by strictly scheduling the arrived λ_u URLLC requests in the same slot. (10d) ensures the unique association of eMBB user k with a single BS j . (10e) and (10f) are the bounds for the decision variables, where p_{\max} denotes the maximum power level that can be allocated for a user. Note that, the upper bound p_{\max} is helpful in reducing the interference from neighboring BSs. The following is the power level, ρ_j for each BS $j \in \mathcal{J}$:

$$\rho_j = \begin{cases} \rho_j(\tau), & \text{for } j \in \mathcal{U}, \\ P_0, & \text{for } j = 0, \\ P_1, & \text{for } j \in \mathcal{S}. \end{cases} \quad (11)$$

D. UAV Energy Model

Every UAV $u \in \mathcal{U}$ has a certain power level $\rho_u(\tau)$ at time instant τ , which comprises the initial power ρ_0 stored in the UAV, the power ρ^u that is harvested by UAV u from renewable energy sources within a unit time. Note that the unit time τ is measured in seconds and is longer than the eMBB TTI T and URLLC TTI t . The UAVs have power consumption in the form

of propulsion power and the power allocation to the cellular users. The propulsion power ρ_h , consumed in the hovering state of the UAV is constant due to the fixed air speed, UAV height and other environmental variables. The power allocation to the set of cellular users associated with UAV u is denoted by $\sum_{k \in \mathcal{K}} P_{uk}$. The surplus power of UAV u at time instant τ , is given by:

$$\rho_u(\tau) = \rho_0 + \rho^u \tau - \sum_{k \in \mathcal{K}} P_{uk} - \rho_h. \quad (12)$$

Note that the surplus power of every UAV has an upper bound ρ_{\max} which denotes the limited power storage capacity of the UAVs. In the absence of the solar energy source at night time or cloudy weather, the UAVs can be switched to other renewable energy sources (e.g., laser, UV, or fuel cells) [45], [49]. We now observe that this surplus power has bidirectional flows of power. The positive power flow is in the form of periodic harvested power and the negative power flow is in the form of power consumption on the downlink communication from UAVs to cellular users and propulsion power. Hence, an efficient system design should well-capture these power flows to improve the overall energy utilization. In this regard, conventional stochastic optimization requires full network knowledge to provide a centralized solution; hence, less efficient. Therefore, we use a stochastic process-based framework of ruin theory to address this challenge and model the surplus UAV power and the probability of ruin of UAV to formulate the stochastic optimization problem. To that end, the probability of ruin at UAV represents the vulnerability of draining out a UAV's power. In particular, it is used to efficiently utilize the available energy of UAVs while performing user association with each UAV.

III. USER ASSOCIATION AND POWER ALLOCATION: A RUIN-BASED SOLUTION

A. Ruin Theory: Preliminaries

In the area of actuarial science [44], ruin theory is applied to express an insurer's vulnerability of bankruptcy. This is performed by modeling the so-called surplus process which represents the insurer's capital at a time instant τ and comprises two opposing cash flows: (a) the periodic income gained from regular insurance premiums, and (b) random claims. The insurer's vulnerability of risk is determined from the probability of ruin which essentially represents the probability of getting a negative surplus. As explained earlier, we will apply *ruin theory* to formulate the surplus power in every UAV u at a time instant τ , and is further used to compute the probability of ruin. The number of cellular users associated with the UAV is then determined based on the probability of ruin of each UAV.

Ruin theory is utilized to model the *UAV surplus power process* which represents the random UAV power levels over time τ . The surplus UAV power depends on three essential factors: a) launch power, b) premium power, and c) claim, that we define next.

Definition 1: The launch power, which is denoted by ρ_0 is defined as the power stored in the UAV at the time of launch.

Definition 2: The premium power, which is denoted by ρ^u is defined as the constant power harvested by UAV u from the renewable energy resource in a unit time τ .

Definition 3: The claims are defined as the random transmit power allocations to the cellular users associated with a UAV.

The UAV surplus power, is composed of constant renewable power harvested at regular intervals, and the power dissipation on providing the communication services to the associated cellular users, i.e., $\sum_{k \in \mathcal{K}_u} P_{uk}$. For simplicity, we ignore the constant hovering power ρ_h in the rest of the article.

Let, $S_u = \sum_{k \in \mathcal{K}_u} P_{uk}$ denote the compound random variable which is composed of two random variables \mathcal{K}_u , and P_{uk} , where \mathcal{K}_u denotes the number of users associated with the UAV u and P_{uk} denotes the power allocated by the UAV u to the associated cellular user k . This compound variable S_u is exponentially distributed with parameter μ . Consequently, the surplus power given in (12) can be formally defined as follows:

$$\rho_u(\tau) = \rho_0 + \rho^u \tau - S_u. \quad (13)$$

The surplus in (13), which represents the UAV power at time instant, τ , is utilized to find the finite-time probability of ruin defined as follows [42].

Definition 4: The finite-time probability of ruin is defined as the probability of getting a negative surplus at any time instant s during a finite time τ . The finite-time probability of ruin is mathematically given by:

$$\psi(\rho_0, \tau) = \Pr[\rho_u(s) < 0, \text{ for some } s \text{ as } 0 < s < \tau], \quad (14)$$

where τ denotes the total number of discrete time units, and s ranges from 0 to τ .

In the surplus process, the depreciation in surplus is modeled using an exponential distribution of a parameter, μ , which represents the distribution parameter of the claims in the surplus process. The exponential distribution is used for the independent time-separated arrival of events. Therefore, the depreciation in the surplus process with exponential distribution in ruin theory [44]. The finite-time probability of ruin, $\psi_k(\rho_0, \tau)$, can be obtained as follows [42]:

$$\psi_u(\rho_0, \tau) = \sum_{j=1}^{\tau} \frac{[\mu c_j(\rho_0)]^{j-1}}{(j-1)!} e^{-\mu c_j(\rho_0)} \frac{c_1(\rho_0)}{c_j(\rho_0)}, \quad (15)$$

where μ denotes the parameter of Poisson distribution for the arrival of claims and $c_j(\rho_0) = \rho_0 + jc$, and $c_1(\rho_0) = \rho_0 + c$ represent the expressions for the accumulated power levels at time instants j and 1, respectively. In our scenario, we model the arrival of cellular users with Poisson process [50]. $\psi_k(\rho_0, \tau)$ represents the probability of ruin of the UAV power at time instant, τ , while ρ_0 denotes the UAV power at time 0.

B. Ruin-Based Problem Formulation

Next, we separate (10a) for $j \in \mathcal{U}$ and embed it to the objective function in the form of the probability of ruin for every UAV u . Then we define a new optimization that is equivalent to (10) (the proof of equivalence is given in

Appendix A), as follows:

$$\max_{\mathbf{x}, \mathbf{P}} \varsigma \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D_{jk}(x_{jk}, P_{jk}) - \xi \sum_{u \in \mathcal{U}} \psi_u(\rho_0, \tau), \quad (16)$$

$$\sum_{k \in \mathcal{K}} P_{jk} \leq \rho_j, \quad \forall j \in \{\{0\} \cup \mathcal{S}\}, \quad (16a)$$

$$\Pr(\gamma_{jk'} \geq \zeta) \geq (1-\epsilon), \quad \forall j \in \mathcal{J}, \quad \forall k' \in \mathcal{K}_u, \quad (16b)$$

$$\sum_{k' \in \mathcal{K}_u} x_{jk'} = \lambda_u, \quad \forall j \in \mathcal{J}, \quad (16c)$$

$$\sum_{j \in \mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K}, \quad (16d)$$

$$0 \leq P_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}, \quad (16e)$$

$$x_{jk} \in \{0, 1\}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}. \quad (16f)$$

The objective is to maximize the sum-rate of the users in the network and minimize the probability of ruin for the surplus power in the UAVs, where ς and ξ are normalizing constants. Before proceeding to the solution, we first simplify the problem by embedding (16c) in the objective function. This is done as follows:

(16c) is an equality constraint which ensures the immediate scheduling of λ_u number of arrived URLLC users in the same time slot t . This scheduling is performed by associating the URLLC user k' with the BS j delivering best SINR $\gamma_{jk'}$. The resultant eMBB rate after URLLC scheduling is expressed as follows:

$$D'_{jk}(x_{jk}, P_{jk}) = (\text{T-t}\lambda_u) R_{jk}, \quad \forall k \in \mathcal{K}_e, \quad (17)$$

where the expression $\text{T-t}\lambda_u$ denotes the remaining duty-cycle for the eMBB communication after scheduling λ_u number of URLLC packets. $\sum_{k' \in \mathcal{K}_u} x_{jk'}$ in (16c) refers to the associated URLLC users which sum up to the number of arrived URLLC users, λ_u . By replacing the expression $\sum_{k' \in \mathcal{K}_u} x_{jk'}$ with λ_u in (9), we get (17).

For the optimal power allocation to the URLLC users, we state the following proposition:

Proposition 1: Power allocation to the URLLC users is performed to meet certain SINR threshold, ζ , which ensures the URLLC reliability as given in (16b). The optimal power allocation to the URLLC users can be performed as follows:

$$P_{jk'}^* = \frac{\mathcal{F}_{\gamma_{jk'}}^{-1}(1-\epsilon)(1+I)}{h_{jk}}, \quad (18)$$

where $\mathcal{F}_{\gamma_{jk'}}^{-1}(1-\epsilon)$ denote the inverse CDF of $\gamma_{jk'}$, and $I = \sum_{j' \in \mathcal{J} \setminus \{j\}} P_{j'k} h_{j'k} + \omega_{jk} \sigma^2$.

Proof: The proof of (18) is given in Appendix B. \square

Note that we analyze the network for a duration in which the power allocation from another BS $j' \in \mathcal{J} \setminus \{j\}$ is known. Therefore, (16b) becomes a convex constraint.

After adjusting (16c) and solving the URLLC power allocation in (18), the remaining power at each BS for the eMBB users is $\rho_j - \sum_{k' \in \mathcal{K}_u} P_{jk'}^*$. The user association and power allocation problem for eMBB users is given as follows:

$$\max_{\mathbf{x}, \mathbf{P}} \varsigma \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D'_{jk}(x_{jk}, P_{jk}) - \xi \sum_{u \in \mathcal{U}} \psi_u(\rho_0, \tau), \quad (19)$$

$$\sum_{k \in \mathcal{K}_e} P_{jk} \leq \rho_j - \sum_{k' \in \mathcal{K}_u} P_{jk'}^*, \quad \forall j \in \{\mathcal{J} \setminus \mathcal{U}\}, \quad (19a)$$

$$\sum_{j \in \mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K}, \quad (19b)$$

$$0 \leq P_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}, \quad (19c)$$

$$x_{jk} \in \{0, 1\}, \quad \forall j \in \mathcal{J}, \quad k \in \mathcal{K}. \quad (19d)$$

It can be observed that problem (III-B) is an MINLP, which is difficult to solve using exhaustive search and branch and bound techniques, particularly for a large network. Furthermore, the binary variable x_{jk} makes the problem combinatorial which may require exponential-complexity to solve using exhaustive search for the number of users. To avoid the difficulty, we convert the problem into simple sub-problems which are solved for each variable separately. In particular, to get a near optimal solution, we first fix the power allocation and solve the problem of user association by employing ruin-based heuristic approach. Then, we solve the power allocation problem using the optimal ruin-based user association solution.

C. Ruin-Based User Association With UAVs

The first sub-problem solves x_{jk} to estimate the possible number of users which can be associated with each UAV. This estimation is performed by modeling the surplus power of a UAV using the probability of ruin. After fixing P_{jk} , the user association sub-problem is given by:

$$\max_{\mathbf{x}} \zeta \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D'_{jk}(x_{jk}, P_{jk}) - \xi \sum_{u \in \mathcal{U}} \psi_u(\rho_0, \tau), \quad (20)$$

$$\sum_{j \in \mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K}, \quad (20a)$$

$$x_{jk} \in \{0, 1\}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}. \quad (20b)$$

For the sake of energy-efficiency, the user association x_{jk} , with every UAV u is performed based on its probability of ruin, $\psi_u(\rho_0, \tau)$, obtained from (15). This is done by limiting the number of associated users with each UAV based on the probability of ruin. Meanwhile, when the probability of ruin of a UAV is high, fewer users are associated to that UAV and vice versa. One meaningful approach for user association is to associate the cellular user k , with that BS which is providing better SINR level γ_{jk} . This SINR-based approach is not energy-efficient and, hence, it is not suitable for the problem of power constrained user association with the UAVs. We propose an approach that combines SINR and probability of ruin-based approach in the following definition.

Definition 5: To incorporate both the SINR and the probability of ruin in the UAV user association problem, we introduce a factor, η_{jk} , defined as follows:

$$\eta_{jk} := \alpha(1 - \psi_u(\rho_0, \tau))\gamma_{jk}, \quad (21)$$

where the term $(1 - \psi_u(\rho_0, \tau))$ denotes the probability of survival and α is a control factor.

It can be observed that the factor η_{jk} consolidates both the SINR and the probability of ruin. Therefore, the cellular user is associated with that UBS that provides a better SINR to the cellular user and has a relatively less probability of ruin.

The user association problem (20) is combinatorial and difficult to solve for the large network. To solve the problem,

Algorithm 1 User Association Algorithm

```

1: Input:  $J, K, P_{jk}, \rho_j$ ;
2: Initialize:  $x_{jk}^* = 0$ ;
3: Step 1:
4: Compute  $\psi_u(\rho_0, \tau)$  from (15);
5: Compute  $\eta_{jk}$  from (21);
6: for  $k = 1$  to  $K$  do
7:   Select single BS  $j$  with  $\max_{j \in \mathcal{J}} \eta_{jk}$ ;
8: end for
9: Step 2:
10: for  $j = 1$  to  $J$  do;
11:   Initialize  $P = \rho_j$ ;
12:   while  $P \geq 0$  do
13:     Find  $\max_{k \in \mathcal{K}} \gamma_{jk}$ ;
14:     Update  $x_{jk}^* = 1$ , and  $P = P - P_{jk}$ ;
15:     Remove  $\max_{k \in \mathcal{K}} \gamma_{jk}$  from  $SINR$  vector  $\gamma_{jk}$ ;
16:   end while
17: end for

```

we present a ruin-based heuristic approach in Algorithm 1 that results to a near optimal solution. The inputs are the following: the total number of BSs, J , the total number of network users, K , fixed power allocation P_{jk} , allocated to each user k , and the total power bound, p_j of BS j . In Algorithm 1, first, the probability of ruin, $\psi_u(\rho_0, \tau)$ is computed in step 4 by using the initial power storage ρ_0 , the harvested power ρ^u and the random claim arrivals. The probability of ruin is further used to compute η_{jk} from (22) in step 5. Then, every cellular user, k , selects the BS j with the maximum value of η_{jk} in step 7. Next, the users are sorted according to the SINR values and are associated with the corresponding BS under the constraints of power level ρ_j of each BS in step 13. The association x_{jk}^* and the remaining BS power P is updated in step 14. The algorithm terminates when either P is zero or all the cellular users are associated. This algorithm gives a near-optimal solution with the complexity of $\mathcal{O}(N)$ for performing user association using the probability of ruin. We will show the optimality gap in the simulation results in Section IV, where it will be observed that the UAV with less surplus power will have a high probability of ruin. Hence, fewer users will be associated with that UAV.

D. Power Allocation to eMBB Users

From the previous section, we obtain the optimal associated users denoted by x_{jk}^* . After performing the ruin-based optimal user association, the next step is to solve the power allocation problem. Thus, the updated value of the achievable rate for the set of the associated eMBB users is given by:

$$R'_{jk} = (T-t\lambda_u) x_{jk}^* \omega_{jk} \log(1 + \gamma_{jk}). \quad (22)$$

The proof of equivalence of (19) and (23) is given in Appendix C. The sub-problem for the power allocation to eMBB users is given as follows:

$$\max_{\mathbf{P}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_e} R'_{jk}, \quad (23)$$

Algorithm 2 Iterative Ruin-Based Resource Allocation Algorithm

- 1: **Input:** $J, K, P_{jk}, \rho_j, \eta_{jk}$;
 - 2: Set uniform power to each BS and user pair $\{j,k\}$ i.e.
 $P_{jk}[0] = \rho_j/K$;
 - 3: Compute γ_{jk} at each user k from the BS j ;
 - 4: **Initialize:** $t = 0$;
 - 5: Associate and allocate power to URLLC users using (18)
 ;
 - 6: **while** $t \leq T_{\max}$ **or** $\epsilon^* \geq \epsilon_0$ **do**
 - 7: $x_{jk}^*[t] = \operatorname{argmax}_x \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D'_{jk}$;
 - 8: Allocate power P_{jk}^* to eMBB users using (24);
 - 9: **Update**
 - 10: $P_{jk}[t] = P_{jk}^*$;
 - 11: $\epsilon^* = P_{jk}[t] - P_{jk}[t-1]$;
 - 12: $t = t + 1$;
 - 13: **end while**
-

$$\text{s.t. } \sum_{k \in \mathcal{K}_e} P_{jk} \leq \rho_j - \sum_{k' \in \mathcal{K}_u} P_{jk'}, \quad \forall j \in \{\{0\} \cup \mathcal{S}\}, \quad (23a)$$

$$0 \leq p_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e. \quad (23b)$$

Problem (23) is convex because the objective function and all of the constraints are convex. To solve this problem, we use a variant of the water-filling algorithm where the power, P_{jk} allocated to a user is limited by a threshold, p_{\max} , and the leftover power is allocated to the other low-gain network users as shown in Fig. 4. The following optimal solution is obtained:

Proposition 2: The optimal power allocation P_{jk}^ is expressed as:*

$$P_{jk}^* = \min \left\{ p_{\max}, \left[\frac{x_{jk}^* \omega_{jk}}{\lambda_j} - \frac{1}{\theta_{jk}} \right]^+ \right\}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e, \quad (24)$$

where θ_{jk} is the channel gain for the user k from BS j defined as:

$$\theta_{jk} = \frac{h_{jk}}{1 + \sum_{j' \in \mathcal{J} \setminus \{j\}} P_{j'k} h_{j'k} + \omega_{jk} \sigma^2}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e. \quad (25)$$

We note that the maximum power that can be allocated to a user is limited by p_{\max} . From (24), we get λ_j^* which denotes the optimal water level chosen such that the following condition is satisfied.

$$\sum_{k \in \mathcal{K}_e} P_{jk}^* = \rho_j - \sum_{k' \in \mathcal{K}_u} P_{jk'}, \quad \forall j \in \mathcal{J}. \quad (26)$$

Proof: To get (26), we get the KKT conditions by computing the Lagrangian function and other necessary conditions of (25). By concurrently solving the KKT conditions we obtain (26). \square

The maximum power bound p_{\max} helps to serve more users by allocating the leftover power to low channel gain users. This is performed by adjusting the water level, λ_j , using (26). This is illustrated in Fig. 4 where the first two users are allocated

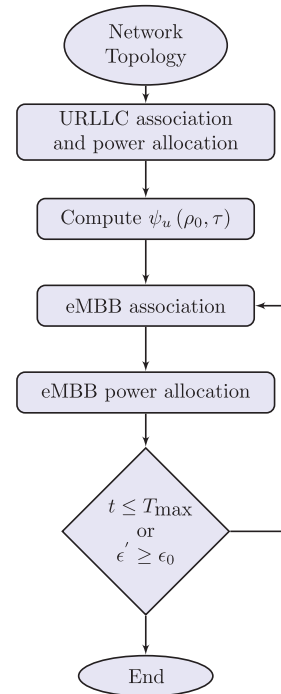


Fig. 3. Systematic diagram of the iterative algorithm.

maximum power, while the leftover power is allocated to the other users by accordingly adjusting the water level, λ_j . The third user is allocated power using (24) based on the available channel gain, θ_{jk} , while the fourth user is not allocated any power because of a very small channel gain.

To solve (20), we present an iterative association and power allocation approach in Algorithm 2. First, a uniform power is allocated to all the user-BS pairs. Then, the users maximizing the network rate under maximum power bounds are selected until the algorithm iteration time t is less than the maximum iteration threshold T_{\max} , or the algorithm convergence parameter ϵ^* is greater than the convergence threshold ϵ_0 . Then, the power allocation for the selected users is performed using the water-filling algorithm. Fig. 3 shows the systematic diagram and flowchart of the iterative algorithm for the association and power allocation. Note that this algorithm adopts water-filling algorithm with the complexity of $\mathcal{O}(N.M)$. The joint algorithm complexity of the proposed algorithm comprising of both ruin-based algorithm and water-filling algorithm is $\mathcal{O}(N.M)$. The algorithm gives a near-optimal solution and we show the optimality gap in the next section.

IV. SIMULATION RESULTS

For our simulation, we consider a geographical area of 4000 m \times 4000 m square. MBS is deployed in the center at a fixed location, whereas 10 SBSs and 5 UAVs are uniformly deployed in the area. The cellular users are randomly located in the geographical area. Statistical results are averaged over several runs of random locations of cellular users, SBSs and UAVs. Other simulation parameters are given in table I.

Fig. 5 shows the network topology which comprises a single MBS and uniformly deployed SBSs, UBSs and the cellular

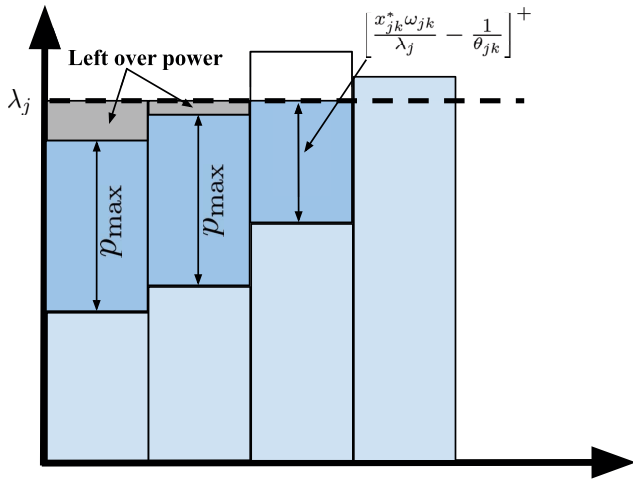


Fig. 4. An illustration of the water-filling algorithm.

TABLE I
SIMULATION PARAMETERS.

Parameters	Values	Parameters	Values
URLLC TTI	0.125 ms	eMBB TTI	1 ms
MBS Radius	500 m	Reliability (ϵ)	99.999%
SBS Radius	100 m	Frequency (f)	2 GHz
UBS Height	200 m	Bandwidth (W)	50 MHz
ρ_o	100 W	ρ^u	5 W
UAV Transmit Power			0.5 W
Path Loss (UBS)			$20 \log(d_{uk}f) - 147.55$
Path Loss (SBS and MBS)			$16.62 + 37.6 \log(d_{uk})$

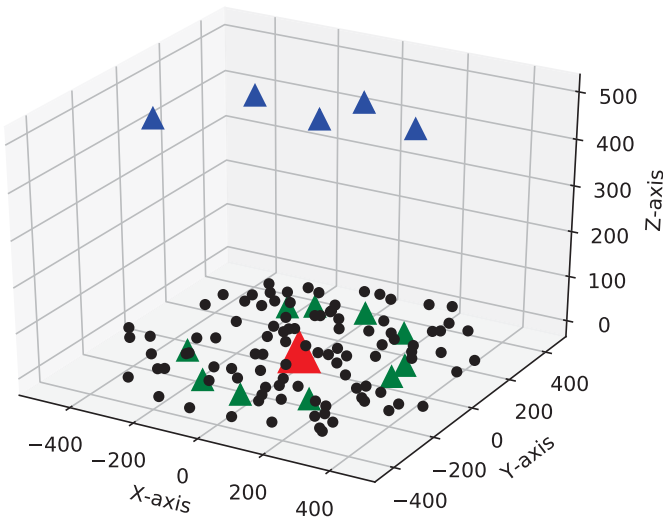


Fig. 5. Network topology consisting of MBS, SBSs, UBSs and the cellular users.

users. The UBSs are deployed at a height of 200 m above the ground level.

Fig. 6 demonstrates the per-user network rate as a function of the number of users. The network rate is calculated after solving the optimization problem for 5 UAVs and 5 SBSs. These results indicate that the UAV-assisted network achieves

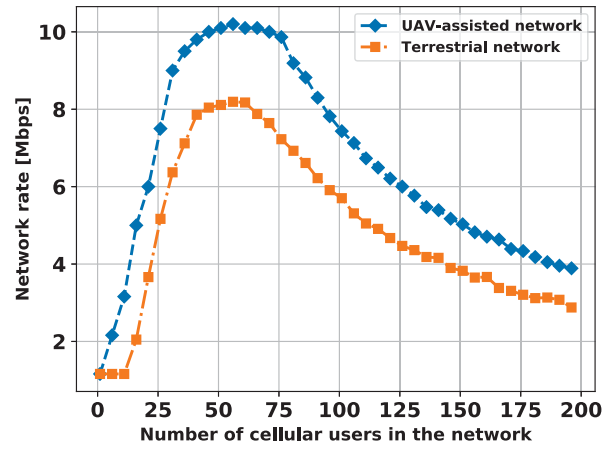


Fig. 6. Network rate vs. number of cellular users in the network.

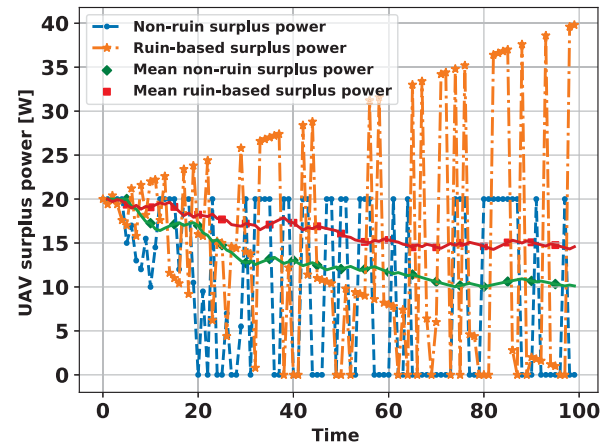


Fig. 7. Total surplus power of all UAVs at different time instants.

a better per-user rate when compared with the terrestrial network. For example, when the number of users in the network is about 75, the UAV-assisted network achieves about 40% more rate when compared with the terrestrial network. This is due to the LoS communication link between UAV and ground users which deliver better SINR as compare to the non-LoS link of the terrestrial network. From Fig. 6, we can also observe that the network rate reduces as the number of users in the network increases. This is due to the limited power resources at BSs which are insufficient to serve all the users in the network. We also observe that the decline in network rate is very slow. This is due to the optimal user association where the users with better SINR are associated with the BS.

Fig. 7 illustrates how the surplus power per UAV varies over time during a single flight of UAV. We show the power allocation to the associated users for 100 TTIs. The optimization problem is solved by running the ruin-based association algorithm and water-filling power allocation algorithm for each TTI. The initial UAV surplus power at the time of launch $t = 0$ is set to be 100 Watts. By controlling the number of the associated users through the probability of ruin, up to 52% higher level of the UAV surplus power is achieved when compared with the non-ruin approach. By preserving the

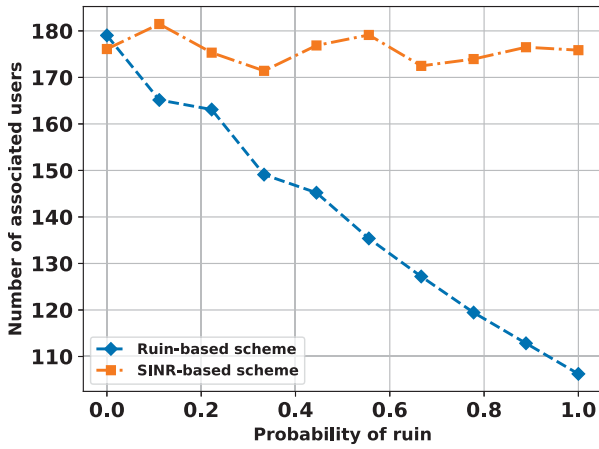


Fig. 8. Number of total users associated with all UAVs vs. the probability of ruin.

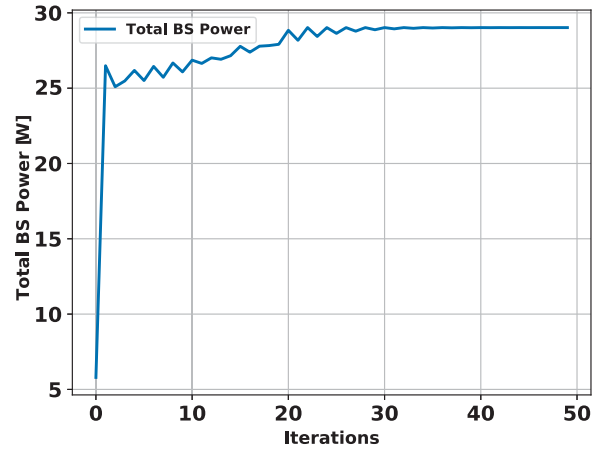


Fig. 11. Plot of convergence.

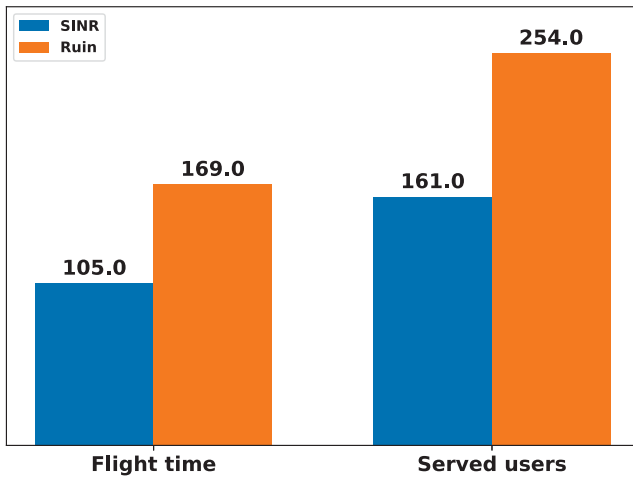


Fig. 9. Comparison of ruin and SINR-based approach for UAV flight time and number of served users.

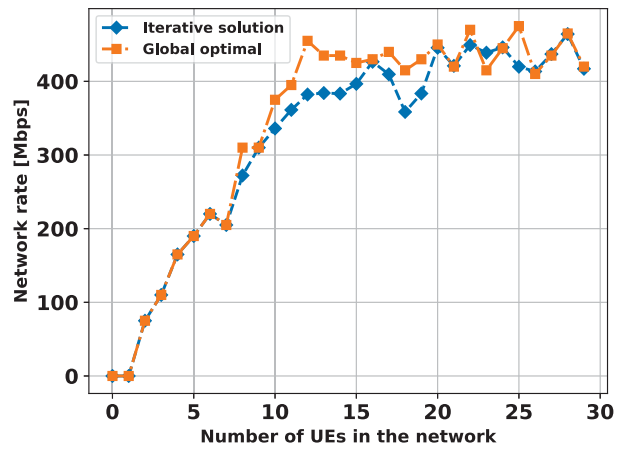


Fig. 12. Network rate vs. number of cellular users in the network.

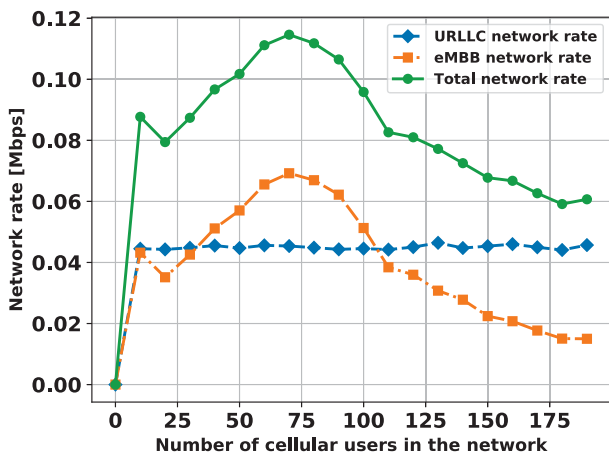


Fig. 10. Network rate vs. number of cellular users in the network.

surplus UAV power as shown by the significant differences in power drops at certain time instants, the ruin-based approach can serve more number of cellular users eventually.

Fig. 8 demonstrates how the number of UAV-associated cellular users varies with the probability of ruin. We compare the proposed ruin-based scheme with a baseline SINR-based scheme, which associates the cellular users with the UAVs to give the best SINR without considering the surplus power of the UAVs. By decreasing the number of associated cellular users with the UAVs, it can be observed that the proposed ruin-based scheme tries to preserve UAV power with an increase in the probability of ruin. The non-associated users are offloaded to other UAVs with less probability of ruin or to the terrestrial network.

Fig. 9 shows the flight time in units of TTIs and the number of served users during a single flight of UAV for the SINR-based and ruin-based approaches. Fig. 9 demonstrates that the ruin-based approach enhances the flight time of UAV by offloading the users to terrestrial network. As a result, exploiting the energy harvested during the enhanced flight duration, more number of cellular users are served by the UAV eventually. For instance, the flight duration of UAV by offloading the users to terrestrial network is 64 TTIs as compared to the SINR-based approach. During 64 TTIs, additional energy is harvested which is further used to serve 93 more users during the UAV flight. Consequently, the proposed ruin-based scheme

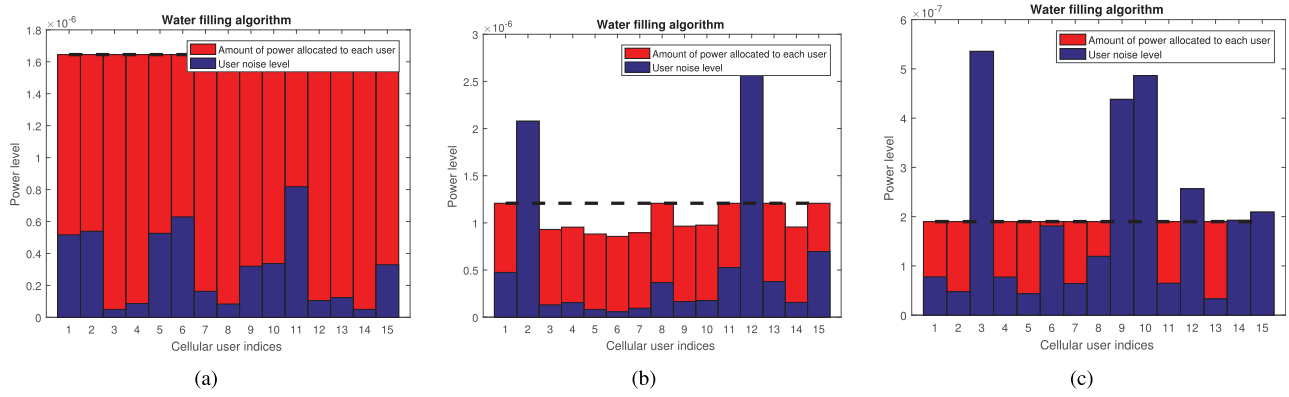


Fig. 13. Scenarios: (a) sufficient transmission power at the UAVs, (b) the high channel gain users are allocated maximum power level p_{max} and the low channel gain users are allocated power proportionally, and (c) all the users have very low channel gain as compared to the available power.

can enhance the flight duration up to 61% and the number of served users in a UAV flight by up to 58%, compared to a baseline SINR-based scheme.

Fig. 10 shows the plot of a network for the two traffic classes of 5G NR, i.e., eMBB and URLLC against the number of network users. From this figure, we can see that the rate of URLLC traffic is not affected by increasing the number of network users. Meanwhile, the eMBB rate significantly decreases as the number of users in the network increases. This is because the URLLC users are given priority over the eMBB users by allocating the resources to satisfy their latency and reliability requirements.

Fig. 11 shows the convergence of power allocation algorithm against the number of iterations. The power allocation is performed to the associated set of users by the BS in an iterative manner. It can be observed that the algorithm converges after 30 number of iterations. With the help of water-filling scheme, the iterative power allocation is performed.

Fig. 12 demonstrates the optimality gap between the proposed and optimal solution. We use the Gurobi optimization tool to obtain the optimal solution of the original problem II-C. We show the optimality gap results for the small network containing up to 30 cellular users. It can be observed that there is no gap for a small network when there are up to 7 cellular users in the network. A very small and negligible gap is observed as the number of cellular users increases in the network. This gap is due to the upper bound of maximum number of iterations T_{max} . This upper bound restricts the iterative algorithm to the near-optimal solution for the large network.

Fig. 13 illustrates three possible cases of the water-filling algorithm for power allocation. We show the results for a different amount of powers to be allocated to the associated cellular users. In the first case Fig. 13(a), there is sufficient available power which is allocated to the associated users based on the proportional noise level. It means that the user with high noise level is allocated less power and vice versa. In the second case Fig. 13(b), there is enough power available that p_{max} is allocated to the low-noise users and high-noise users are allocated power based on the water level. In the third

case Fig. 13(c), the available power is insufficient; therefore, the power is allocated to each user based on the noise level while satisfying the water level feasibility.

V. CONCLUSION

In this article, we have studied the UAV-assisted cellular networks to enhance the cellular network capacity. We have formulated a joint optimization problem for the user association and power allocation for the 5G NR traffic classifications. First, we have performed the user association and power allocation to the URLLC users under reliability and latency constraints. Then, by utilizing the probability of ruin to estimate the possible number of cellular users to be associated with each UAV, we have solved the user association problem. Based on the probability of ruin of the UAV, the cellular traffic was offloaded by associating the cellular users with the other UAVs or the terrestrial network. Then, we have iteratively solved the power allocation problem using the water-filling scheme. Simulation results have demonstrated the effectiveness of the proposed ruin-based energy-efficiency scheme in terms of increasing the flight time of UAVs and the number of served cellular users.

APPENDIX A

PROOF OF EQUIVALENCE OF (10) AND (16)

(10a) is separated for the UBSs $j \in \mathcal{U}$ as follows:

$$\sum_{k \in \mathcal{K}} P_{jk} \leq \rho_j, \quad \forall j \in \mathcal{U}, \tag{27}$$

where $\rho_j = \rho_0 + \rho t$ denoted the power level of UAV j . By rearranging (27), we get that

$$\rho_0 + \rho t - \sum_{k \in \mathcal{K}} P_{jk} \geq 0, \quad \forall j \in \mathcal{U}. \tag{28}$$

Inequality (28) refers to the positive surplus power for every UAV which is the definition of the probability of ruin. Therefore, inequality (28) is equivalent to minimizing the probability of ruin.

APPENDIX B

PROOF OF POWER ALLOCATION TO URLLC USERS

From (16b), $\Pr(\gamma_{jk'} \geq \zeta)$ can be expressed as CDF $F_{\gamma_{jk'}}(\zeta)$. So we get:

$$F_{\gamma_{jk'}}(\zeta) \geq (1 - \epsilon), \quad (29)$$

From here, we can easily get the following expression for ζ

$$\zeta \geq \mathcal{F}_{\gamma_{jk'}}^{-1}(1 - \epsilon) \quad (30)$$

The maximization of the eMBB data rate under the constraint (16b) gives boundary solution $\gamma_{jk'} = \zeta$ for the optimal power allocated to the URLLC users. The optimal power is given as follows:

$$P_{jk'}^* = \frac{\mathcal{F}_{\gamma_{jk'}}^{-1}(1 - \epsilon)(1 + I)}{h_{jk}}, \quad (31)$$

where $I = \sum_{j' \in \mathcal{J} \setminus \{j\}} P_{j'k} h_{j'k} + \omega_{jk} \sigma^2$.

APPENDIX C

PROOF OF EQUIVALENCE OF (19) AND (23)

The objective function of problem (19) is given as follows:

$$\varsigma \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} D'_{jk} - \xi \sum_{u \in \mathcal{U}} \psi_u(\rho_0, \tau). \quad (32)$$

It can be seen that the factor $\xi \sum_{u \in \mathcal{U}} \psi_u(\rho_0, \tau)$ is constant when observed from the perspective of power allocation and therefore can be ignored in the optimization problem (23). Then after the URLLC association $x_{jk'}$ according to Proposition 1 and the ruin-based eMBB association x_{jk} , the eMBB data rate is given as follows:

$$R'_{jk} = (T-t\lambda_u) x_{jk}^* \omega_{jk} \log(1 + \gamma_{jk}), \quad (33)$$

which is the objective function of the problem (23).

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