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Intercell Interference Coordination for UAV Enabled URLLC using Cognitive Radio

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ABSTRACT: Ultra-reliable and low latency communications (URLLC) will be the backbone of the upcoming sixth-generation (6G) systems and will facilitate mission-critical scenarios. A design accounting for stringent reliability and latency requirements for URLLC systems poses a challenge for both industry and academia. Recently, unmanned aerial vehicles (UAV) have emerged as a potential candidate to support communications in futuristic wireless systems due to providing favorable channel gains thanks to Line of-Sight (LoS) communications. However, usage of UAV in cellular infrastructure increases interference in aerial and terrestrial user equipment (UE) limiting the performance gain of UAV-assisted cellular systems. To resolve these issues, we propose low-complexity algorithms for inter cell interference coordination (ICIC) using cognitive radio when single and multi-UAVs are deployed in a cellular environment to facilitate URLLC services. Moreover, we model BS-to-UAV (B2U) interference in downlink communication, whereas in uplink we model UAV-to-BS (U2B), UAV-to-UAV (U2U), and UE-to-UAV (UE2U) interference under perfect/imperfect channel state information (CSI). Results demonstrate that the proposed perfect ICIC accounts for fairness among UAV especially in downlink communications compared to conventional ICIC algorithms. Furthermore, in general, the proposed UAV-sensing assisted ICIC and perfect ICIC algorithms yield better performance when compared to conventional ICIC for both uplink and downlink for the single and multi-UAV frameworks.

KEYWORDS: Ultra-reliable and low latency communications (URLLC), unmanned aerial vehicles (UAV), inter cell interference coordination (ICIC), channel state information (CSI).

I. INTRODUCTION

Ultra-Reliable and low-latency communications are one of the key services which is present in the current fifth-generation (5G) as well as futuristic sixth generation (6G) networks. Comparably, 5G Ultra-reliable and low latency communications (URLLC) cannot satisfy all the key performance indicators (KPIs) of wide and diverse mission-critical applications such as virtual/augmented reality (VR/AR), Industry 5.0, Meta-Universe, unmanned aerial vehicles (UAVs) control, non-payload communications (CNPC), tactile Internet, etc. As such, to provide adequate services to these applications, 6G networks are envisioned to satisfy additional KPIs integrated with URLLC such as high energy efficiency, spectrum utility, network availability, ultra-high reliability, as well as low latency and the round-trip delay. Moreover, depending on the mission critical application at hand, the ultra-high reliability target can drop to a lower value, i.e., 5G networks are not designed to cater to such stringent reliability targets for facilitating URLLC services. Under such conditions, 6G networks come to the rescue and aim to enhance URLLC services by improving both fronts, namely reliability and latency targets by at least two magnitude folds. Presently, for radio access networks (RAN), 5G networks can realistically achieve the target of 1 ms transmission delay. Nonetheless, transmission delay amounts to a small portion of end-to-end (E2E) delay, whereas other delay types such as processing, queuing, round trip hybrid automatic repeat request (HARQ), and packet decoding delays also factor in and contribute significantly to the overall E2E delay, which in turn could deter URLLC targets by becoming bottlenecks in networks. Additionally, latency and reliability are present on the opposite end of the same spectrum, i.e., they are inversely proportional. Therefore, these relevant issues about latency and reliability have not been properly investigated by present 5G networks. Moreover, URLLC systems generate short block length packets which follow the so-called finite block length capacity formula. As such, URLLC systems are not throughput-centric but are latency and reliability centric which signals a shift in paradigm from previous wireless communication technologies.

The wireless transmission of video data captured by Unmanned Aerial Vehicles (UAVs) has started to receive attention in various cyber-physical systems, including surveillance, public safety, and traffic monitoring. In a typical

UAV network, a flying UAV, also known as drone, equipped with a camera captures high-quality images and videos in real-time from the sky for users located at the Ground Station (GS). At present, a flying UAV equipped with a camera is commercially available. For example, DJI Phantom 4 UAV can rise at 6 m/s, fly at 72 km/h, swerve at 250°/s and deliver 2K real-time images and videos. The main advantage of a UAV network is that the deployment of UAVs can be agile and re-configurable due to flexible mobility and the ability to perform tasks autonomously and collaboratively. As a matter of fact, in the UAV network, the involved UAVs cooperate with each other and manage their actions through the exchange of information, e.g., status information, sensor data, and commands. Recently, efficient placement of UAVs has attracted significant research attention to address challenges like the optimal deployment considering energy efficiency, deployment and throughput maximization. Besides, the UAV path planning considering different communication and network constraints is rigorously to enhance the network lifespan or even provide consistent service during critical missions, battery charging approaches have been designed. These approaches include charging of battery at night through a high energy laser beam or wireless power transfer and equipping the UAVs with solar panels. However, to the best of our knowledge, none of the existing works focus on the design of distributed task scheduling techniques for the UAVs in response to the dynamics of real-time tracking applications, where objects dynamically arrive and move around the network. To this end, in this work, we focus on an important problem of efficiently scheduling the data traffic of the UAVs to track moving objects in real-time across many geographical areas.

Despite the widespread applications of the UAVs, scheduling data traffic under dynamic scenarios tender many new challenges. Specifically, the lifespan and performance of the UAV networks are primarily limited by the on-board energy, which is limited due to the UAV's size and weight constraints. Therefore, energy-efficient task scheduling for maximizing the information bits per unit energy consumption of the UAV is of utmost importance. Recently, task scheduling under dynamic application scenarios in the UAV networks has received considerable attention, as it is significantly different from the terrestrial networks the traditional queue-length based MaxWeight task scheduling has failed to deliver optimal throughput. Subsequently, many novel scheduling techniques have been designed recently in the context of routing protocols by leveraging link duration adaptive Q-Learning or independent of routing by leveraging ant colony optimization, meta learning. However, none of these works have considered the dynamic traffic flows while designing their scheduling techniques. Besides, several throughput optimal scheduling techniques have been proposed under dynamic traffic scenarios by leveraging game theory and reinforcement learning. Moreover, in most of these works, Round-Robin Strategy (RRS) has been proposed for task scheduling, where a schedule at the beginning of communication is constructed by dividing the time into fixed-length rounds. By rotating the lead role responsibility among the UAVs, the RRS balances the energy consumption in the UAV networks. However, the cost of message exchanges during the lead role assignment creates a significant overhead.

The policy closest to our work is the distributed task scheduling policy designed in that addressed the lifespan enhancement issue for Wireless Sensor Networks (WSNs). But this work does not fulfil the essential performance of the UAV networks, e.g., real-time capturing of various KPIs like throughput, end-to-end delay. This is because irregular network connectivity due to high movement is more prevalent in UAV networks than WSNs. 5G is suitable for Internet of Vehicles (IoV) communication, so the resource allocation of IoV under 5G environment is an important research topic. The 3rd Generation Partnership Project (3GPP) has finished the standardization work of vehicle-to-vehicle (V2V) communications. Three available communication modes are suggested for IoV, including traditional cellular network mode, Ad-hoc mode and device-to-device (D2D) mode. The operating frequency of the Ad-hoc network is 5.9GHz, of which the vehicle communication standard. Ad-hoc network can complete self-organization of vehicle communication. However, it has been pointed out that there are many problems in Ad-hoc networks such as wireless channel access delay, the received information cannot meet the timeliness requirements, and the lack of communication quality assurance. At the same time, Ad-hoc network can only provide short life cycle and intermittent link connection. The communication link will be limited by the wireless range and the scarcity of roadside infrastructure. Moreover, a single Ad-hoc network will bring broadcast storms and intolerant delays. The long-term evolution system (LTE) does not meet the requirements for transmitting vehicle channel state information (CSI) due to large round trip delay. Therefore, this communication mode is not suitable for V2V communication when there are large amount of vehicles. In traditional cellular network, all the vehicular communications must be forwarded by a base station (BS). This results in wasted energy, transmission delays, and heavy burdens on the backhaul link. The D2D-enabled V2V link provides a direct communication link to effectively reduce communication delay and energy consumption. Therefore, the D2D-enabled vehicle communication, which is capable of achieving a reliable connection and meeting the vehicle's timely communication requirements, could be applied to the V2V link.

II. REVIEW OF LITERATURE

C. W. Chen in 2020 proposed that the worldwide flourishing of the Internet of Things (IoT) in the past decade has enabled numerous new applications through the internetworking of a wide variety of devices and sensors. More recently, visual sensors have seen their considerable booming in IoT systems because they are capable of providing richer and more versatile information. Internetworking of large-scale visual sensors has been named Internet of Video Things (IoVT). IoVT has its own unique characteristics in terms of sensing, transmission, storage, and analysis, which are fundamentally different from the conventional IoT. These new characteristics of IoVT are expected to impose significant challenges to existing technical infrastructures. In this article, an overview of recent advances in various fronts of IoVT will be introduced and a broad range of technological and system challenges will be addressed. Several emerging IoVT applications will be discussed briefly to illustrate the potentials of IoVT in a broad range of practical scenarios.

W. Wang in 2021 proposed that the fundamental problem of Placement of unmanned Aerial vehicles achieving 3D Directional coverage (PANDA), that is, given a set of objects with determined positions and orientations in a 3D space, deploy a fixed number of UAVs by adjusting their positions and orientations such that the overall directional coverage utility for all objects is maximized. First, we establish the 3D directional coverage model for both cameras and objects. Then, we propose a Dominating Coverage Set (DCS) extraction method to reduce the infinite solution space of PANDA to a limited one without performance loss. Finally, we model the reformulated problem as maximizing a monotone submodular function subject to a matroid constraint and present a greedy algorithm with $1 - 1/e$ approximation ratio to address this problem. We conduct simulations and field experiments to evaluate the proposed algorithm, and the results show that our algorithm outperforms comparison ones by at least 75.4%. Also, in comparison to AID and DBRS, DDP4V has fewer dispersed packets, which results into reduced retransmissions. For 200 automobiles/km², all these techniques accomplish 35–40% of the needed cars. However, the coverage also faces some restrictions since data packets only reach vehicles on the same side as the originating vehicle. Similarly, DDP4V delivers 90% coverage for 400 vehicles/km², which is 30% greater than prior techniques. It is observed that the proposed protocol reduces broadcast storms by employing a wagon wheel to choose the next forwarding vehicle. In high-traffic areas, it outperforms standard techniques. Similarly, it employs a patchwork of vehicles outside of the impacted region to convey data. The industrial IoT-based VANETs provide an effective tool to monitor and control traffic besides reducing the number of traffic accidents.

A. Baltaci, E. Dinc, M. Ozger, A. Alabbasi in 2021 proposed that Addressing a plethora of use cases, drones are gaining attention in the industry and increasingly appear in the sky. Emerging concepts of flying taxi enable passengers to be transported over several tens of kilometers. Therefore, unmanned traffic management systems are under development to cope with the complexity of future airspace, thereby resulting in unprecedented communication needs. Moreover, the long-term increase in the number of commercial airplanes pushes the limits of voice-oriented communications, and future options such as single-pilot operations demand robust connectivity. In this survey, we provide a comprehensive review and vision for enabling the connectivity applications of aerial vehicles utilizing current and future communication technologies. We begin by categorizing the connectivity use cases per aerial vehicle and analyzing their connectivity requirements. By reviewing more than 500 related studies, we aim for a comprehensive approach to cover wireless communication technologies, and provide an overview of recent findings from the literature toward the possibilities and challenges of employing the wireless communication standards. After analyzing the proposed network architectures, we list the open-source testbed platforms to facilitate future investigations by researchers. This study helped us observe that while numerous works focused on cellular technologies to enable connectivity for aerial platforms, a single wireless technology is not sufficient to meet the stringent connectivity demands of the aerial use cases, especially for the piloting operations. We identified the need of further investigations on multi-technology heterogeneous network architectures to enable robust and real-time connectivity in the sky. Future works should consider suitable technology combinations to develop unified aerial networks that can meet the diverse quality of service demands of the aerial use cases.

W. Wang, H. Dai, C. Dong, F. Xiao, X. Cheng in 2021 proposed that the fundamental problem of placement of Unmanned Aerial Vehicles for anisotropic monitoring Tasks (VISIT). That is, given a set of objects on 2D area, place a fixed number of UAVs by adjusting their coordinates and orientations subject to Gaussian bias, such that the overall monitoring utility for all objects is maximized. We develop a theoretical framework to address VISIT. First, we establish the monitoring model whose quality of monitoring (QoM) is anisotropy with respect to monitoring angle and

monitoring distance. To the best of our knowledge, we are the first to consider anisotropic QoM. Then, we propose an algorithm consisting of area discretization and Monitoring Dominating Set (MDS) extraction, to reduce the infinite solution space to a limited one without performance loss. Finally, we prove that the reformulated problem can be modeled as maximizing a monotone submodular function subject to a matroid constraint and present a greedy algorithm with $1-1/e-\epsilon$ approximation ratio to address it. We conduct both simulations and field experiments to evaluate our algorithm, and the results show that our algorithm outperforms comparison algorithms by at least 41.3%.

A. Rahmati in 2021 proposed a transmission mechanism aiming to improve the data rate between a base station (BS) and a user equipment (UE) through deploying multiple relaying UAVs. We consider the effect of interference incurred by another established communication network, which makes our problem challenging and different from the state of the art. We aim to design the 3D trajectories and power allocation for the UAVs to maximize the data flow of the network while keeping the interference on the existing communication network below a threshold. We utilize the mobility feature of the UAVs to evade the (un)-intended interference caused by (un)-intentional interferers. To this end, we propose an alternating-maximization approach to jointly obtain the 3D trajectories and the UAVs transmission powers. We handle the 3D trajectory design by resorting to spectral graph theory and subsequently address the power allocation through convex optimization techniques. We also approach the problem from the intentional interferer's perspective where smart jammers chase the UAVs to effectively degrade the data flow of the network. We also extend our work to the case for multiple UEs. Finally, we demonstrate the efficacy of our proposed method through extensive simulations.

Z. Wang and L. Duan in 2021 proposed the unmanned aerial vehicle (UAV) technology is a promising solution for rapidly providing wireless communication services to ground users, where a UAV has limited-service coverage and needs to fly through users at different locations for serving them locally. The existing UAV deployment studies largely assume the users' demands do not change during UAV deployment. When the users' demands dynamically change over time, the key challenge is how to adapt the UAV deployment strategy to the partial and even outdated observations on the users' activities given the UAV's flying speed limit. In this paper, we study dynamic UAV deployment to learn and adapt to the time-varying user activities, where the activity pattern of a user (if out of the UAV service coverage) is hidden from the UAV and follows a time-slotted Markov chain that switches between active and idle states. We formulate the learning-and-adaption based UAV deployment problem as a partially observable Markov decision process (POMDP) to maximize the total discounted hit rate of active users, where the UAV decides for itself whether to chase an active user in a distant location (with delayed reward) or to wait for the idle user in the current location to return to the active state (with smaller service probability) over time. We show there is a fundamental delay-reward tradeoff, and prove that the UAV will optimally follow a threshold-based policy by waiting at an idle user for a time threshold before moving to another user. We also show the UAV is more likely to move if the temporal correlation of each user's idling pattern is stronger or the travel distance between users is shorter. Furthermore, we extend to a more general scenario where the UAV does not even know the parameters of each user's temporal activity distribution, and apply Q-learning to develop another threshold-based deployment policy for a multi-user scenario.

III. PROPOSED SYSTEM

According to studies have been conducted by the 3rd Generation Partnership Project (3GPP), which highlights the disadvantage of utilizing a UAV in a cellular infrastructure as it could lead to increased interference in a system containing both aerial and ground user equipment (UE). Thus, only relying on UAV Line of Sight (LoS) links without considering interference will not attain the visionary goal of large-scale UAV deployment in cellular infrastructure for futuristic wireless communication systems. A few works in open technical literature as outlined, have discussed intercell interference coordination (ICIC) techniques in cellular environments to mitigate the adverse effects of interference when UAV are deployed. In two user interference channels for the two UAV servicing them. The authors optimized the UAV positioning and transmit power to maximize the sum throughput. However, the authors considered LoS channels for only two users which give limited insights. Multi-UAV framework concerning interference between UAV deployed in adjacent cells for uplink and downlink communications.

Low-complexity algorithms for ICIC using cognitive radio when multi-UAVs are deployed in a cellular environment to facilitate URLLC services. Moreover, we model BS-to-UAV (B2U) interference in downlink communication, while in the uplink we model UAV-to-BS (U2B), UAV-to-UAV (U2U), and UE-to-UAV (UE2U) interference under perfect/imperfect channel state information (CSI). Our results show that our proposed perfect

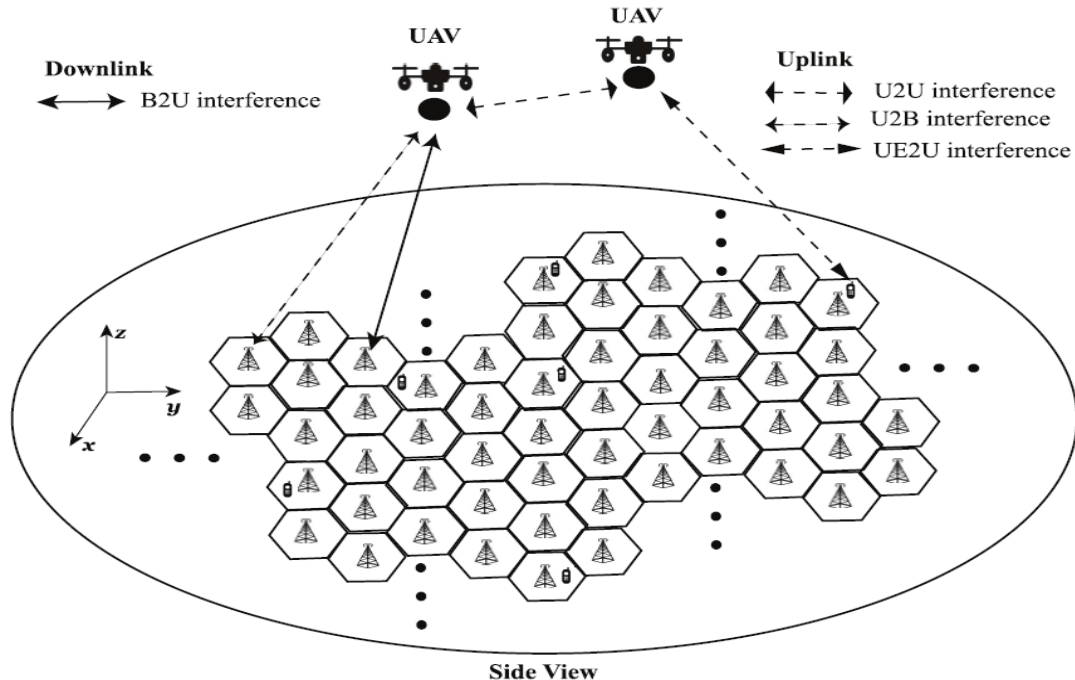


Fig 1.0 Proposed System model

Both downlink and uplink communications facilitated by UAV deployed in hexagonal cells as shown in Fig. 4.1. Accordingly, a simplistic assumption is made that outside interference is negligible. In our model, BS are primarily placed at the center of each cell with circumradius given by r_c . Additionally, terrestrial UE and UAV are positioned randomly in the given cell environment. As such, each UE and UAV is considered to be assigned to the BS in the cell it is located in or above. Furthermore, each UE gets random resource blocks (RB) assigned such that upon each assignment every previous RB allocation is considered in the following way: there is no resource sharing allowed such that no UE or BS can utilize the same requested RBs in neighboring cells of nearest q tiers. Equivalently, if q is unity, then no two neighboring cells can have UE or BS using the same RB. Similarly, if q is two, then we look at two neighbors, i.e., no neighbors of any neighbors of the considered cell may be using the requested RB. Resultantly, strong inter-cell interference (ICI) is mitigated. Additionally, the RB allocation for UAV is performed following the aforementioned neighbor principle relative to its serving BS. It is worth mentioning, that downlink communication is established between BS and UAV, and conversely, uplink communication is established between UAV and BS. According to the data rate R_{dl} , $u_l(n)$ of each UAV k at each RB n in the uplink and downlink communications for short URLLC packets.

SINGLE-UAV INTERFERENCE

The channel dispersion, which refers to the channel variability. For the sake of generality, not approximate channel dispersion equal to unity as only for high Signal to- noise ratio (SNR), such an assumption holds, whereas for low SNR it becomes invalid. The second term in, is the finite block length penalty term. Thereafter, for the downlink communication between BS and UAV, we define interference $I_{dl}(k, n)$ and SINR $\gamma_{dl}(k, n)$ as

$$I_{dl}(k, n) = \sum_{i \in \mathcal{J}(n) \setminus \{j_k\}} P_i(n) F_i(k, n), \quad (1)$$

where $p_{ul}(k, n)$ is the transmission power of UAV k in RB n , $G_j(k, n)$ is the uplink channel power gain from UAV k to BS j in RB n , and σ^2 is the Gaussian noise power at the receiver of any BS. Moreover, $I_{ul}(j_k, n)$ denotes the total uplink interference at UAV k 's serving BS j_k from all other non- k UAVs in RB n . Additionally, another important interference is the maximum interference UAV k causes to any other non- j_k BS using the same RBs, which is given as

$$I_{ul}(k) = \max_{n \in \mathcal{N}_{ul}(k), j \in \mathcal{J}(n) \setminus \{j_k\}} p_{ul}(k, n) G_j(k, n), \quad (2)$$

Propose three algorithms UAV-enabled common (CMN)- ICIC, UAV-enabled cognitive-sensing based superior (CSS)- ICIC, and UAV-enabled cognitive-sensing based (CSB)- ICIC. Algorithm 1 outlines UAV-enabled CSS-ICIC, which is repeated over random initializations L_{in} times, then all the results are averaged over L_{avg} iterations. Furthermore, for Algorithm 1, the UAV-enabled CMN-ICIC. determine \mathcal{N}_{dl}, ul by simply assigning the UAV random RB with neighbor criterion in mind, and by setting $p_{ul}(n) = P_{ul} \forall n$. Additionally, M_d denotes the number of RB candidates in the downlink, and UAV-enabled CSBICIC sets M_d to the number of available RBs after UE RB allocation. In other words, UAV-enabled CSB-ICIC is equivalent to UAV-enabled CMN-ICIC if we set M_d or M_u equal to the number of available RBs after UE RB allocation. Hence, Algorithm 1 represents all the proposed algorithms with a few changes. Additionally, for the proposed schemes, including UAV-enabled CMN-ICIC, CSS-ICIC, and CSBICIC for the downlink, the power control is simple: the BSs always use peak available power P_{dl} to maximize the UAV's achievable rate. Similarly, for the UAV-enabled CMN-ICIC, in the uplink, peak power P_{ul} is always used. Conversely, UAV-enabled CSS-ICIC and CSB-ICIC both utilize for power control in uplink communications to maximize the UE's data rate. To determine the sum complexity, Algorithm 1 UAV-Enabled CSS-ICIC.

MULTI-UAV INTERFERENCE CASE

For the conventional ICIC, a requested number of RB is simply assigned randomly. However, in the UAV-sensing-assisted ICIC proposed, a more complex algorithm is at play wherein a given number of candidates are first randomly picked out complying with the neighbor requirement, of which those with the lowest sensed interference are chosen to be assigned to the UAV. Now, outline the UAV-sensing assisted ICIC scheme for multi-UAV framework, whereas the conventional ICIC would eliminate the entire candidates part and determine $\mathcal{N}_{dl}, ul(k)$ by simply assigning the UAV random RB with neighborhood criterion, and by setting $p_{ul}(k, n) = P_{ul}, \forall k \forall n$. Further, M_d or M_u denotes the number of RB candidates in the downlink/uplink, and a perfect ICIC takes M_d or M_u equal to the total number of RBs in the downlink/uplink. Moreover, N_d or N_u is the number of RBs the UAV requests. Additionally, UAVs become operational one after another, and RB allocation for each UAV is to be done only upon it becomes operational in the service area. This avoids an endlessly iterative process where UAVs would constantly be changing their allocation to account for changes in the environment. Here, Algorithm 2, outlines the program executed in each UAV, whereas Algorithm 3, outlines the scheme we use to simulate the whole environment and extract real data rates and interferences.

where $\mathcal{N}_{ul}(k)$ denotes the RBs set for the uplink that is allocated to UAV k by its serving BS. Conversely, $\mathcal{N}_{dl}(k)$ denotes the RBs set for the downlink, respectively. In both the conventional and UAV-sensing-assisted ICIC for the downlink, the power control is simple: BS always use peak available power P_{dl} to maximize the UAV's achievable rate in the downlink. Similarly, in the conventional ICIC in the uplink peak power P_{ul} is always used. However, in the uplink in the UAV-sensing-assisted model outlined in the power control is more complicated. Here, generalize it to the k th UAV as

$$p_{ul}(k, n) = \min \left\{ 1, \frac{\Gamma_U \rho_k^{\alpha_L}}{E_{ul}(k, n)} \right\} P_{ul}, \quad (3)$$

where Γ_U is a defined threshold of the BS receiver noise power σ^2 , $E_{ul}(k, n)$ is the sensed uplink transmission at UAV k in RB n , α_L denotes the LoS path-loss exponent, and ρ_k has a complex expression for distance as outlined. Moreover, the main idea behind $E_{ul}(k, n)$ as described in detail in is that we do not have the knowledge of the CSI, hence we have to predict it from sensed UE uplink transmissions. Thus, the fundamental difference here is that the sensed transmissions will also include transmissions from other UAV. This will result in a higher $E_{ul}(k, n)$ and hence a lower $p_{ul}(k, n)$ than in [31]. The formulation is given as

$$E_{ul}(k, n) = P_{ul} \sum_{j \in \mathcal{J}(n)} E_j(k, n), \quad (4)$$

IV. RESULT AND DISCUSSION

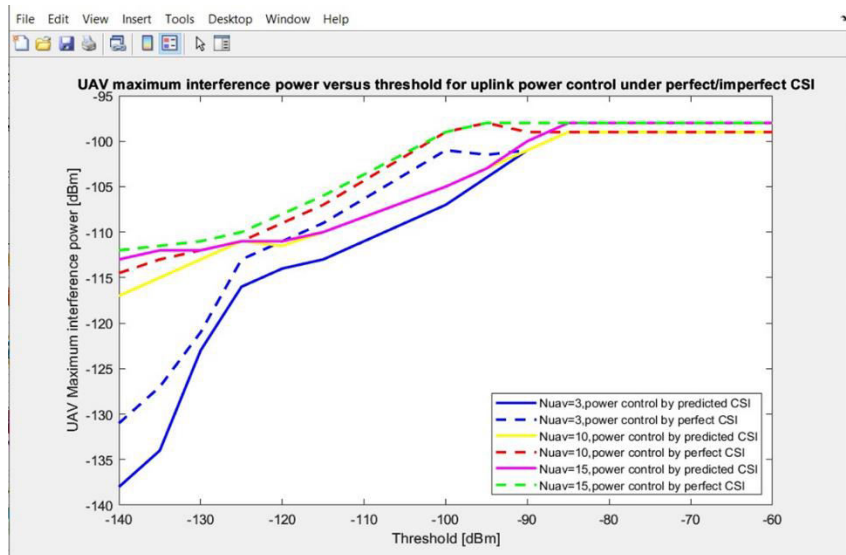


Fig. 4.1 UAV Maximum Interference Power Vs Threshold For Uplink Power Control Under Perfect/Imperfect Csi.

Since a higher number of candidates means more iterations in the **for** loop, this translates to more calculation time and energy expenditure by the UAV. In this regard, we could optimize the time complexity of the UAV-enabled CSB-ICIC using vectorization of loops, which moderately increases the memory resources. Nevertheless, this is not an issue for modern UAVs equipped with a powerful system of chips (SoC)..

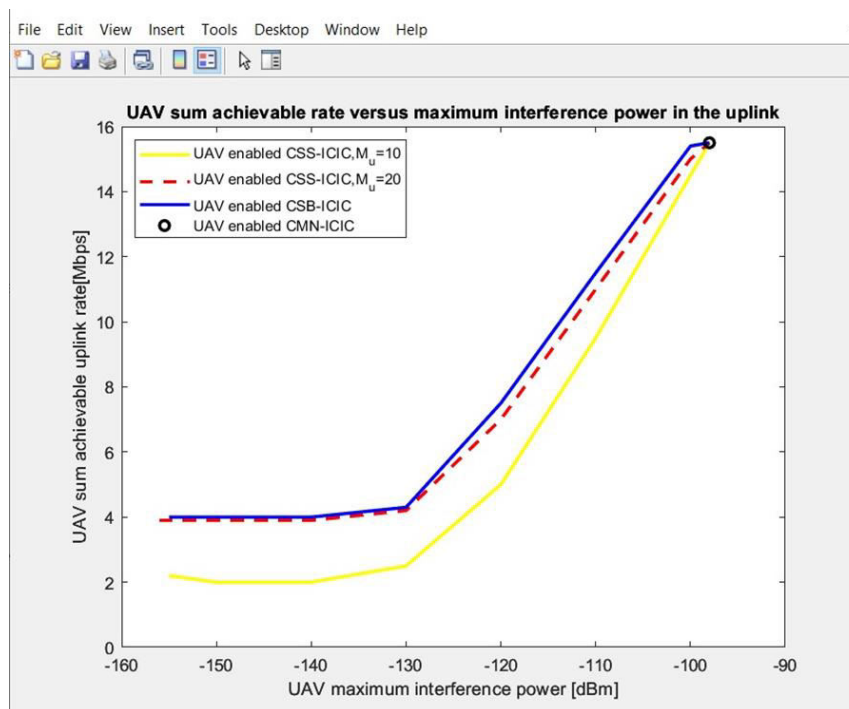


Fig 4.2 UAV Sum Achievable Rate Vs Maximum Interference Power in The Uplink

In Fig. 5.2, demonstrate how the UAV sum uplink rate and maximum interference vary when changing the thresholds for the UAV-enabled CSS-ICIC and UAV-enabled CSB-ICIC. Since there is no threshold for UAV-enabled CMN-ICIC, there is only one point for it in the plot. It is to be noted that on the plot, the slopes on the left side are negative. To further elaborate on this effect, we again plot the UAV sum uplink rate and maximum interference with variable block lengths M and decoding error probabilities ϵ . outage.

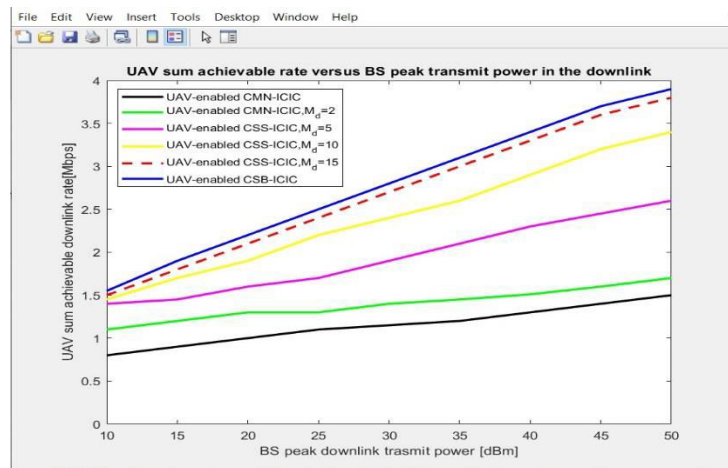
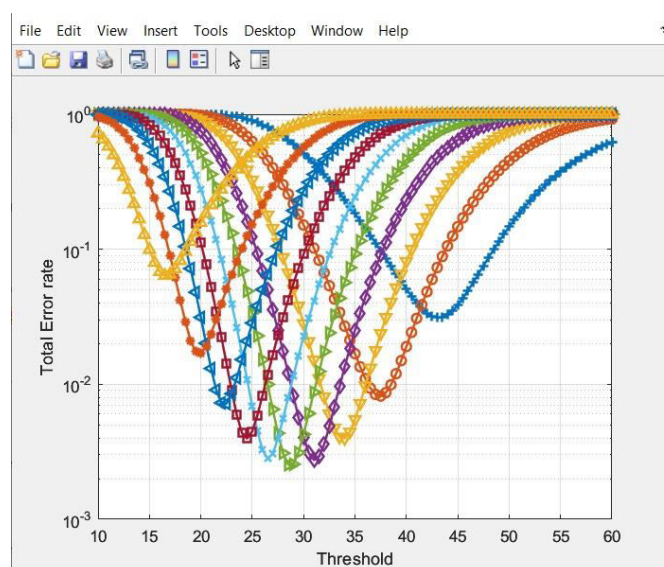


Fig 4.3. UAV Sum Achievable Rate Vs Bs Peak Transit Power in The Downlink

Fig. 5.3 shows that the left tails of the curves are sloping down. Due to monotonicity, there is a clear trade-off between interference and data rate in the Shannonian equation with short block length data rate due to non-monotonicity; such a trade-off does not necessarily exist. Consequently, we do not have to sacrifice one for the other if we happen to also want to constrain ourselves below a certain interference level, e.g., if we are required to keep interference below -140 dBm which is achieved by appropriately adjusting the threshold U , then we can simply choose the leftmost point on the curve and be assured that we will both decrease the interference and maximize the data rate under our constraint $I_{ul} \leq -140$ dBm.



4.4. Total Error Rate Vs Threshold

The sum uplink rate and maximum interference vary with each other by varying thresholds to obtain these values. Since for the conventional ICIC, there are no thresholds to vary, there is only one point for it on the and compare it to peak

downlink power Pdl. Here, we observe that the conventional ICIC gives the worst results and the perfect UAV-assisted ICIC gives the best results. Furthermore, we see that the average data rate among deployed UAVs gets worse as the number of UAV NUAV grows, which is intuitively expected, as the UAV have to share more of the same RB and hence the probability of interference is greater.

V. CONCLUSION AND FUTURE WORK

In ICIC for the single and multi- UAV framework to facilitate URLLC services under perfect/ imperfect CSI using cognitive radio. The goal was to mitigate strong ICI in such single and multi-UAV-assisted cellular networks. To achieve this goal, we modelled BSto- UAV (B2U) interference in downlink communication, whereas in the uplink we modelled UAV-to-BS (U2B), UAVto- UAV (U2U) and UE-to-UAV (UE2U), respectively. low-complexity algorithms namely perfect ICIC, UAV-sensing assisted ICIC and perfect ICIC. Results showed that the proposed perfect ICIC provided fairness among UAVs especially in downlink communications compared to conventional ICIC algorithms. Lastly, we demonstrated in general, that the proposed UAV-sensing assisted ICIC and perfect ICIC algorithms gave better performance than conventional ICIC for both uplink and downlink for the single and multi-UAV framework. A novel centralized time-division multiple access (TDMA)-based scheduling protocol for practical vehicular networks based on a new weight-factor-based scheduler. A roadside unit (RSU), as a centralized controller, collects the channel state information and the individual information of the communication links within its communication coverage, and it calculates their respective scheduling weight factors, based on which scheduling decisions are made by the RSU. In addition, a resource-reusing mode among multiple vehicle-to-vehicle (V2V) links is permitted if the distances between every two central vehicles of these V2V links are larger than a predefined interference interval.

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