Analysis of UAV Radar and Communication Network Coexistence With Different Multiple Access Protocols

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Abstract—Unmanned aerial vehicles (UAVs) are expected to be used extensively in the future for various applications, either as user equipment (UEs) connected to a cellular wireless network, or as an infrastructure extension of an existing wireless network to serve other UEs. Next generation wireless networks will consider the use of UAVs for joint communication and radar and/or as dedicated radars for various sensing applications. Increasing number of UAVs will naturally result in larger number of communication and/or radar links that may cause interference to nearby networks, exacerbated further by the higher likelihood of line-of-sight signal propagation from UAVs even to distant receivers. With all these, it is critical to study network coexistence of UAV-mounted base stations (BSs) and radar transceivers. In this paper, using stochastic geometry, we derive closed-form expressions to characterize the performance of coexisting UAV radar and communication networks for spectrum overlay multiple access (SOMA) and time-division multiple access (TDMA). We evaluate successful ranging probability (SRP) and the transmission capacity (TC) and compare the performance of TDMA and SOMA. Our results show that SOMA can outperform TDMA on both SRP and TC when the node density of active UAV-radars is larger than the node density of UAV-comms.

Index Terms—Coexistence, guard zone, HPPP, multiple access, sensing and communication, stochastic geometry, UAV communication, UAV radar detection.

I. INTRODUCTION

RECENTLY, various different applications of cellular-connected unmanned aerial vehicles (UAVs) have been getting significant attention due to their cost-efficient deployment and controllable mobility. UAVs are utilized in many fields such as environmental monitoring and surveillance [1], public safety [2], video broadcasting [3], and delivery [4]. Moreover, UAV-mounted base stations (UAV-BS) and user equipment (UAV-UE), as well as UAV-mounted radars (UAV-radar) are commonly considered in sensing and communication applications, since the UAVs are available to quickly change position to serve users at the outage area, and/or surveil/track the location of detected moving targets. Joint design of the radar and communication systems is considered as one of the key research areas for wireless networks beyond 5G systems which can benefit significantly from the use of autonomous UAVs.

In the meanwhile, as the demand for using wider bandwidths has been increasing to support higher throughput and massive connectivity, the band of operation for broadband wireless networks has been moving to higher frequencies such as millimeter-wave (mmWave) and sub/THz bands that are also commonly used by radar systems. Some traditional radar bands, including certain bands below 6 GHz, are also being opened for shared use with communication networks due to the increasing congestion in the dedicated spectrum for cellular networks. Recently, the spectrum coexistence between terrestrial 5G wireless networks and airborne radars has emerged as a critical technological challenge [5], [6]. Future deployments of commercial 5G networks carry a risk to interfere with the existing radar operations in bands presently dedicated by the Federal Communications Commission (FCC) for radar use, such as the military radars in 3.1-3.55 GHz, radar altimeters in 4.2-4.4 GHz, and weather radiometers in 24 GHz [5], [7]. All these developments call for rigorously studying the coexistence scenarios for radar and communication networks and coming up with strategies for effective spectrum sharing [8]. The concept of spectrum sharing has been investigated in cognitive radio where multiple communication networks can share the same spectrum [9]. The cognitive radio allows unlicensed users to access licensed bands under the condition that the induced interference to the licensed users does not reach an unacceptable level, while coexistence shares the frequency band for airborne radar with terrestrial communication networks. Although the possibility of radar and communication coexistence via the cognitive radio concept has been investigated [8], [10] where either a communication receiver or a radar receiver senses the unoccupied spectrums and avoids mutual interference between radar and communication, it is not feasible to fairly assign hierarchical primary and secondary roles between the radar and communication systems. Moreover, the radar and the

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communication waveform knowledge need to be exchanged for optimal system design.

Stochastic geometry-based techniques are commonly used in the literature for obtaining closed-form expressions on the performance of wireless networks where transmit sources are randomly deployed in the spatial domain [11]. For example, the analysis of accumulated interference from multiple nodes following a homogeneous Poisson point process (HPPP) is useful to evaluate the capacity of wireless networks [11]. In this paper, we specifically investigate UAV radar sensing and communication network coexistence scenarios. In particular, we consider scenarios where radar transmission and data transmission are coordinated by two different multiple-access protocols: spectrum overlay multiple access (SOMA) and time-division multiple access (TDMA). In SOMA, radar sensing and data communication share the same spectrum so that the spectrum is overlapped. On the other hand, in TDMA, radar detection and communication are separated by time. In particular, SOMA is the protocol where the radar signal is superimposed (overlapped) on top of the communication signal in the power domain [8], [12]. It implies that radar sensing and data communication utilize the identical frequency band in a non-orthogonal manner, and we evaluate the performance for both considering ratios for their transmit powers.

We utilize stochastic geometry-based analysis where UAVs are randomly located in 3D space following a two-dimensional homogeneous Poisson point process (HPPP). We individually analyze the radar detection performance and the data communication performance using the successful ranging probability (SRP) and the transmission capacity (TC), respectively.

Contributions of this paper can be summarized as follows:

- We derive closed-form expressions for SRP and TC on the UAV radar and communication coexistence scenario where UAVs are placed following HPPP with a guard zone. To our best knowledge, it is the first time that closed-form performance metrics are derived for both radar sensing and data communication in UAV network coexistence.
- We analyze the performance of SRP and TC in SOMA and TDMA, respectively. We also investigate behaviors of SRP and TC depending on the node density, radius of the guard zone, power splitting factor in SOMA, and time division factor in TDMA. We investigate the operation of radar and communication in coexistence using two feasible protocols. Moreover, for each protocol, we optimize and analyze the behavior of the system for configurable parameters.
- We analytically compare TDMA and SOMA on SRP and TC and show that TDMA outperforms SOMA on SRP while SOMA is better than TDMA on TC in the general condition. Furthermore, we analyze the condition that SOMA can be superior to TDMA on both SRP and TC metrics. We believe that the comparison by closed-form expressions and numerical results are helpful to understand the trade-off between system parameters in designing radar and communication network coexistence and give guidance for deciding on the multiple access protocols for different operational scenarios."

The rest of this paper is organized as follows. Section II presents the literature review. In Section III, we describe the UAV radar and communication network coexistence design. In Section IV, we provide the signal propagation model when UAVs are distributed by HPPP. In Section V, we derive the closed-form expressions of the SRP and TC. In Section VI, we analyze SRP depending on the system parameters and the multiple access protocols. In Section VII, we analyze the TC depending on the system parameters and the multiple access protocols. In Section VIII, we compare the SRP and TC performance of SOMA and TDMA. In Section IX, we show the simulation results to verify the analysis in previous sections, and Section X provides concluding remarks.

II. LITERATURE REVIEW

The operation of UAVs on BSs and radar detectors has been investigated in the literature. A flying UAV-BS can maximize the capacity or minimize the outage of networks by optimizing UAV trajectory [32], [33]. In [34] and [35], the trajectory and precoder of UAV-BS are optimized to maximize physical layer secrecy. Cellular-connected UAV-BS with NOMA to mitigate the interference has been studied in [36], [37], and [38], while a stochastic geometry-based analysis has been considered in [36]. In [39], a UAV-radar is used in measuring the depth of the snow on the sea. Human detection and classification by a UAV-radar have been studied in [40]. Target detection using radar imaging from UAV-radar has been investigated in [41]. In [42], the feasibility of a surveillance system using a UAV-radar has been explored.

The study of coexistence networks has been explored in the literature. In [43], a beamforming approach has been studied to facilitate the coexistence between downlink (DL) multi-user-multiple-input-multiple-output (MU-MIMO) communication and MIMO radar system. In [44], the joint design of the radar and communication system for the coexistence of MIMO radar and MIMO communication has been studied. Moreover, UAV communication and radar sensing network coexistence that utilizes the spectrum for both purposes has been investigated for an efficient and flexible system design [45]. In [46], joint UAV communication and cooperative sensing network based on beam sharing scheme has been explored.

Stochastic geometry-based network analysis has been thoroughly investigated in the literature. TC is analyzed in ad hoc networks with different spatial diversity techniques where transmitting nodes are distributed by an HPPP [13], and this work is extended to the wireless information and power transfer (SWIPT)-based ad hoc networks in [14]. In [15], packet loss probability depending on the packet size, packet duration, and SINR are derived in downlink ultra-reliable and low-latency communications (URLLC) scenarios where distributed antenna ports are randomly placed following an HPPP. In [16], [17], [18], and [31], the effect of radar interference on the radar detection performance is analyzed and SRP is evaluated using stochastic geometry. More specifically, the geometric layout of vehicles on a road where the locations of vehicles on a certain lane are decided by a unidimensional HPPP model is investigated in [16] and [17]. In [17] and [31], radar cross-section (RCS) characteristics are modeled and
analyzed using HPPPs for automotive radar network scenarios. In [19] and [20], the effects of different directional antenna patterns, node densities, and antenna array sizes on coverage probability are studied for mmWave networks. The locations of BSs and the eavesdroppers are randomly distributed by independent HPPPs in [21], and closed-form expression of secrecy probability for secure communications is explored. Closed-form analysis of network performance using stochastic geometry techniques have also been studied in UAV networks in [22], [23], [24], [25], [26], [27], [28], [29], and [30]. In [22], coexisting UAV-to-UAV links and uplink (UL) ground-BS to ground-user links are considered. Then, coverage of two different scenarios are studied, where the spectrum for each link is either reused, or it is allocated in a dedicated manner. The literature review with representative works related to stochastic geometry-based wireless network performance analysis is summarized in Table I. To the best of our knowledge, the study of radar networks based on stochastic geometry has been limited, and UAV communication and radar network coexistence scenario has not been investigated yet.

III. SYSTEM MODEL

We consider UAV networks where radar nodes and communication nodes coexist. Radar-mounted UAVs (UAV-radar) detect and track a target on the ground by transmitting radar signals and receiving the reflected signals from the target. On the other hand, UAVs that are equipped with a BS (UAV-comms) communicate with a ground user. We assume that UAV-radar and UAV-comms follow two-dimensional independent HPPP where the node densities are $\lambda_r'$ and $\lambda_d'$ respectively. All UAVs fly at a fixed identical height $h_{UAV}$. Fig. 1 describes two different network representations of the radar detection scenario and the communication scenario in the HPPP model. The guard zone with radius $r_0$ is considered between two UAVs, or between a UAV and a user to protect them from potential strong interference. The distance between a UAV-radar and a target in the radar detection scenario and the distance between a UAV-comm and a served user in the communication scenario is $R_0$. UAV-radar are assigned to the random spectrum access with duty cycle $\delta$, and the rest of UAV-radar remain inactive UAV-radar in the networks. Stochastic geometry is widely used in the analysis of coverage wireless communication, which is based on the SINR threshold criteria in statistical methods as listed in Table I. In radar networks, the target detection performance depends on the SINR of the received signal, which is similar to wireless networks. Therefore, it is feasible to adopt stochastic geometry in radar networks. Although the number of radar transmitters may not be large and random enough to be studied using stochastic geometry, with the increasing proliferation of radar and communications devices and UAVs, we believe that the use of stochastic geometry techniques will be meaningful to study dense deployments of communications and radar.

In the radar and communication coexistence, UAV-radar and UAV-comms need to coordinate the time and spectrum resources for radar and data transmissions. We consider two different multiple access schemes: SOMA where radar signal and data signal share the same spectrum during transmission time, and TDMA where the time for radar and data transmission is scheduled at separate time slots. We assume centralized coordination between the two networks where information between UAV-radar and UAV-comms can be exchanged by terrestrial BS towers. For instance, cellular-connected UAV networks [32] can realize the coordination between UAV-radar and UAV-comms by exchanging the information through terrestrial BSs. Fig. 2 illustrates different radar and data allocations depending on multiple access schemes. The power allocated to radar and communication is determined by power splitting factor $\phi$ for SOMA, and the time duration assigned to radar and communication is decided by time division factor $\tau$ for TDMA. Note that the interference behavior in this network coexistence is dependent on the multiple access. In this paper, we focus on the analysis and comparison of SOMA and TDMA on data transmission and radar detection. The key parameters are summarized in Table II.
In this work, we do not consider multiple antenna schemes in UAV-radar or UAV-comms. It is well-known that adopting the multiple antenna scheme in data transmission improves TC by utilizing the degree of freedom in the spatial domain [47]. The beamforming precoder can be designed by the maximum ratio combining (MRC) or zero-forcing (ZF) methods, which improves the signal strength of the desired signal while mitigating the interference signal strength [35]. However, precoder designs in the multiple antenna schemes generally require the channel state information (CSI) from the users and interferers, which brings additional overhead costs due to the CSI feedback protocol.

IV. SIGNAL PROPAGATION MODELS IN HPPP

In this section, we describe signal and interference models in HPPP when SOMA and TDMA are adopted respectively. Throughout this paper, we denote SOMA and TDMA as s.o. and t.d. at the superscript.

A. Radar and Data Signal Models

1) SOMA: We place a typical UAV-radar with the origin \((0, 0, h_{UAV})\) and distance from the target at \((x_t, y_t, 0)\) is \(R_0 = \sqrt{x_t^2 + y_t^2 + (h_{UAV})^2}\) as in Fig. 1a.

We adopt a path loss model for air-to-ground (A2G) channel links where a height-dependent probabilistic line-of-sight (LoS) is considered due to the blockage by the ground objects. The probability that LoS is secured between a UAV-radar and a target is given by [48] and [49]

\[
P_{\text{LoS}} = \Pr (\mu | h_{UAV}, R_0 = 1) = \frac{1}{1 + a_1 \exp \left(-a_2 \left(\frac{\sin^{-1} \left(h_{UAV} / R_0\right)}{180} - a_1\right)\right)},
\]

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where \( \mu[h_{\text{UAV}}, R_0] \in \{0, 1\} \) denotes the binary air-to-ground channel state, and parameters \( a_1, a_2 \) are determined by the environment. Similarly, probability of non-line-of-sight (NLoS) is \( P_{\text{NLoS}} = P_r(\mu[h_{\text{UAV}}, R_0] = 0) = 1 - P_r(\mu[h_{\text{UAV}}, R_0] = 1) \). In this work, we assume that the Doppler effect and the beam misalignment effect by the UAV wobbling and fluctuation and navigation [50], [51], [52] can be compensated and/or they are negligible [53]. Their effects can be studied in future work.

Next, the power of the received signal that is reflected back from the target depending on the A2G channel state can be expressed as [16],

\[
P_{r_0}^\omega = \left( \frac{(1 - \phi)P_{Tx}G_s}{4\pi R_0^2} \right) \left( \frac{\sigma S_c}{4\pi R_0^2} \right) G_p,
\]

(2)

where \( s \in \{\text{LoS}, \text{NLoS}\} \) denotes the state of the A2G channel, and \( P_{Tx}, G_s, \sigma, S_c, G_p \) indicate transmit power, Tx antenna gain, and path loss exponent depending on the state of A2G channel, and \( \sigma, S_c, G_p \) denote radar cross-section (RCS) of the target, the effective aperture of radar receiver, and the processing gain. Swerling I model is considered for the RCS and the RCS of the target follows the exponential distribution, \( \sigma \sim \frac{1}{2} e^{-\frac{\pi}{2}} \) [17].

The effective area is given by

\[
S_e = \frac{G_r c^2}{4\pi f_c^2},
\]

(3)

where \( c, f_c \) denote the speed of light and the carrier frequency. The power of the reflected back radar signal depending on the A2G channel state in (2) can be rewritten as

\[
P_{r_0}^\omega = \left( \frac{(1 - \phi)P_{Tx}G_sG_oG_p}{4\pi f_c^2 R_0^2} \right) c^2 \sigma.
\]

(4)

Then, the power of the reflected back radar signal from the binary state of the A2G channel can be expressed as

\[
P_{r_0} = \mu[h_{\text{UAV}}, R_0] [P_{r_0}^\omega \text{LoS}] + (1 - \mu[h_{\text{UAV}}, R_0]) [P_{r_0}^\omega \text{NLoS}].
\]

(5)

In the communication scenario as in Fig. 1b, a typical user is located at the origin and it receives the signal from the serving UAV-comm at \((x_t, y_t, h_{\text{UAV}})\), which is at a distance of \( R_0 = \sqrt{x_t^2 + y_t^2 + (h_{\text{UAV}})^2} \) from the user. The power of the received signal of the user depending on the A2G channel state is given by

\[
P_{d}^\omega = \phi P_{Tx}G_tG_oG_p c^2 \left( \frac{\sigma R_0}{4\pi f_c^2} \right) h_0,
\]

(6)

where \( h_0 \sim \exp(1) \) represents Rayleigh small-scale fading. The ratio of transmit power for the radar and the data signals is decided by the power splitting factor \( \phi \) in SOMA where the sum of radar and data transmit power becomes \( P_{Tx} \), as illustrated in Fig 2. Note that the power split factor determines the power level separately at the UAV-radars and UAV-comms, and it does not indicate that it splits the power of different source signals at a single transmitter. Essentially, our motivation is to understand how the UAV-radar and UAV-comms performance would be individually affected by different transmit power ratios at the two systems. Similarly, the power of the received signal of the user from the binary state of the A2G channel is given by

\[
P_{d}^\omega = \mu[h_{\text{UAV}}, R_0] [P_{d}^\omega \text{LoS}] + (1 - \mu[h_{\text{UAV}}, R_0]) [P_{d}^\omega \text{NLoS}].
\]

(7)

2) TDMA: The received signal power of the radar signal and the data signal depending on the A2G channel state in TDMA are expressed as

\[
P_{d}^{t,d} = \frac{P_{Tx}G_tG_oG_p c^2 \sigma}{(4\pi f_c)^3 R_0^2},
\]

(8)

\[
P_{d}^{t,d} = \frac{P_{Tx}G_tG_oG_p c^2 \sigma}{(4\pi f_c)^3 R_0^2} h_0.
\]

(9)

Since the radar detection and communication are separately conducted in different time slots in TDMA, transmit power is not adjusted as in SOMA.

B. Effective Radar and Communication Node Densities

The PPP in this network introduces the guard zone and it can be modeled by the Matérn hard-core point processes (MHCPP) type-II, which can be further approximated by the HPPP model.

1) SOMA: The approximated effective node density of the radar and the communication from MHCPP type-II can be written as [54]

\[
\lambda_{t}^{\text{e.o}} = \frac{1 - \lambda_{t'}^{\omega}}{\pi r_0^2}, \quad \lambda_{d}^{\text{e.o}} = \frac{1 - \lambda_{d'}^{\omega}}{\pi r_0^2},
\]

(10)

where \( \lambda_{t'}^{\omega} = \delta \lambda_t' \) is the active UAV-radar node density, and \( \delta \) is the duty cycle.

2) TDMA: The effective node density of the radar and the communication from MHCPP type-II can be written as

\[
\lambda_{t}^{t,d} = \frac{1 - \lambda_{t'}^{t,d}}{\pi r_0^2}, \quad \lambda_{d}^{t,d} = \frac{1 - \lambda_{d'}^{t,d}}{\pi r_0^2},
\]

(11)

where \( \lambda_{t'}^{t,d} = \delta \lambda_t' \) is the active UAV-radar node density. Note that the duty cycle \( \delta \) in SOMA increases to \( \frac{1}{\pi} \) in TDMA as much as the reduced radar transmission time by \( \tau \), since it is assumed that the total number of active UAV-radar nodes during the time period is the same for both SOMA and TDMA. Since the effective node density of UAV-comms for TDMA and SOMA is equal, we merge the notation of the node density as \( \lambda_{d} = \lambda_{d'}^{t,d} = \lambda_{d'}^{t,d} \).

C. Interference Models

In this subsection, we obtain the power of interference coming from nearby active UAV-radars and UAV-comms in the HPPP model.

1) SOMA: Since the radar detection and communication occupy the same spectrum band at the same time, the aggregated interference power from UAV-radars and UAV-comms...
can be expressed as
\[
P_i^{s,o} = \sum_{r_i \in \Phi(\lambda_i) \cap \mathcal{R}_0} \frac{\phi P_{Tx} G_i G_r c^2}{(4\pi)^2 f_i^2 r_i^{\alpha_i}} h_i + \sum_{r_j \in \Phi(\lambda^\infty) \cap \mathcal{R}_0} \frac{(1-\phi) P_{Tx} G_i G_{r_j} c^2}{(4\pi)^2 f_j^2 r_j^{\alpha_j}} h_j,
\]
(12)
where \( r_i \in \Phi(\lambda_i) \cap \mathcal{R}_0 \) means a two-dimensional HPPP with a density \( \lambda_i \) and \( r > r_0, G_i \) and \( \alpha_i \) are Rx antenna gain and path-loss exponent from the UA to UA interfering signals, respectively, \( h_i, h_j \) represent small-scale fading from the interference, and \( r_i, r_j \) are distance between a typical UAV-radar user or an interferer. Since the radar detection and communication are carried out together in SOMA, the interference power at both the typical UAV-radar (Fig. 1a) and the typical information receiver (Fig. 1b) is the same: \( P_i^{s,o} = P_i^{d,o} = P_i^{t,o}. \)

2) TDMA: The interference comes only from the UAV-raders in the radar detection scenario. Likewise, the interference comes only from UAV-comm in communication scenarios. Then the aggregated interference power for each case can be expressed as
\[
I^{s,d}_r = \sum_{r_i \in \Phi(\lambda_i^s) \cap \mathcal{R}_0} \frac{P_{Tx} G_i G_r c^2}{(4\pi)^2 f_i^2 r_i^{\alpha_i}} h_i,
\]
(13)
\[
I^{t,d}_r = \sum_{r_j \in \Phi(\lambda_i^t) \cap \mathcal{R}_0} \frac{P_{Tx} G_i G_r c^2}{(4\pi)^2 f_j^2 r_j^{\alpha_j}} h_j.
\]
(14)

V. PERFORMANCE ANALYSIS OF RADAR DETECTION AND DATA COMMUNICATION

In this section, we discuss performance evaluation metrics for two different scenarios. Specifically, we derive the SRP in the radar detection scenario and the TC in the communication scenario.

A. Successful Ranging Probability

SRP is the probability that a UAV-radar succeeds in detecting the target, which is decided by the signal-to-interference-plus-noise ratio (SINR). SRP is defined by
\[
P_{sr,r}(\gamma_{th}) = Pr(\gamma_{0} > \gamma_{th}),
\]
(15)
where \( \gamma_{0} = \frac{P_{r}}{1 + N_{0}} \) and \( N_{0} \) are SINR of the received radar signal and the noise power, respectively. In addition, \( \gamma_{th} \) denotes SINR threshold where the target is successfully detected. From the binary state of the A2G channel in (5), (15) can be rewritten as
\[
P_{sr,r}(\gamma_{th}) = P_{LoS}[P_{sr,r}(\gamma_{th})]^{LoS} + P_{NLoS}[P_{sr,r}(\gamma_{th})]^{NLoS},
\]
(16)
where \( [P_{sr,r}(\gamma_{th})]^{s} = Pr(\gamma_{0} > \gamma_{th}) \) and \( \gamma_{0} = \frac{P_{r}}{1 + N_{0}}. \) In what follows, we derive the closed-form expression of SRP in both SOMA and TDMA.

1) SOMA: SRP in (16) can be derived from (4), (12) as follows:
\[
[P_{sr,r}(\gamma_{th})]^{s} = \Pr\left(\frac{P_{r}^{s,o}}{P_{r}^{s,o} + N_{0}} > \gamma_{th}\right) = \Pr\left(\frac{(1-\phi)P_{Tx}G_jG_p c^2}{P_{r}^{s,o} + N_{0}} > (4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}\right) \\
\approx \Pr\left(\sigma > (4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}\right) \\
\approx \int_{0}^{\infty} \left\{ 1 - \Phi\left(\frac{(4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}}{(1-\phi)P_{Tx}G_jG_p c^2}\right) \right\} f_{\sigma^2}(y)dy \\
\approx \int_{0}^{\infty} e^{-\frac{(4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}}{(1-\phi)P_{Tx}G_jG_p c^2}} f_{\sigma^2}(y)dy \\
= \mathcal{L}_{\sigma^2}(z) = \left(\frac{(4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}}{(1-\phi)P_{Tx}G_jG_p c^2}\right)
\]
(17)
where the approximation comes from the interference limit regime assumption, \( F_{\sigma}(X) = 1 - e^{-\frac{X}{\sigma^2}} \) is the cumulative distribution function (CDF) of \( \sigma, \) and \( f_{\sigma^2}(x) \) is the probability density function (PDF) of \( P_{\sigma^2}. \) \( \mathcal{L}_{\sigma^2}(z) \) indicates Laplace transform of the PDF of \( P_{\sigma^2}. \)

\( \mathcal{L}_{\sigma^2}(z) \) can be derived as follows. The interference term can be rewritten as \( P_{\sigma^2} = I_{1} + I_{2} \) where \( I_1, I_2 \) are the first and the second terms in (12) respectively. Then, we can obtain [15]
\[
\mathcal{L}_{I_1}(z) = \exp\left\{-2\pi\lambda_1 A_1(z)(z\phi K_1)^{\frac{\alpha_1}{\alpha_1}}\right\},
\]
\[
\mathcal{L}_{I_2}(z) = \exp\left\{-2\pi\lambda_2 A_2(z)(z(1-\phi) K_1)^{\frac{\alpha_1}{\alpha_1}}\right\},
\]
(18)
where \( A_1(z) = B\left(\frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right) - B\left(\frac{1}{1+z\alpha_1K_1 r_0}, \frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right), A_2(z) = B\left(\frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right) - B\left(\frac{1}{1+z(1-\phi) \alpha_1 K_1 r_0}, \frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right), K_1 = \frac{P_{r} G_j G_p c^2}{(4\pi)^2 f_j^2}, \) \( B(a, b) \) is the beta function, and \( B(x; a, b) = \int_{0}^{\infty} u^{a-1}(1-u)^{b-1}du \) is the incomplete beta function. Then, we can derive
\[
\mathcal{L}_{\sigma^2}(z) = \mathcal{L}_{I_1}(z)\mathcal{L}_{I_2}(z) \\
= \exp\left\{-2\pi\left(\frac{\alpha_1}{\alpha_1}\right)^{\frac{\alpha_1}{\alpha_1}} \lambda_1 A_1(z) + (1-\phi) \frac{\alpha_1}{\alpha_1} A_2(z)\right\}.
\]
(19)

Then, the closed-form expression of SRP in SOMA can be obtained (20), as shown at the bottom of the next page.

2) TDMA: SRP can be derived from (8), (13) as follow:
\[
[P_{sr,r,d}(\gamma_{th})]^{s} = \Pr\left(\frac{P_{r}^{t,d,o}}{P_{r}^{t,d,o} + N_{0}} > \gamma_{th}\right) = \mathcal{L}_{\sigma^2}(z) = \left(\frac{(4\pi)^2 f_j^2 R_{0}^{2\alpha_j}\gamma_{th}}{(1-\phi)P_{Tx}G_jG_p c^2}\right)
\]
(24)
\[
\mathcal{L}_{\sigma^2}(z) = \exp\left\{-2\pi\frac{\alpha_1}{\alpha_1} A_3(z)\left(z\phi K_1)^{\frac{\alpha_1}{\alpha_1}}\right}\right\},
\]
(25)
where $A_3(z) = B\left(\frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right) - B\left(\frac{1}{1 + z K(r_0^{-\alpha_1})}, \frac{2}{\alpha_1}, 1 - \frac{2}{\alpha_1}\right)$. Note that detailed mathematical steps are skipped, since many steps are similar to (17), (18). Then, the closed-form expression of SRP in TDMA can be expressed (21), as shown at the bottom of the page.

**B. Transmission Capacity**

TC is defined by the achievable data rate given an outage constraint multiplied by the spatial density and the data transmission time duration [13], [14]. At first, the outage probability can be expressed as

$$\Pr_{\text{out}}(\beta_{th}) = \Pr(\beta_0 < \beta_{th}),$$

(26)

where $\beta_0 = \frac{P_{\text{th}}}{\bar{P}_c}$ is SINR of the received data signal, and $\beta_{th}$ is a target SINR.

Considering the binary state of the A2G channel in (7), (26) can be rewritten as

$$\Pr_{\text{out}}(\beta_{th}) = P_{\text{LoS}}[\Pr_{\text{out}}(\beta_{th})]_{\text{LoS}} + P_{\text{NLoS}}[\Pr_{\text{out}}(\beta_{th})]_{\text{NLoS}},$$

(27)

where $[\Pr_{\text{out}}(\beta_{th})]^s = \Pr(\beta_0^s > \beta_{th})$ and $\beta_0^s = \frac{P_{\text{th}}^s}{\bar{P}_c^s}$. Then, TC is given as

$$C_{\text{s.o.}} = P_{\text{LoS}}[C_{\text{s.o.}}]_{\text{LoS}} + P_{\text{NLoS}}[C_{\text{s.o.}}]_{\text{NLoS}},$$

(28)

$$C_{\text{t.d.}} = P_{\text{LoS}}[C_{\text{t.d.}}]_{\text{LoS}} + P_{\text{NLoS}}[C_{\text{t.d.}}]_{\text{NLoS}},$$

(29)

where $C_{\text{s.o.}}, C_{\text{t.d.}}$ denote transmission capacity of SOMA and TDMA, respectively. Next, we derive the closed-form expression of TC in both SOMA and TDMA.
1) SOMA: Outage probability in (26) can be derived as
\[
[Pr_{\text{out}}(\beta_{th})]^s = 1 - Pr\left(\frac{P_{d}^{t,d} \cdot s}{P_{d}^{t,d} + N_0} > \beta_{th}\right)
\]
\[
= 1 - \int_{0}^{\infty} \left[1 - F_{t,h}(4\pi)^2 f^2 R_0^2 \beta_{th} y \right] \frac{\partial P_{t,x} \cdot G_t \cdot G^2}{\partial \beta_{th}} dy
\]
\[
= 1 - L_{t,h} \cdot \left(4\pi)^2 f^2 R_0^2 \beta_{th} \right) \frac{\partial P_{t,x} \cdot G_t \cdot G^2}{\partial \beta_{th}}
\]
(30)

where \( F_{t,h}(X) = 1 - e^{-X} \). From (19), (28), and (30), the closed-from expression of the TC in SOMA is given (22), as shown at the bottom of the previous page.

2) TDMA: Outage probability in TDMA can be derived as
\[
[Pr_{\text{out}}(\beta_{th})]^s = 1 - Pr\left(\frac{P_{d}^{t,d} \cdot s}{P_{d}^{t,d} + N_0} > \beta_{th}\right)
\]
\[
= 1 - L_{t,h} \cdot \left(4\pi)^2 f^2 R_0^2 \beta_{th} \right) \frac{\partial P_{t,x} \cdot G_t \cdot G^2}{\partial \beta_{th}}
\]
(31)

The Laplace transform of \( L_{t,h} \) can be derived as
\[
L_{t,h} = \exp\{-2\pi \lambda d \int_{r_0}^{\infty} \left[1 - e^{-zK_h r^{-\alpha_t}}\right] \right\}
\]
\[
= \exp\{-2\pi \lambda d A_{t,h}(z) \frac{\gamma}{\alpha_t} \}
\]
(32)

From (28), (31), (32), the closed-form expression of the TC in TDMA can be derived (23), as shown at the bottom of the previous page.

C. Approximation of SPR and TC for A2G Channel Model

The expressions of SPR and TC in (27), (28), (29) are formulated by the sum of two probabilistic channel conditions (Los, NLoS) due to the binary state A2G channel model. For analysis tractability, we can simplify the expressions by merging two path loss exponent \( \alpha_{\text{Los}}, \alpha_{\text{NLoS}} \) into a single effective path loss exponent \( \bar{\alpha} \) in an approximate sense. For instance, from (21), SPR of TDMA (27) can be rewritten as

\[
Pr_{\text{out}}^{t,d}(\gamma_{th}) \approx P_{\text{LoS}} \exp\left[-2\pi \lambda d \cdot \bar{C}_2 \right]
\]
\[
\cdot \left(\frac{4\pi G_t \cdot R_0^2 \cdot \gamma_{th}}{G_r \cdot G_{r,\sigma}}\right)^{\frac{\gamma}{\alpha_t}}
\]
\[
+ P_{\text{NLoS}} \exp\left[-2\pi \lambda d \cdot \bar{C}_2 \right]
\]
\[
\cdot \left(\frac{4\pi G_t \cdot R_0^2 \cdot \gamma_{th}}{G_r \cdot G_{r,\sigma}}\right)^{\frac{\gamma}{\alpha_t}}
\]
\[
= \exp\left[-2\pi \lambda d \cdot \bar{C}_2 \right]
\]
\[
\cdot \left(\frac{4\pi G_t \cdot R_0^2 \cdot \gamma_{th}}{G_r \cdot G_{r,\sigma}}\right)^{\frac{\gamma}{\alpha_t}}
\]
\[
\cdot \left(\left(\frac{4\pi G_t \cdot R_0^2 \cdot \gamma_{th}}{G_r \cdot G_{r,\sigma}}\right)^{\frac{\gamma}{\alpha_t}} \right) \]
2) TDMA: In the same manner of obtaining (36) for SOMA, the maximum node densities of the UAV-radar $\lambda^t_{d,s}$ with the given target SRP and SINR threshold can be expressed from (21) as

$$\lambda^t_{d,s} = \frac{-\log P_{s,r}(s)\alpha_1}{2\pi \left(\frac{4\pi C_3 G_{th}^2 \gamma_{th}}{\sigma_0 \bar{G}_t}\right)^{\frac{2}{\alpha_1}} \bar{C}_2}.$$ (37)

B. Radius of Guard Zone

Guard zone constrains the minimum distance between nodes to avoid strong interference. As the minimum distance increases, the power of the interference decreases. This implies that SRP is reduced as radius of guard zone $r_0$ increases. When we design networks with target SRP ($P_{s,r}(s)$) and the SINR threshold $\gamma_{th}$, the minimum radius of the guard zone $r_0$ that satisfies the target performance can be obtain by solving (20) in SOMA and (21) in TDMA for $r_0$.

C. Power Splitting Factor $\phi$ in SOMA

Power splitting factor $\phi$ determines the transmit power ratio between UAV-comms and UAV-radios in SOMA where the radar signal power proportionally decreases as $\phi$ increases. From the closed-form expression of the SRP in (20), the terms that are affected by $\phi$ are $\left(\frac{\phi}{1-\phi}\right)^{\frac{d}{2}}$ and $B\left(\frac{1}{1+\left(\frac{\alpha_1 \gamma_{th}}{\alpha_1 \gamma_{th} + \bar{G}_t}\right)^{\frac{d}{2}}}, \frac{2}{\alpha_1}, 1-\frac{2}{\alpha_1}\right)$. Since $\frac{\phi}{1-\phi}$ and incomplete beta function are monotonic increasing functions, it is easily proved that the SRP is decreasing function with respect to the power splitting factor $\phi$. This can be intuitively interpreted as higher transmit power of UAV-comms increasing the power of the interference signal.

Proposition 1: When $0 \leq \phi \leq 0.5$, the impact of the UAV-comm node density $\lambda_d$ on SRP is less than the UAV-radar node density $\lambda^r_{r,o}$. When $\phi = 0.5$, the impact of the communication node density $\lambda_d$ on SRP is equal to the radar node density $\lambda^r_{r,o}$, while when $0.5 < \phi \leq 1$, the impact of the communication node density $\lambda_d$ on SRP is greater than the radar node density $\lambda^r_{r,o}$.

Proof: From (20), we can observe that varying $\phi$ only affects the node density of UAV-comm $\lambda_d$ term, not the node density of UAV-radar $\lambda^r_{r,o}$ term. Then, when $\phi = 0.5$, $\frac{\phi}{1-\phi}$ becomes 1, which leads to the result that the impact of $\lambda_d$ becomes the same as the impact of $\lambda^r_{r,o}$. On the other hand, when $\phi$ is greater than 0.5, $\frac{\phi}{1-\phi}$ becomes greater than 1 as well, which makes the multiplying term by $\lambda_d$ becomes greater than the multiplying term by $\lambda^r_{r,o}$. In the same way, when $\phi$ is less than 0.5, the multiplying term by $\lambda_d$ becomes less than the multiplying term by $\lambda^r_{r,o}$.

Proposition 1 implies that the power of interference is affected by the ratio between the node density of UAV-comm ($\lambda_d$) and the UAV-radar ($\lambda^r_{r,o}$) and when $\phi$ is given, a different ratio of UAV-comm and UAV-radar node density can improve SRP, which is observed in Fig. 6 of Section IX.

D. Time Division Factor $\tau$ in TDMA

As we mention in Section IV-B, the increase in $\tau$ reduces radar transmission time and increase the duty cycle, which results in higher node density of the active UAV-radar $\lambda^t_{d,s}$. The effective UAV-radar node density $\lambda^t_{d,s}$ in the HPPP approximation is proportionally increased by $\lambda^t_{d,s}$ in (11).

VII. NETWORK DESIGN STRATEGY FOR TRANSMISSION CAPACITY

In this section, we analyze TC depending on network design parameters. We find the node densities that maximize the TC and we investigate the impact of the radius of guard zone. We also investigate the effect of the power splitting factor and the time division factor on the TC.

A. Node Densities

As the node density of the UAV-comm $\lambda_d$ increases, SINR is decreased by the larger number of interferers but the higher node density can increase the capacity of the unit area. Because of this trade-off, we can find the maximum node density $\lambda_d$ that maximizes TC.

1) SOMA: When target SINR $\beta_{th}$, the UAV-radar node density $\lambda^r_{r,o}$, radius of guard zone $r_0$, and the power splitting factor $\phi$ are given, we can find the $\lambda_d$ that maximizes the TC from (22). The term in (22) that is affected by $\lambda_d$ are written as

$$D_1 = \lambda_d \log(1 + \beta_{th}) \exp \left(-2\pi \lambda_d \bar{C}_3 \left(\frac{G_{th}^2 \gamma_{th}}{\bar{G}_t}\right)^{\frac{2}{\alpha_1}} \right),$$ (38)

where $\bar{C}_3$ is calculated from $C_3$ in (22) with $\alpha_s = P_{LoS}\alpha_{LoS} + P_{NLoS}\alpha_{NLoS}$. From (38), the first and the second derivative of transmission capacity with respective to $\lambda_d$ can be expressed as

$$(C^{\alpha,o})' = \log(1 + \beta_{th}) \exp \left(-2\pi \lambda_d C'_3 \right) \left(1 - 2\lambda_d C'_3 \right),$$ (39)

$$(C^{\alpha,o})'' = 4\pi C'_3 \log(1 + \beta_{th}) \exp \left(-2\pi \lambda_d C'_3 \right) \left(\pi \lambda_d C'_3 - 1 \right).$$ (40)

where $C'_3 = \bar{C}_3 \left(\frac{G_{th}^2 \gamma_{th}}{\bar{G}_t}\right)^{\frac{2}{\alpha_1}}$. Then, transmission capacity is maximized at

$$\lambda_d = \frac{1}{2\pi C'_3} \quad \text{(SOMA)}. \quad (41)$$

In SOMA, the node density of UAV-radar $\lambda^r_{r,o}$ also increases the power of interference, which reduces the TC. In (22), the terms that include the radar node density $\lambda^r_{r,o}$ are given as

$$D_2 = \lambda_d \log(1 + \beta_{th}) \exp \left(-2\pi \left(\frac{1 - \phi}{\phi}\right)^{\frac{2}{\alpha_1}} \lambda^r_{r,o} C'_4 \right),$$ (42)

where $C'_4 = \bar{C}_3 \left(\frac{G_{th}^2 \gamma_{th}}{\bar{G}_t}\right)^{\frac{2}{\alpha_1}}$. From the above equation, it can be found that TC is a decreasing function of the $\lambda^r_{r,o}$.
2) TDMA: Similarly to SOMA, we can optimize the UAV-comm node density $\lambda_d$ in TDMA. From (23), the TC can be rewritten as

$$C_{t.d.} = \tau \lambda_d \log(1 + \beta_{th}) \exp(-2\pi\lambda_d C_3').$$

Then, the optimal UAV-comm node density that maximizes TC can be derived as

$$\lambda_d^* = \frac{1}{2\pi C_3'} \text{(TDMA).}$$

In addition, the TC in TDMA is not affected by $\lambda_d^{\text{th}}$.

Remark 1: From the above analysis, TC is maximized at $\lambda_d^* = \frac{1}{2\pi C_3'}$ for both SOMA and TDMA. On the other hand, the TC in SOMA decreases as $\lambda_d^* \phi^\alpha_{\text{r}}$ increases, while TC in TDMA is independent of $\lambda_d^{\text{th}}$.

B. Radius of Guard Zone

Guard zone improves SINR and it reduces the effective node density $\lambda_d$ from (10). Therefore, as radius of guard zone, $r_0$, increases TC would be either improved by higher SINR or degraded by the lower node density. Since it is mathematically tractable to obtain the first and the second derivatives of TC with respect to $r_0$ in (22) and (23), we observe the effect of $r_0$ by simulations. From simulation results in Fig. 3b, it is observed that the maximum TC decreases as the $r_0$ increases from 5 m to 25 m, which implies that the TC is a decreasing function of $r_0$ in a typical parameter setup.

C. Power Splitting Factor $\phi$ and Time Division Factor $\tau$

In SOMA, TC is improved as $\phi$ increases since the transmit power of UAV-comm becomes higher, which improves SINR. The terms in (22) that are affected by $\phi$ are $(\frac{1-\phi}{\phi})^{\frac{r_0}{\alpha}}$ and $B\left(\frac{1}{1+(1-\phi)C_3\phi_0^{\alpha_1}}, \lambda_d^* \frac{1}{\alpha_1}, \frac{2}{\alpha_1} \right)$. Since $\frac{1-\phi}{\phi}$ is a decreasing function and an incomplete beta function is a monotonic increasing function, it is easily proved that TC is an increasing function in terms of $\phi$.

In TDMA, $\tau$ decides the time duration of the data transmission, and larger $\tau$ increases TC. From (23), it is observed that TC is linearly increasing with respect to $\tau$.

From the analysis of SRP and TC in Section VI and Section VII, we observe several trade-offs of SRP and TC depending on the system parameters. The higher node density $\lambda_c$ decreases both SRP and TC except in TC in TDMA, which does not change the performance. Higher node density $\lambda_d$ decreases SRP in SOMA, while the optimal $\lambda_d$ that maximizes TC exists for TC in both SOMA and TDMA. Larger radius of guard zone $r_0$ increases SRP but decreases TC for both TDMA and SOMA. Power splitting factor $\phi$ and time division factor $\tau$ are proportional to TC while inversely proportional to SRP.

VIII. PERFORMANCE COMPARISON OF SOMA AND TDMA

We compare the performance of SRP and transmission capacity between two different multiple access strategies to give intuition in the design of UAV radar sensing and communication network coexistence. We consider two different scenarios when $\phi = \tau = 0.5$: case 1 and case 2. In case 1, we analyze the condition where the node density of UAV-comms and active UAV-radar are equal, and we compare SOMA with TDMA by SRP and TC. In case 2, we analyze the condition that the node density of UAV-radar is greater than that of UAV-comms, and we find the condition that both SRP and TC of SOMA are higher than those of TDMA.

A. Case 1: $\lambda_d^* = \lambda_c^* \neq 0$

We first analyze a special case that $\lambda_d^* = \lambda_c^* \neq 0$ and $\phi = \tau = 0.5$ where the active UAV-radar and the UAV-comm node density are equal and the resources allocation of the data transmission and the radar detection are the same. In this condition, SRP of SOMA and TDMA can be rewritten
Note that the condition that outage probability is greater than \( \frac{3}{4} \) is a generally desirable condition. Therefore, in case 1 \( (\lambda_d = \lambda_r \neq 0 \text{ and } \phi = \tau = 0.5), \) TDMA outperforms SOMA for SRP, but SOMA is better than TDMA for TC.

**B. Case 2:** \( \lambda_d' < \bar{\lambda}_r. \)

We can also analyze another special case where \( \lambda_d' < \bar{\lambda}_r, \phi = \tau = 0.5, \) and an additional condition that the UAV-radar node density \( \lambda'_r \) is sufficiently small. Then, the effective UAV-radar node densities \( \lambda_{r}^{s,o}, \lambda_{r}^{t,d} \) in (10), (11) can be approximated by the first order Taylor expansion at \( \lambda'_r = 0 \) as \( \lambda_{r}^{s,o} \approx \delta \lambda'_r \) and \( \lambda_{r}^{t,d} \approx 2 \delta \lambda'_r. \) In this condition, we can have the following proposition.

**Proposition 4:** The SRP of SOMA is greater than the SRP of TDMA in case 2 where \( \lambda_d' < \bar{\lambda}_r, \) the radar node density \( \lambda'_r \) is sufficiently small, and \( \phi = \tau = 0.5. \) It implies that when the utility of radar sensing is significantly larger than that of data communication, the SRP performance of SOMA can be better than that of TDMA. That is, when \( \lambda_d' < \bar{\lambda}_r, \) the reduction of duty cycle by increasing the available time duration is more beneficial to increase the SRP when it is compared with the orthogonal spectrum utilization.

**Proof:** From (20) and (21), we can obtain SRP in case 2 as follows:

\[
\begin{align*}
Pr_s^{s,o} (\gamma_{th}) &= \exp \left\{ -2\pi (\lambda_d + \delta \lambda'_r) C_2 \frac{4 \pi G_r R_{0,\lambda}^{2} \log(\gamma_{th})}{\sigma_0 G_r \sigma} \right\}, \\
Pr_s^{t,d} (\gamma_{th}) &= \exp \left\{ -2\pi (2 \delta \lambda'_r) C_2 \frac{4 \pi G_r R_{0,\lambda}^{2} \log(\gamma_{th})}{\sigma_0 G_r \sigma} \right\}.
\end{align*}
\]

(46)

Then, we can easily prove that \( Pr_s^{s,o} > Pr_s^{t,d} (\gamma_{th}) \) if \( \lambda_d' < \delta \lambda'_r = \bar{\lambda}_r. \)

Next, we can also obtain the following proposition regarding TC.

**Proposition 5:** In the case that \( \phi = \tau = 0.5, \) TC of SOMA is greater than TDMA, where \( Pr_t^{t,d} (\beta_{th}) < \frac{3}{4}, Pr_t^{s,o} (\beta_{th}) < \frac{3}{4}. \) It implies that SOMA is generally a better option than TDMA with respect to the TC unless channel quality is extremely bad.

**Proof:** From (22), (23) as

\[
\begin{align*}
C_s^{s,o} &= \lambda_d \log(1 + \beta_{th}) \exp \left\{ -4\pi \lambda_d C'_3 \right\}, \\
C_t^{t,d} &= \frac{1}{2} \lambda_d \log(1 + \beta_{th}) \exp \left\{ -2\pi \lambda_d C'_3 \right\}.
\end{align*}
\]

(47)

Then, we can derive the following proposition.

**Proposition 3:** In case 1, the transmission capacity of SOMA is greater than TDMA, when outage probability \( Pr_t^{t,d} (\beta_{th}) < \frac{3}{4}, Pr_t^{s,o} (\beta_{th}) < \frac{3}{4}. \) It implies that SOMA is generally a better option than TDMA with respect to the TC unless channel quality is extremely bad.

**Proof:** From (47), \( C_s^{s,o} > C_t^{t,d} \), if the following inequality holds:

\[
\begin{align*}
\lambda_d \log(1 + \beta_{th}) (\exp \left\{ -2\pi \lambda_d C'_3 \right\})^2 &> \frac{1}{2} \lambda_d \log(1 + \beta_{th}) (\exp \left\{ -2\pi \lambda_d C'_3 \right\})^2 \\
&\implies \exp \left\{ -2\pi \lambda_d C'_3 \right\} > \frac{1}{2}, \\
&\implies 1 - Pr_t^{t,d} (\beta_{th}) > \frac{1}{2}, \\
&\implies Pr_t^{s,o} (\beta_{th}) < \frac{3}{4}, \\
&\implies Pr_t^{t,d} (\beta_{th}) = 1 - (\exp \left\{ -2\pi \lambda_d C'_3 \right\})^2 < \frac{3}{4},
\end{align*}
\]

(48)

where \( I_1 = \sum_{j} \frac{1}{\rho_{r_0} G_r \sigma_0^2} \frac{2 \rho_{r_0} C_2}{(4\pi)^2 (\delta r_j)} h_j. \)
TABLE III
PARAMETER SETTINGS FOR UAV RADAR AND COMMUNICATION NETWORK COEXISTENCE ANALYSIS

| Parameter                                | Value          |
|------------------------------------------|----------------|
| Transmit power ($P_{\text{TAX}}$)        | 20 dBm         |
| Transmitter antenna gain ($G_{t}$)       | 10 dB          |
| Receiver antenna gain ($G_{r}$)          | 10 dB          |
| Receiver antenna gain from the interference ($G_{t1}$) | -10 dB         |
| Target distance ($R_{0}$)                | 50 m           |
| UAV height ($h_{\text{UAV}}$)            | 25 m, 40 m     |
| Average RCS ($\delta$)                   | 30 dBm         |
| Path-loss exponents ($\alpha_{\text{LoS}}, \alpha_{\text{NLoS}}$) | [2.1, 3.2]    |
| Path-loss exponent from the interference ($\alpha_{t1}$) | 2.5           |
| Processing gain ($G_{p}$)                | 10 dB          |
| Duty cycle ($\delta$)                    | 0.1            |
| Carrier frequency ($f_{c}$)              | 35 GHz         |

Fig. 4. The SRP and the TC depending on SINR threshold where $\lambda'_{d} = 0.00025$, $\lambda'_{r} = 0.005$, $\tau_0 = 5$ m, $\phi = 0.5$, $\tau = 0.5$. Two different UAV heights $h_{\text{UAV}} = 25$ m, 40 m are compared. In case 2, SOMA outperforms TDMA on both the SRP and the TC.

Remark 2: From Proposition 4 and Proposition 5, SOMA can outperform TDMA in both SRP and TC, if the conditions in Proposition 4 and Proposition 5 are satisfied. This implies that the active UAV-radar node density is greater than the UAV-comm node density ($\lambda'_{d} < \lambda'_{r}$) while the outage probability considering the interference only from the active UAV-radars is less than 0.5. Moreover, when the first condition holds, the second condition is generally desirable since the target outage probability is mostly less than 0.5 and the interference coming from the UAV-comms is smaller than the active UAV-radars.

IX. SIMULATION RESULTS

In this section, we evaluate the performance of UAV radar and communication network coexistence based on simulation and analysis. SRP and TC with SOMA and TDMA are presented with the change of the different parameters. We consider 35 GHz carrier frequency for mmWave communication and Ka-band radar. The key parameters are listed in Table III.

A. SRP and TC Dependence SINR Threshold and Radius of Guard Zone

In this subsection, we compare SOMA and TDMA by SRP and TC depending on radius of guard zone and SINR threshold. In Fig. 3, we show SRP and TC of both SOMA and TDMA with $\lambda'_{d}$, $\lambda'_{r}$ and $\phi$, $\tau$ by case 1 in Section VIII-A. As we discuss in Proposition 2 and Proposition 3, TDMA outperforms SOMA in SRP while SOMA is superior to TDMA in the TC. We also observe that as radius of guard
Fig. 6. Change of SRP as $\phi$ increases with different ratios of the node density of the UAV-radar and the UAV-comm ($\gamma_{th} = -10\, \text{dB}$, $h_{\text{uav}} = 40\, \text{m}$), which is analyzed in Proposition 1.

Fig. 7. Change of SRP and TC depending on the UAV-radar node density where $\lambda'_r = 0.01$, $r_0 = 5\, \text{m}$, $\beta_{th} = 0\, \text{dB}$, $\gamma_{th} = -10\, \text{dB}$, $\phi = 0.5$, $\tau = 0.5$, $h_{\text{uav}} = 40\, \text{m}$.

zone $r_0$ increases, SRP improves but TC degrades, which is matched to the analysis in Section VI-B and Section VII-B. In addition, It is observed that as UAV height $h_{\text{uav}}$ decreases, the performance of both SRP and TC degrades. This is due to the fact that higher path loss from NLoS reduces the received signal strength and leads to subsequently lower SINR.

Fig. 8. Change of SRP and TC depending on the UAV-comm node density where $\lambda'_d = 0.01$, $r_0 = 5\, \text{m}$, $\beta_{th} = 0\, \text{dB}$, $\gamma_{th} = -10\, \text{dB}$, $\phi = 0.5$, $\tau = 0.5$, $h_{\text{uav}} = 40\, \text{m}$.

Fig. 4 shows SRP and TC with a system configuration in case 2 in Section VIII-B. It is observed that both SRP and TC could be better in SOMA if we consider case 2, which is mentioned in Remark 2. Note that in a general system parameter setting, we obtain SRP and the TC performance of case 1. Just like Fig. 3, we also observe that reducing the height of the UAV leads to a decrease in both SRP and TC.

B. SRP and TC Dependence Power Splitting Factor and Time Division Factor

In this subsection, we evaluate SRP and TC depending on $\phi$ in SOMA and $\tau$ in TDMA. Fig. 5a shows that as $\phi$ increases TC improves but SRP decreases as we discuss in Section VI-C and in Section VII-C, which represents the impact of the different power ratio between the radar signal and the data signal on SRP and TC. In, Fig. 5b, it is observed that TC increases as $\tau$ becomes large. On the other hand, the SRP slowly decreases as $\tau$ increases when we compare it with $\phi$ in SOMA.

Fig. 6 show the effect of the different radio of the active UAV-radar node density $\lambda'_r$ and the UAV-comm node density $\lambda'_d$ on the SRP in SOMA. It is observed that when $0.1 < \phi < 0.5$, higher UAV-comm node density achieves higher SRP while when $0.5 < \phi < 1$, higher active UAV-radar...
node density achieves higher SRP, which can be interpreted by Proposition 1.

C. SRP and TC Dependence Node Density of UAV-Radar and UAV-Comm

In this subsection, we simulate the dependence of SRP and TC on the node density of the UAV-radar ($\lambda_v$) and the UAV-comm ($\lambda_d$). As we discuss in Section VI-A and Section VII-A, Fig. 7a shows that SRP is a decreasing function of $\lambda_v$ for both SOMA and TDMA. On the other hand, the decreasing slopes of TDMA and SOMA are similar, which implies that the SRP gap between the two protocols is similar regardless of the density of $\lambda_v$.

In Fig. 7b, we observe that TC decreases as $\lambda_v$ increases in SOMA, while the TC is not affected by $\lambda_v$ in TDMA. However, TC in TDMA is dramatically lower than SOMA, especially when $\lambda_v$ is low, which means that SOMA achieves significant gain compared with TDMA when $\lambda_v$ is low.

In Fig. 8a, we observe that SRP is a decreasing function of $\lambda_d$ in SOMA, while SRP is not affected by $\lambda_d$ in TDMA. It is also observed that SRP is rapidly reduced as $\lambda_d$ increases, which implies that SRP in SOMA is sensitive to $\lambda_d$. Fig. 8b shows that TC is maximized at $\lambda_d^* = 0.0115$ for both SOMA and TDMA, which can be derived from Remark 1 and (10). Furthermore, after the peak value of TC from the optimal $\lambda_d^*$, TC in SOMA and TDMA slowly decreases as $\lambda_d$ increases.

X. CONCLUSION

In this paper, we investigate the coexistence of UAV radar and communication network. We deploy UAV-raders and UAV-comms by using HPPP where UAV-raders detect and track targets and UAV-comms communicate with their serving users in the same frequency band. We take into account two different multiple-access protocols, SOMA, and TDMA, to operate both radar signals and data signals simultaneously. We analyze the performance of SRP in the radar detection scenario and TC in the data communication scenario. We show that in general, TDMA outperforms SOMA on SRP, while SOMA outperforms TDMA on TC. However, SOMA can achieve higher SRP and a higher TC when the node density of UAV-raders is higher than that of UAV-comms, with the additional condition of achieving an acceptable outage probability. We also find the UAV-comm node density that maximizes TC by deriving the first and the second derivative of its analytic form and analyze the behavior of SRP and TC depending on the node density, the radius of the guard zone, the power splitting factor, and time division factor.

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