SPECTRUM SHARING FOR UAV COMMUNICATIONS

Spatial Spectrum Sensing and Open Issues

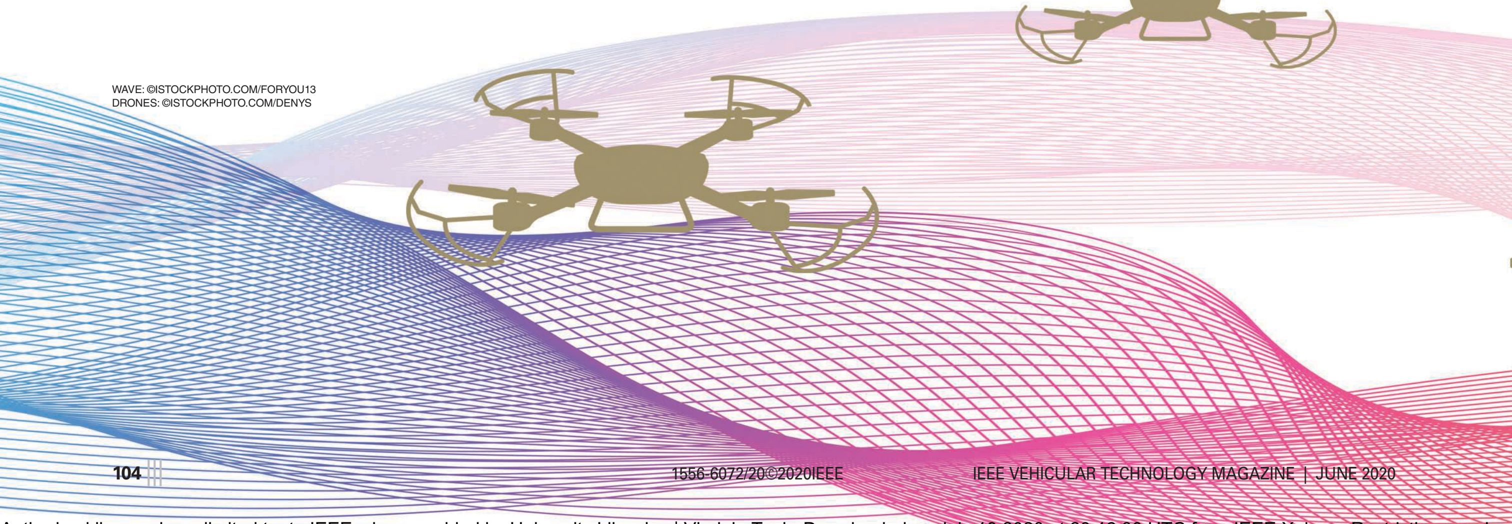
Bodong Shang, Vuk Marojevic, Yang Yi, Aly Sabri Abdallah, and Lingjia Liu

Unmanned aerial vehicles (UAVs) are attracting increasing attention for applications such as video streaming, surveillance, and delivery using reliable line-of-sight (LOS) links. Nevertheless, due to the large radio-frequency (RF) transmission footprint from a UAV transmitted to ground nodes, UAV communications may significantly deteriorate the performance of cochannel ground communication links. With the lack of a dedicated spectrum, researchers need to design efficient spectrum-sharing policies for UAV communications to enhance spectral efficiency (SE) and control interference-to-ground communications. One technique for spectrum sharing is spatial spectrum sensing (SSS), which enables devices to sense spatial spectrum opportunities and reuse them aggressively and efficiently by controlling the SSS radius. The goal of this article is to introduce the fundamentals, challenges, and applications of SSS for UAV spectrum access and discuss open research problems for realizing UAV spectrum sharing, including dynamic spectrum access for swarm UAV networks, artificial intelligence (AI)-enabled UAV spectrum access, blockchain-based UAV spectrum access, multichannel access for UAVs, and the integration of UAVs into cellular networks.

Digital Object Identifier 10.1109/MVT.2020.2980020
Date of current version: 30 March 2020

Background of UAV Spectrum Sharing

In future wireless networks, as UAVs become more available, mobile users will not be restricted to terrestrial mobile stations. As shown in Figure 1, there are many applications for UAVs in wireless networks, such as UAV swarm networks in disasters, UAV-assisted vehicle-to-everything (V2X) communications [1], UAV-enabled smart city development, traffic offloading in hotspots, and surveillance and Internet of Things (IoT) networks. The wireless network architecture will become a 3D structure, incorporating terrestrial and aerial network nodes, which are more dynamic than the fixed terrestrial communications network that we have today. In the development of aerial platforms, the spectrum access for UAV communications is significant in the design and management of the holistic communications network. As opposed to the non-LOS (NLOS) transmissions in most ground communications, aerial communications—including air-to-air (A2A), air-to-ground (A2G), and ground-to-air (G2A)—enjoy reliable wireless transmissions by resorting to lower signal attenuation due to fewer obstacles. In A2A communications, the signal experiences almost free-space propagation. In A2G and G2A communications, the occurrence probability of an LOS or NLOS connection is a function of the elevation angle between the UAV and ground node



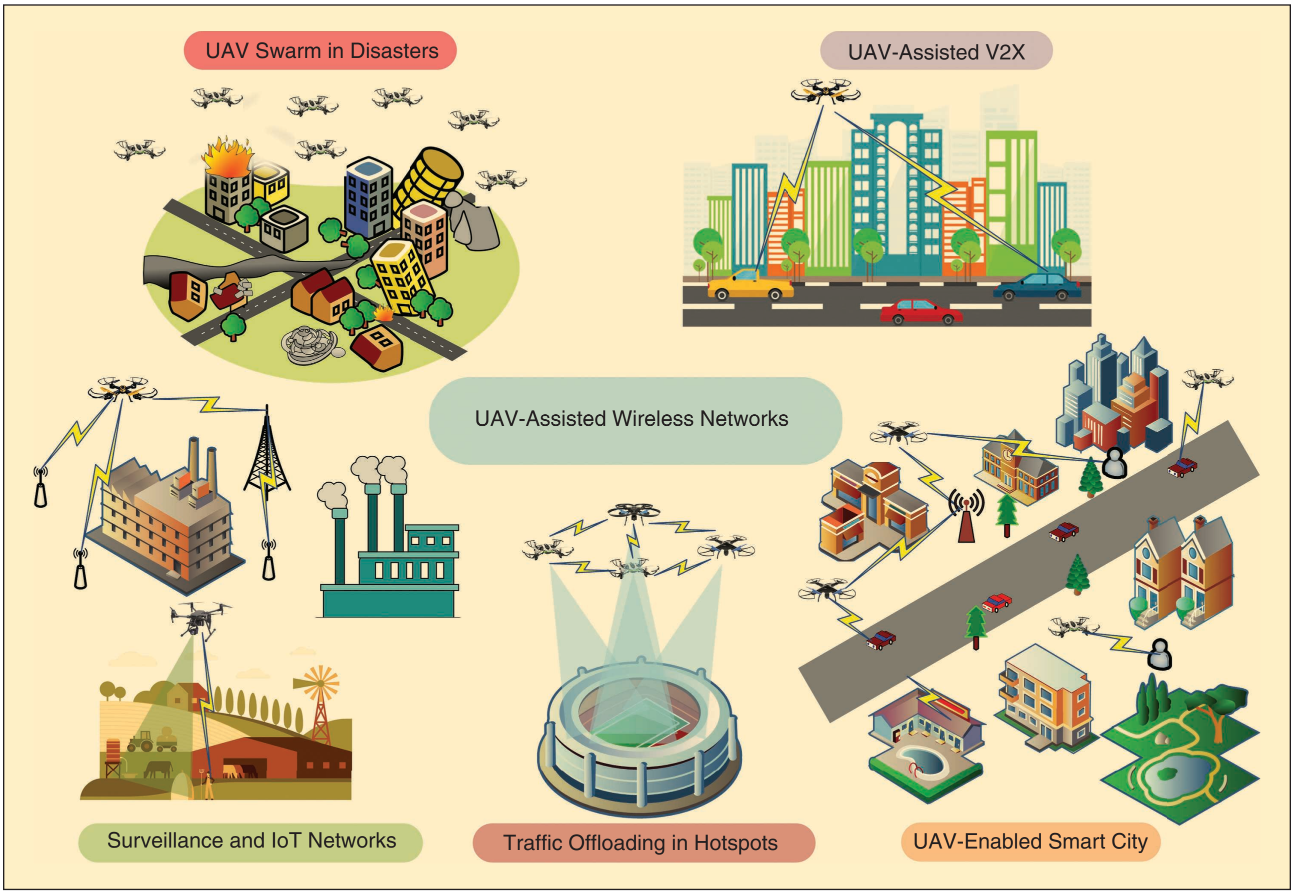


FIGURE 1 Applications of UAVs in wireless networks.

and the environment, such as rural, urban, dense urban, or others.

UAV communications typically occur in unlicensed spectrum, including the 2.4- and 5.8-GHz industry, science, medicine bands [2]. For small- and medium- range UAV applications, multihop 802.11 or Zigbee technologies are considered according to their throughput and range demands [3]. For high-throughput applications, additional wireless technologies and spectra need to be considered. When operating in an unlicensed spectrum, UAVs may suffer from security threats and attacks that impact the transmission of confidential information. Moreover, with the drastic increase in the number of wireless devices (such as tablets, smartphones, and sensors) that also operate in unlicensed spectrum, the unlicensed spectrum is becoming overcrowded, and UAVs will face spectrum scarcity in the near future.

The use of a licensed spectrum, on the other hand, would enable wide-scale and high-quality connectivity for UAVs with enough capacity to support various services and increasing usage levels. For instance, sharing the licensed spectrum used for cellular communications with UAVs can significantly improve the communication their performance. However, the interference generated by the UAVs needs to be well managed to limit its effect on primary users. Therefore, network designers need to take the negative impact of implementing UAV communications into account and come up with efficient spectrum-sharing strategies for the coexistence of UAVs and terrestrial communications devices.

Enabling spectrum sensing for UAVs will allow UAVs to opportunistically exploit licensed spectrum holes and improve the SE of the overall wireless ecosystem.

In this article, we extend the SSS originally introduced for device-to-device (D2D) communications [4]–[6] to spectrum access for UAVs. Note that SSS can be integrated into 5G networks [7] and motivates UAVs to sense spatial spectrum opportunities and reuse licensed spectrum opportunities. Ground users are regarded as primary users and UAVs as secondary users. The SSS sphere of a UAV is a sphere centered at the UAV with radius R_s. This is illustrated in Figure 2. The objective is to maximize the SE of UAV networks by optimizing the UAV SSS radius while guaranteeing the SE of terrestrial primary users above a certain threshold.

SSS: Fundamentals and Challenges in 3D UAV Networks

Fundamentals of SSS

SSS is a spectrum access technique with controllable interference for sharing spectrum between primary and secondary users. A sensing device (secondary user) performs SSS at the beginning of each time slot. The test statistic of the received signal strength at the sensing device during SSS is denoted by Γ. The energy detection threshold is represented by ε. If the test statistic Γ is greater than ε, the sensing device will transmit with probability β_1; otherwise, it will transmit with probability $\beta_0(\beta_0 > \beta_1)$. That is, if there are fewer primary users in the proximity of the sensing device (the sensing device is in the spatial spectrum hole of the primary users' network), the sensing device can access the spectrum with a high probability. One useful tool to analyze SSS networks is stochastic geometry, which captures large-scale interference by modeling different types of network nodes at various point processes. Due to the elegant mathematical derivations in stochastic geometry, the network performance in terms of channel access probability, coverage probability, SE, and so forth can be obtained without doing numerous random experiments.

In signal detection theory, two performance metrics are considered to reflect SSS performance. These are the false alarm probability P_{fa} and the miss-detection probability P_{md}. To clarify P_{fa} and P_{md}, we first define two events used in the calculation of the these probabilities. Let H^0 be the event where there is no primary user in the sensing region of the sensing device, and

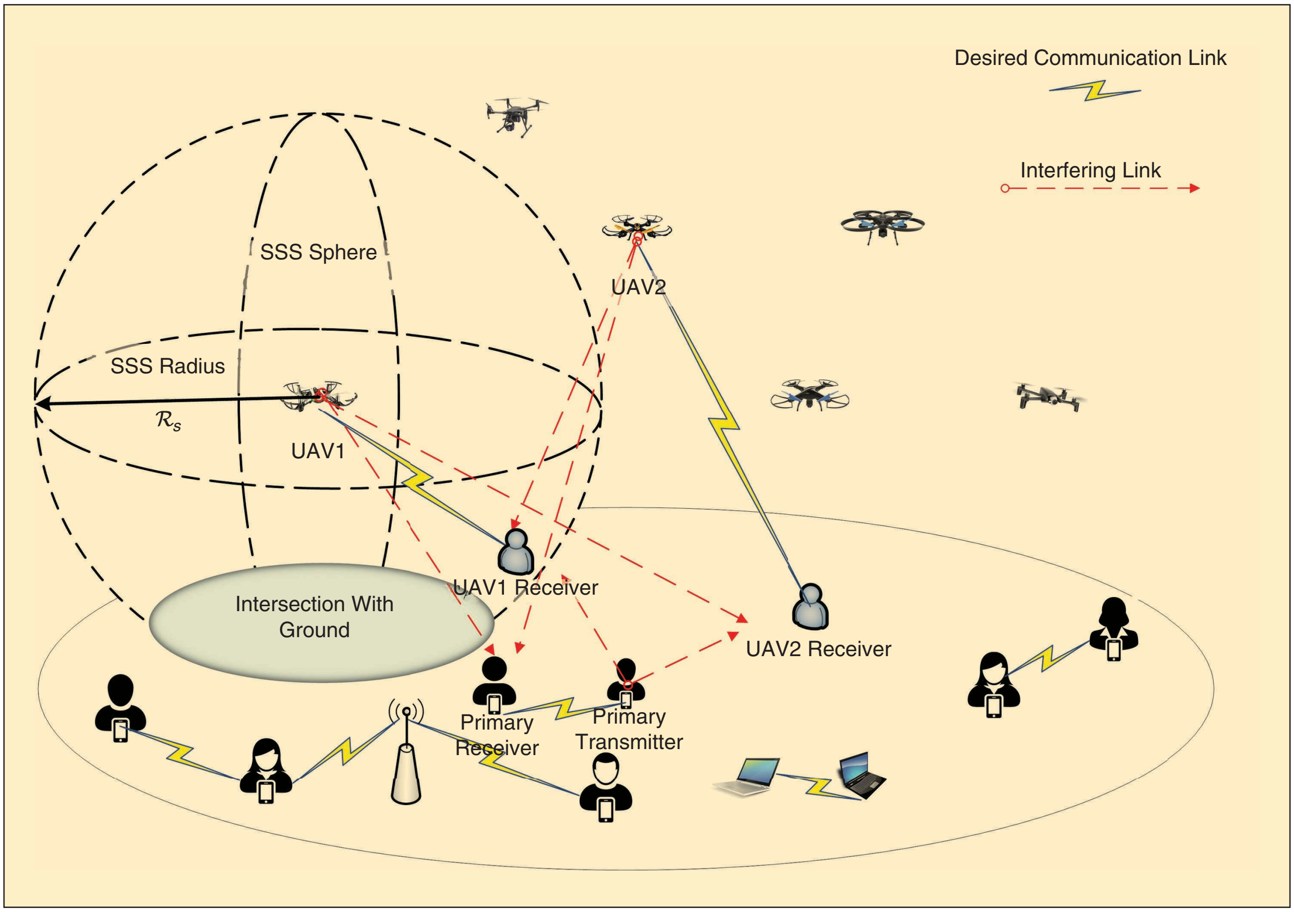


FIGURE 2 An example of 3D SSS for UAVs.

let H^1 be the event where there is at least one primary user in the sensing region of the sensing device. The sensing region is a circular region centered at the sensing device with a radius of R_s. The false-alarm probability is the probability that the test statistic Γ is greater than the energy detection threshold ε for event H^0. The miss-detection probability is the probability that Γ is less than ε for event H^1. Therefore, for event H^0, the sensing device can access the spectrum with probability $P^0 = P_{fa}\beta_1 + (1 - P_{fa})\beta_0$, while, for event H^1, it can access the spectrum with probability $P^1 = (1 - P_{md})\beta_1 + P_{md}\beta_0$.

In detection theory, the Neyman-Pearson criterion says that one can either minimize P_{md} while not allowing P_{fa} to exceed a predefined value or minimize P_{fa} subject to a constraint on P_{md}. According to the constraint in the Neyman-Pearson criterion, we can set the false-alarm probability at a constant value, which indicates that the SSS radius and the energy detection threshold are mapped to each other. Thus, in practical engineering design, one can adjust ε for tuning R_s.

Challenges of SSS in 3D Networks

As it is different from SSS in 2D networks, realizing SSS for UAV communications faces many challenges.

3D Channel Modeling

The channel model for UAV communications becomes more complex than that of ground communications. To better characterize the SSS performance, more accurate channel models of A2G and G2A signal transmissions need to be explored. For a flying UAV, the received signals from ground primary users during SSS include LOS signals, NLOS signals, and multiple reflected components, all of which cause multipath fading [8]. The occurrence probabilities of an LOS and NLOS link are a function of the elevation angle between the UAV and ground transceiver and the communication environment. The small-scale fading in A2G and G2A transmissions can be described by a Nakagami or Rician distribution [9].

Height-Dependent Spectrum Access

UAVs flying at different heights experience different received signal strengths generated from ground primary users because of the changing elevation angle. In the NLOS connection, the path loss is higher than in the LOS connection due to shadowing effects and the signal reflections from obstacles. Therefore, the test statistic Γ at a UAV during the SSS may vary with the UAV's height, which influences the UAV's channel access probability.

Unknown Distributions of Aggregated Received Powers for SSS

To evaluate SSS performance for UAV communications, we need to obtain the false alarm and the miss-detection probabilities. Since the false alarm and miss detection cases are conditioned on the events H^0 and H^1, respectively, we need to attain the distributions of the aggregated received signal strengths generated from ground primary users under H^0 and H^1. However, due to the complex 3D channel model, these conditional distributions are unknown at present and impede the analysis of SSS for UAV communications.

3D UAV Network Interference

In the network where UAVs and ground nodes coexist, characterizing the interference generated from UAVs is more challenging than that of terrestrial networks. This is because UAVs are distributed in a 3D airspace with a maximum allowable flight height. Furthermore, although given a certain SSS radius R_s, UAVs at different heights have various spectrum access probabilities due to the diverse test statistics during SSS. Therefore, tractable methods need to be developed to approximately depict the interference in such 3D networks and facilitate the analysis of coverage probability and SE of UAV networks and terrestrial primary user networks.

SSS for D2D communications in homogeneous cellular networks is studied in [4] and [5]. Closed-form expressions of the conditional aggregated received powers for SSS can be derived for performance optimization because of the simple network setup. In [6], SSS was investigated for two-tier, user-centric heterogeneous networks. Although a data-driven approach can be used to obtain the false alarm and miss-detection probabilities for terrestrial systems, the analytical framework needs to be redesigned to evaluate 3D UAV network interference, where the density of UAVs may vary with height. Therefore, a new analytical framework combined with data-driven approaches is needed for implementing SSS in UAV networks.

SSS-Based UAV Spectrum Access

To fully utilize the spatial spectrum holes in 3D wireless networks for UAV communications, introducing SSS as a technique for opportunistic UAV spectrum access not only improves the SE of the entire network but also enables management of the RF interference generated from UAV transmitters to ground communications networks. In this section, we discuss the objectives and constraints of SSS-based UAV communications and introduce a machine learning-assisted stochastic geometry approach to analyze the SSS performance of such heterogeneous networks. Finally, we focus on a case study to demonstrate the advantages of implementing SSS for UAV spectrum access.

SSS-Based UAV: Objectives and Constraints

Since the ground users usually pay monthly fees to the operator for utilizing the licensed spectrum in telecommunications, we consider that the operator-controlled ground users share the licensed spectrum with flying

UAVs. The ground users are the primary users, and the UAVs are the secondary users. Like the SSS in ground communications, let UAVs have an SSS radius where the sensing region is a sphere centered at the UAV. Based on the sensing sphere of a UAV, let us define the event H^0 and H^1 for SSS-based UAV spectrum access, where H^0 denotes that there is no ground primary user in the sensing sphere and H^1 denotes that there is at least one ground primary user. Under these definitions, we can further characterize the false-alarm and miss-detection probabilities.

Note that, if the UAV's flight height is lower than the sensing radius of the UAV, there will be an intersection region between the sensing sphere of the UAV and the ground, as shown in Figure 3; otherwise, there will be no intersection region. If there is no intersection region, the miss-detection case does not exist. More precisely, since it is impossible for a ground primary user to enter the sensing sphere of the UAV, we can treat the miss-detection probability as zero. Furthermore, the radius of the intersection region can be calculated using the Pythagorean theorem based on the UAV's SSS radius and the UAV's flight height, while the projection of the UAV on the ground is at the center of the intersection region. Therefore, if the UAV's flight height is lower than the sensing radius of the UAV, the events H^0 and H^1 are equivalent to the events for which, respectively, there is no ground primary user in the intersection region and there is at least one ground primary user in the intersection region.

Optimization Problem

The fundamental problem under consideration is then cast as a network SE maximization problem, which is subject to the constraint that the data rate of a typical ground/primary user should not be lower than a certain threshold. The optimization variable can be the SSS radius. The maximization problem is given by

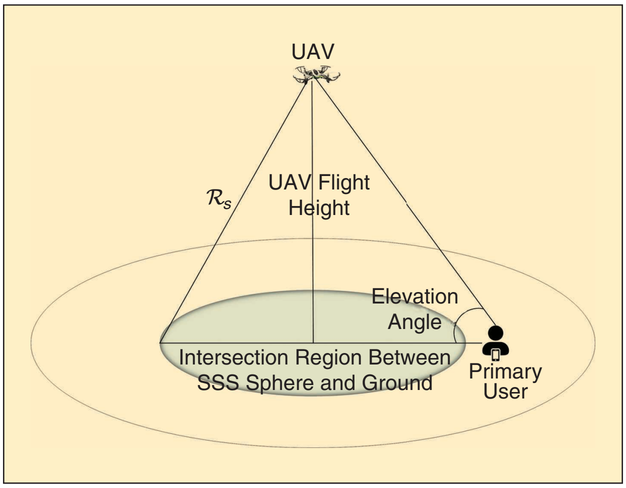


FIGURE 3 The intersection region between UAV's SSS sphere and ground.

$$\max_{R_s} \ \mathrm{SE}_V \quad \text{s.t.} \ R_D \geqslant \text{Ö}\,\vartheta,$$

where SE_V denotes the SE of the UAV network, R_D is the data rate of a typical secondary user, and ϑ indicates the data rate threshold of secondary users' communications. A small value of the SSS radius leads to a high spectrum-access probability of UAVs and thus severe interference generated by UAVs, while a large value of the SSS radius results in a low spectrum-access probability of UAVs, which reduces the SE of UAV networks. Therefore, there is a tradeoff between aggressive spectrum reuse and lower interference. The objective can be the SE of the UAV or the SE of the entire network containing UAVs and ground primary users. The constraint here is to guarantee the performance of the communications of primary users.

System-Level Performance Evaluation

The tool of stochastic geometry is used to evaluate the performance of SSS-based UAV communications from a system-level perspective by capturing the spatial locations of network nodes. To characterize the density of UAVs, one needs to obtain the distributions of aggregated received signal strengths at a UAV conditioned on events H^0 and H^1 for the calculations of false-alarm and miss-detection probability during SSS. Due to the complex 3D channel model, these conditional distributions of the aggregated received signal strength at a UAV are difficult to characterize mathematically. To be specific, applying the inverse Laplace transform of a Laplace transform of the aggregated received signal strengths at a UAV can attain its probability density function. However, there are many integrals in the calculation of the inverse Laplace transform and the integrals on the imaginary domain, which leads to algorithm deficit.

To overcome this issue, one can leverage machine learning to train the distributions of the aggregated received signal strength at a UAV conditioned on events H^0 and H^1. The conditional distributions of the aggregated received signal strength generated from ground primary users at a UAV can be approximated by log-normal distributions, which are observed from experiments where most values fall near the vertical axis [10]. The mean and standard deviation of log-normal distributions are expected to be determined based on real data. Accordingly, given network parameters (ground primary users' density, flight height of the UAV, SSS radius of the UAV, and the small-scale fading parameter), we can obtain the mean and standard deviation of the approximate log-normal distributions shown in Figure 4.

Since the mean and standard deviation are continuous, regression tools can be utilized to train these parameters of log-normal distributions, which can be solved by a parametric or a nonparametric approach. For the parametric approach, a polynomial function with

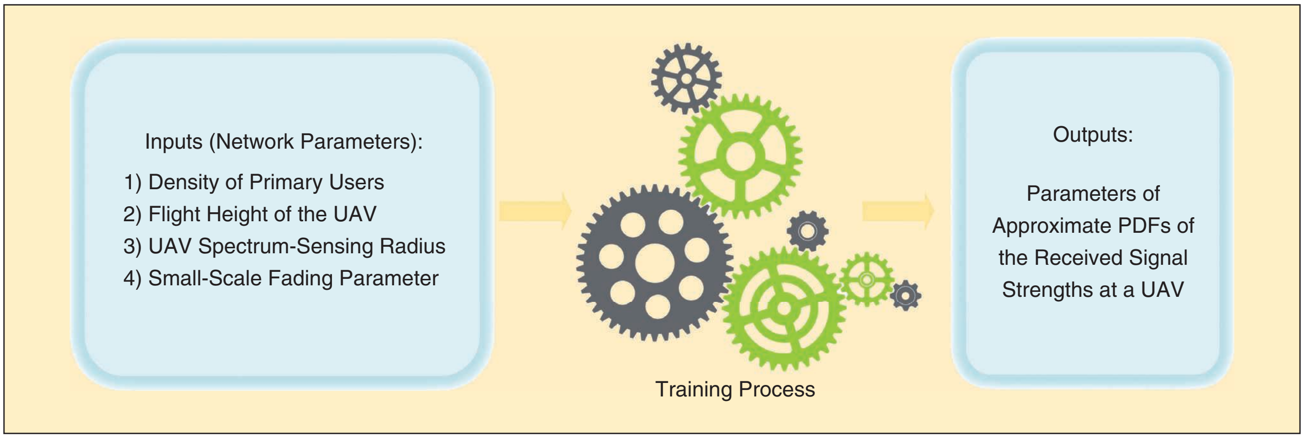


FIGURE 4 The inputs and outputs of the machine learning-assisted approach. PDF: probability density function.

coefficients in each term can be regarded as the hypothesis function, and the coefficients are updated in each iteration based on the gradient of the cost function in the training process. For the nonparametric approach, a series of query points is generated to match the points in the data set, which utilizes the local data information at a query point. The nonparametric approach usually exhibits more accuracy in approximation than the parametric approach, while the parametric approach can give an exact form of hypothesis function, which facilitates intuition analysis.

Case Study

Simulations are conducted to evaluate the performance of SSS-based UAV spectrum access. We simulate a 3D UAV and ground primary user network, as shown in Figure 5, where the UAVs sense and access the channel opportunistically as secondary users. Three spectrum access policies are compared: random UAV spectrum access (where a UAV can access the spectrum with a certain probability), SSS-based UAV spectrum access (where a UAV can access the spectrum based on the SSS), and distance-based UAV spectrum access (where a UAV can access the spectrum with probability β_0 under event H^0 and with probability β_1 under event H^0). For random UAV spectrum access, given a required minimum SE of primary user networks, we first characterize the UAVs' maximum random-access probability, which guarantees the required minimum SE of primary user networks, and then evaluate the SE of UAV networks based on this maximum random-access probability. For SSS- and distance-based UAV spectrum access, given a required minimum data rate of a typical primary user, we first obtain the minimum UAV spectrum-access radius, ensuring the minimum required data rate of a typical primary user, and then measure the SE of UAV networks based on the minimum UAV spectrum-access radius. It is worth noting that distance-based UAV spectrum access requires the exact positions of UAVs and thus increases the system's signaling overhead. However, both

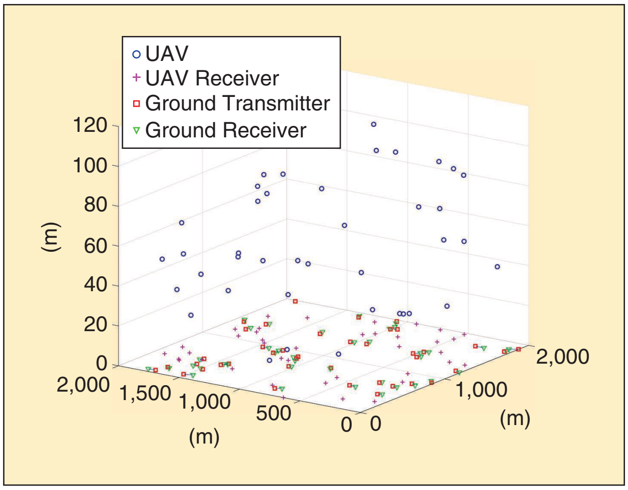


FIGURE 5 The 3D communication networks where primary transmitters are uniformly distributed on the ground, primary receivers are in the proximity of primary transmitters, and UAVs are uniformly distributed in the allowable flight region within the height of 10 and 100 m.

random UAV and the SSS-based spectrum access have low complexity, as they access the spectrum in distributed ways based on several system parameters.

The ground primary users are uniformly distributed with the density of $1e\text{-}5/\text{m}^2$ [11]. The UAVs are randomly located in an aerial region within a height of [10m, 100 m]. Considering that each UAV communicates with a ground receiver, we assume that the UAV density is the same as that of the ground users. The transmission power of UAVs and primary users is 200 mW [11]. The considered channel model is based on the model in [11] and [12], and the small-scale fading for UAV communications is assumed to be Nakagami-m fading with the parameter $m = 2$ [13]. Rayleigh small-scale fading is assumed for the ground communications, and the path loss exponent is 4 [11], [14]. The target false-alarm probability of UAVs is chosen as 0.1 [4]–[6], [14]. We assume $\beta_0 > \beta_1$ to ensure the different spectrum access probabilities based on the detected energy for the SSS-based method and the appearance of primary users in the distance-based method. Next, we set $\beta_0 = 0.8$ and $\beta_1 = 0.16$, according to [4]–[6]. The bandwidth is 10 MHz, and the noise power is –110 dBm [11]. The desired link distances of primary users are 30 m [14], and the distance between the ground receiver and the projection of UAV on the ground is uniformly distributed in [1 m, 100 m]. The signal-to-interference-plus-noise ratio (SINR) thresholds are set as –5 dB for both primary users and UAV receivers [14]. The required minimum data rate of a typical primary user is 2 Mbits/s.

Figure 6 shows the data rate of a typical primary user with respect to UAV spectrum-access radius, where the typical primary user is at the origin of the ground region of interest. For both the SSS- and the distance-based UAV spectrum-access methods, the data rate of a typical primary user increases with the UAV spectrum-access radius. For the SSS-based approach, a smaller value of the UAV spectrum-access radius makes the UAV less aware of the radio environment; thus, the average channel access probability of UAVs increases, which results in the decrease of primary users' SINR due to the increased interference. Therefore, there exists a minimum UAV spectrum-access radius, guaranteeing the required minimum data rate of a typical primary user. For the distance-based approach, a smaller value of the UAV spectrum-access radius decreases the probability of detecting a primary user in the UAV detection sphere. This also increases the average channel access probability of UAVs and thus generates more interference-to-ground users. Similarly, for random UAV spectrum access, there is a maximum access probability to ensure that the required minimum data rate of a typical primary user is met. The three aforementioned UAV spectrum policies can guarantee the primary users' average data rate.

Figure 7 suggests that, given a required minimum data rate of a typical primary user, SSS- and distance-based UAV spectrum-access methods can both achieve satisfactory SE gains of about 62% and 49%, respectively, compared to the random UAV spectrum-access method. This demonstrates the advantage of the proposed SSS-based UAV spectrum access. When the UAV spectrum-access radius is relatively small (<150 m), the distance-based method outperforms the SSS-based method in terms of the SE of UAV networks because UAVs access the spectrum more aggressively using the distance-based method as opposed to the energy detection-driven SSS-based method.

Open Research Issues

Besides the proposed SSS-based UAV spectrum access, many other spectrum-sharing approaches also need to be investigated for various UAV applications.

Spectrum Sharing for Swarm UAV Networks

In future wireless networks, multiple UAVs may form a swarm UAV network to complete a mission collaboratively, such as holographic beamforming, multiazimuth surveillance, and flying distributed multiple-input, multiple-output (MIMO). The spectrum sharing among the UAV swarm needs to be investigated to facilitate more efficient data transmissions. The major concerns are the fairness and the interference among UAVs in the proximity. In some scenarios, lead UAVs send command and control information to other UAVs. Therefore, for the design of UAV spectrum-sharing policies, the priority of the lead UAV spectrum

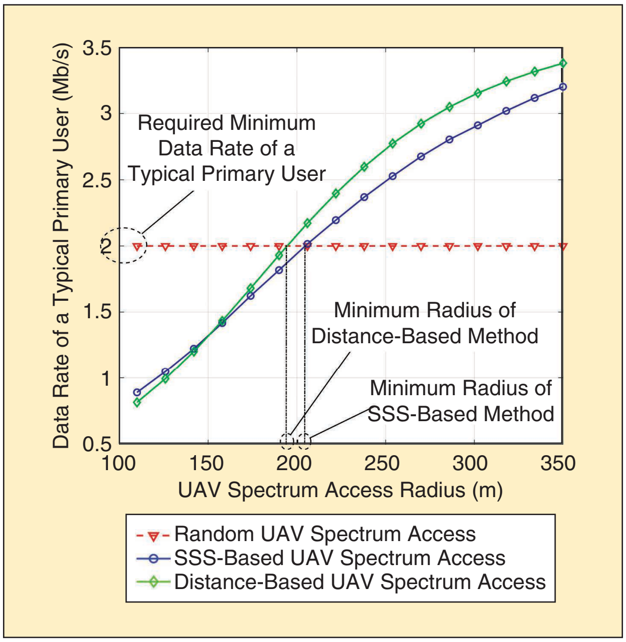


FIGURE 6 The data rate of primary users over the UAV spectrum-access radius.

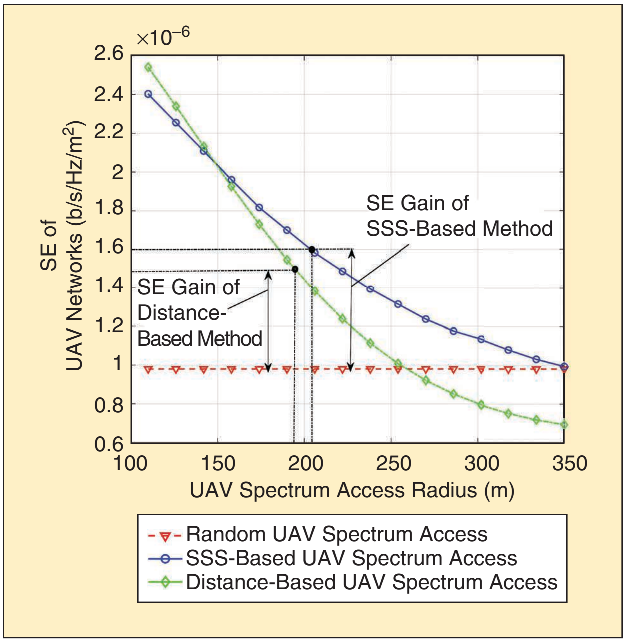


FIGURE 7 The SE of UAV networks over the UAV spectrum-access radius.

access should be higher than for the others. In addition, according to the 3rd Generation Partnership Project's realistic antenna patterns, the power leakage in the side lobes of the radiated beam from the ground base stations with multiple antennas varies with the altitude of the UAV. Thus, spectrum sharing for swarm UAV communications in a realistic network setup needs to be investigated in the future.

Cooperative SSS

If multiple UAVs are in proximity of one another, they can cooperatively perform SSS and exchange the detected signal strength values for channel access decisions in shared spectrum. Such cooperative SSS can potentially improve the sensing efficiency and communication performance of primary users because multiple distributed sensors combined will lower primary users' miss detection. However, one of the difficulties in cooperative SSS is the determination of cooperative UAVs, which may have independent trajectories. For example, if two UAVs are far apart, there is less benefit in exchanging their detected signal strength values due to the nearly independent environments.

AI-Enabled UAV Spectrum Access

SSS-based UAV spectrum access can be realized using statistical information. Other UAV spectrum-access strategies can be developed based on real-time network information (including wireless channel, UAV aerial position, and transmit power). Although these approaches can achieve better performance, they require more information, and the associated overhead of transferring this information will be costly due to the mobility of UAVs and the limited energy resources on UAVs. AI provides a suitable framework for such strategies. To be specific, supervised learning can be used to optimize the decision of UAV spectrum access based on the collected data set, which includes the locations of primary users, the signal strengths at UAVs and primary users, the network environment parameters, and so forth. On the other hand, model-free methods, such as reinforcement learning, may provide us near-optimal solutions for UAV spectrum access where the network environment is unknown and UAVs need to conduct spectrum access in a distributed fashion.

Multichannel Access

Orthogonal multiple access can be achieved through scheduling, by knowing the position and footprint of UAVs on terrestrial users. Nonorthogonal multiple access (NOMA), discussed for beyond-5G networks, can leverage different UAV positions or transmission powers to successively cancel overlapping transmissions at the intended receiver. Furthermore, when NOMA is implemented in UAV MIMO communications, the precoding and detection design under the 3D channel model needs to be investigated to improve the UAV network capacity. Research has shown that orthogonal channel access mechanisms, such as those used for 4G LTE, are suitable for A2G communications and that parameters can be optimized depending on the band and UAV velocity [15]. For spectrum coexistence employing either channel access paradigm, the research challenges include tracking of UAV locations and channels while maintaining a reasonable signaling overhead.

Cellular System Integration

Cellular networks were designed and optimized for terrestrial users. For cellular downlinks, antennas are tilted downwards, meaning that most UAVs see only side lobes. Moreover, while on the ground, cells can be defined; cell boundaries in the air are less clear, overlap, and are a function of the height, due in part to the side lobes and nulls. 5G beam-based systems, where certain beams can be dedicated to UAVs, are a promising solution to alleviate this problem. Data need to be collected with open testbeds in different environments and with different antenna configurations to evaluate strategies and allow effective sharing. The integration of UAVs into heterogeneous wireless networks, such as V2X networks [1], and spectrum sharing between UAVs and moving vehicles are of importance in future mobile systems.

Blockchain-Based UAV Spectrum Sharing

In contemporary UAV networks, multiple applications such as mobility control and surveillance reporting require precise commands and clean wireless channels. Security is one of the major concerns of UAV networks, since malicious users may try to attack the network to preempt legitimate spectrum resources and wiretap vital information transmissions of UAV communications. Conventional, centralized certification approaches require additional infrastructure cost and administrative and transaction expenses with efficiency problems. Blockchain has gained attention for its enhancement of secure transactions: it can provide a trusted and distributed database for participants and be inherently resistant to the modifications of the stored data within the blockchain. Each recorded block includes the previous cryptographic hash, a timestamp, and the transaction data. The database is verified by participants and updated with a virtual currency for each party. Considering the limited onboard energy of UAVs, designing efficient blockchain-based algorithms for UAV communications while mitigating the power consumption rates is a significant challenge.

Conclusions

In this article, we focused on spectrum sharing for UAV communications and proposed SSS for spectrum access. A comprehensive background of UAV spectrum sharing was provided. The fundamentals of SSS and the challenges of implementing SSS in UAV 3D networks were discussed. SSS-based UAV spectrum access was investigated with the objective of maximizing the SE of UAV networks and the constraint of the required minimum SE of primary user networks. We introduced a machine learning-assisted system-level framework to evaluate the performance from the system-level perspective and demonstrated the advantage of SSS-based UAV spectrum access. Our results show that SSS-based UAV spectrum access outperforms random and distance-based UAV spectrum access in terms of the SE of UAV networks while managing the interference to primary users. The article also provided a discussion on important open problems related to spectrum sharing between terrestrial and UAV communications, identifying important research areas for spectrum sharing in UAV swarms, cooperative SSS, AI and NOMA-enabled UAV channel access, cellular system integration, and blockchain-based UAV spectrum sharing.

Acknowledgment

Lingjia Liu is the corresponding author for this article. The work of Bodong Shang and Lingjia Liu was supported in part by the National Science Foundation under grant NSF/CNS-1811720. The work of Vuk Marojevic and Aly Sabri Abdalla was supported in part by the NSF PAWR program under grant CNS-1939334.

Author Information

Bodong Shang (bdshang@vt.edu) received his M.S. degree from Xidian University, Xi'an, China. He is currently pursuing his Ph.D. degree at Virginia Polytechnic Institute and State University, Blacksburg. His research interests include unmanned aerial vehicles, the Internet of Things, and mobile edge computing.

Vuk Marojevic (vuk.marojevic@msstate.edu) is an associate professor in electrical and computer engineering at Mississippi State University, Starkville. His research interests include resource management, vehicle-to-everything communications, and wireless security with application to cellular communications, mission-critical networks, and unmanned aircraft systems.

Yang Yi (yangyi8@vt.edu) received her Ph.D. degree computer engineering from Texas A&M University, College Station. She is an associate professor in the Department of Electrical and Computer Engineering at Virginia Polytechnic Institute and State University, Blacksburg. Her current research interests include very-large-scale integrated circuits and systems, computer-aided design, and neuromorphic computing.

Aly Sabri Abdallah (asa298@msstate.edu) is a Ph.D. candidate in the Department of Electrical and Computer Engineering at Mississippi State University, Starkville. His research interests are wireless security and scheduling and congestion control for vehicular ad hoc and unmanned aerial vehicle networks.

Lingjia Liu (ljliu@vt.edu) received his Ph.D. degree in electrical and computer engineering from Texas A&M University, College Station. He is an associate professor in the Bradley Department of Electrical and Computer Engineering at Virginia Polytechnic Institute and State University, Blacksburg. His research interests include machine learning for wireless communications, 5G and beyond, and the Internet of Things.

References

[1] B. Shang, L. Liu, J. Ma, and P. Fan, "Unmanned aerial vehicle meets vehicle-to-everything in secure communications," *IEEE Commun. Mag.*, vol. 57, no. 10, pp. 98–103, Oct. 2019. doi: 10.1109/MCOM.001.1900170.

[2] Y. Saleem, M. H. Rehmani, and S. Zeadally, "Integration of cognitive radio technology with unmanned aerial vehicles: Issues, opportunities, and future research challenges," *J. Netw. Comput. Appl.*, vol. 50, pp. 15–31, Apr. 2015. doi: 10.1016/j.jnca.2014.12.002.

[3] D. Lee, J. Lim, and H. Baek, "An airborne communication relay scheme for IEEE 802.11 WLAN based network," in *Proc. 2018 IEEE Int. Conf. Information Networking (ICOIN)*, pp. 426–431. doi: 10.1109/ICOIN.2018.8343153.

[4] H. Chen, L. Liu, T. Novlan, J. D. Matyjas, B. L. Ng, and J. Zhang, "Spatial spectrum sensing-based device-to-device cellular networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 11, pp. 7299–7313, Nov. 2016. doi: 10.1109/TWC.2016.2600561.

[5] H. Chen, L. Liu, H. S. Dhillon, and Y. Yi, "QoS-Aware D2D cellular networks with spatial spectrum sensing: A stochastic geometry view," *IEEE Trans. Commun.*, vol. 67, no. 5, pp. 3651–3664, May 2019. doi: 10.1109/TCOMM.2018.2889246.

[6] B. Shang et al., "Spatial spectrum sensing-based D2D communications in user-centric deployed HetNets," in *Proc. 2019 IEEE Global Commun. Conf. (GLOBECOM)*, pp. 1–6. doi: 10.1109/GLOBECOM38437.2019.9013184.

[7] R. Atat, L. Liu, H. Chen, J. Wu, H. Li, and Y. Yi, "Enabling cyber-physical communication in 5G cellular networks: Challenges, spatial spectrum sensing, and cyber-security," *IET Cyber-Phys. Syst., Theory Appl.*, vol. 2, no. 1, pp. 49–54, 2017. doi: 10.1049/iet-cps.2017.0010.

[8] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *Proc. 2014 IEEE Global Commun. Conf. (GLOBECOM)*, pp. 2898–2904. doi: 10.1109/GLOCOM.2014.7037248.

[9] W. Khawaja, I. Guvenc, and D. Matolak, "UWB channel sounding and modeling for UAV air-to-ground propagation channels," in *Proc. 2016 IEEE Global Commun. Conf. (GLOBECOM)*, pp. 1–7. doi: 10.1109/GLOCOM.2016.7842372.

[10] B. Shang and L. Liu, "Machine learning meets point process: Spatial spectrum sensing in user-centric networks," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 34–37, Jan. 2020. doi: 10.1109/LWC.2019.2940442.

[11] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Unmanned aerial vehicle with underlaid device-to-device communications: performance and tradeoffs," *IEEE Trans. Wireless Commun.*, vol. 15, no. 6, pp. 3949–3963, June 2016. doi: 10.1109/TWC.2016.2531652.

[12] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 569–572, Dec. 2014. doi: 10.1109/LWC.2014.2342736.

[13] P. K. Sharma and D. I. Kim, "Random 3D mobile UAV networks: Mobility modeling and coverage probability," *IEEE Trans. Wireless Commun.*, vol. 18, no. 5, pp. 2527–2538, May 2019. doi: 10.1109/TWC.2019.2904564.

[14] M. Salehi, A. Mohammadi, and M. Haenggi, "Analysis of D2D underlaid cellular networks: SIR meta distribution and mean local delay," *IEEE Trans. Commun.*, vol. 65, no. 7, pp. 2904–2916, July 2017. doi: 10.1109/TCOMM.2017.2691704.

[15] J. Kakar and V. Marojevic, "Waveform and spectrum management for unmanned aerial systems beyond 2025," in *Proc. 2017 IEEE 28th Int. Symp. Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pp. 1–5. doi: 10.1109/PIMRC.2017.8292533.

VT