Newsletter

IEEE ComSoc Technical Committee on Cognitive Networks (TCCN)

June 2024

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1. Chair’s Message

Dear TCCN Colleagues:

Time flies. The current team of TCCN officers started Jan. 2023, and it has been one and half years of our term. We are grateful for your kind support and participation in TCCN activities! Our term will end by December this year. There will be an election of new officers, where all the officer positions will be open for reelection. The Nomination and Election Subcommittee led by Dr. Lingyang Song (TCCN past chair) will send a call for nominations in the fall on the TCCN mailing list. I would strongly encourage our members to consider a self-nomination or nominating a colleague.

Another recent opportunity is to nominate co-chairs for IEEE ICC 2026 symposia and SACs. We distributed the call for nominations on the mailing list, received a large number of nominations, and recommended the top six candidates to ICC 2026 TPC Chairs. The TPC chairs will make their selections and the final sections need to be approved by the GITC. Please be aware that there will be a call for nominations for co-chairs of IEEE GLOBECOM 2026 symposia and SACs in the fall.

As you may know, TCCN has the annual TCCN Recognition Award and TCCN Publication Award to recognize its outstanding members. See the TCCN award website for more information: *https://cn.committees.comsoc.org/awards/* The Award Subcommittees have been approved at the recent TCCN meeting, which will be led by Dr. Lingyang Song as well. Please look out for call for nominations on the TCCN mailing list.

Every year, TCCN can nominate up to four members for the ComSoc Distinguished Lecturer (DL) program. As you can see from the ComSoc DL website (*https://www.comsoc.org/membership/distinguished-lecturers*), many existing DLs are our members. There will be a call for nominations in the fall as well, with a deadline of Aug. 15, 2024. In addition, we’d be happy to help our members with applications for IEEE Senior Member and IEEE Fellow. Please feel free to let us know if you are applying and need our help with the nomination and/or endorsement.

Last year, TCCN was one of the five TCs funded by the ComSoc TC Video Compaign Program, with $1,000 from ComSoc TC Board to create a short video. This effort was led by our secretary Dr. Hongliang Zhang. Working with IEEE TV, a short video has been created which will be very helpful for publicity and member recruitment. Please check out the video at: *http://ieeetv.ieee.org/player/embed_play/233876/auto*

TCCN was also one of the few TCs funded by the ComSoc TC Innovation Projects Program last year. Led by Dr. Boya Di, we received $8,000 from ComSoc TC Board and hosted two invited talks on cutting-edge technologies at our in-person TC meeting at IEEE GLOBECOM 2023 in Kuala Lumpur, Malaysia, Dec. 2024. This year, TCCN also secured $6,000 from the ComSoc TC Innovation Projects Program. With this funding, Boya and Hongliang plans to hold a joint event with the ComSoc Asia Pacific Board (APB) in Bejing, China in August, which is a workshop for young professionals featuring a number of invited talks. Please look out for the announcement (on the TCCN mailing list) and all are welcome!

Again, I'd like to take this opportunity to discuss the two specific areas that we need to make further improvements. First, we need to recruit more members, given that machine learning and spectrum related research are becoming mainstream topics in our field. Anyone who subscribes to our mailing list becomes a TCCN member, and a ComSoc member that has attended two out of five past TCCN meetings becomes an active member, who is eligible for awards, voting, and running for an elected officer position. The streamlined membership subscription website is: *https://cn.committees.comsoc.org/voting-members/*. Please spread the words and encourage your friends, colleages, and more important, your students to subscribe.

Second, we need to have more submissions to the Cognitive Radio and AI-Enabled Networks (CRAEN) Symposium at IEEE ICC and GLOBECOM. This is a symposium primarily sponsored by TCCN, and we recommend our members to serve as symposium co-chairs. In recent years this symposium is facing direct competition with the SAC on Machine Learning for Communicaitons. For IEEE GLOBECOM 2024, the symposium chairs, Drs. Yuan Ma and Walaa Hamouda, did an excellent job and got 130+ submissions. Please kindly consider submitting your work and encourage your colleagues and students to submit to the ICC/GC CRAEN Symposium.

Thanks to our Newsletter Director Dr. Dola Saha! I hope you enjoy reading this issue of TCCN newsletter. If you have any suggestions or comments, please do not hesitate to contact me.

Sincerely,
Shiwen Mao,
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TCCN Chair

Bio: SHIWEN MAO is a professor and Earle C. Williams Eminent Scholar Chair, and Director of the Wireless Engineering Research and Education Center (WEREC) at Auburn University, Auburn, AL, USA. His research interests include wireless networks, multimedia communications, and smart grid. He is a Distinguished Lecturer of IEEE Communications Society and the IEEE Council of RFID, and is the Editor-in-Chief of IEEE Transactions on Cognitive Communications and Networking. He received the IEEE ComSoc MMTC Outstanding Researcher Award in 2023, IEEE ComSoc TC-CSR Distinguished Technical Achievement Award in 2019, and NSF CAREER Award in 2010. He is a co-recipient of the 2022 Best Journal Paper Award of IEEE ComSoc eHealth TC, the 2021 Best Paper Award of Elsevier/KeAi Digital Communications and Networks Journal, the 2021 IEEE Internet of Things Journal Best Paper Award, the 2021 IEEE Communications Society Outstanding Paper Award, the IEEE Vehicular Technology Society 2020 Jack Neubauer Memorial Award, the 2018 Best Journal Paper Award and the 2017 Best Conference Paper Award from IEEE ComSoc MMTC, the 2004 IEEE Communications Society Leonard G. Abraham Prize in the Field of Communications Systems, and several ComSoc service and conference best paper/demo awards. He is a Fellow of the IEEE.

2. Newsletter Director's Note

Dear Colleagues:

It is my great pleasure to introduce the newsletter that features intriguing visionary articles from leaders in the field. In this letter, we have four articles from ten domain experts as listed below:

1. Integrated Sensing and Communications: An Evolution of Cognitive Radio Creating a Revolution in Cognition
2. Cognitive Dynamic Spectrum Sharing with New Radio Techniques
3. Towards an Intelligent Sensing Technique
4. Shared Spectrum for Low and Mid-band Private 5G Networks

The experts (listed below) have all shared their insights for future cognitive communication systems and the challenges ahead of us in tackling those topics.

1. Prof. Christos Masouros, University College London, United Kingdom
2. Prof. Hang Liu, The Catholic University of America, USA
3. Dr. Son Dinh, Meta, USA
4. Dr. Cheng-Yu Cheng, The Catholic University of America, USA
5. Prof. Yue Gao, Fudan University, China
6. Dr. Zhe Chen, Fudan University, China
7. Dr. Zihang Song, King's College London, United Kingdom
8. Prof. Rahim Tafazolli, University of Surrey, United Kingdom
9. Prof. Robert W. Stewart, University of Strathclyde, United Kingdom
10. Dr. Louise H. Crockett, University of Strathclyde, United Kingdom

I would like to sincerely thank all the contributors for taking the time to share their thoughts with the readers of the TCCN newsletter in their busy schedule.

This newsletter wouldn't have been possible without continuous efforts from the co-editors, Prof. Junqing Zhang and Prof. Mingjie Feng. I whole-heartedly thank both the co-editors for their endeavors to bring together all the articles for our readers.

I hope all of you will cherish reading the articles as I did.

Sincerely,

Dola Saha
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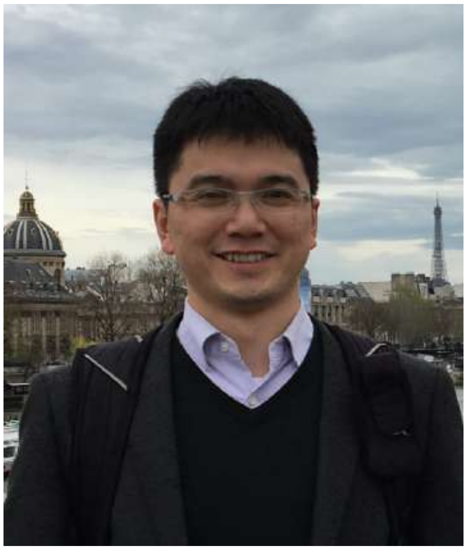
Newsletter Director

Dola Saha is an Associate Professor in the Department of Electrical & Computer Engineering at University at Albany, SUNY. She co-directs the Mobile Emerging Systems and Applications (MESA) Lab at UAlbany. She was a faculty fellow at Jet Propulsion Laboratory, Caltech, NASA in summer of 2022. She was a visiting faculty at the Air Force Research Laboratory in summers of 2020 and 2021. She is the Vice Chair of the IEEE ComSoc TCCN SIG for AI and Machine Learning in Security and has been appointed a member of the SUNY Innovations Policy Board. Prior to that, she was a Research Assistant Professor in the Department of Electrical & Computer Engineering at Rutgers University. Before that, she was a Researcher in the Mobile Communications and Networking group at NEC Laboratories America. She received Best Paper Award in DySPAN 2015 and 2021. She received her Masters and Doctorate degrees from the Department of Computer Science in the University of Colorado Boulder. She is the recipient of Google Anita Borg Scholarship for her academic credentials. Her research interests lie in the crossroads of Machine Learning for Wireless Communication, Wireless Security, Wireless Signal Processing, and Architectures of Software Defined Radios with focus on systems design and practical evaluation.

Newsletter Editors



Junqing Zhang is a Senior Lecturer (Associate Professor) at the Department of Electrical Engineering and Electronics, University of Liverpool, UK. He received his Ph.D. in electronics and electrical engineering from Queen's University Belfast, UK in Jan. 2016. He served as the TPC co-chair of AI and Machine Learning for Communications and Networking (AMCN) of ICNC 2025, Signal Processing for Communications Symposium of IEEE ICC 2023, IEEE/CIC ICCC 2022, IEEE INFOCOM 2023, 2024 DeepWireless Workshop, ACM 2023 WiseML Workshop, IEEE WCNC 2023 Workshop on Trusted Communications with Physical Layer Security (TC-PLS) and IEEE GLOBECOM 2018 TCPLS Workshop. His research interests include wireless security, physical layer security, key generation, radio frequency fingerprint identification, and wireless sensing.

Mingjie Feng is currently a Professor at Wuhan National Laboratory for Optoelectronics, Huazhong University of Science and Technology. He received his Ph.D. degree in electrical and computer engineering from Auburn University, Auburn, AL, USA, in 2018. He was a Postdoctoral Research Associate with the Department of Electrical and Computer Engineering, University of Arizona, Tucson, AZ, USA. He was a Research Scientist with Intelligent Fusion Technology, Germantown, MD, USA. He is a recipient of various awards, including Best Paper Award of Digital Communications and Networks, Best Reviewer of IEEE Transactions on Wireless Communications, and Chinese Government Award for Outstanding Self-financed Students Abroad. He is an associate editor of IEEE Networking Letters and Digital Communications and Networks. He was or is a Technical Program Committee Member of various IEEE conferences, including IEEE INFOCOM, IEEE MASS, IEEE ICC, IEEE WCSP, IEEE CSCN, and IEEE CCNC.

3. Integrated Sensing and Communication: An Evolution of Cognitive Radio Creating a Revolution in Cognition

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The idea of Cognitive Radios, pursuing radios that obtain and exploit awareness of their environment, has been extensively studied in the context of spectrum reuse from different communication systems. More recently, Integrated Sensing and Communications (ISAC) systems have come about as an evolution from the spectrum co-existence between radar and communication systems. ISAC systems enable devices with both sensing and communication functionalities, enhancing hardware reuse, energy efficiency and therefore aid in achieving sustainable wireless networks. The also offer significant performance gains compared to the interference-limited spectrum co-existence. Finally, embedding the sensing functionality in a communications network, offers profound opportunities for environment awareness, and offers a revolution in cognition breaking down barriers in implementing Cognitive Radios. In this newsletter I overview the evolution of Cognitive Radio and spectrum co-existence technologies into Communications-Radar coexistence. In then discuss ISAC as a step change from spectrum-coexistence and overview the significant gains it offers. Finally, I highlight two recent research directions where sensing-based cognition can assist in the intelligence of the wireless links, one related to vehicular communications and one related to security.

3.1 Background

While 5G is being launched worldwide, discussion for 6G is already taking shape. One unanimous view is that 6G mobile radios should be empowered by great intelligence, the kind of intelligence that allows each radio to make wise decisions that optimise its quality-of-experience over time and impact the network in a constructive way. 'Intelligent' radio is not a new concept. In fact, back in 1998, Mitola formalised this concept and coined it cognitive radio, (also known as Mitola radio by many). This concept refers to a futuristic mobile communication device that goes beyond the possession of any hardware flexibility and is gifted the intelligence to access the spectrum anytime anywhere according to the environment and its need. Cognitive radio (CR) has been researched ever since with a peak in interest in the 2010s, with the acknowledgement that the spectrum in many locations is over-booked but under-utilised.

The CR paradigm can be mainly classified into two types: the first one, interweave, where an unlicenced user uses advanced spectrum-sensing techniques to detect spectrum holes (op-portunities) in the licensed bands that are not being used by the licenced users, and transmits its own signals in the detected free bands. It must stop transmission as soon as the licenced users returns to the used bands so as not to cause any interference. The interweave approach has been considered for secondary spectrum usage in the TV bands in the IEEE 802.22 standard. The second CR paradigm, which is known as spectrum-sharing CR, allows licenced and unlicenced users to coexist with each other, as long as the performance of the licenced user is not jeopardised. This can again be of two types, i.e., underlay and overlay. In underlay CR, the unlicenced user operates under an interference constraint to the licenced transmission, so that a threshold performance is guaranteed. On the other hand, the overlay CR is a more collaborative approach where the unlicenced user, in return for its access to the spectrum, facilitates the licenced transmission, aside from its own transmission, and uses a fraction of its power to relay the message to the licenced user, in addition to the transmission of its own message, to compensate for the interference that is caused by its own transmission.

3.2 Cognitive Radio and Radar-Communication Spectrum Coexistence

Coexistence of Radar and Wireless Systems: Communications-Radar Spectrum Sharing (CRSS) came about as an evolution of cognitive radio, initially involving diverse communication systems, to the coexistence of radar and commercial wireless systems, motivated by the increasing cohabitation of traditional radar spectra from communications. Some examples of coexisting systems in various bands include the following:

- *L-band (1-2 GHz)*: This band is primarily used for long-range air-surveillance radars, such as Air Traffic Control (ATC) radar, which transmit high-power pulses with modest bandwidth. The same band, however, is also used by 5G NR and FDD-LTE cellular systems as well as the Global Navigation Satellite System (GNSS) both in their downlink (DL) and uplink (UL) [1].
- *S-band (2-4 GHz)*: This band is typically used for airborne early warning radars at considerably higher transmit power [2]. Some long-range weather radars also operate in this band due to moderate weather effects in heavy precipitation [3].

Frequency Band	Radar Systems	Communication Systems
L-band (1-2GHz)	Long-range surveillance radar, ATC radar	LTE, 5G NR
S-band (2-4GHz)	Moderate-range surveillance radar, ATC radar, airborne early warning radar	IEEE 802.11b/g/n/ax/y WLAN, LTE, 5G NR
C-band (4-8GHz)	Weather radar, ground surveillance radar, vessel traffic service radar	IEEE 802.11a/h/j/n/p/ac/ax WLAN
MmWave band (30-300GHz)	Automotive radar, high-resolution imaging radar	IEEE 802.11ad/ay WLAN, 5G NR

Figure 3.1: Radar-Communications spectrum co-existence

Communication systems present in this band include 802.11b/g/n/ax/y WLAN networks, 3.5 GHz TDD-LTE and 5G NR [4].

- *C-band (4-8 GHz)*: This band is more sensitive to weather patterns. Therefore, it is assigned to most types of weather radars for locating light/medium rain [3]. On the same band, radars are operated for battlefield/ground surveillance and vessel traffic service (VTS) [3]. Wireless systems in this band mainly include WLAN networks, such as 802.11a/h/j/n/p/ac/ax [5]
- *MmWave band (30-300 GHz)*: This band is conventionally used by automotive radars for collision avoidance, as well as by high-resolution imaging radars [6]. However, it is bound to become busier, as there is a huge interest raised by the wireless community concerning mmWave communications, which are becoming part of the 5G NR standard [7]. Currently, the mmWave band is also exploited by the 802.11ad/ay WLAN protocols [5].

To address the spectrum scarcity issue, relevant research has largely focused on the competitive spectrum co-existence of the separate radar and communication systems, through dynamic spectrum access solutions, resource allocation, interference management [8]. These approaches, however, still inevitably result in the two systems competing for the same resources, and therefore exhibit interference-limited, non-scalable performance with significant signaling overheads for coordination [9]. Most importantly, co-existence solutions alone do not address the challenges with energy, hardware, complexity that arise with the independent growth of radar and communication systems.

Notably, there are parallels between the radar signal processing and that of communications, including between beamforming for communications and for radar, hypothesis testing for target detection and signal detection, millimeter-wave communication channel estimation and radar angle detection, among others. There are also duplications in devices, such as between phased arrays for radar and for communications, MIMO radar and MIMO communications, while multi-static radars can be paralleled to cooperative communications. This provides a clear opportunity for addressing the above challenges beyond spectral co-existence. A more recent line of research aims at enabling the convergence of the two technologies into dual-functional radar-communication (DFRC) systems and devices, that can serve sensing and communications with a single transmission, a single spectrum use and ultimately a common infrastructure. Already, communication industries identify DFRC systems as a key capability in their future roadmap.

The motivation behind this integration of functionalities comes from the fact that future wireless networks will underpin smart city applications, urban security, infrastructure monitoring, smart mobility, and applications such as augmented reality and digital twins. Network KPIs for 6G involve Gb/s data rates; cm-level localization; μs-level latency; Tb/Joule energy efficiency [10] Networks will also need to support the UN's Sustainable Development Goals to ensure sustainability, net-zero emissions, resilience and inclusivity [11] The global Smart City market value is projected to exceed $2.5 trillion by 2025, with numbers of sensors and transmitters expected to grow to more than 40 billion by 2027. The UK communications industry is investing on dense cell deployment for 5G and beyond, with Access Points (APs) being deployed on buildings, lampposts, and other street furniture. At the same time, remote sensing based on radar principles is now used for traffic incident detection, urban security solutions, non-intrusive health monitoring [12]. Spectrum is particularly scarce and in 2018, the 3.4GHz band of just 20MHz, already occupied by radar systems, was auctioned for a colossal £168m to mobile network operators to provide small-cell services. Ofcom plans to release additional millimeter-wave radar bands for communications. In the transport industry, the 5G Automotive Association estimates close to 200 million connected vehicles already on the roads worldwide with an average of 200 sensors per car. Automotive radars, lidars and cameras are used for short/long-range obstacle detection, navigation and park assistance. Meanwhile, the next-generation vehicle-to-everything (V2X) network will require the deployment of antenna arrays for ultra-reliable Gbps data transmission [13]. The industry identifies as a major challenge the growing population of radio frequency (RF) systems and transmitters, at a time where we are in the middle of a Silicon crisis, with chip-shortage causing £multibillion losses for numerous sectors. The independent growth of sensing and communication systems is not sustainable and will lead to a congestion of devises, emitters and sensors, followed by an unprecedented spectrum and energy demand.

3.3 Step change to joint Radar-Communication transmission

With the integration of sensing and communications (ISAC) through DFRC technologies, transmissions for sensing and communications, previously competing for the same resources, can be jointly optimised. This can enable new sensing capabilities through the dense cellular deployment to obtain a truly perceptive cellular network that, aside of next generation communications, supports remote sensing for traffic monitoring, incident detection, infrastructure monitoring, and security – cognition brought at the core of the network's operation. It has obvious gains in reducing hardware, and offers orders-of-magnitude improvements in the cost-, spectrum-, and energy-efficiency of the multifunctional network. It can turn radar applications, which are on the rise in the smart city ecosystem, into a commodity. ISAC technologies promise multi-fold gains:

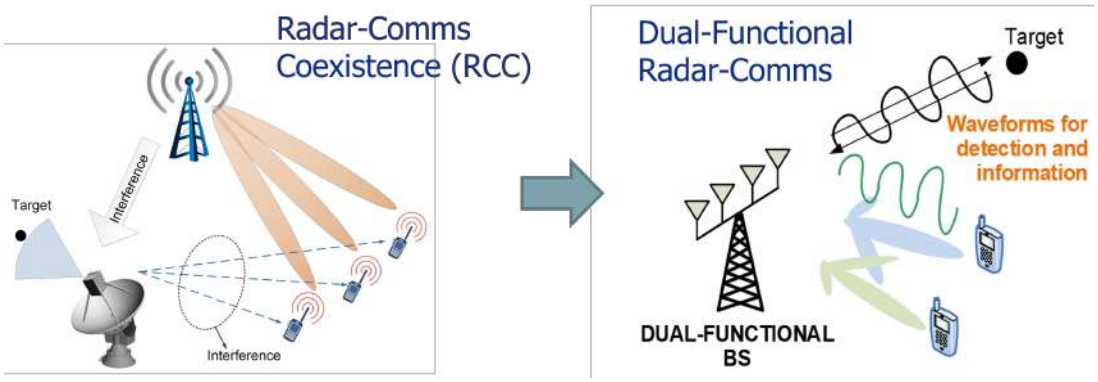

Figure 3.2: The step change from Rada-communications spectrum co-existence (RCC) to Dual-Functional Radar-Communications (DFRC)

- *Hardware and Energy efficiency*: by allowing hardware reuse for both sensing and communications, and replacing separate communication devices and radar sensing devices, which also represent separate power consumers, ISAC enables a hardware and energy efficient solution where both functionalities happen from a single device, a single power consumer. Aside from the obvious hardware gains, this also translates in savings in silicon demand, at a time when we are still experiencing the results of the chip crisis;
- *Spectrum Efficiency*: ISAC enables the use of a single chunk of spectrum for dual functionality, circumventing the need to allocate separate spectra for radar vs communication systems, and therefore making space in the spectrum for the multitude of other applications that demand it;
- *Trade-offs through co-design*: by co-designing radar and communications systems from the same signal, the same transmission and the same device, one can incorporate flexible trade-offs where priority is given to the radar operation in radar-critical scenarios such as aviation, or to communications in communication-critical scenarios such as remote surgery, but also achieve operating points anywhere in between, where performance of communications is gracefully traded-off with radar performance.
- *Mutual performance benefits through co-design*: beyond the trading-off of performance, the co-design allows the opportunity to exploit synergies between the two, where the sensing functionality can assist the communication performance and vice versa. Indeed this allows a breakthrough in achieving true cognition from the communication network, where the sensing can help build real-time environment awareness.

While the above benefits are significant, the implementation of ISAC systems is non-trivial as it requires a redesign of the transmission methodologies that need to accommodate the dual radar - communications functionality. This is particularly challenging, as existing communication signalling, that has been developed fro five decades from 1G to 5G, is not fundamentally tailored for sensing functionality, and vice versa. Furthermore, critical smart cities operations often necessitate communication links and radar systems with extreme reliability, i.e. error-free operation close to 100% of the time. ISAC signals are generally designed following three philosophies, namely, sensing-centric design (SCD), communication-centric design (CCD), and joint design (JD) approaches [14] [15], as follows.

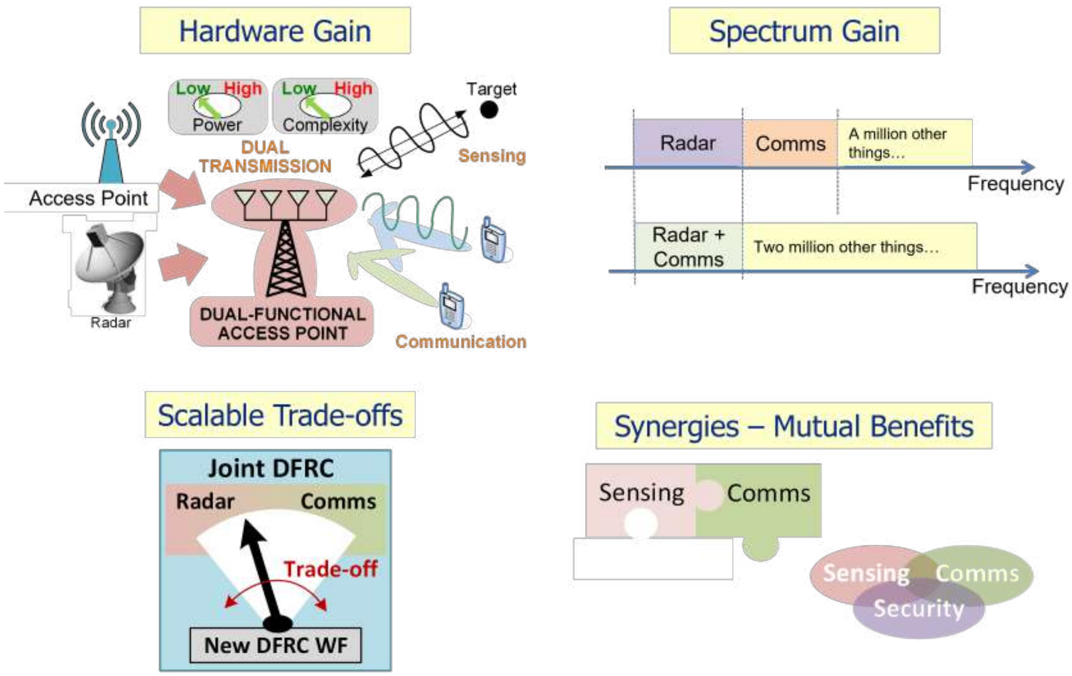

Figure 3.3: A summary of ISAC gains

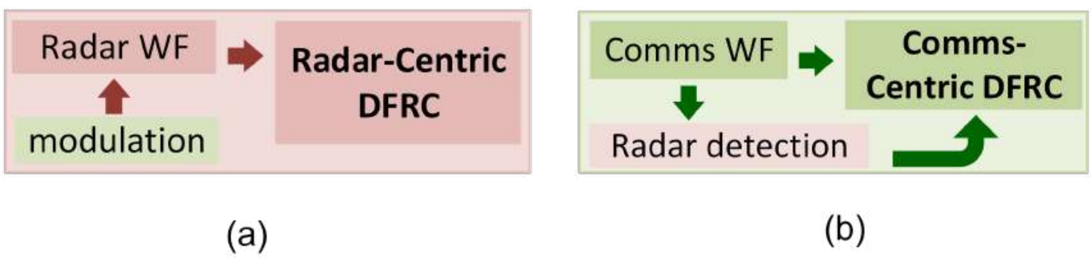

Figure 3.4: (a) Radar-centric DFRC design (b) Communication-centric DFRC design

1. *Sensing-Centric Design*: SCD aims to incorporate the communication functionality into existing sensing waveforms/ infrastructures. This typically involves employing a sensing waveform and transceiver and piggy-backing communication bits. This can be in the form of sidelobe signalling, where the sidelobes of the radar waveform are exploited for communication, or index modulation where parameters of the radar system (frequency/antenna/polarization/bandwidth) are used as indices to build a communication constellation with which to convey information. As radar signals are not fundamentally designed to convey information bits, the data rates typically achieved with SCD are rather limited, but with a very minor sacrifice in radar performance
2. *Communication-Centric Design*: In contrast to SCD, communication-centric design implements the sensing functionality over an existing communication waveform/system. In principle, any communication waveform can be utilized for mono-static sensing, as the waveform is fully known to the transmitter. Nevertheless, the randomness

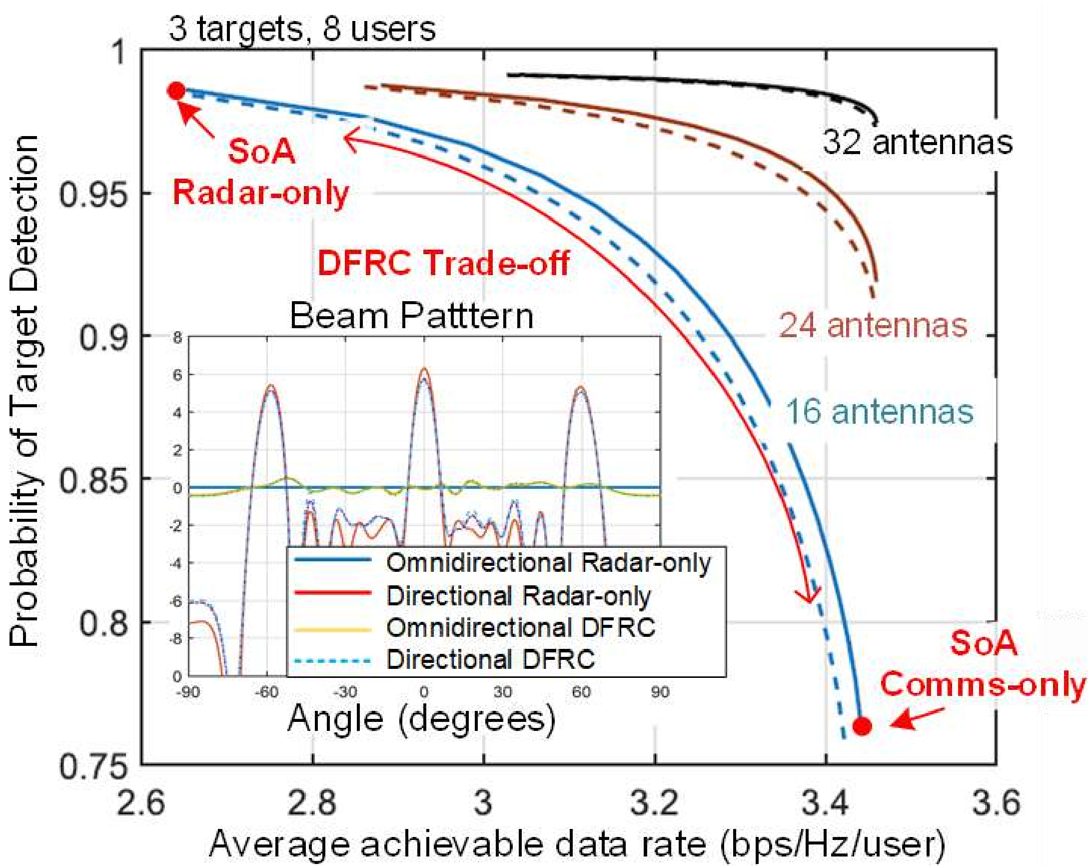

Figure 3.5: Communications-Radar tradeoff achieved by joint design

brought by the communication data may considerably degrade the sensing performance of the system. Typically either the data symbols are used, but with limited sensing performance due to their poor autocorrelation properties, or preambles and reference signals typically found in a LTE frame are used. These have good autocorrelation properties, that are suitable for radar estimation. Nevertheless, the sensing performance is typically limited and difficult to tune.

3. *Joint Design*: As mentioned above, while the SCD and CCD schemes realize ISAC to a certain extent, they do not offer flexible and scalable tradeoffs between S&C. The most recent solution involves the design of joint waveforms tailored, from the start, for the dual radar and communications (DFRC) functionality [16] [17]. This research line typically involves optimizing a weighted sum of a communication performance metric, such as multi-user interference / signal-to-noise ratio (SNR) / data rate, and a radar metric such as detection probability / estimation accuracy / proximity to ideal beampattern that illuminates the directions of radar targets. This allows such signalling to offer a scalable tradeoff between radar and communications performance (Fig. 3.5), most recently demonstrated in over-the-air proof-of-concept experiments (Fig. 3.6).

Figure 3.6: Proof of concept DFRC experiments in UCL. The communications-sensing trade-off over the air.

3.4 Cognition and Environment Awareness through ISAC

The co-design of sensing and communications promises new horizons in the development of cognition in the wireless network, creating a truly perceptive wireless network. Different facets of the perceptive network will involve different types of synergies between sensing and communication, where the sensing will augment the 'awareness' of the communication network, in turn assisting in optimising its own operation and its bottom-line communication performance. Below I overview two characteristic examples.

3.4.1 Sensing-assisted vehicular communications

High-mobility is a key challenge in establishing and maintaining high data-rate links. The state of the art in vehicular communications involves beam-steering, training and tracking, and resource allocation for downlink communication from a Road Side Unit (RSU) to a vehicular user (VU). Solutions involve sparsity-driven beam-steering [18], beam-index search approaches [19], beam prediction based on mobility models [20]. Such communication-only approaches require frequent link estimation and feedback from the VU, and the high mobility implicates significant signalling overhead, channel state information (CSI) errors, and latency that is far from the 5G performance requirements [19]. Beam misalignment and network outages can jeopardise the performance and safety of smart mobility technologies such as connected cars.

The DFRC functionality, however, offers paradigm-shifting opportunities in this space by exploiting radar functionalities to inform the beam-steering. This is distinctly different, as the radar functionality is exploited for a common goal with the communication operation. Typical radar parameters such as angles of arrival (AoA), velocity and acceleration can be used to steer the communication beam without the need of feedback signalling, as shown in Fig. 3.7(a). Initial DFRC solutions for vehicular beam-steering [12] have shown significant gains over communication-only approaches, offering enhanced data rates and avoiding network outages, as shown in Fig 3.7(b). However, they are dependent on the existence of analytically tractable vehicle trajectory models, apply to a limited number of VUs, and do not scale to the scenarios of the future with multiple VUs and complex trajectories. Ongoing work focuses on extending to more complex scenarios.

Similarly, beyond beam-steering, highly mobile VUs implicate frequent cell handovers

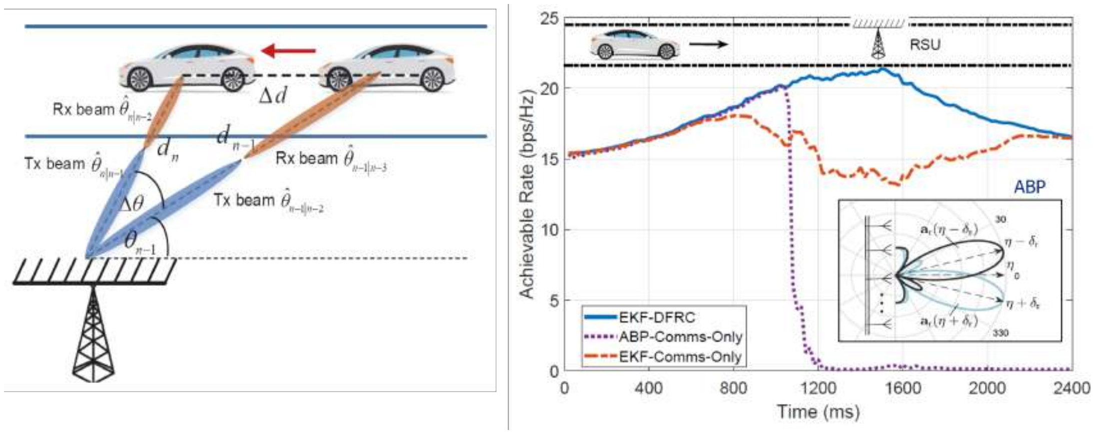

Figure 3.7: (a) sensing-assisted vehicular beamsteering (b) resulting achievable rate for a DFRC approach based on extended Kalman filtering (EKF-DFRC) compared to communication only approaches with adaptive beam-pair (ABP) selection and EKF. The result shows a significantly improved performance avoiding network outages

and significant signalling between RSUs, that likewise incur latency and outages [21]. The state of the art involves cooperative multi-point (CoMP) approaches [22], cloud-enabled [23] and data-driven predictive handover [24]. Again the use of the radar functionality means that an adjacent RSU can detect a VU entering its coverage area, with minimal or no coordination with the neighbouring APs. This can drastically cut the overheads and latency in the communication link, and yield high gains in the communication rates, and the reliability of the links.

For the evaluation of reliability and robustness of ISAC-enabled beam tracking, a case study of utilizing 5g New-Radio (5G NR) waveform in vehicle-to-infrastructure (V2I) networks was elaborated in [25] carried out in a ray-tracing simulation. For clarity, let us briefly overview the beam-tracking oprtation for conventional and ISAC systems:

A. Conventional NR Beam Tracking: During the initial access phase in 5G NR, the gNodeB transmits a set of SSBs over a 20ms period, with each SSB pointing towards different directions. The user end (UE) then measures the reference signal received power (RSRP) of each SSB and determines the best transmit beam, which it feeds back to the gNodeB. The gNodeB then transmits a more refined CSI-RS beam, and the UE goes through the same procedure to determine the best receive beam via beam sweeping. Once the initial access phase is complete, the UE operates in the connected mode.

B. ISAC NR Beam Tracking: Exploiting the ISAC signal can improve the overall throughput by releasing overheads of some specific reference signals. For example, in a single user MIMO (SU-MIMO) V2I case, the CSI-RS report contains channel information such as RI, PMI, and CQI. The PMI and CQI indicate the precoding direction and the channel quality, respectively, but these can be reduced with sensing-assisted communications. Specifically, the UE's motion parameters, such as distance, velocity, azimuth angle, and elevation angle, can be estimated from the measured echoes using 2D-FFT and 2D-multiple signal classification (MUSIC) algorithms. Finally, the state prediction can be achieved via the Kalman filtering algorithm.

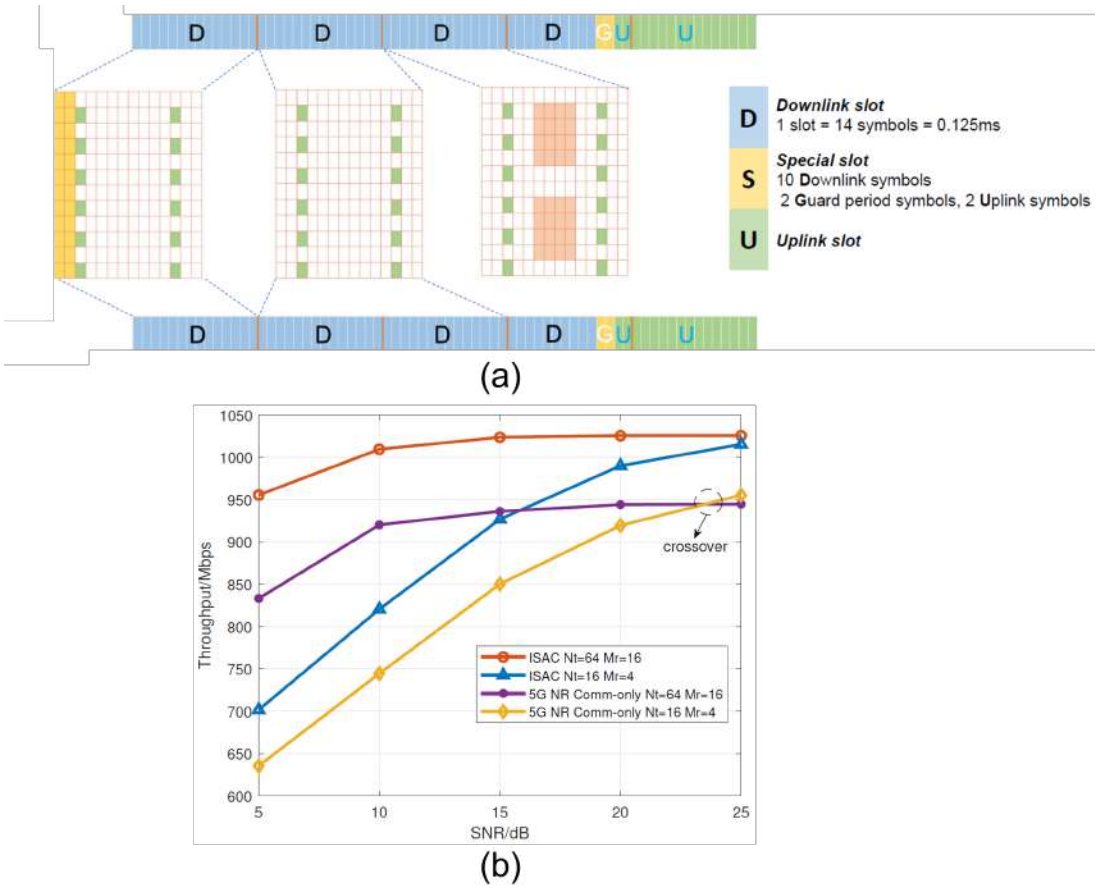

Figure 3.8: Vehicular ISAC: (a) conventional NR frame ve ISAC frame, (b) Throughput comparison between ISAC and communication signals where N_t and M_r denote the number of transmit ISAC antennas and receive communication antennas

To compare the above approaches, a ray-tracing simulation is necessary, incorporating NR frames and parameters, which are illustrated in Fig. 3.8 (a), highlighting the reduction in overheads resulting from the exploitation of the ISAC technique instead of CSI-RS and uplink feedback. Thanks to these benefits, the throughput of the ISAC-enabled signal is generally improved relative to the communication-only benchmark, as demonstrated in Fig. 3.8 (b).

3.4.2 Sensing-assisted security

Traditional cryptographic techniques at the network layer [26] face a number of issues, most importantly an increasing vulnerability with the relentless growth of computational power. Critically, cyber threats start from the acquisition of access to wireless traffic, and this has motivated decades-long research in security solutions at the physical (PHY) layer.

There is an abundance of communications-only PHY layer security approaches, ranging from secure beamforming [27], jamming [28], artificial noise design [29], as well as coopera-

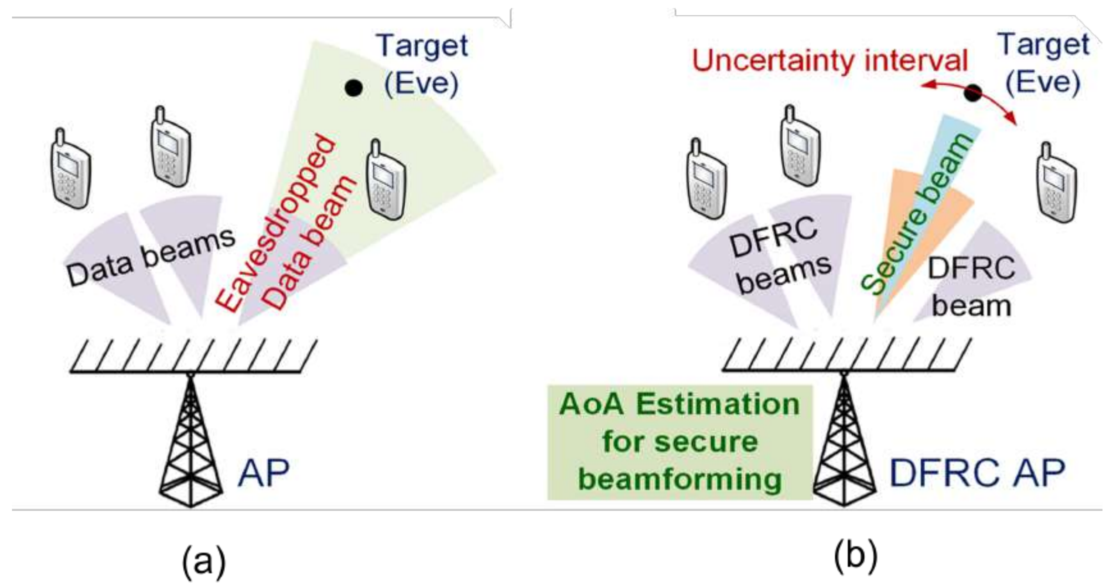

Figure 3.9: Sensing-assisted PHY security: (a) jeopardised transmission without environment awareness, (b) sensing assisted Eavesdropper identification and secure transmission

tive security designs [30]. There is also a large amount of literature in the context of covert and low probability of intercept (LPI) transmission in the context both of communications [31], and of radar signaling [32]. The fundamental challenge persists however, in that secure and LPI communication signalling is not tailored for radar operation and vice versa.

The major limitation of a large class of PHY security solutions stems from the need for knowing the eavesdroppers' (Eves) channels, or direction as a minimum [27]. The sensing capability of DFRC has an enabling role for PHY security, where the detected targets' (Eves') AoAs can be used to enable null steering and secure beamforming [33], and provides new ground for the development of sensing-assisted secure communications.

An example approach to enable PHY security for communication data transmission, assisted by the sensing functionality, involves a two-stage process [33]. At the first sensing-only stage, the dual-functional access point (AP) emits an omnidirectional waveform for Eve detection, which then receives echoes reflected from both CUs and Eves located within the sensing range. Typically, the location information of each CU is known to the AP. Thus, it is possible to obtain angle estimates of non-recognised entities that could be potential Eves contained in the reflected echo by removing known CUs' angles. The estimation performance is measured by the Cramer-Rao Bound (CRB).

The next stage involves a weighted optimization problem to jointly minimize the CRB of targets/Eves and maximize the secrecy rate, subject to beampattern constraints as well as a transmit power budget. A key novelty in this setup is that the accuracy of the channel information in the secrecy rate, is a function of the sensing performance. Specifically, to avoid any false dismissal detection, the main lobe of the beampattern is designed to be wide, with a width depending on the estimation accuracy. Afterwards, by improving estimation accuracy, the main lobe can become narrower, the secrecy rates more accurate,

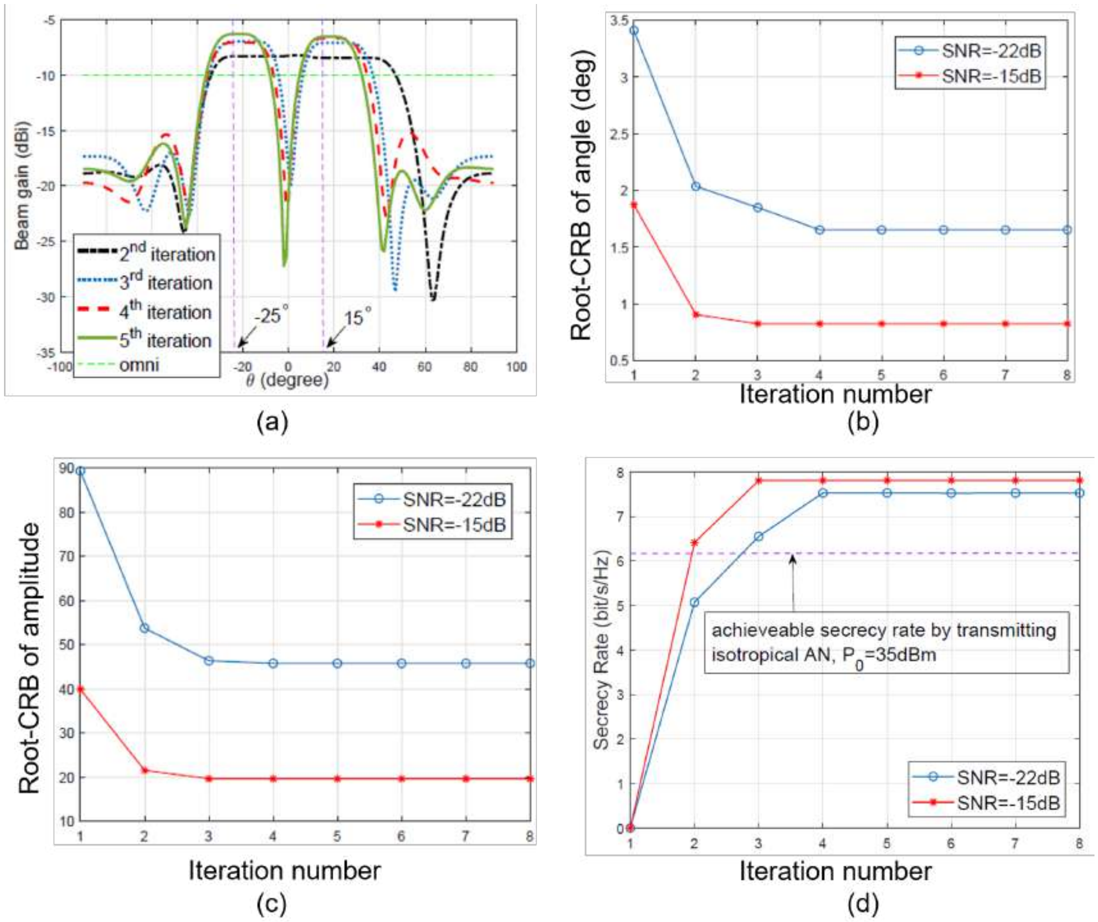

Figure 3.10: Sensing-assisted PHY security: (a) sensing beampattern evolution with increasing iterations as the sensing estimation improves, (b) CRB detection amplitude improving with increasing iterations, (c) CRB detection amplitude improving with increasing iterations, (d) bottom-line secrecy rate performance with increasing iterations

increasing the degrees of freedom in improving the joint DFRC performance. It is clear that sensing and security functionalities provide mutual benefits, resulting in improvement of the mutual performances with every iteration of the optimization, until convergence.

The results in Fig 3.10 (a) show first the evolution of the sensing beampattern as the estimation of the Eve's direction improves, resulting in ever-narrowing beams. The resulting improvement in the sensing performance evidenced in 3.10 (b), (c) results in better characterisation of the Eve's direction, a more accurate formulation of the secrecy rate and in turn in an improvement of the bottom-line security performance in 3.10 (d); evidence of how the improvement in the sensing performance synergistically enhances the secure communication end-goal. The work in [33] is a first evidence of how the environment cognition and awareness that the new sensing functionality can unlock in future cellular networks, can enable secure transmission approaches that were previously inapplicable.

3.5 Conclusion

Cognition has been a pursuit in wireless networks for a long time, to unlock network intelligence, awareness of its environment, and adaptivity to changes. The emergence of sensing as a key functionality of wireless networks of 6G and beyond, has the potential to enable cognition and network intelligence of an unprecedented scale. This article has overviewed the evolution of radar-communication systems technologies from competitive co-existence to their integration, an active area of research that has the potential of multi-fold gains in the network performance, and an essential pathway to delivering the exciting applications that the future networks will support.

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4. Cognitive Dynamic Spectrum Sharing with New Radio Techniques

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THIS article discusses the impact of advances in radio technologies such as massive multiple-input multiple-output (MMIMO), non-orthogonal multiple access (NOMA), and rate-splitting multiple access (RSMA) to interference management and spectrum sharing in next-generation mobile networks. It presents the cooperative transmission schemes that exploit these new radio features as well as dynamic spectrum access to enhance network performance and spectrum utilization.

4.1 Introduction

Mobile traffic is growing at a very rapid rate. Dynamic spectrum access (DSA) is considered as a promising spectrum sharing paradigm to improve spectrum utilization and alleviate the spectrum scarcity problem. It allows unlicensed secondary users (SUs) or tertiary users to access the licensed spectrum bands of primary users (PUs) under certain constraints. 5G New Radio (NR) supports services with different spectrum licensing terms, including exclusive-use licensed spectrum, shared spectrum, and unlicensed spectrum. Various DSA techniques have been proposed and studied for a number of years, however, they have not been widely deployed in the real world due to implementation complexity, interference, quality of services (QoS) guarantee concerns, and other challenges.

Advances in radio technologies such as massive multiple-input, multiple-output (MMIMO) and non-orthogonal multiple access (NOMA) [1, 2] significantly increase network throughput and improve spectrum efficiency. More recently, rate-splitting multiple access (RSMA) [3, 4] has emerged as a new promising scheme for unifying non-orthogonal transmission, multiple access, and interference management in future wireless networks. In more detail, MIMO and massive MIMO (MMIMO) are the key enabling technologies for 4G and 5G mobile networks to enhance network capacity and spectrum efficiency for meeting the exploding increase in data traffic demand and user numbers. MIMO employs multiple antennas with signal processing to transmit/receive multiple data streams to/from multiple users simultaneously on the same frequency channel. Traditional MIMO in 4G networks typically use a few antennas to transmit and receive data. MMIMO employs an antenna array with a large number of elements at the base stations (BSs) or access points (APs), which enables many directional signal beams, each focusing a great amount of signal energy on an intended mobile terminal through beamforming processing. The more antenna elements a BS/AP is equipped with, the more possible signal paths and the higher total throughput. 5G networks support massive MIMO in sub-6GHz bands and millimeter-wave bands with 64 or more antenna ports. NOMA is another technique to yield network throughput and spectral efficiency gain via power allocations of multiple signals. Different power levels are used to transmit different signals at the same time on the same frequency channel with superposition coding (SC) at the transmitter to superpose user messages in the power domain. A receiver receiving the superposition transmission can decode the stronger signal components and then use successive interference cancellation (SIC) to remove them to decode the other signal components.

MMIMO provides a spatial dimension for multiple access, space-division multiple access (SDMA), to serve multiple users in the same time frequency resource with multi-antenna signal processing. The intended signal is decoded at the receiver by treating any residual multiuser interference as noise. NOMA allows superposing multiple signals in the power domain to serve multiple users in the same time frequency resource, and the intended signals are obtained at the receiver by successfully decoding stronger signals and then canceling them out, i.e., decoding and removing multiuser interference. RSMA further bridges the two common interference management approaches, treating interference as noise and fully decoding and canceling interference, and subsumes orthogonal multiple access (OMA), MIMO-based SDMA, and SIC-based NOMA as special cases. Specifically, each of the user messages is split into common and private parts, and the common parts are combined as a common message. The common message and the private messages are independently pre-coded and transmitted in different streams. A receiver first decodes the common stream by treating all private streams as noise. After canceling the decoded common stream out of the received signal, the receiver decodes the intended private stream by treating other private streams as noise [5]. This provides flexibility in interference management and can trade off interference cancellation and signal decoding with interference as noise. If the common stream is turned off, RSMA becomes SDMA, and the interference among the private streams is treated as noise. If one message is encoded as the common stream and the other message is encoded as the private stream, RSMA is then like NOMA to decode the private stream after decoding and cancelling the interference of the common stream.

These new radio technologies can more effectively handle multiuser interference that is a major obstacle in dynamic spectrum sharing to achieve high spectrum utilization. However, they also introduce new challenges for the upper-layer algorithm and protocol design to fully exploit their capabilities for optimal network performance. It is vital to develop a new framework unifying DSA, MMIMO, NOMA, and RSMA to enhance spectrum sharing and network capacity, given that next-generation (5G beyond and 6G) mobile networks are expected to incur more severe interference with more users and heavier traffic.

There can be different models for dynamic access to shared spectrum through cognitive radio (CR) capability. In interweave or underlay DSA models that most existing research focused on, unlicensed secondary users of the spectrum can access the licensed spectrum bands of primary users to transmit data only when the PUs are not using the spectrum or when the interference from the SUs are tolerable by the PUs, i.e. below a certain threshold, through techniques such as spectrum sensing and interference management [6, 7]. Alternatively, the PUs and SUs can cooperate in DSA, also known as the cooperative cognitive radio network (CCRN) model [8], to achieve flexible spectrum sharing. Cooperative DSA and spectrum sharing can perform more effectively than uncooperatively shared access and benefit both parties. Novel network architecture and protocols are needed to facilitate cooperation. Specifically, it is worth investigating the joint optimization of various elements in the network system and designing efficient algorithms to leverage underlying physical-layer MMIMO, NOMA, and RSMA technologies in cooperative cognitive radio networks for significant performance gains and new network functionalities. Furthermore, advances in AI and machine learning enable us to design intelligent cognitive mechanisms to optimize interference management and dynamic access to shared spectrum.

In this article, we discuss novel cooperative transmission schemes that exploit new radio features as well as dynamic spectrum access to enhance network performance and spectrum utilization. As an example, considering a legacy macrocell network and multiple cognitive small cells to cooperate in dynamic spectrum sharing, the macrocell network is assumed to own the spectrum band and be the primary network (PN), and the small cells act as the secondary networks (SNs). The secondary access points (SAPs) of the small cells can cooperatively relay traffic for the primary users in the macrocell network, while concurrently accessing the PUs' spectrum to transmit their own data opportunistically through MMIMO, NOMA, and RSMA. The legacy macrocell network does not have to have advanced radio functionalities. Such cooperation can create a "win-win" situation:

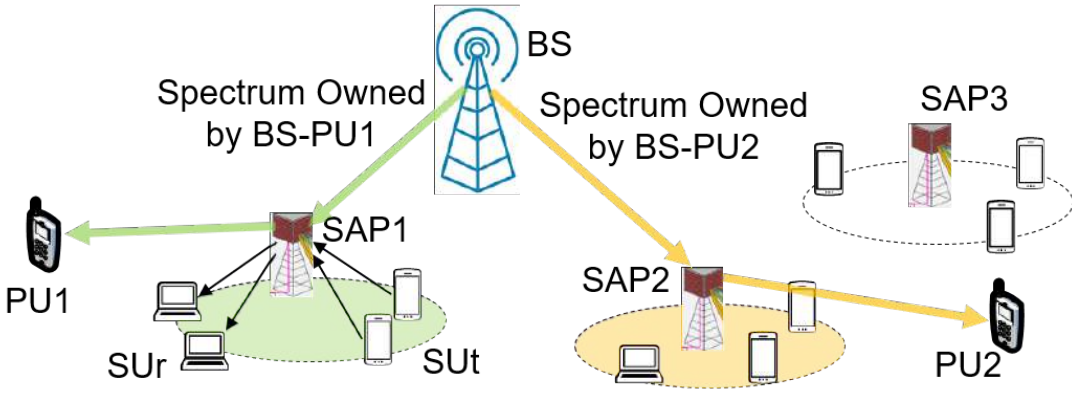

Figure 4.1: A scenario for cognitive cooperative relaying and spectrum sharing with MMIMO, NOMA, and RSMA

the throughput of PUs will be significantly increased with the help of SAP relays, and the SAPs are able to utilize the PUs' spectrum to serve their secondary users with high spectrum efficiency gains. In this way, the dynamic spectrum access by the small cells will not interfere with the licensed spectrum but improve the performance of the incumbent primary network.

4.2 Cognitive Cooperative Relaying and Spectrum Sharing with New Radio Features

As an example in Fig. 4.1, there exists a group of small cells in the coverage area of a legacy macrocell base station. The legacy BS serves a number of PUs. A PU may be allocated a licensed subchannel for data delivery in a time slot via orthogonal frequency-division multiplexing (OFDM) in a traditional cellular system. Thus, we define a link between the macrocell BS and PU as the primary link (PL). For ease of explanation, we assume the legacy BS and PUs are equipped with a single antenna and no NOMA or RSMA capability. The cognitive cooperative relay (CCR) scheme can be extended to the case in which a BS and PUs are equipped with MMIMO, NOMA, or RSMA.

Small cells can be private networks in public venues, stadiums, or industrial facilities deployed by enterprises and other organizations, which have no licensed spectrum but take advantage of advanced radio functions to serve their customers and extend the mobile networking ecosystem through dynamic spectrum sharing. Let's suppose each small cell SAP be equipped with cognitive radio as well as MMIMO and NOMA interference cancellation capability, which can dynamically access to the subchannels in the licensed spectrum of the legacy PUs to serve its SUs opportunistically. With cooperative DSA, an SAP can relay traffic for the PU, while borrowing the PU's subchannel to transmit/receive the secondary data to/from its SUs using MMIMO and NOMA. The algorithms can be designed for a PU to select an SAP as a relay and the SAP to serve SUs in the small cell while relaying PU data to optimize overall system performance.

If a PU_i does not have a relay during a transmission time slot t, the BS will directly send

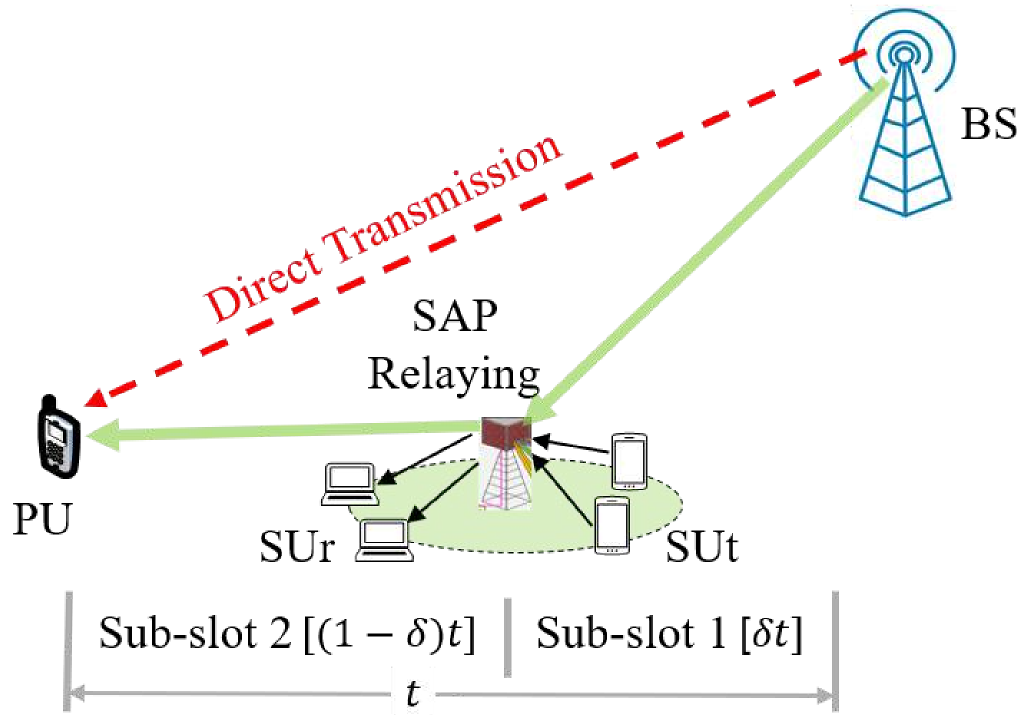

Figure 4.2: MMIMO, NOMA, and RSMA transmissions

data to PU_i on the subchannel allocated to PU_i. If a SAP_j acts as a relay for a PU_i in time slot t, we call SAP_j and PU_i forms partnership. Thus, the time slot t is divided into two sub-slots as shown in Fig. 4.2. In sub-slot 1, the BS will transmit PU_i's data on the subchannel allocated to PU_i and the partner SAP_j will receive the PU_i's data. Meanwhile, SAP_j will schedule K SUs in its small cell, $\text{SU}_{j,k}, k = 1, 2 \dots K$ to transmit secondary uplink traffic on its partner's subchannel. SAP_j utilizes its MMIMO beamforming and NOMA signal cancellation capabilities to receive the secondary uplink traffic, while receiving the primary data. It leverages MMIMO to decode the messages from its SUs, and then it subtracts these messages from the superposed signal it received by carrying out SIC to decode the information from the legacy BS for PU_i. The PU signal is not interfered by the SU signals thanks to SIC. It is possible to apply SIC in decoding the SU messages although this will increase signal processing complexity. In addition, SAP can control the transmit power of the SUs to adjust their achievable throughput.

In sub-slot 2, SAP_j forwards the primary data to PU_i and simultaneously transmits K downlink secondary traffic streams to its SUs in the small cell, $\text{SU}_{j,k}$ with MMIMO and NOMA. A legacy PU receives the signal and simply decodes its own message by treating any residual SU information as noise. As a SU has NOMA capability, it may try two approaches to obtain its message, depending on its MMIMO channel state and SAP's power allocation strategy. First, it can decode the PU's message and then use SIC to subtract this message from its received signal, and finally decode its own information. Second, it may decode its own message directly by treating PU's information as noise.

Further, if the secondary small cells support RSMA capability, SAP and SUs can utilize

MMIMO and RSMA to facilitate cooperative relaying. In sub-slot 1, SAP_j accesses the subchannel allocated to its partner PU_i and receives the signal sent from the incumbent BS to PU_i, along with the uplink signals from K SUs through MMIMO and uplink RSMA. The message $m_{j,k}$ of a $\mathrm{SU}_{j,k}$ is split into two parts $m_{j,k,1}$ and $m_{j,k,2}$, which are independently encoded into two streams and the two streams are respectively allocated with certain powers and superposed in transmission at $\mathrm{SU}_{j,k}$. This can be considered as dividing $\mathrm{SU}_{j,k}$ into two virtual users, $\mathrm{SU}_{j,k,1}$ and $\mathrm{SU}_{j,k,2}$. SAP_j decodes the received SU streams to get messages $\{m_{j,k,1}, m_{j,k,2} | k = 1, 2, \ldots, K\}$ using SIC. It then decodes PU_i's signal with the interference of SU's signals removed. In sub-slot 2, SAP_j first splits each of the SU messages $m_{j,k}, k = 1, 2, \ldots K$, into two sub-messages, the common sub-message $m_{j,k,c}$ and the private sub-message $m_{j,k,p}$. The common sub-messages of all users $m_{j,1,c}, \ldots, m_{j,K,c}$ are combined into one common message $m_{j,c}$ and encoded into a common stream $s_{j,c}$. The private sub-messages of K SUs, $m_{j,1,p}, \ldots, m_{j,K,p}$ are independently encoded into K private streams, $s_{j,1}, \ldots, s_{j,K}$. SAP_j allocate power and forwards the primary data stream to PU_i while transmitting SU common stream $s_{j,c}$ and SU private streams $s_{j,1}, \ldots, s_{j,k}$ to its SUs with MMIMO and downlink RSMA. PU_i simply decodes its own message by treating the interference from the SU common and private streams as noise. A $\mathrm{SU}_{j,k}$ first decodes the common stream $s_{j,c}$ to $m_{j,c}$ by treating the interference from the PU stream and all SU private streams as noise. $m_{j,c}$ information is then removed from the received signal using SIC, and $\mathrm{SU}_{j,k}$ decodes its private stream $s_{j,k}$ into $m_{j,k,p}$ by treating the residual interference from the PU stream and other SU private streams as noise. $\mathrm{SU}_{j,k}$ reconstructs the original message $m_{j,k}$ by extracting $m_{j,k,c}$ from $m_{j,c}$, and combines $m_{j,k,c}$ and $m_{j,k,p}$ into $m_{j,k}$. MMIMO beamforming precoding matrix can be designed to deliver the PU stream, SU common stream, and private streams with low complexity or based on certain optimization objectives, e.g., maximizing overall PU and SU throughput, etc. Note that other RSMA designs can also be used in cooperative spectrum sharing and relaying, and a message can be split into more than two sub-messages in some RSMA schemes,

A set of strategies affect the achievable throughput of PU and SAP transmissions, including (i) a PU should decide whether to allow SAP to access its frequency channel for cooperative relaying or just use its channel by itself for direct transmission from BS to PU. (ii) In the former case, the best MMIMO-NOMA-RSMA SAP relay for a PU needs to be selected. (iii) The MMIMO-NOMA-RSMA relay transmission and power allocation strategies should be decided, including the size of sub-slots 1 and 2 as well as the power allocation for SU data stream transmission and PU data stream relaying. (iv) If RSMA is used in secondary small cell transmissions, the partition for each SU message and the power allocation of the sub-message streams should be determined as well.

To optimize network performance, different cooperative relaying and spectrum sharing algorithms can be designed. We can model the system of multiple PUs and multiple SAPs as a Nash bargaining game and an algorithm is designed to derive the optimal relay selection, sub-slot partition, transmit power allocation, and MMIMO, NOMA or RSMA transmission strategy. Specifically, the utility function of a player (a PU or SU) is defined, which can depend on its achievable rate. PUs and SUs achieve a Nash Bargaining Solution (NBS) that is a Pareto optimal operation point in terms of the overall utility. The problem can also be simplified by decomposing it into two sub-problems, relay selection and transmission strategy optimization. First, it can be assumed that a PU_i has selected a SAP_j as its cooperative relay. The objective is to maximize the total utility of the PU and SAP by jointly determining the optimal sub-slot size and the power allocation and strategy of the SAP PU data stream relay and secondary data stream transmissions. A distributed two-side matching game can be used to solve the relay selection problem among multiple PUs and multiple SAPs, aiming to optimize the utilities of all the entities with fairness. Alternatively, the interplay of multiple PUs and multiple SUs can be modeled as a multi-leader multi-follower Stackelberg game, where the PUs act as leaders and set the prices for their channel leasing according to the SAP demands and the prices set by other PUs. SAPs are the followers that determine which PU to partner with as the relay as well as relay transmission strategy and power allocation based on the prices set by different PUs and the channel conditions to the different PUs, and their own network conditions. Joint optimization algorithms with a sequential decision-making process can then be developed for the players, i.e., each of the PUs and SAPs maximizes its own utility through the game.

The above model-based optimization methods are often very hard to capture all the dynamic factors and achieve the optimization under uncertain non-stationary network environments. In addition, the problems are usually NP-hard and it is hard to find effective algorithms with low computational complexity, scalable to large systems, and adaptive to environments. On the other hand, a stochastic framework, instead of a deterministic one, can capture the underlying dynamics and explore the synergy between PUs and SAPs for optimal performance. Further, a data-driven machine learning approach allows the system to learn the best policy in stochastic environments without the requirement for prior network statistical knowledge. For example, to deal with unknown network environments and user mobility, one can develop a multi-agent stochastic Stackelberg game framework and associated deep reinforcement learning (DRL) algorithms to model the interaction and achieve optimal performance of PUs and SAPs. Each entity runs a DRL agent to maximize its expected long-term utility. PU DRL agents are the leaders and learn the optimal policy to set the channel leasing price according to the queue states, channel states, predicted SAP reaction, and price decisions of other PUs. SAP DRL agents are the followers and find the best policy to determine the PU to partner with, the relay transmission, and power allocation strategies based on the prices set by different PUs, their channel states, and queue states.

Regardless of the success of machine learning techniques, there are many remaining challenges. First, a DRL agent learns an optimal policy by repeatedly interacting with the environment. The agent uses deep neural networks (DNN) to map the state to action with the trained optimal policy to maximize a reward function. Most existing learning-based algorithms are well-trained for a specific environment. They may not work well when applied to new environments. In a new network environment, training is needed to find the optimal policy. Especially, when the wireless environment is not stable or changes or the network system is complex with a large state or action space, the training process may not be able to converge to the optimal policy promptly. In addition, machine learning models, particularly supervised learning, should be trained with a large amount of real data. It is challenging to collect a large amount of data for mobile networks with emerging radio technologies. It is possible to integrate model-based optimization and data-driven machine learning approaches to develop new algorithms that can improve performance, lower algorithm complexity, allow a trained model to quickly adapt to new environments, and reduce the dependency on real measurement data. However, it remains a challenge to develop such high-performance efficient ML algorithms.

4.3 Conclusion and Future Work

Advances in radio technologies such as MMIMO, NOMA, and RSMA will significantly increase the capacity and efficiency of next-generation (5G beyond and 6G) mobile networks. These new radio technologies also enable more effective dynamic spectrum sharing schemes and interference management. However, they introduce new challenges. More comprehensive frameworks are needed to analyze the fundamental limits and gain a deep understanding of these new radio techniques under dynamic network environments and various resource constraints. To obtain full benefits, more intelligent algorithms and protocols should be developed, leveraging machine learning or combined model-based optimization and data-driven ML approaches to exploit the capabilities brought by new radio features and dynamic spectrum access for optimal spectrum utilization and network performance.

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5. Towards an Intelligent Sensing Technique

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Due to the rapid development of terrestrial and non-terrestrial networks, increasingly crowded spectrum cannot meet the requirement of future communication services and motivates the dynamic spectrum access or spectrum sharing technologies. Indeed, spectrum sensing technology pose an important and fundamental role for those technologies. However, to perform spectrum sensing with largely wideband spectrum is a non-trivial task. Conventional Nyquist-rate sampling and processing are really challenge due to the significant power consumption, high costs, and hardware complexity associated with high-speed analog-to-digital converters. To overcome the sampling rate bottleneck, sub-Nyquist sampling methods draw an attention to many researchers, and become a promising solution for wideband spectrum sensing tasks. Over the past decade, the sub-Nyquist sampling methods based on compressed sensing, has been extensively studied, leveraging the sparse frequency domain features of wideband signals. According to sub-Nyquist sampling methods, various studies have focused on utilizing lower complexity algorithms to enhance the accuracy of spectrum reconstruction. Furthermore, recent numerous studies have explored spectrum sensing using machine learning techniques to enhance both accuracy and efficiency. Moreover, except for spectrum sensing, wireless signals are also used to sense physical targets and environments via all kinds of advanced learning algorithms.

5.1 Introduction

The advent of 5G has imposed stricter demands on Cognitive Radio (CR) devices. Enhanced Mobile Broadband (eMBB), one of the primary applications of 5G, aims for higher speeds via wider bandwidths and boosting the baseband data rate. A notable aspect of 5G is its use of millimeter wave (mmWave) frequency bands, which in most countries are allocated at 28 GHz, 39 GHz, 60 GHz, etc. For instance, the 28 GHz mmWave band offers a maximum bandwidth of 1.4 GHz, significantly larger than the approximately 100 MHz bandwidth used by 4G LTE signals in the 800 MHz to 2600 MHz range. According to FCC committee members at Mobile World Congress Americas (MWCA) 2018, as networks become denser in the 6G era, blockchain-based Dynamic Spectrum Access (DSA) technology is expected to be a key trend.

Using conventional sensing technology to cover a wider spectrum imposes greater demands on the analog-to-digital converter (ADC). However, high-speed ADCs are expensive, and energy-intensive, making them unsuitable for CR devices [1]. Many of the research works on wideband spectrum sensing (WSS) that involves dividing the wideband into multiple narrow bands (a.k.a multi-band or multi-channel sensing) fails to effectively monitor spectrum usage in real-time [2, 3].

The Compressive Sensing (CS) method exploits the sparsity of signal spectra in the frequency domain and can reconstruct the signal spectrum from sub-Nyquist sampling points [4]. The essence of CS theory is that if a signal is sparse or compressible on a particular orthogonal basis, we can recover the signal from sub-Nyquist sampling points. For wideband multi-band signals, which are typically sparse in the frequency domain, the two features of applying CS are that 1) Compressed sampling can be conducted at sub-Nyquist rates. 2) Sampling and compression can occur concurrently, allowing the elimination of redundant information in the signal. The compressed data can be processed directly in the CPU using convex optimization or matching pursuit methods. In contrast to the Nyquist resolution requirements for WSS, Compressive Spectrum Sensing (CSS) transfers the burden of high-speed ADCs to the back-end spectrum recovery algorithms.

The signal models for WSS encompass multi-band or line spectrum signals, sparse or non-sparse signals, and signals with known or unknown carrier frequencies. Depending on the specific signal model, the minimum sub-Nyquist sampling frequency necessary for accurate reconstruction of the power spectrum. In various signal models, the required minimum sub-Nyquist sampling frequency for reconstructing the spectrum or power spectrum is different [5, 6]. Yen et al. explored the power spectrum reconstruction issue for non-sparse signals using the multi-coset sampling scheme, based on the statistical properties of stationary signals. They determined the necessary and sufficient conditions for perfectly reconstructing the power spectrum in a noise-free scenario [7]. D. Cohen et al. introduced a general framework for power spectrum perception using Nyquist samples and suggested a power spectrum reconstruction algorithm to achieve the minimum sampling rate [8]. The minimum sampling rate necessary for perfect reconstruction of the power spectrum without noise can be summarized as follows:

1. Non-sparse spectrum: When the spectrum isn't sparse, the required minimum sampling rate is half the Nyquist sampling rate.
2. Sparse spectrum and known support: When the frequency spectrum is sparse and the carrier frequency is known, the required minimum sampling rate is half the Landau rate, i.e., the Lebesgue measure of the occupied bandwidth [9].
3. Sparse spectrum and blind recovery: When the frequency spectrum is sparse and the carrier frequency is unknown (blind case), the required minimum sampling rate is the Landau rate [10].

Typically, performing CSS involves two steps. The first step is random sampling. The sparse observation matrix usually needs to satisfy the Restricted Isometry Property (RIP), Null Space Property (NSP), spark constraints, and coherence constraints [11]. Section 5.2 reviews several mainstream compressive sampling methods. The spectrum reconstruction methods are briefly reviewed in Section 5.3. Learning methods for spectrum sensing are summarized in Section 5.4. Wireless sensing for physical targets and environments are introduced in Section 5.5. Finally, the conclusion is given in Section 5.6.

5.2 Compressive Sampling Methods

In practical applications, creating a fully random measurement matrix within the hardware circuit proves to be challenging. As a result, researchers have extensively studied partially-random sensing matrices [12]. Various Nyquist sampling circuits have been proposed in practice [13], including random demodulator, modulated wideband converter (MWC), and multi-coset sampler. These designs have gained considerable attention due to their relatively straightforward implementation. Both random demodulator and MWC achieve partial randomness by mixing pseudo-random sequences, while the multi-coset sampler achieves partial randomness through varying sampling delays. Building on these designs, compressed sampling can be implemented using traditional sampling circuits with low-speed ADCs. Additionally, software-defined radio (SDR) offers an existing physical layer foundation for realizing spectrum sensing. As technology advances in areas such as antennas, front-ends, ADC, and digital signal processing, some pioneering research works have successfully implemented CSS functions within the physical layer, which are discussed in the following.

5.2.1 Random Demodulator

Introduced in 2010, the random demodulator comprises a multiplier, a pseudo-random sequence generator, a low-pass filter, and a sub-Nyquist rate ADC. The input signal is initially multiplied with a Nyquist-rate pseudo-random sequence, causing the signal spectrum to convolute with the dispersed-distributed spectrum of the pseudo-random sequence. After filtering, only the low-frequency components are retained, but the spectrum information can still be recovered from low-rate samples $x[n]$ (Fig. 5.1) [14]

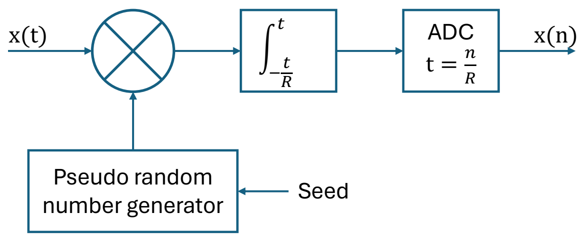

Figure 5.1: Random demodulator.

The random demodulator has been extensively utilized in wideband spectrum sensing to lower the sampling rate requirements and alleviate the digital signal processing burden. Candes et al. have introduced a non-uniform sampling (NUS) system integrated into a custom sample-and-hold chip designed for wideband compressive spectrum sensing [15]. The NUS employs a pseudo-random bit sequence generator to discard some Nyquist sampling points by controlling the ADC's output switch. With an average sample rate of 236Msps, the implementation is capable of achieving an effective instantaneous bandwidth (EIBW) ranging from 800 MHz to 2 GHz, with a bandwidth capacity of up to 100 MHz. However, the random demodulator is highly sensitive to the signal model and demonstrates superior recovery performance with line-spectrum signals. In cases of model mismatch, the recovery results become inaccurate. From a hardware standpoint, mixers were originally designed to up-convert or down-convert single-frequency signals. Conversely, in a random demodulator, the mixer is employed to combine a multi-band signal with a pseudo-random sequence. This unconventional use of the mixer introduces numerous harmonics at the mixer's output, which restricts the broader adoption of the random demodulator.

5.2.2 Modulated Wideband Converter

Yonina C. Eldar et al. have proposed the modulated wideband converter (MWC) and corresponding recovery algorithms in 2010. The MWC method establishes the relationship between the measured value and the signals via Fourier analysis, and reconstruct the signals using the CS recovery algorithm[16, 17]. The structure of the MWC is illustrated in Fig. 5.2, which includes multiple parallel channels sampled at the sub-Nyquist rate. Each channel of the MWC is similar to random demodulators (shown in Fig. 5.1). The input signal $x(t)$ is divided into P branches, each of which is then mixed with one of P distinct pseudo-random sequences from $p_1(t)$ to $p_p(t)$ before sampling. This operation shifts the frequency spectrum of the input signal to the low-frequency band. An array of low-pass filters is utilized to eliminate high-frequency components, and the resulting filtered signals are sampled using a low-speed ADC channels.

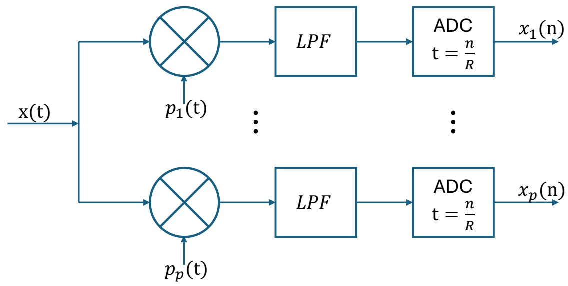

Figure 5.2: Modulated wide-band converter.

The time-domain reconstruction model of the MWC corresponds to the multi-measurement vector (MMV) problem. This approach has been demonstrated to enhance the success rate of recovering sparse solutions compared to the single measurement vector (SMV) method used by the random demodulator [18, 19, 20]. MWC-type hardware implementation has been realized on board as the Xampling analog-to-digital converter in 2010 [17]. The circuit contains an analog power splitter front end and four parallel mixing and filtering instances, achieving compressive sampling of a 2GHz-band signal with 120MHz arbitrary spectrum occupancy. The average sample rate is as low as 280 MHz, which is 14% of the Nyquist rate and 2.33 times the Landau rate. Based on the circuits, a CSS platform is presented with an external FPGA-based pseudo-random sequence generator and SDR-based digital signal processor [21, 22]. An on-chip realization of an MWC-type sampler is presented as a random modulator pre-integrator (RMPI) [23]. The RMPI prototype is integrated on a millimeter-scale IBM 90 nm digital CMOS chip with eight mixing and filtering signal channels. In cooperation with external ADCs, it can achieve up to 2 GHz EIBW with a 320 MSPS aggregate digitization rate [24].

5.2.3 Multicoset Sampler

The multicoset sampling method can be implemented on a time-interleaving ADC (TI-ADC) platform. By controlling the sampling delay of each ADC, a compressed sampling perception matrix can be constructed. Fig. 5.4 illustrates the structure of the multicoset sampler, which includes p-channel delay filters and p-channel low-speed ADCs. Each delay filter applies an exclusive delay $c_i/R(i = 1, ..., p)$ to the original signal. During the signal acquisition process, the signal to be measured enters the ADC for sampling through different delay filters with randomly-set delays. As a result, a subset of the Nyquist samples is acquired from each channel, and all the p subsets form a compressed subset chosen non-uniformly from the Nyquist samples.

Similar to the reconstruction process of MWC, the reconstruction of a multicoset sampler can be divided into two steps. First, the MMV model is constructed through the covariance matrix of the p-channel sampling data. The MMV recovery algorithm is then used to solve the support set of the wideband sparse spectrum.

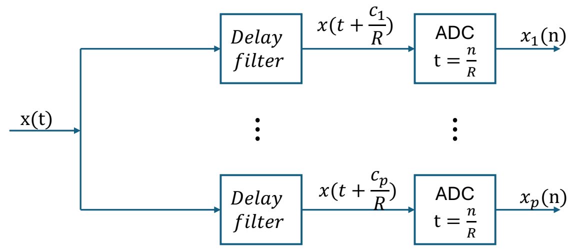

Figure 5.3: Multicoset sampler.

Figure 5.4: Prototype of multicoset sampler using SDRs.

A real-time multi-gigahertz processing platform for multicoset sampler and recovery algorithms working on the mmWave band has been realized based on SDR systems [25]. Both the transmitter and receiver have modular configurable hardware operating at mmWave frequency centered at 28.5GHz. Pseudo-random symbols modulated by 64-QAM and Verizon 5G OFDM waveform spanning the bandwidth of 100MHz can be transmitted with multiple component carriers, with reconfigurable frequencies. A single high-speed ADC samples the baseband signal at the receiver with a 3.072GHz sampling clock. The multicoset sampler behavior is simulated by discarding a subset of raw digital samples acquired by the single 3.072G ADC, effectively forming parallel signal branches. The platform is configurable on parameters like active channels and the center frequency at the Tx side, and the co-set number, average sample rate, channel delays, and window length at the Rx, providing an ideal testing environment for multicoset sampling and recovery performance under different configurations.

5.3 Spectrum Reconstruction Methods

Given the observation matrix A and the sparse matrix ϕ, the original spectrum can be reconstructed by solving the underdetermined equations

$$\arg\min \|\mathbf{X}\|_{2,1} \quad \text{s.t.} \quad \|\mathbf{Y} - \mathbf{A}\boldsymbol{\phi}\mathbf{X}\|_2 < \epsilon, \tag{5.1}$$

where X and Y refer to the original signal and the compressive measurement, respectively, and ϕ is usually treated as the inverse discrete Fourier transform (IDFT). The high-dimensional original signal X can be accurately reconstructed or with high probability from the compressive measurement Y.

There are mainly two types of methods for solving the equations of such underdetermined matrices:

1. Convex optimization reconstruction algorithm based on basis pursuit (BP) [26]. This type of algorithm is primarily the convex optimization algorithm based on the 1-norm minimization constraint [27]. This type of algorithm is characterized by high signal recovery accuracy but high computational complexity, which is generally the cube of the signal dimension. Similar lv-minimization methods are proposed to reduce measurements [28].

2. Greedy algorithms, including orthogonal matching pursuit (OMP) algorithm [29] for SMV model, simultaneous OMP (SOMP) algorithm [30] for MMV model, compressed sampling matching pursuit (CoSaMP) algorithm [31], hard thresholding pursuit (HTP) algorithm, and joint-block HTP (JB-HTP) algorithm for joint-block sparse signal [32], etc. This type of algorithm is characterized by low computational complexity, but the reconstruction effect is not as good as the convex optimization algorithm. Greedy algorithms usually require prior knowledge of signal sparsity to optimize recovery performance and minimize iteration time. In the absence of prior information, sparsity estimation methods based on Bayesian information theory are often applied to obtain an estimation of the signal support [33].

Table 1 shows the comparison between different recovery algorithms, where each algorithm's time complexity is estimated concerning signal length N, compressed data length M, and estimated sparsity kc. For different sensing scenarios and different sub-Nyquist sampling parameters, a proper greedy algorithm should be chosen for better performance [34].

5.4 Learning Methods for Sub-Nyquist Spectrum Sensing

During the operation of a CR system, its operating parameters (such as transmission power, perception strategies, coding methods, modulation methods, communication protocols, etc.) and the surrounding electromagnetic environment (channel fading, multipath effects, changes in signal-to-noise ratio, etc.) often change [35], [36]. This makes it difficult to represent the entire system model with simple models, which affects the accuracy of spectrum sensing results [37]. Machine learning offers a significant advantage over traditional spectrum sensing algorithms by learning from data and calculating the required parameters for spectrum sensing.

Spectrum sensing based on machine learning can be considered a problem that uses machine learning algorithms to find cognitive radio system models and parameters [38]. If the prior information about the PU signal is known, the supervised learning method can better utilize prior knowledge in constructing the cognitive model and training a high-performance spectrum sensing model. In an unfamiliar electromagnetic environment, unsupervised learning-based spectrum sensing technology can explore the surrounding environment's characteristics through autonomous learning and adaptively calculate the parameters required by the spectrum sensing system model to avoid prior information. The PU signal is detected in the scene. This article will classify and discuss machine learning algorithms in spectrum sensing from two aspects: supervised learning and unsupervised learning.

5.4.1 Supervised Learning

Supervised learning algorithms require labeled data for training, mainly including k-nearest neighbors (KNN), support vector machine (SVM), and artificial neural network (ANN). KNN is one of the simplest models in supervised learning. Data points with similar characteristics are generally in close proximity according to a specific distance metric, regardless of the data points' distribution [39]. KNN first divides the training dataset into several groups, where each group corresponds to a unique decision or action. When a new signal arrives, it will be classified into a specific group, and the appropriate decision will be made. For example, the received PU signal's power strength is used as the core radio environment data for spectrum detection or even PU localization in CR networks [40], [41].

When the learning dataset's signal is not linearly separable, KNN is no longer applicable. Using kernel functions, the SVM algorithm maps the data from its original space to a higher dimension where the data becomes linearly separable. The SVM algorithm is based on the structural risk minimization criterion. By adding a regularization term or penalty term representing the model's complexity to the empirical risk, the over-fitting problem is avoided to a certain extent, and it shows superior performance, especially for relatively small training examples [33]. An SVM model for medium access control (MAC) protocol identification has been proposed to enable CR devices to distinguish four types of MAC protocols, namely TDMA, CSMA/CA, pure ALOHA, and slotted ALOHA, of any existing transmissions to avoid potential interference to PUs and existing SUs [42]. Under a low-SNR scenario and limited training data, SVM is proven to have high efficiency in successive spectrum hole detection.

ANN is an adaptive system, which has been widely used in cognitive radio. It can simulate arbitrary nonlinear mapping by modeling the relationship between input and output. The basic mathematical expression can be expressed as

$$o = f\left(\sum_{n=1}^{N} w_n x_n\right) \tag{5.2}$$

where x1, x2, ... xn are inputs of ANN and w1, w2, ... wn are the relative weights learned from the labeled data. The proper decision or action towards new signals will be decided by its output o. The ANN algorithm is based on the empirical risk minimization criterion. Training network parameters can reduce the metric distance between the network output and the training data label to minimize the empirical risk. A related approach has shown that a multi-layer perceptron can effectively reduce sensing energy and improve spectrum utilization [43]. The convolutional-neural-network (CNN)-based spectrum sensing model is proven to provide higher detection probability than cyclostationary detection in the -20 dB range [44].

5.4.2 Unsupervised Learning

In CR, SUs must operate on any available frequency band, at any time and place. As a result, it is very likely that the radio frequency environment's working conditions, such as noise or interference level, noise distribution, or user traffic, are known in advance [45]. Therefore, CR devices must learn independently in an unknown RF environment without training samples and explore the radio environment in which they are located. They then need to discover the observed data patterns to find possible spectrum holes. Compared to supervised learning, unsupervised learning is more suitable for cognitive radio application scenarios [46, 47, 48].

The unsupervised learning classification algorithm, also known as the clustering algorithm [49], can automatically divide samples into multiple disjoint clusters according to their inherent properties without requiring a labeled training dataset. Commonly used unsupervised learning algorithms include the K-means algorithm and Gaussian mixture model (GMM) algorithm.

The K-means algorithm aims to find a specific classification method so that the classified data has a higher degree of similarity within the class. For data with ordered attributes, the optimization strategy is to minimize the sum of Minkowski distance within the classified cluster, namely

$$\arg\min_{C} \left\{ \sum_{x_i, x_j \in C} \mathrm{dist}_m(x_i, x_j) \right\} \tag{5.3}$$

where $\mathrm{dist}_m(x_i, x_j) = \left(\sum_{k=1}^{l} |x_{ik} - x_{jk}|^l\right)^{\frac{1}{l}}$ denotes the Minkowski distance between x_i and y_i, l is an integer and usually picked as 2 (Euclidean distance). The smaller the Minkowski distance is, the more similar the data sets are. An empirical mode decomposition and k-means-based approach has been proposed to remove the redundant noise components in the nonstationary or nonlinear sampling signal and shows improvement in sensing performance [50]. The K-means algorithm built on the minimum description length principle can further eliminate the false alarm rate [51].

Unlike the K-means algorithm, GMM uses Gaussian distribution to describe the distribution of data in clusters. It assumes that each cluster corresponds to a Gaussian probability distribution. For a sample of data, each cluster may have a corresponding generation probability. The posterior likelihood will determine the cluster division of the data. The posterior probability gives the probability that each Gaussian model produces the sample data. The most considerable posterior probability model can be considered the cluster that the sample data should be divided into. In the unsupervised case, the GMM model's training can generally be realized based on the expectation-maximization (EM) algorithm [40, 52].Sparse Bayesian learning (SBL) method combines prior distribution and observation model to construct the posterior distribution, infers it using Markov Chain Monte Carlo or

Table 5.1: Different machine learning algorithms and their features

Category	Algorithm	Characteristics
Supervised Learning	KNN	One-to-one mapping
	SVM	One-to-one mapping Applicable for linearly non-separable data
	ANN	Better mapping relationship between data and action Overfitting problem
	CNN	High precision and low latency Good flexibility
	MLP	Excellent feature mapping ability Straightforward in design
Unsupervised Learning	K-means	Non-gradient optimization algorithm Hard decision Requires relatively independent input variables Sensitive to initial setup
	GMM	Soft decision Requires knowledge of data distribution Overfitting problem
	SBL	Good robustness in noise and interference situation Sparsity prior High resolution

variational Bayesian methods, and reconstructs the original signal for efficient and robust spectrum sensing. For better comparison, the commonly used machine learning algorithms in spectrum sensing mentioned above and their features are summarized in Table 1.

5.5 Beyond Spectrum Sensing

Except for spectrum sensing, wireless signals are also applied to sense physical targets and environments. Wireless sensing techniques play a pivotal role in addressing numerous real-world engineering challenges, such as digital health [53], activity recognition [54], and object recognition/detection [55]. Existing sensing methods involve measuring physical inputs from the environment and converting them into data that can be interpreted by either humans or machines using rule-based approaches. However, these methods often fall short when dealing with the vast and complex data generated by modern wireless sensing techniques. To break through this limitation, wireless data-driven algorithms (a.k.a algorithmic wireless sensing), are employed to automatically identify patterns in sensor data and map them to desired outputs. Nonetheless, practical challenges such as noise, interference, and domain discrepancies can adversely impact the performance of sensing and learning. Blindly applying algorithms can lead to overfitting and reduced generalizability. Consequently, data-driven sensing should be considered a combined sensing and learning approach that tackles issues specific to sensing scenarios.

In this section, four aspects of algorithmic wireless sensing are considered to overcome the challenges of existing wireless sesning. First, it achieves cross-domain sensing that adapts to different environments, devices, and users with distinct data features. Second, it enables large-scale sensing with data collected in a distributed manner. Third, it enables large-scale sensing with data collected in a distributed manner. Fourth, it deals with imperfect signals by compensating for the defects using prior knowledge.

5.5.1 Cross-Domain Learning for Wireless Sensing

Basic algorithmic sensing involves utilizing a black-box algorithm to directly map sensor data to the desired output. However, this approach encounters a significant challenge known as domain shift. Domain shift occurs when the algorithm's performance degrades during inference because the domain (i.e., device, environment, or user) differs from the one used during training. Conventionally, addressing domain shift requires the laborious process of collecting and labeling new datasets. To overcome this challenge, the authors in [56] have proposed a framework that incorporates additional generalization logic (e.g., knowledge transfer and data generation) on top of the black-box algorithm, enabling the generalization of sensing functionality from the training domain to the "unseen" target domains. Consequently, deep-learning models for sensing systems can be trained once but remain adaptable to other domains, thus providing more flexible services.

An example of employing algorithms for cross-domain sensing is RF-Net [57], which uses meta-learning to perform human activity recognition (HAR) in new environments. RF-Net learns a robust distance metric for generalization instead of directly tuning the deep-learning model, allowing it to adapt to new domains with minimal labeled data and achieve rapid domain adaptation. Similarly, SiWa [58] identifies in-wall materials by using adversarial learning to eliminate domain influence and adapt to different wall types. It is noteworthy that the concept of "domain" is not restricted to environment, device, or user; any factors causing different training and test data distributions can be considered domains. For instance, Adv-4-Adv [59] addresses adversarial defense by treating attacks with varying adversarial perturbations as different domains and learning a robust, domain-invariant representation.

5.5.2 Large-Scale Wireless Sensing

Large-scale wireless sensing entails the collection and analysis of data from numerous sensors distributed across a geographical area. However, the high cost of sensors presents a significant challenge, limiting the scalability of such deployments. To address this issue, Octopus [60] has designed as a cost-effective and flexible wideband MIMO sensing platform. This platform reduces the cost to one-tenth of previous designs and maximizes the efficacy of various learning algorithms through its adaptable hardware. In addition to developing proprietary low-cost platforms, another viable solution for large-scale sensing is crowdsensing [61, 62, 63, 64, 65], where individual sensors voluntarily contribute their data to a centralized platform. Crowdsensing leverages existing infrastructure, such as networked mobile devices, eliminating the need for expensive hardware and making it well-suited for scenarios where traditional sensing methods are impractical, excessively costly, or insufficiently comprehensive.

A notable example of crowdsensing is AutoFed [66], which utilizes sensors on self-driving cars to collect data for training a neural network for object detection. While AutoFed employs existing onboard radar and lidar sensors without enhancing the hardware design, it delves deeper into understanding and integrating the distributed vehicles into a cohesive system. To combat the privacy and communication concerns associated with traditional crowdsensing, AutoFed adopts federated learning (FL). FL enables multiple devices to collaborate on a model without sharing their data by having each client train a local model with its own data and send it to a central server for aggregation into a global model. This approach ensures data privacy and minimizes communication costs. However, integrating FL with large-scale sensing introduces challenges related to annotation, modality, and environment heterogeneities. To overcome these challenges, novel algorithm designs, including an innovative loss function and client selection process, have been developed.

5.5.3 Resource-Constrained Wireless Sensing

Many existing sensing tasks are performed on resource-constrained edge devices, necessitating the optimization of algorithmic sensing to accommodate limited computational resources. One example is HAR-SANet [67], a human activity recognition system that includes a hardware design and a signal processing pipeline specifically tailored for resource-constrained edge devices. This system utilizes efficient deep learning techniques such as channel splitting, grouped convolutions, depth-wise convolutions, and pointwise convolutions. These methods reduce both computation and storage complexity, making the sensing functionality feasible on less powerful edge devices. Another example is Sound of Motion [68], a lightweight wrist-tracking system that employs a suite of lightweight signal processing procedures to integrate IMU and acoustic sensing results for tracking purposes. A notable innovation in Sound of Motion is the use of the Sliding Goertzel DFT [69] to detect the arrival time of acoustic signals. This method extracts only the energy concentrated around the carrier frequency, thereby avoiding unnecessary data processing and making it suitable for resource-constrained smartwatches.

5.5.4 Signal-Enhanced Sensing

Algorithms can significantly enhance sensing by improving imperfect signals. One example is contact-free vital sign monitoring, which uses various sensing media (e.g., light, acoustic, and radio waves) to measure vital signs such as breath and heart rate. These signals are often degraded by noise and interference from other sources (e.g., multi-person interference). An early work, V^{2}iFi [70], employs a signal-processing method called multi-sequence variational mode decomposition to jointly extract vital signs from multiple signal sequences. This enables V^{2}iFi to accurately estimate the driver's vital signs, capturing even subtle heart rate variability.

Real-world sensing signals may exhibit diverse statistical properties that cannot be effectively processed by a single signal processing method such as filtering. In such cases, more advanced deep learning algorithms can be utilized to handle imperfect sensing signals. For instance, the variational encoder-decoder [71, 72, 73] leverages the in-phase quadrature

(IQ) signal of the radar baseband to achieve fine-grained vital sign waveform recovery through the generalizability afforded by variational inference. As an enhancement, Breath-Catcher [74] enables simultaneous tracking and respiration monitoring, with its algorithms effectively monitoring vital sign signals even amidst interference from walking human subjects. Another related work, MoVi-Fi [75], uses deep contrastive learning to perform blind signal source separation, extracting vital sign waveforms from imperfect signals contaminated by various sources. However, it is important to note that algorithmic sensing for imperfect signal recovery can incur high computational costs. Therefore, physical separability is sometimes used to ensure more robust sensing results [76, 77].

5.6 Conclusion

Sub-Nyquist sampling methods based on compressed sensing have been extensively investigated, capitalizing on the sparse nature of wideband signals in the frequency domain. These methods have spurred numerous studies aimed at developing lower complexity algorithms to improve spectrum reconstruction accuracy. Additionally, recent research has increasingly focused on applying machine learning techniques to spectrum sensing, significantly enhancing both accuracy and efficiency. Beyond spectrum sensing, advanced learning algorithms have also been employed to utilize wireless signals for sensing physical targets and environmental conditions.

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6. Shared Spectrum for Low and Mid-band Private 5G Networks

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IN this article we review the background to the growth and increased interest in 'shared' spectrum mobile/wireless networks, considering factors around spectrum availability and licensing, Radio Frequency (RF) bands that are available, and the advent of Software Defined Radio (SDR) deployments enabled by multichannel devices sampling at RF (multi-GHz) rates. The article will present our recent experience of building private 5G standalone networks for a number of emerging use cases, and demonstrate scenarios where shared spectrum approaches have helped to solve problems that unlicensed (Wi-Fi), or licensed (the mobile network operators, MNOs) systems have difficulty providing the required Quality of Service (QoS).

6.1 Introduction

Over the past few decades, the term "spectrum crunch" (never enough!) has become associated with the evolving use of the Radio Frequency (RF) spectrum, for applications ranging from broadcast radio (starting in the 1920s), to TV (from the 1950s), to radio point-to-point communications (from the 1960s), and the 1G to 5G evolution of mobile and wireless communications (late 1980s to present). Quite simply the spectrum crunch means that the available RF spectrum is nearly always running out in the face of escalating demand, new use cases and ever-increasing data rates. This problem has been addressed over the last 100 years by technology evolution allowing higher frequency bands to be used. For example, from the 1970's, the introduction of consumer TV was driven by the availability of new electronics, and RF technology for analogue broadcasting and receivers that worked in and around 400 – 700 MHz hands (termed 'Ultra High Frequency', or UHF). When wireless and mobile networks began to appear, technology had once again moved on, and early analogue and digital mobile/cell phones typically used 800 MHz and the low 1 GHz band. From the late 1980s onwards, the monetary value of spectrum was recognised by governments the world over, and many billions of dollars of revenue was created by selling and licensing the rights to various radio spectrum bands for mobile/wireless. The selling / auctioning and licensing of certain spectrum bands occurred alongside the many civic and defence allocations of dedicated RF spectrum (military, aviation, emergency services etc). In terms of 'unlicensed' and public use bands, there is a well-shared story that IEEE 802.11 (Wi-Fi) was given the 'microwave ovens' band at 2.4GHz, as it appeared to have minimum value due to the perceived interference experienced from cooking! Of course, IEEE 802.11 / Wi-Fi is one of the stellar successes of the wireless revolution, and it has made very best use of unlicensed spectrum (where 'unlicensed' effectively means: you can use it, just play by the agreed rules!).

6.1.1 From 100's of MHz to Several 10's of GHz

In recent years, with the appearance of 4G and 5G, and now thinking towards 6G, technology has allowed us to move to even higher frequency bands. This includes bands from 3.5 to 4GHz, which are widely used by Mobile Network Operations (MNOs) / cell providers, and the new 6GHz bands. Now 'mmwave' (20 GHz and higher) bands are now available too, and offer very wide channel bandwidths. However, there exists an issue that, as we move to higher RF bands to obtain more available bandwidth, the propagation characteristics of the RF signal change. Indeed for many mmwave RF signals, there can be little-to-no propagation through walls, and significant attenuation over wireless channels of 10's of metres, meaning that the use-cases are more applicable for indoor line of sight (LoS), or 'densified' outdoor environments with many small cells [**mmwaveprop**].

For this reason, the 'spectrum crunch' will continue to be an issue in the low bands (typically quoted as 600 MHz to 1 GHz) and mid bands (typically 1 to 3 GHz) used in 5G/6G, where RF propagation extends much further and signals can penetrate walls and diffract around obstacles. Consequently, there is intense usage pressure on these bands. Therefore, while the need for more spectrum will be addressed by moving to higher RF frequency bands, for many use cases such as outdoor, wide area networks, the low and mid bands remain the most desirable options, and sometimes the only viable options.

Over the next few pages, we review on the evolution of 5G private networks operating in 'shared spectrum' bands. The example use case presented is for (video) broadcast and live events applications, and from the perspective of UK spectrum regulation (with some comparisons made to international equivalents). One very important enabler of these networks is Software Defined Radio (SDR) equipment, which provides the flexibility to customise radio configurations, and to operate in non-standard bands (i.e. those not defined as part of the 3GPP standards, and therefore not widely supported by mass-market radio chips). Using SDR equipment also brings the potential to develop and deploy custom radio functionality, such as spectrum monitoring, to inform the selection and use of available bands.

6.2 Temporal and Spatial Spectrum Sharing

Fortunately, although the RF spectrum is a finite natural resource, it is non-depleting, and can be reused both temporally and spatially. The primary responsibility for RF spectrum management is assumed by national regulators around the world, who often work together across borders to harmonise regulations internationally, alongside the ITU (International Telecommunications Union) [**itu**].

Traditionally, spectrum has been managed using fixed allocations: bands of frequencies are designated as either 'licensed' (users apply and pay a fee to gain access to the band, or bands designated for users such as emergency services) or 'unlicensed' (any user equipment can access the band, provided that it adheres to the applicable rules, Wi-Fi being the best-known example). These designations usually apply across a whole country or region, which is a simple and robust system, but it creates unfortunate instances of spectrum under-utilisation. To give an example, consider an RF band that is licensed across a whole country, but the licensee only wishes to use the band in cities – legally, this prevents use of the licensed spectrum in rural areas, where it lies fallow. The whole issues of national licensing is one that is being reconsidered in many countries, and a recent treatise of this is given in [**WilliamWebbBook**].

With new technologies, the use of spectrum can be 'sensed' (an aspect of so-called cognitive radio) and therefore there is potential for the available spectrum to be shared among users more flexibly. The challenge of managing access to the RF spectrum in a fair and efficient manner, and maximising the benefit that can be generated from it, is still a work in progress in may countries. However, now that Citizens Broadband Radio Service (CBRS) in the USA, and band n77 in the UK, have demonstrated the value of 'sharing', this is a fertile and promising avenue for the future of spectrum management.

6.3 Shared Spectrum Strategies and Regulators

In a number of countries, new 'shared' bands have been designated that permit reuse of the spectrum geographically, or enable tiered classes of licensed users to operate in the same band. Two notable examples that adopt these respective mechanisms are Shared Access bands in the UK [**Ofcom:July2019**], and the Citizens Broadband Radio Service (CBRS) in the USA [**FCC:CBRS**]. Shared bands of both types provide an opportunity for networks to be deployed by private (and often small) operators, and tailored according to their requirements. 5G private networks operating in shared bands are a key opportunity for new connectivity options, and the focus of this article.

6.3.1 Shared and Local Access Licences in the UK

In the UK, spectrum is managed by an autonomous regulator at the direction of the Government — the Office of Communications (Ofcom). Spectrum is allocated for licensed

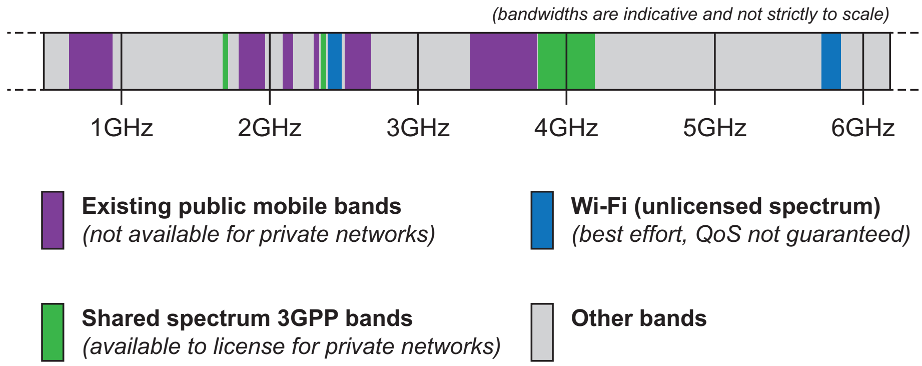

Figure 6.1: General Spectrum map from low bands to mid bands.

bands and unlicensed bands, and also for Shared Access bands [**Ofcom:July2019**]. When Ofcom introduced this change in 2019, the following Shared Access bands were defined:

- **1,781.7 – 1,785 MHz** paired with **1,876.7 – 1,880 MHz** (*spectrum available* = 6.6 MHz)
- **2,490 – 2,500 MHz** (*spectrum available* = 10 MHz)
- **3.8 – 4.2 GHz** (*spectrum available* = 400 MHz)

An additional mmwave shared band was allocated between 24.25 and 26.5 GHz, restricted to indoor use only, which we will not consider within the scope of this discussion around low and mid-band RF. It is also worth noting TV White Space (TVWS), a previous shared spectrum access strategy from around 2012. TVWS exploited the frequency bands vacated upon switching from analogue to digital television; however unfortunately, this approach was ultimately unsuccessful, due in part to a lack of affordable equipment.

Taking into consideration the 5G bands licensed to MNOs in the UK, unlicensed spectrum, and the UK Shared Access bands, we can form a view of the spectrum allocated to these purposes in the RF spectrum up to 6 GHz. This is illustrated in Figure 6.1, which allows comparison of the relative bandwidths available, and confirms that the available Shared Spectrum bandwidth is considerable. In fact, the n77 400 MHz band (from 3.8 to 4.2GHz) provides almost as much spectrum as all of the 5G spectrum allocated to the UK's four incumbent MNOs, combined.

Shared Access bands are licensed on a local basis. In other words, a prospective operator can apply for a desired frequency band and bandwidth (which is normally a multiple of 10 MHz), at a desired location. This mode of licensing enables reuse of the shared bands in a geographical sense across the UK: multiple licences for the same band can be granted, provided that the licensed sites are far enough away from each other to prevent co-interference. Licences are granted on a first-come-first-served basis, subject to an interference assessment based on licenses already granted in the vicinity.

There are two types of UK Shared Access licenses: Low Power and Medium Power. Low Power licences permit the required number of base stations to be deployed within a circular area of 50m radius. Multiple such licences can be obtained if needed to serve a larger area, e.g. to cover an industrial site. Medium Power licences enable higher power transmissions, and are generally only applicable for rural areas. Full details of both licence types are available in [**Ofcom:July2019**]. To give an indication of cost: at the

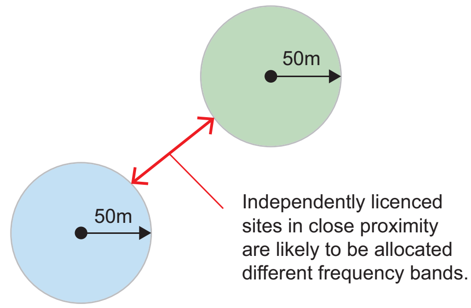

Figure 6.2: Licences granted in relative proximity.

time of writing, spectrum licenses are available in the 3.8 – 4.2 GHz band for £80 per 10 MHz per annum. Applications and allocations of these licences are processed directly by the regulator Ofcom and all successful applications will receive a licence with maximum antenna height, maximum EIRP and an RF frequency range, and specific geographical coordinates. Typically a licence lasts for one year, and is renewable. Failure to use any allocated licences for a set period of time, may constitute a violation of the licence and as such it may be revoked.

Local Access Licences

As well as the shared access bands, in 2019 Ofcom also introduced the process and intention of 'local access licences', whereby any RF bands currently allocated to national MNOs/cell providers that were not being used in locations (e.g. rural areas), then an application to use these frequencies could be made. Using these spectrum bands is altogether more challenging than using the shared access bands given the negotiation required with MNOs/cell providers and the initial time limit on licences, making business models challenging if only a few years available and the licence might then be revoked.

Similar to the UK, there are other shared spectrum activities across the globe, notably CBRS in the USA [**FCC:CBRS**] as well as shared access schemes in Europe. In Aotearoa New Zealand, the Goverment office, MBIE, has allocated 5G spectrum bands [**IMSC**], spanning the entire nation to Māori rather than being confined to traditional lands or specific locations. This allocation, part of the 3.5 GHz band, stems from historical treaties of Waitangi aimed at equitable resource distribution for the benefit of all living in Aotearoa New Zealand.

6.4 5G Private Networks

5G is most often associated with mobile cellular networks that serve the public via monthly subscriptions and pay-as-you go plans. Such networks are therefore often referred to as "public" 5G networks, even though they are owned and operated by private companies (MNOs). MNOs have long-term spectrum licences (typically at great cost!) and traditionally, exclusive use of their allocated spectrum (although this is no longer strictly true in the UK [**Ofcom:July2019**]).

With the introduction of Shared Access bands, there is now suitable spectrum available for *private* deployments of 5G. Given that licenses to shared bands are granted on the basis of location, licence-holders have access to large bandwidths of uncontended spectrum in the area of their network deployment. This contrasts with operating a Wi-Fi network in an unlicensed band, which may be busy with other users, and consequently offers no guarantees in terms of interference, or attainable Quality of Service (QoS).

From a standards perspective, 5G differs from Wi-Fi and provides a different set of technical parameters, performance characteristics, and logistical considerations. The distinguishing capabilities of 5G are often stated as [**ITU:5GVision**]:

- Enhanced Mobile Broadband (eMBB)
- Ultra-Reliable Low Latency Communications (URLLC)
- Massive Machine Type Communications (MMTC)

For many applications, Wi-Fi remains the most appropriate choice, due to various factors including its ubiquity, lack of spectrum licensing requirements, and the low cost of Wi-Fi equipment. From a performance viewpoint, Wi-Fi is often “good enough" and its capabilities are still improving, for instance with the release of Wi-Fi 6 in 2021, and Wi-Fi 7 planned for 2024 [**IEEE:Wi-Fi**]. However, a number of applications can benefit from the enhanced capabilities of 5G, and the opportunity to use uncontended spectrum via Shared Access licences. Together with advancement of SDR technology, the conditions are ideal for developing new innovations and compelling use cases with private 5G networks.

An example sector that can benefit greatly from private 5G is media, events, and broadcasting. Next, we will look at a case study based on our ongoing activities in this area.

6.4.1 Private 5G ’Killer’ Use Case: Live Event Networks

In the broadcasting industry, wireless links are often required for creating content outside of a television studio. This can include, for instance, live news-gathering and sporting events, where there is no permanent infrastructure for carrying video traffic. The captured content needs to be transferred from the broadcast camera(s) to a central production location (e.g. the television company’s premises) over a backhaul network, or to a local production hub at the event location, where the programme is prepared for broadcast (known as “remote production"). Where multiple cameras are used to film a live event, their feeds are combined to form an integrated programme for broadcast.

Particularly for a live, remote production scenario with multiple cameras, we can therefore summarise the following demanding requirements:

- Significant bandwidth required to carry broadcast quality video (scales with number of cameras).
- High QoS over the wireless network to achieve picture / audio quality and seamless broadcast.
- Very low latency, deterministic links to enable effective combination of camera feeds.

Private 5G networks can fulfil the requirements of live broadcast applications, as described above, very well. This is particularly true as local Shared Access licences provide access to wide bandwidths of uncontended spectrum. Pre-planning is implied, to ensure that the required spectrum licence has been acquired in advance, however this is realistic for venues such as sporting stadia or other events venues. Another crucial aspect is that, due to the private nature of the network, its operator can apply a configuration that suits the needs of the application — in this case broadcast requires far greater capacity in the uplink (to transfer data from the camera to the production hub or basestation) than in the downlink. This is the opposite to public mobile cellular networks, which are biased towards the downlink in order to support subscribers downloading or streaming content to their phones.

Private 5G for Live Broadcast

In May 2023, working with the BBC R&D, and Neutral Wireless Ltd, StrathSDR supported the design and deployment of an 8 cell private 5G network in London to support King Charles III Coronation with coverage map shown in Figure 6.3. With near 100,000 people in the 'The Mall' (a one km road from Buckingham Palace to Trafalgar Square broadcasters looking to use the mobile network(s) for live uplink of HD cameras would not get the QoS (quality of service) required. With a private network and 50MHz of 'quiet' and contended n77 spectrum from 3.8 to 4.2 GHz, the private 5G supported 20 international broadcasters with 60 devices only on the network (each authorised via a private network SIM card). We believe this is the shape of things to come for private 5G networks for major sporting and civic events.

6.4.2 The ON-SIDE Project

The broadcasting applications featured in the previous section are just one use case enabled by private 5G networks. There are many other opportunities to be investigated, and great scope for innovation.

A concurrent 5G development theme is the concept of "open networks". There is a drive in the industry, supported by several national governments, to make 5G network equipment more open to competition. The goal is for the various components of the 5G Radio Access Network (RAN) to be interoperable, thus allowing a 5G network to be composed of components sourced from different vendors, thereby lowering barriers to entry and increasing competition in the market.

During 2023 – 2025, the University of Strathclyde Software Defined Radio (StrathSDR) group is taking part in the project, "Open Networks – Shared Spectrum Innovation and Design Environment" (or "ON-SIDE" for short), with funding from the UK Government's Department for Science, Innovation and Technology via its *Open Networks Ecosystem* competition. ON-SIDE is led by Cisco, and includes partners at AMD, BBC Research and Development, Glasgow City Council, Neutral Wireless, Scottish Wireless, and the University of Glasgow. The project aims to investigate how private 5G networks can best enable a range of use cases, based on Shared Spectrum and using an "open network" philosophy. In doing so, ONSIDE considers new spectrum licensing methods for use within the network, with shorter term licences (for instance, granting local licences for a few minutes, rather than a year).

A defining feature of the ON-SIDE project is its access to spectrum. For this project, Ofcom

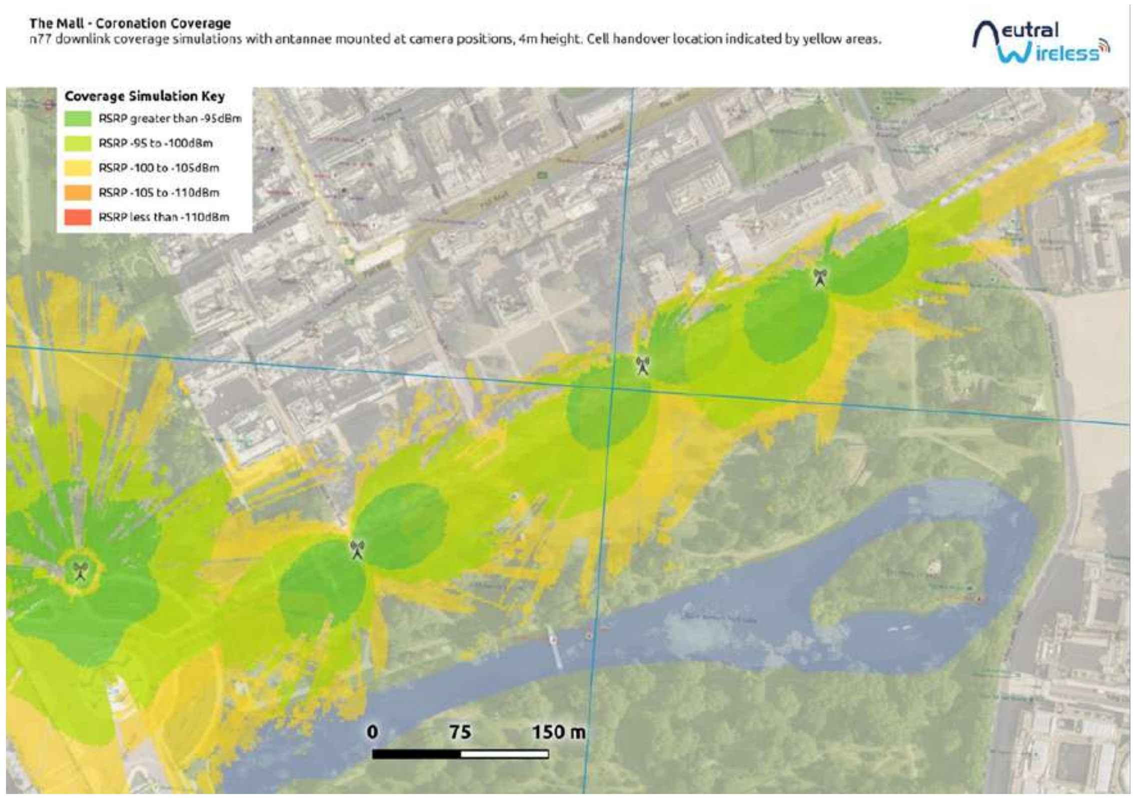

Figure 6.3: Coverage across the eight n77 cells from Buckingham Palace, London (lower right), down The Mall.

Figure 6.4: Popup n77 private 5G network mast (circled in red) serving the area just in front of Buckingham Palace.

has awarded a Glasgow city-wide licence of more than 750 km^2 for the frequency range of 3.8 – 4.2 GHz band. This means that the allocated spectrum can be managed locally by the project, across the Glasgow metropolitan area (defined as a radius of 15 km from the centre). We refer to this as a “spectrum sandbox", i.e. a spectrum resource that can be used for real-world experimentation, design, and innovation — transferring research out of the lab and into authentic application scenarios.

6.4.3 Spectrum Management in 5G Private Networks

The Glasgow Spectrum sandbox vision, although initially part of a research and innovation project, represents a realistic candidate scenario in future 5G and advanced networks: a block of Shared spectrum frequencies is locally licensed to a particular site, and the site owner must then manage access to that spectrum within their network, ideally in an efficient and effective way!

Consider the scenario of a University campus network. This would require multiple adjacent spectrum licences to cover the entire area of the campus. We’ll consider that the University has obtained a contiguous 100 MHz spectrum allocation between 3.8 and 3.9 GHz. One option would be to subdivide this frequency band and use it geographically across the campus in a cellular pattern; another would be to permit random access of the spectrum in a similar manner to Wi-Fi. However there could also be adaptability built into the spectrum management approach, for instance to allocate more spectrum where and when it is needed — such as for busy events like graduation ceremonies, open days, and other special occasions.

In this context, ON-SIDE considers the key issue of developing tools and methods for dynamic spectrum management within a local network, such as the Glasgow sandbox. We conceive of this solution as comprising:

- A spectrum database.
- Spectrum sensing technology.
- A cognitive engine for spectrum allocation decisions.

6.5 Enabling Technologies

SDR is the fundamental enabling technology for 5G private networks. Using SDR devices, networks and their constituent radios and processing elements can be configured to target the licensed spectrum band(s), and to optimise for the applicable use case(s). For instance, if a 5G private network operates in an allocated band at 3.8 – 3.9 GHz, and serves a broadcast use case, it will require a different setup compared to an industrial Internet of Things (IoT) application operating in the 2.49 – 2.5 GHz band. An SDR device can be reconfigured to support either application, or even both simultaneously, with minimal hardware changes (limited to front end RF filters, antennas, etc.).

In 5G, the Radio Access Network (RAN) is commonly split into three components:

- Radio Unit (RU).
- Distributed Unit (DU).

- Centralised Unit (CU).

These components can exist as physically separate devices, or (for the DU and CU) as virtualised elements within a data centre, for instance.

The RU is situated closest to the antenna and operates at the highest sampling frequencies. Depending on the applicable “functional split" (which defines the demarcation of processing between the RU, DU, and CU) the RU can implement most, if not all, of the Physical (PHY) layer. Therefore, it is imperative that the RU is capable of supporting the RF frequencies and bandwidths necessary for 5G systems. In recent years, advances in data converter technology (Digital-to-Analogue Converters (DACs) and Analogue-to-Digital Converters (ADCs) mean that high fidelity sampling at multiple GHz is now possible. As a result, the Shared Access bands discussed in this article can be directly digitised at RF frequencies, with modulation, demodulation and all other PHY processing undertaken digitally, aside from key front end functionality such as antennas, RF filters and amplifiers.

The AMD Zynq UltraScale+ Radio Frequency System on Chip (RFSoC) platform is an enabling device for SDR implementations [**AMD:RFSoC**]. The Zynq RFSoC is an integrated, single-chip solution comprising three main elements:

- A **Processing System (PS)**, featuring Arm applications and real-time processors;
- **Programmable Logic (PL)**, equivalent to that of an FPGA (Field Programmable Gate Array);
- **Radio Frequency Data Converters (RFDCs)**, with each device having multiple RF-DACs and RF-ADCs, and their associated Digital Upconverters (DUCs) and Digital Downconverters (DDCs), respectively. Typically there are 8 or 16 RF-DACs, and 8 or 16 RF-ADCs, depending on the specific RFSoC part.

A high level overview of the Zynq RFSoC device is shown in Figure 6.5.

There is also a 5G-optimised variant, the RFSoC DFE, which additionally features *hardened* versions of key 5G processing blocks such as Digital Pre-Distortion (DPD), equalisation, and other computationally demanding operations, meaning that this functionality has been optimised and implemented in dedicated silicon on the device.

From an SDR perspective, the Zynq RFSoC architecture is interesting and also powerful. The RF-DACs and RF-DACs can both sample at multiple GHz with up to 14-bit resolution; all of the Shared Access bands mentioned in this article can therefore be directly digitised with no external analogue Intermediate Frequency (IF) stages. The integration of these data converters with FPGA-based PL, and a PS, means that custom hardware and software can both be implemented and tightly coupled [**StrathSDR:RFSoCbook**].

Looking beyond current implementations and licensing mechanics in Shared Access bands, to achieve more dynamic sharing than is currently possible, radios will require both spectrum database integration (a software solution), and also spectrum sensing to monitor the spectral activity within the locality of the deployed network. On the Zynq RFSoC, spectrum sensing can leverage a ‘spare’ RF-ADC channel to capture and process frequency band(s) of interest. With plentiful FPGA logic available, there is great potential to implement a range of different spectrum sensing techniques, which may include energy detection all the way to sophisticated machine learning algorithms.

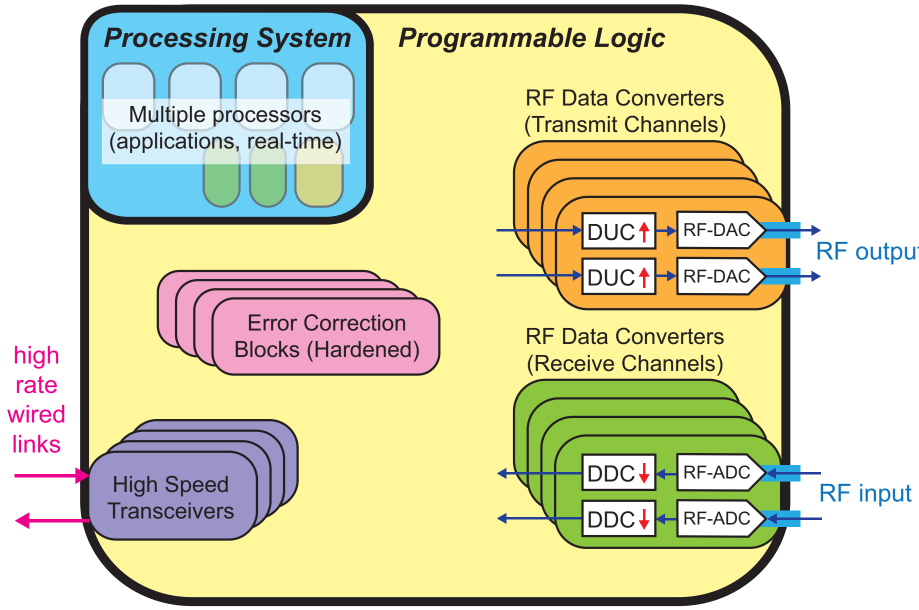

Figure 6.5: A simplified view of the Zynq RFSoC device architecture.

Using the RFSoC 4x2 development board [**AMD:RFSoC4x2**], we have also developed a spectrum analyser that runs entirely on the RFSoC device, using AMD's PYNQ software / hardware framework [**AMD:PYNQ**] and illustrated in Figure 6.6. RF-ADCs capture the signal; the signal processing functionality is implemented in the PL; and the PS hosts the software, including the GUI (users interface with the spectrum analyser via a simple web browser). This work demonstrates the ability of the Zynq RFSoC device to support spectrum monitoring over GHz bandwidths, and its potential as a platform for cognitive radio applications. The spectrum analyser and several other projects are available on an open-source basis from the StrathSDR GitHub repository [**StrathSDR:GitHub**], and the interested reader is invited to use this material towards their own projects.

6.6 Outlook and Conclusions

The short-term outlook for 5G private networks is very positive. With the increasing capabilities of SDR technology, easier access to SDR hardware and software, and an expanding ecosystem, there is great potential to not only deploy — but also to optimise — 5G private networks for a range of different applications.

The advance towards shared spectrum licensing models in the UK, USA and elsewhere is also a significant development. Access to spectrum is the most basic requirement for developing radio systems, and these bands now enable access to potentially 100's of MHz of spectrum in a locally licensed manner. As highlighted in this article, we have successfully leveraged the combination of SDR technology and UK Shared Access licences to deploy high capacity broadcast networks in very congested areas where other wireless technologies, in particular public mobile and Wi-Fi networks, could not cope. There are many other use cases for private 5G networks, including those yet-to-be-identified, which will drive the

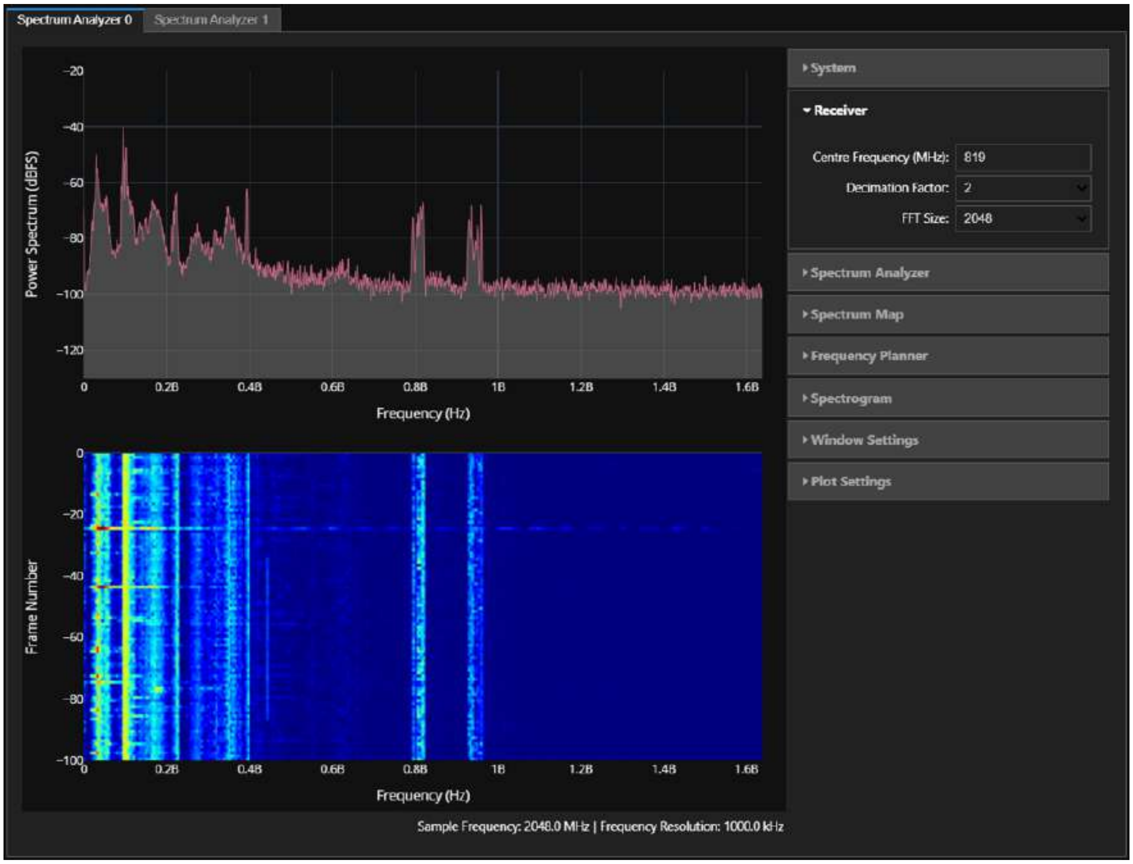

Figure 6.6: A screenshot of the single-chip spectrum analyser implemented using the RFSoC 4x2 development board.

growth of this market in the years to come.

As for cognitive radio — where does that fit in?

In truth, the answer is probably that cognitive radio is not (yet, in 2024) a critical component for this initial phase of 5G private network deployment. At the current time, shared spectrum is managed primarily through spectrum databases, and therefore the radios (implemented using SDR platforms) require to be *adaptable*, but not necessarily to be *cognitive* in the sense that they make decisions on spectrum access. Even so, spectrum sensing, awareness of the local radio environment and artificial intelligence are useful capabilities for radios to have: this information can augment and inform the interference models upon which the centralised spectrum databases operate. The requirement for cognitive radio in 5G private networks has not arrived yet in the consumer market, but with an evolving spectrum licensing landscape, and 6G on the horizon, it may not be too long before private networks truly are cognitive!

Acknowledgment

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