Al-Furat Journal of Innovations in Electronics and Computer Engineering (FJIECE)
ISSN -2708-3985

Optimization Techniques for Spectrum Sharing between MIMO Radar and Wireless Communication Systems: A Review

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https://doi.org/10.46649/fjiece.v4.1.14a.25.9.2025

Abstract. *For more than a decade, the need to share the frequency spectrum between radar and wireless communication systems has emerged due to the massive increase in demand for communication services and the availability of underutilized radar bands. At the same time, spectrum sharing between radar and wireless communication systems faces the problem of interference that affects the performance of both systems, which has attracted researchers to find effective solutions to reduce interference in an environment where both systems share the radio spectrum. In this paper, we review the most prominent optimization methods that have been used to share the frequency spectrum and reduce interference between radar and wireless communication systems.*

Keywords: *Spectrum Sharing; MIMO Radar; Communication System; Optimization Techniques; Interference Mitigation.*

1. INTRODUCTION

To keep pace with the massive increase in the number of wireless users and devices, the Federal Communications Commission (FCC) and National Telecommunications and Information Administration (NTIA) has been focusing on emerging solutions that are capable to spectrum sharing between different spectrum users by suggested sharing 100 MHz in the frequency band 3550–3650MHz spectrum with wireless communication users [1].There is an increasing demand to share radar frequency bands such as the navigation radar spectrum with communication systems due to the increasing number of communication users and the limited radio frequency spectrum, especially in the L, S band. Radar and wireless communications are often viewed as a source of interference between each other, so there is a need to find ways to reduce interference between the two systems by separating them in time or space [2]. To address these shortcomings, spectrum sharing between communications and radar has been developed as a viable solution. Optimization theory provides systematic methods for designing radar waveforms, frequency precedes, and beamformers that can coexist with the communications signals. This paper provides a systematic review and classification of optimization techniques for improving spectrum sharing between radar and cellular systems. The respite of this paper is arranged as follows. Section 2 describes the system model MIMO radar and BS model. then in Section 3 propose a review about Optimization techniques of Spectrum sharing and approaches. Finally, conclusions in Section 4.

2. SYSTEM MODELS

The system modeled to joint radar and communication which contains of a MIMO- radar and MIMO communication systems operating in the spectrum shared. The system model proposes that the radar detect the target by radiating power toward the target and receiving echo waveform. In the base station side, the communication does not occur in the direct path between the radar system and targets. Instead, the echoes from the target will interfere with the MIMO-communication systems as shown in Figure 1 [3].

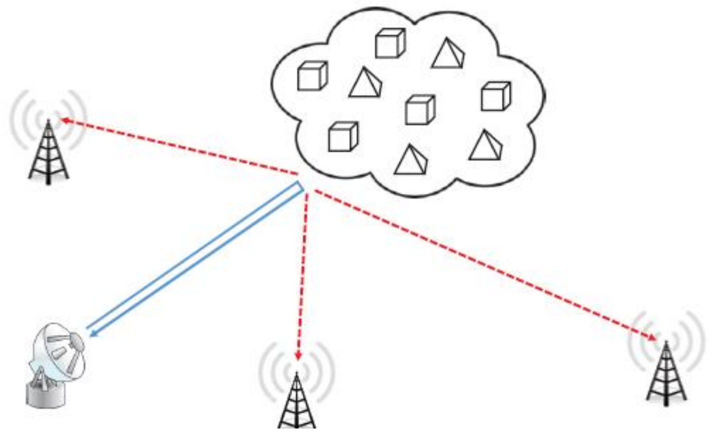

Fig. 1. MIMO radar-MIMO communication model Spectrum Sharing

This section will define MIMO radar, communication system, And interference channel model.

2.1. MIMO RADAR MODEL

MIMO (Multiple-Input Multiple-Output) radar is one of the latest developments in modern radar technology. It relies on the use of multiple antennas to transmit and receive simultaneously. This multiplicity gives the radar additional capabilities compared to traditional single-antenna or multi-antenna radars with uniform transmission. The basic idea is to transmit perpendicular waves from each antenna and then receive the reflections independently, creating a virtual array larger than the actual size of the antennas. This improves spatial accuracy in estimating angles and increases the range available for differentiating between targets, even in complex situations such as close proximity or in environments rich in reflections[4] the transmit signal is given as

$$\boldsymbol{x}(n) = [\mathrm{x}_1(\mathrm{n})\ x_2(n)\ x_3(n) \ldots x_M(n)] \qquad (1)$$

where $x_M(n)$ is transmit baseband signal from the M_{th} radar's antenna element at time index n [5].

Al-Furat Journal of Innovations in Electronics and Computer Engineering (FJIECE)
ISSN -2708-3985

2.2. COMMUNICATION SYSTEM

BS is considered the central component of cellular networks, communication system consists of K base stations, each equipped with N_{BS} transceiver antennas, serving as the bridge between user equipment (UE) and the core network. It typically consists of antennas, radio processing units, digital units, and backhaul links that connect it to the rest of the network. The BS's function is not limited to providing geographic coverage, but also includes managing spectrum resources, organizing simultaneous communications between users, and supporting advanced technologies such as MIMO and beamforming. If $s_j(n)$ is the signals transmitted by the j_{th} user equipment in the i_{th} cell, then the received signal at the ith BS receiver can be written as

$$\boldsymbol{y}_i(n) = \sum \boldsymbol{H}_{ij}\boldsymbol{s}(n) + \boldsymbol{w}(n) \quad \text{for } 1 \leqslant i \leqslant \text{K and } 1 \leqslant j \leqslant L_{ij} \quad (2)$$

where $H_{ij}$is the channel matrix between the i_{th} base station and the j_{th} user equipment and w(n) is the additive white Gaussian noise [4], then the signal received at the base station when share the spectrum with the MIMO radar as follow

$$\boldsymbol{y}_i(n) = \boldsymbol{H}_i\boldsymbol{x}(n) + \sum \boldsymbol{H}_{ij}\boldsymbol{s}(n) + \boldsymbol{w}(n) \quad (3)$$

where $H_i$is the interference channel matrix between the N_{BS} base station antennas and N_R MIMO Radar antennas.

2.3. INTERFERENCE CHANNEL MODEL

MIMO radar faces real challenges, most notably the computational complexity resulting from processing a large number of channels, in addition to the need to carefully design orthogonal waves to avoid interference during reception. Another challenge arises when the radar operates in frequency bands shared with communications systems, requiring advanced solutions for spectrum sharing and interference mitigation[6]. This interference is understood through two alternate channels: a channel from the radar antennas to the BS antennas $\boldsymbol{H}r\rightarrow c$ and a reverse channel from the BS antennas to the radar antennas $\boldsymbol{H}c\rightarrow r$ Both are typically frequency-selective and time-varying, and may be modelled as Rayleigh, Rician (when a line-of-sight path is present) or another channel distribution , creating energy leakage through the side lobes and imperfect filter passes. Spectral coexistence is therefore viewed as a matter of fine-tuning the coupling of these two channels or shaping the signal so that the energy is projected onto spaces that do not reach the sensitive receiver.

3. SPECTUM SHARING OPTIMIZATION TECHNIQUES AND APPROACHES

This paper will adopt five main pillars to divide the approaches of RF spectrum sharing optimization between MIMO radar and cellular communications systems, as follows:

3.1. Spatial Projection / Nulling (NSP)

Null-space projection is one of the methods for achieving spectral coexistence between radar and communications. The basic idea is based on a mathematical property of interference of radar-communication channels If the interference channel is represented by a matrix **H** , the null space of this matrix contains all vectors that, when passed through the channel, yield zero at the receivers. Therefore, if projected the radar signal onto the null space of **H** , the signal component arriving at the communications system is zero (no interference occurs). Mathematically, this projection can be obtained through singular value decomposition (SVD) of the channel matrix, where the vectors corresponding to the null singular values are used to construct the projection matrix. The major advantage of this method is that it completely eliminates interference (perfect interference cancellation). However, it has some limitations such as the size of the zero-space depends on the rank of the matrix, H. If the channel is full-rank, the radar may not have any freedom to transmit and assumes perfect channel knowledge (CSI) between the radar and the communications system, an assumption that may be unrealistic in practical settings. Therefore, NSP was considered the starting point, and later improvements such as Switched NSP, Small-Singular-Value Subspace Projection (SSSVSP), and more complex methods based on joint design or probabilistic optimization have emerged to overcome its limitations. In [7] presents the idea of projecting radar waveforms onto the null space of the interference channel to permit spectrum coexistence with communication systems. Assuming the radar (modeled as a collocated MIMO radar) has wisdom of the interference channel information , it adapts its transmitted signals so that they do not leak into the communication system's reception space. The authors analyze the performance impact of this projection using maximum likelihood estimation and Cramér–Rao bounds, comparing cases with and without null-space projection. Simulation results show that, with an optimal number of antennas and proper selection of null-space thresholds, radar target detection and direction estimation remain close to conventional performance, while interference to communication systems is effectively mitigated. This work established null-space projection as a foundational optimization technique for radar–communication coexistence. In [5] presents an optimization-based framework for designing constant-envelope (CE) MIMO radar waveforms that can coexist with LTE/WiMAX systems. The authors extend the classical beampattern matching problem by introducing an additional constraint: the waveform must lie in the null space of the interference channel to the communication system. For stationary maritime radars with slowly varying channels, the null-space projection (NSP) is incorporated directly into the nonlinear optimization problem, ensuring both desired beampattern shaping and interference avoidance. For moving radars with fast changing channels, CE waveforms are first designed via unconstrained optimization and then projected onto the null-space afterward. The optimization leverages covariance matrix synthesis with constant-envelope constraints, solved using spherical coordinate parameterization and selective channel-state-based NSP algorithms. Simulation results demonstrate that selecting the interference channel with the largest null-space dimension yields beampatterns that closely match desired shapes while ensuring zero interference. In [8] proposes a radar-centric spatial method to mitigate interference in coexistence scenarios. The authors extend the concept of null-space projection (NSP) from a single interference channel to multiple channels created by several LTE base stations. To minimize radar performance degradation, they introduce an interference-channel-selection algorithm that chooses the channel with the maximum null-space dimension, onto which radar signals are projected using a modified and more efficient NSP algorithm. Analytical models and simulation evaluated through metrics such as Cramér–Rao bounds, maximum likelihood estimation of target angle, and radar beampattern prove that carefully selecting the best channel significantly reduces the loss in radar detection accuracy while ensuring zero interference to LTE. In [9] frames existence as an optimization through null-space projection. The radar selects largest null-space dimension of interference channel with the and projects its waveform, accordingly, minimizing distortion while ensuring zero interference to LTE.

The optimization is formulated as choosing the projection matrix which better preserves the radar wave structure under the null-space constraint., and detection is analysed using the generalized likelihood ratio test GLRT framework. This approach highlights the trade-off between maintaining radar detection capability and strictly protecting LTE systems, with channel selection serving as the key optimization mechanism. In [10] develops a radar centric spectrum sharing strategy that relies on two layers of optimization. First, the authors propose the "overlapped MIMO" architecture, where the transmit antenna array is partitioned into several overlapping subarrays. This design increases the effective virtual aperture size and provides stronger sidelobe suppression compared to conventional MIMO, which is critical in reducing unintentional interference leakage. The optimization problem here is to determine the optimal number of subarrays K that maximizes the effective aperture $(M_T - K+1)$ K By solving this discrete optimization, the radar gains additional spatial degrees of freedom. The second layer of optimization is the application of null-space projection (NSP). With knowledge CSI of the communication system, the radar computes a projection matrix (via singular value decomposition) and projects its signals into the null-space of the interference channel. This guarantees zero interference to the communication receivers. The overlapped MIMO formulation makes NSP feasible even when the number of physicals transmit antennas M_T is not larger than the number of communications receive antennas, since the overlapping scheme effectively enlarges the transmit dimension. In [11] turns coexistence into a two-step selection-and-projection optimization. First, at each pulse, the radar selects the LTE BS whose channel gives the least distortion if the radar signal projected, it choice the channel whose harmless subspace will change the waveform the least. Second, the radar projects its signal either into the null-space (SNSP zero interference) or, if that space is too small, into the subspace spanned by small singular values (SSSVSP very low but nonzero leakage), which preserves the radar beampattern better. Practically, compute SVD for each candidate channel, score how much the projection would alter the signal, choice the best, then transmit. This optimization employments small waveform change for rigorous LTE protection. Together, these two optimizations subarray selection and NSP projection produce a coexistence framework that not only satisfies rigorous interference constraints but also improves radar beampattern quality. The results show that overlapped MIMO with NSP beats conventional MIMO by simultaneously achieving higher sidelobe clampdown, better virtual array resolution, and robust coexistence with communication systems.

3.2. Information-Theoretic Power / Spectrum Allocation

The information-perspective spectrum and power allocation approach addresses the coexistence issue between radar and communications by redistributing power across frequencies or carriers to maximize the mutual information of communications or improve the signal-to-noise ratio and interference of radar. Instead of relying on spatial projection, the spectral envelope of the transmitted signals is reshaped to balance the requirements of the two systems within overall constraints including transmitted power, interference masks, and waveform similarity constraints. These formulations have the advantage of being transformable into convex problems that can be efficiently solved using standard software tools such as waterfilling algorithms or linear programming, enabling a precise mathematical description of the trade-off between communications reliability and radar detection capability. In [12] suggests an information-theoretic algorithm to design waveform of MIMO radars to allow coexistence with communication systems. The core idea is to maximize the mutual information (MI) between the target response and the radar's received signal while satisfying practical constraints such as preventive interference to LTE/WiMAX systems, avoiding clutter, and ensuring total power and low peak-to-average power ratio (PAPR). The problem is formulated as a convex optimization over the power spectral density (PSD), and the solution exhibits a water-filling structure, allocating more power to frequencies where the target response controls over clutter. To recover time-domain signals, the authors employ a Cyclic Projection CP Algorithm, which engenders unimodular sequences with good auto- and cross-correlation properties. Numerical results demonstrate that the proposed approach effectively balances target detection performance with interference mitigation requirements, focus on a fundamental trade-off between improved spectral shaping and sidelobe extinction. In [13] expresses coexistence as two distinct optimization problems in the frequency domain. In the target characterization case, the goal is to maximize the mutual information between the radar return and the received signal, while respecting constraints on per-subcarrier interference (to protect the communication system) and a total radar power budget. This problem results in a limited distribution of the power needed to fill the gaps across the OFDM subcarriers. In the case of target detection, the goal becomes maximizing the received signal-to-interference-to-noise ratio (SINR) of the radar, which is formulated as a linear finite optimization problem under the same interference and power constraints, concentrating power on the appropriate subcarriers. Using second-order channel statistics and circuit approximations, both problems are easily solved, and the results highlight a key trade-off: a mutual information-based design service a wide frequency bandwidth distribution, while a SINR-based design service concentrating power on a smaller number of subcarriers. In [2] Coexistence is formulated as a joint optimization of communication power distribution and radar estimation accuracy in a multiple-access channel model. At the radar receiver, a cascade interference cancellation (SIC) algorithm is designed to repeatedly separate the returned radar signals and decode the communication signals, effectively reducing crosstalk. In the communications domain, transmission contrast is optimized via a two-dimensional space-filling algorithm across both frequency (spectrum-splitting) and spatial eigenmodes, maximizing data rate under power constraints. The result is a multiple-access (MAC) performance frontier that jointly characterizes the radar estimation rate and communication throughput, exhibiting superior trade-offs compared to isolated operation. In [14] authors formulates coexistence as a joint optimization problem, where the variables are the radar transmit power, the radar receive filters, and the communications codebook covariance matrix. The goal is to maximize the mutual information of the communications system while ensuring that the radar achieves the lowest signal-to-disturbance ratio (SDR) at each resolution cell under clutter. Because the problem is non-convex, the authors use a block-coordinate ascension (alternating maximization) approach: each variable is optimized in turn while holding the others constant. The results demonstrate that this joint design significantly improves communication rates and radar robustness compared to separate designs, especially under severe clutter conditions.

3.3. *Joint Radar–Comms Co-Design / Alternating Optimization*

The radar-communications co-design approach approaches the problem as a single, intertwined system. The radar transmit waveform/modulator, the radar receive filter, and the communications transmit heterodyne/modulator are redesigned simultaneously to achieve a dual goal: enhancing radar performance (typically by increasing detection quality or SINR) while maintaining communications quality of service (rate or reliability) within power, interference, and waveform similarity constraints. Because the interaction between these variables generates a highly correlated, non-convex problem, the Alternating Optimization (Block-Coordinate) framework is adopted: a set of variables is fixed, a third is optimized, and the roles are then swapped periodically until monotonic convergence is achieved. In practice, the sub-problems are solved using standard convex tools such as SDP/SOCP/SDR for the transmit layer and closed or semi-closed formulations for the receive filter, with the possibility of introducing clutter models and waveform similarity constraints to preserve the radar beam geometry. This approach is distinguished by the fact that it does not merely eliminate interference or shape the spectrum, but rather balances the two ends of the system in design through a single objective function and shared constraints, enabling the coordinated exploitation of spatial, temporal, and spectral degrees of freedom. In [15] formulates coexistence as a joint optimization problem, where the variables are the radar transmit power, the radar receive filters, and the communications codebook covariance matrix. The goal is to increase the mutual information MI of the communications system while ensuring that the radar achieves the lowest signal-to-disturbance ratio (SDR) at each resolution cell under

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ISSN -2708-3985

clutter. Because the problem is non-convex, the authors use a block-coordinate ascension (alternating maximization) approach: each variable is optimized in turn w formulates coexistence as a joint precoder–covariance optimization under clutter. The objective is to maximize radar SINR while guaranteeing communication rate and power constraints. Because clutter depends nonlinearly on the radar precoder, the original problem is highly non-convex. To make it tractable, the authors optimize a lower bound on SINR using an alternating optimization algorithm: the communication covariance update is solved via one SDP, while the radar precoder update shown to admit a rank-one solution is solved through a sequence of more efficient SOCP problems. This optimization balances interference protection and clutter suppression, enabling robust radar–communication coexistence. In [16] paper develop coexistence in chaos as a joint optimization across three variables: the radar's spatial-temporal transmission waveform, the radar's receive filter, and the communications transmission contrast. The goal is to maximize the radar's signal-to-noise ratio (SINR) while attach to the communications rate and power constraints of both systems, with the addition of a waveform similarity constraint to keep the radar code close to the reference. Because chaos makes the problem non-convex, the authors use an alternating optimization: updating the communications contrast via convex programming, updating the radar's receive filter in a closed-form SINR, and then updating the radar code with an executable reformulation iteratively to monotonic convergence. The result is a chaos-aware joint design that significantly improves SINR robustness and coexistence compared to partial designs. In [17] formulates coexistence as a non-convex joint optimization of three design variables: the radar transmit waveform, the radar receive filter, and the communications transmit covariance matrix. increasing the communications throughput while maintaining the required radar signal-to-noise ratio, enforcing waveform similarity, and meeting power constraints is the objective of paper. Because the problem is non-convex, the authors developed an alternating optimization AO framework: using two fixed variables, the third optimizes in turn the communications covariance is updated through a convex logarithmic detection program, the radar filter is updated using a closed-form expression to maximize the signal-to-noise ratio, and the radar waveform is optimized through semi-definite relaxation with first-order recovery. This iterative process converges monotonically, and the results demonstrate that the joint design achieves higher communications throughput without compromising radar detection, outperforming single-sided (radar-only or communications-only) designs. In [18] Coexistence is treated as an optimization for interference reduction. Using matrix completion (MC) radar sampling, the communication system designs transmission contrast matrices to minimize the effective interference power (EIP) at the radar receiver, taking into account average capacity and power constraints. Two optimization strategies are proposed: a non-cooperative approach, in which only the overall interference is minimized, and a cooperative approach, in which the radars share their sampling scheme, allowing for more precise interference suppression. Furthermore, a joint optimization of radar sampling and communication contrast is proposed, solved through alternate optimization, which significantly reduces the effective interference power while ensuring the feasibility of matrix completion. In [19] A joint optimization framework is presented that designs three components: the communication transmission covariance matrices , the radar transmission precoder and the radar subsampling scheme. The goal is to rising the effective signal-to-noise ratio (SINR) of the radar while satisfying communication rate and power constraints. Because the problem is non-convex, the authors propose an alternating optimization algorithm that sequentially solves the communication covariance (a convex subproblem), the radar subsampling (via allocation optimization using a Hungarian algorithm), and the radar transmission precoder (via sequential convex programming and SDP). This iterative scheme ensures monotonic convergence and shows that MIMO-MC radars, cheers to sparse sampling, can coexist more efficiently than conventional MIMO radars, saving up to 60% of data samples.

3.4. Subspace / Power Mixing Beyond NSP, IA AND NOMA

This approach goes beyond the limitations of zero-space projection through two central concepts: interference alignment (IA) and power-domain mixing with cascade cancellation (NOMA + SIC). In IA,

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ISSN -2708-3985

the transmit and receive spaces are reconfigured so that interference components are packed into a low-order space at the receiver, freeing up a clean dimension(s) for useful signal transmission. The essence of optimization here is to minimize the “order of the interference space” while preserving communication degrees of freedom and radar diversity. In [20] proposes an interference alignment (IA)-based joint optimization of pre-encoders and decoders for spectrum sharing. The basic idea is to minimize the rank of interference subspaces so that radar and communication signals occupy orthogonal spaces without overlapping. To ensure system performance, this optimization involves two main constraints: the multiplexing gain for communication users and the diversity order for radar users. Since direct rank minimization using rank and norm constraints is non-convex and NP (non-deterministic polynomial-time) hard , the problem is reduced to a fissile norm minimization with convex matrix inequality. The solution is obtained through mutual optimization, repeatedly updating the pre-encoders and decoders until convergence. Analytical estimation using GLRT and ML estimation confirms that using quasi-unitary encoder-decoder matrices and feasible IA, radar detection performance approaches the non-interference state, while communication achieves the desired spatial degrees of freedom. In [21] presents a cooperative NOMA scheme, in which the cellular base station redirects the radar signal and transmits user data simultaneously by superimposing them in the power band. At the receiver, cascade interference cancellation (SIC) is applied to separate the radar and communication signals. The optimization problem essentially consists of allocating the power parameters α_0, α_1,…, α_K, where α_0 dominates the radar component, and the remaining parameters dominate the user data. A high α_0 improves the radar detection probability, while a low α_0 reduces the outage probability and increases the total communication throughput. The paper derives closed-form outage probabilities and achievable rate bounds to attendant the selection of these parameters, demonstrating that appropriate power-allocation optimization leads to a balanced operating point where both radar detection and communication throughput are significantly improved compared to conformist NSP or zero-power designs. In [22] A unified framework called IACRS is presented, in which radar and aviation communications share spectrum using a MIMO architecture. Inspired by non-orthogonal multiple access (NOMA), the system synthesizes radar and communications signals into a power domain and uses cascade interference cancellation (SIC) at the receiver to mitigate inter-functional interference. The fundamental challenge is a joint optimization problem: maximizing a weighted sum of communications throughput and radar sensing quality (measured by SCNR) while meeting minimum data rate requirements, radar detection thresholds, and transmit power limits. Because the problem is non-convex and has tightly coupled variables, the authors propose an alternating optimization algorithm AO that decomposes it into two subproblems: base station transmit beamforming with power allocation, and airborne receiver beamforming. To address the non-convex first-order constraints, they develop a penalty-based method and a successive first-order constraint relaxation (SROCR) scheme. The results confirm that this integrated NOMA-inspired design significantly improves aerial communications reliability and radar sensing performance compared to standard schemes.

3.5. *RIS & Learning-Driven Designs / AI METHODS*

This approach address the coexistence of radar and communications across three intertwined design layers: a communications modulator, a radar waveform, and a reconfigurable intelligent surface (RIS) that modulates the phase of reflections in a controlled manner. The main point of the matter here is extreme non-convexity with strict practical constraints (RIS element uniformity, interference limits to radar, waveform similarity, and power budgets), making traditional optimization methods prohibitively complex or slow in dynamic environments. Therefore, convex approaches are being replaced or supplemented by learning methods: (1) Deep Reinforcement Learning (DRL) to learn continuous policies that jointly adjust the transmitter, RIS, and waveform; (2) Meta-Reinforcement Learning (Meta-RL) to accelerate adaptation to changing channels and scenarios by leveraging past experience; and (3) Unsupervised Learning based on neural networks to generate phase-coded waveforms that balance radar orthogonality and spectral notching without the need for supervisory data.this approach offer a balanced performance trade-off between radar detection quality and communication service quality in the presence of RIS. In [23] paper studies spectrum sharing as a joint optimization problem, where the communications precoder, radar waveform, and phase configuration of a smart reconfigurable surface (RIS) are designed together. The goal is to maximize the mutual information of the communications system while ensuring that the overall transmission power is consistent, that the RIS elements satisfy the unity parameter condition, that the radar-directed interference remains below a certain threshold, and that the radar waveform is similar to the desired reference. Because this problem is highly non-convex, traditional convexity optimization tools are ineffective. Instead, the authors employ deep reinforcement learning (DRL), specifically the deep deterministic policy gradient (DDPG) and double-delayed deep deterministic policy gradient (TD3), which enable the exploration of continuous decision spaces and the incremental learning of efficient transmission and reflection strategies. The results demonstrate that DRL, especially DDPG, can find solutions that maximize communication throughput, while RIS minimizes interference of the base station-radar, achieving a strong balance between radar detection and communication performance. In [24] paper addresses the coexistence issue by formulating a joint optimization problem for the cellular precoder, the radar transmission waveform, and the phase shift matrix of a reconfigurable smart surface (RIS). The goal is to maximize mutual communication information while adhering to power limits, radar waveform similarity, RIS unit coefficient constraints, and interference thresholds to protect radar performance. Since this optimization is highly non-convex, the authors employ meta-reinforcement learning (MRL), which relies on prior learning tasks to quickly adapt to new environments. Unlike traditional block coordinate descent (BCD) or standard reinforcement learning methods such as deep deterministic policy gradient (DDPG) and TD3 (double deferred DDPG), the meta-reinforcement learning approach reduces training costs and converges faster. Simulation results confirm that combining deep reinforcement learning (MRL) with RIS deployment reduces interference from the base station to the radar and improves data rates, achieving better trade-offs compared to traditional and other deep reinforcement learning-based methods. Difference between the two studies is that the study [22] relies on traditional deep reinforcement learning algorithms (DDPG and TD3) to solve the non-convex spectrum sharing optimization problem between radar and communications using RIS systems, while the [23] study makes significant progress through deep reinforcement learning (Meta-RL), which leverages past learning experiences to adapt more quickly to new environments and channel conditions, reducing training time and improving solution efficiency while maintaining the same goal and constraint optimization framework. In [24] proposes designing phase-coded, fixed-parameter MIMO radar waves for spectrum sharing by training a solution mapping network (SMN) end-to-end using unsupervised learning. Instead of manually organised solutions, the SMN outputs phase codes whose loss is defined as a weighted combination of three terms: the peak sidelobe level (PSL), the integrated sidelobe level (ISL), and a spectrometer that penalizes power within the split (forbidden) bands. The paper explicitly states that this formulation is minimal, non-convex, and NP-hard, motivating the use of learning as a practical alternative. Architecturally, the SMN uses parallel convolutional blocks (conv–ReLU–pool) followed by fully connected layers; random sequences are fed, phase codes are produced, and an Adam optimizer is used to minimize the unsupervised loss. Experiments confirm that the network can successfully sculpt spectral notches while maintaining waveform verticality, highlighting the balance between verticality (PSL/ISL) and spectral suppression (SM). In [25] When radar and communication systems encounter sparse multipath propagation, the main challenge is to exploit useful nonlinear echoes for radar detection while keeping interference to the communication link under control. To address this, the authors formulated waveform design as an optimization issue that maximize the radar's signal-to-noise ratio (SINR) while sufficient constraints on communication rate, transmission power, and waveform similarity to a reference signal. Since the problem is highly non-convex due to the multipath structure and the fractional target, they developed a suboptimal algorithm using successive convex approximation (SCA) and semi-definite programming

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ISSN -2708-3985

(SDP). This iterative approach gradually optimizes the radar waveform until convergence. The results demonstrate that by combining the multipath returns through optimized waveforms, the radar achieves stronger detection performance while maintaining communication quality [26]. Figure (2) shows Interference Channel and Optimization Methods. Table (1) provide the overall review of Optimization Methods.

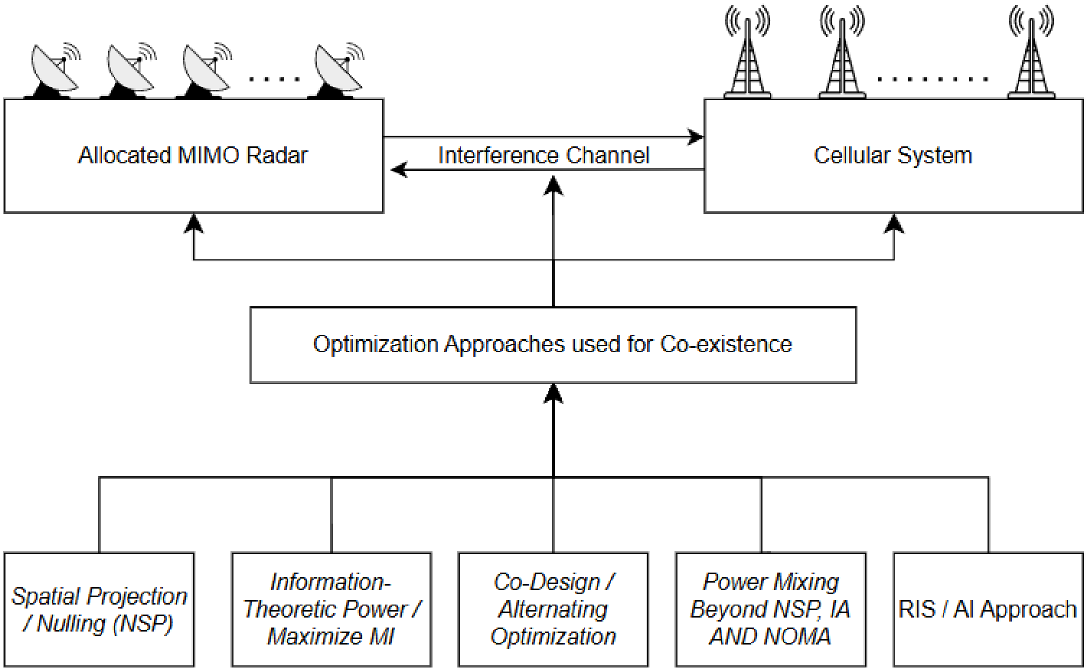

Fig. 2. Block Diagram of Interference Channel and Optimization Methods for MIMO Radar–Communication Spectrum Sharing

Table 1. Comparative Table of Spectrum Sharing Research Between MIMO Radar and Cellular System

Ref	Optimization Approach	Algorithm Used	Contribution	Research Gap
[2]	Power & covariance allocation (multi-access view)	Successive Interference Cancellation (SIC) + 2D water-filling	Introduced a Multiple-Access Channel (MAC) perspective for radar–comms sharing; joint formulation with SIC decoding	Assumes perfect CSI and ideal MAC; does not consider practical fading or partial CSI
[5]	Beampattern design + Null-Space Projection (NSP)	FACE mapping + spherical parametrization	Integrated radar beampattern shaping with NSP to protect LTE/WiMAX	Limited to perfect CSI; no robustness to fast-varying channels
[6]	Null-Space Projection	SVD-based projection	First proposal of NSP for spectrum sharing to null radar interference	Ignores clutter and partial CSI; assumes static channel
[7]	Channel selection + NSP	SVD + best-channel selection	Selects the interference channel with largest null-space dimension to minimize radar loss	No channel variation or mobile LTE

[8]	NSP with detection analysis	GLRT detection framework	Analyzed impact of NSP on radar detection performance (Pd/Pfa)	Provides no alternative when null-space is too small
[9]	Overlapped-MIMO + NSP	Combinatorial subarray search + SVD	Introduced overlapped-MIMO structure to enlarge effective null-space for NSP	Increases complexity; no validation under realistic fading
[10]	Switched NSP / SSVSP	Null-space & small-SV subspace switching	Proposed switched projection between true null-space and small-SV subspace for robustness	Computationally heavy; challenging for real-time operation
[11]	Information-theoretic PSD allocation	Convex optimization (PSD shaping + cyclic projection)	Maximized mutual information with interference spectral masks	No consider multipath fading or partial CSI
[12]	OFDM subcarrier power allocation	Water-filling + linear programming	Designed power allocation across OFDM carriers to balance MI and interference protection	No fully address waveform similarity constraints
[13]	Information-theoretic (MI in clutter)	Block coordinate ascent	Maximized communication MI under per-cell SDR constraints in cluttered radar channels	Assumes full CSI; does not treat partial or uncertain channels
[14]	Joint radar–comms co-design (SINR + rate)	Alternating optimization (SDP/SOCP)	Jointly optimized radar SINR with comms QoS under clutter	High computational complexity; limited real-time feasibility
[15]	Joint waveform/filter/covariance	Alternating optimization	Recent co-design balancing radar SINR and comms QoS	No robustness analysis for fast-varying or incomplete CSI
[16]	Joint SINR–rate optimization	Alternating maximization + SDR	Improved comms rate while preserving radar SINR	Relies on convex relaxations with high computational cost
[17]	Matrix Completion + precoding	Alternating optimization	Introduced matrix completion for radar with precoder co-design	Strong sparsity assumption; sensitive to incomplete CSI
[18]	Joint sampling + precoding	Hungarian assignment + SDP	Combined radar subsampling with comms covariance optimization	Heavy complexity; requires centralized solver
[19]	Interference Alignment (IA)	Nuclear norm relaxation + alternating optimization	Applied IA to minimize interference subspace rank	Needs perfect CSI; fragile to channel mismatch
[20]	NOMA power allocation	Closed-form outage analysis + SIC	Introduced cooperative NOMA-based sharing balancing radar Pd and comms sum-rate	Depends on perfect SIC; performance degrades with noise
[21]	NOMA-inspired joint beamforming	Alternating optimization + SROCR (rank relaxation)	Proposed integrated design (IACRS) using NOMA-like superposition and SIC	Needs practical validation in airborne fading scenarios
[22]	Joint radar/comms/RIS optimization	Deep Reinforcement Learning (DDPG/TD3)	Used DRL to jointly tune radar waveform, comm precoder, and RIS	Sample efficiency and training stability remain challenges
[23]	RIS + Meta-RL	Meta-reinforcement learning	Achieved faster adaptation of RIS phases and precoders	Limited experimental validation; focus on simulation

[24]	**Neural phase-coded waveform design**	**Unsupervised CNN solution mapping**	**Generated constant-modulus, phase-coded radar waveforms with spectral notches**	**Still experimental; lacks hardware validation**
[25]	**Multipath-aware SINR waveform design**	**Successive convex approximation + SDP**	**Designed SINR-oriented radar waveform exploiting multipath**	**High complexity; not suitable for real-time scenarios**

4. CONCLUSIONS

Recent studies of coexistence methods between radar and communications systems have shown that formulating the problem as an optimization problem is the most effective path to achieving coexistence without sacrificing the performance of either system. Approaches have progressed from traditional solutions based on null-space projection to more complex models such as information-theoretic optimization and joint co-design using reciprocal optimization algorithms, to more advanced techniques such as interference alignment, power domain spectrum sharing (NOMA), and modern designs supported by reconfigurable smart surfaces (RIS) and deep reinforcement learning (DRL/Meta-RL) algorithms. Some research has also addressed practical scenarios such as multipath channels or missing channels, which are addressed using matrix completion methods. These developments reflect the field's transition from idealized models assuming full CSI and simplified Rayleigh channels to more realistic environments involving Rician LoS, clutter, and practical constraints such as spectral similarity or power. Based on this, it can be argued that the future direction revolves around integrating artificial intelligence and machine learning tools with classical optimization frameworks to reduce computational complexity and accelerate the achievement of near-optimal solutions in dynamic and complex environments. Furthermore, the integration of rigorous mathematical models and data-driven learning will provide a more flexible platform for addressing new challenges in coexisting radar and communications systems, especially with the increasing demand for radio spectrum for future applications such as airborne radars, autonomous vehicles, and 6G networks.

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