Optimizing Integrated Sensing and Communication (ISAC)

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Abstract

This report presents a comprehensive investigation into resource allocation strategies within Integrated Sensing and Communication (ISAC) systems, with a particular focus on optimizing antenna distribution between radar sensing and data transmission tasks. The study evaluates how beamforming can be utilized to control signal direction and improve overall system efficiency.

To achieve this, two algorithmic approaches were implemented: a convex optimization method (CVX) for accurate and optimal antenna allocation under strict constraints, and a Greedy heuristic algorithm designed for faster computation under limited processing resources. The performance of both methods was evaluated through MATLAB-based simulations, analyzing their effectiveness under varying sensing and communication thresholds, power levels, and path loss conditions.

The results highlight the trade-offs between computational complexity and solution accuracy, providing insight into the practical deployment of ISAC systems in real-world wireless networks. The report concludes with a discussion on possible improvements, including the integration of advanced multi-objective optimization techniques and adaptive algorithms for dynamic environments.

Key words: Integrated Sensing and Communication (ISAC), Beamforming, convex optimization (CVX), Greedy algorithm, resource allocation, radar sensing, wireless communication, multi-objective optimization, robustness, computational efficiency, real-time systems.

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List of Abbreviations

BER – Bit Error Rate

BPSK – Binary Phase Shift Keying

CVX – Convex Optimization Solver

ISAC – Integrated Sensing and Communication

MIMO – Multiple-Input Multiple-Output

MISO – Multiple-Input Single-Output

SIMO – Single-Input Multiple-Output

SISO – Single-Input Single-Output

MRT – Maximum Ratio Transmission

MRC – Maximum Ratio Combining

SNR – Signal-to-Noise Ratio

RCS – Radar Cross Section

ULA – Uniform Linear Array

AWGN – Additive White Gaussian Noise

PL – Path Loss

Q(x) – Q-function (Gaussian Tail Probability Function)

B_s – Sensing Bandwidth

B_u – Communication Bandwidth

E_b/N_0 – Energy per Bit to Noise Power Spectral Density Ratio

P_s – Transmit Power for Sensing

P_u – Transmit Power for Communication

H_s – Sensing Channel Matrix

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CHAPTER 1 - Introduction

1.1. Background

Integrated Sensing and Communication (ISAC) represents an innovative approach to wireless networking, gaining increasing recognition as a key technology for future wireless network development. ISAC integrates the previously independent functions of communication and sensing into a single, unified system. Traditional communication technologies focused on improving data transmission capabilities, maximizing spectral efficiency, and maintaining reliable operations with minimal latency. Meanwhile, radar-based sensing technology developed independently to provide accurate detection and precise location determination, ensuring robust performance in diverse environmental conditions. These separate developments led to the creation of specialized networks that operated independently from one another [1-6].

The evolution of 5G technology, marking the beginning of the fifth generation of wireless networks, laid the foundation for the development of 6G technologies, which aim to combine data monitoring and communication systems into a unified framework. This convergence is driven by the growing demand for data-intensive applications in sectors such as autonomous driving, smart cities, intelligent transportation, and industrial IoT systems. These environments increasingly require high-speed communication systems coupled with precise, real-time sensing capabilities. For example, autonomous vehicles rely on highly accurate environmental perception systems, which must be integrated with reliable communication networks to ensure safe operations. Similarly, smart cities are using synchronized sensing-communication platforms to optimize traffic flow, manage energy resources, and ensure safety.

However, the application of ISAC technologies faces several challenges, primarily due to the conflicting requirements of sensing and communication functions. Communication systems demand reliable connections, high data rates, low latency, and strong resistance to interference, while sensing systems require accurate target detection, precise spatial awareness, and resilience to environmental disturbances. To address these challenges, effective resource management techniques–such as spectrum control, antenna engineering, and power regulation–are necessary to meet the varying performance demands of both communication and sensing systems [7].

Beamforming technology plays a critical role in optimizing resource allocation within ISAC systems. By using antenna arrays and advanced signal processing algorithms, beamforming allows for the precise steering and control of electromagnetic signals. This capability improves reception power, reduces interference, and maximizes resource utilization. As wireless environments become increasingly dense and complex, beamforming has become even more essential, enabling dynamic and efficient resource allocation in ISAC systems.

1.2. Objectives and Significance

The primary goal of this thesis is to investigate and implement specialized beamforming techniques for ISAC systems. This study focuses on a scenario involving 12 antennas, 4 transmitters and 8 receivers used for radar sensing and uplink communication. The research defines measurable performance limitations related to communication reliability and sensing accuracy in order to evaluate the effectiveness of resource management strategies. CVX optimization techniques are employed to identify optimal antenna resource distributions and transmit power levels, achieving an effective balance between reliable communication and accurate sensing.

In addition to CVX optimization, the thesis introduces the Greedy algorithm as a complementary optimization method. The Greedy algorithm offers a computationally efficient alternative, enabling real-time performance and addressing resource constraints, particularly in comparison to the more computationally intensive convex optimization approach. This research conducts simulation tests to compare the results of CVX optimization, which provides an ideal solution, with the Greedy algorithm, which offers efficient, albeit approximate, solutions. This comparative analysis provides valuable insights into the advantages and limitations of both methods.

The research further investigates how key factors–such as communication and sensing limits and transmit power–affect ISAC system performance. Numerical simulations are conducted to explore how variations in these parameters influence system efficiency, reliability, and robustness, providing practical guidelines for ISAC deployment in real-world applications.

In conclusion, the thesis highlights the current limitations of ISAC research and suggests potential directions for future studies. The introduction of channel state information (CSI) robust optimization and multi-objective optimization methods is recommended to better handle the trade-offs between communication and sensing performance. These advancements will support the continued development and implementation of ISAC technologies, positioning them as essential for next-generation wireless communication and environmental sensing systems.

CHAPTER 2 - Literature review

2.1 Overview of ISAC Technologies

ISAC combine the previously separate functionalities of communication and radar sensing, creating a unified structure that addresses the growing needs of modern applications. As wireless technology evolves, ISAC systems have emerged as a solution to challenges presented by high-speed communication and real-time sensing demands in dynamic environments. This fusion of technologies has become essential due to its potential in driving next-generation networks such as 5G and beyond, which are heavily reliant on both accurate sensing and robust data transmission.

Traditional communication systems focused on maximizing spectral efficiency and minimizing response delays, while radar sensing systems aimed for high accuracy in target detection and environmental resilience. However, the convergence of these technologies in ISAC systems introduces new challenges, particularly in balancing the performance of both communication and sensing operations [8-12].

In this review, we explore the development, optimization techniques, and real-world applications of ISAC, focusing on how beamforming and resource allocation strategies can address these challenges.

The figure 2.1 illustrates the scenarios of use cases in ISAC. The environmental monitoring. Through ISAC satellites cooperate with environmental sensors to track weather conditions along with water pollution levels and atmospheric elements as well as natural calamities. Aim point improves both the accuracy of forecasts and quickens the speed of emergency response procedures. The smart home system follows people while recognizing movements and managing equipment and healthcare needs for securing comfort alongside safety as well as energy performance. The smart traffic, where ISAC provides immediate machine communication while identifying environmental factors to enhance both autonomous driving security and convoy coordination. The smart industry, where ISAC performs two important tasks in manufacturing by coordinating robot systems while facilitating virtual reality auctions real-time remote operations hazard detection and protected entry systems. Sensing as a Service processes user data together with communication channel information to enable smart city operations and precise data sharing and collaborative data handling. The space and drones. Through ISAC implementation satellites and UAVs receive enhanced abilities to perform surveillance operations and communication and rescue operations that deliver precise real-time data.

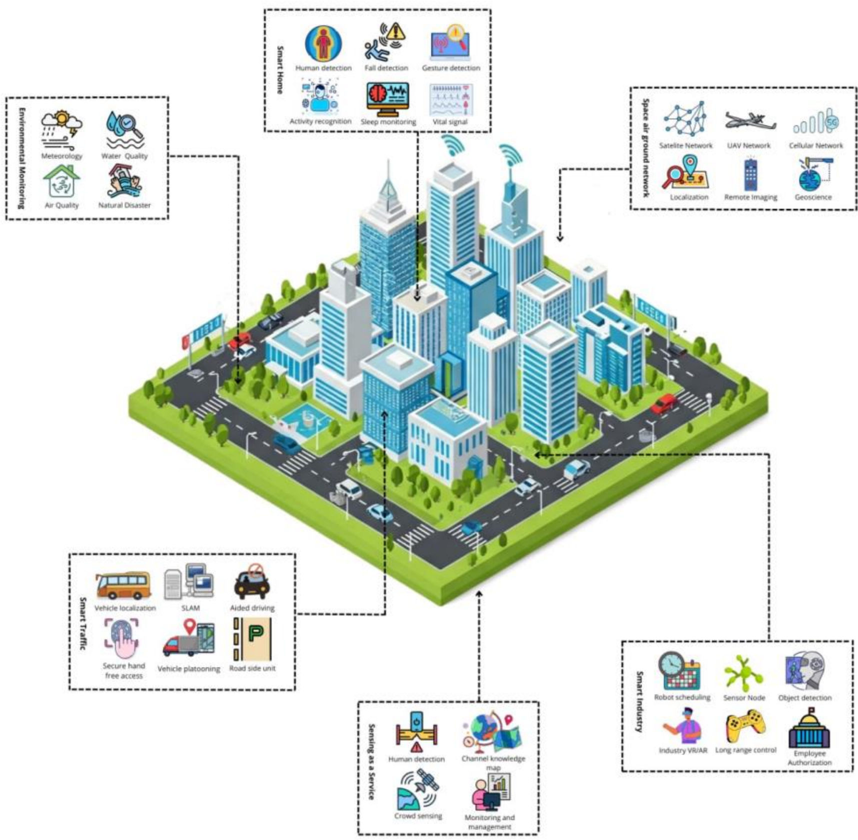


Figure 2.1: Uses cases of ISAC

Modern literature demonstrates substantial impact towards the clarification of ISAC systems alongside their operational methods. Meng et al. (2024) presents a research study about cooperative ISAC networks which use multi-cell cooperation to extend sensing areas while enhancing interference management. The system can acquire more detailed environmental data by deploying distributed sensing architectures according to their findings which reveal these critical advantages. The authors present a new set of measurement metrics called Cramér-Rao lower bound (CRLB) which allows network operators to evaluate and boost sensing performance in ISAC systems.

Rivetti, S. et al., "Secure Spatial Signal Design for ISAC in a Cell-Free MIMO Network" [38]. The research concentrates on producing safe ISAC solutions for cell-free Multiple Input Multiple Output (MIMO) networks. The figure 2.2 illustrates the Cell-free MIMO network where ISAC APs serve communication users while sensing an Eve.

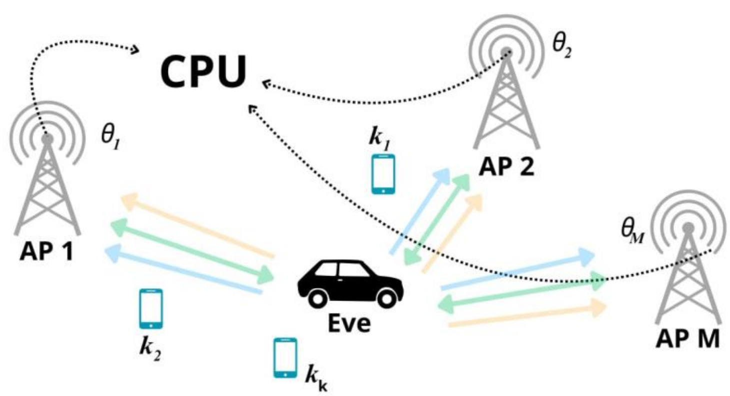


Figure 2.2: Cell-free MIMO network where ISAC APs serve communication users while sensing an Eve [38]

A waveform design for ISAC combines artificial noise (AN) for secret protection and preserves target detection while supporting efficient communication exchange. The authors employ semi-definite relaxation to reach a sensing-communication balance through optimization of the Cramer-Rao bound (CRB). Distributed ISAC access points integrated with cooperative artificial noise-based strategies present new solutions for an unexplored segment of ISAC operations. The paper presents a visible relationship showing how sensing outcomes interact with communication system capabilities. Semi-definite relaxation methodology enables effective solution of complex problems with proof of relaxed problem tightness under particular circumstances. The practical deployment of systems might be affected by eventual backhaul link errors because the proposed scheme relies on error-free conditions. The simulation uses only two access points within a limited network which could provide incomplete insights about bigger system performance. Research is required to evaluate how the approach performs with MIMO networks that have a large scale.

Zhong, K., et al., "Joint Waveform and Beamforming Design for RIS-Aided ISAC Systems" [59]. A MIMO-based ISAC system with reconfigurable intelligent surfaces (RIS) incorporates simultaneous optimization of waveforms and passive beamforming techniques according to the manuscript. The figure 2.3 shows RIS-aided ISAC System Model.

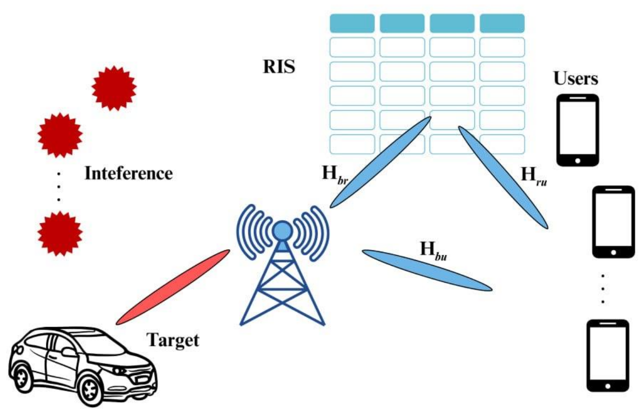


Figure 2.3: The RIS-aided ISAC System Model [59]

The authors resolve the fractional Signal to Interference Noise Ratio (SINR) problem using Block Coordinate Descent (BCD) that executes Element-wise Closed-Form (ECF) procedures aided by Dinkelbach's optimization. The timing of RIS integration with ISAC systems stands optimal because the system performs exceptionally well by diminishing multi-user interference

(MUI). The solution becomes efficient through the combination of BCD method with ECF methods for computational optimization. The proposed research design manages radar SINR and communication signal interference to display superior results than standard methods. Using simulations with established snapshot count parameters and restricted scenario limitations these researchers establish conditions to generalize their research data. The research omits a discussion on how the performance of the system gets affected by element breakdowns in RIS or environmental drifts. The evaluation strength needs better validation through the execution of extra analysis using industry standards during testing.

Leyva, L., et al., "MU-MIMO and Multi-Beam ISAC Hybrid Beamforming Design" [22]. The proposed design combines analog and digital (HAD) beamforming methods to serve ISAC functions in MIMO systems with multiple users and beams. The authors develop a direct design procedure that solves both communication performance requirements and radar requirements by an iterative optimization framework instead of traditional two-stage methods. The figure 2.4 illustrates The considered multi-user/multi-beam ISAC scenario. An ISAC transmitter BStx jointly communicates with K single-antenna UEs and steers Q RSbs for target detection [22].

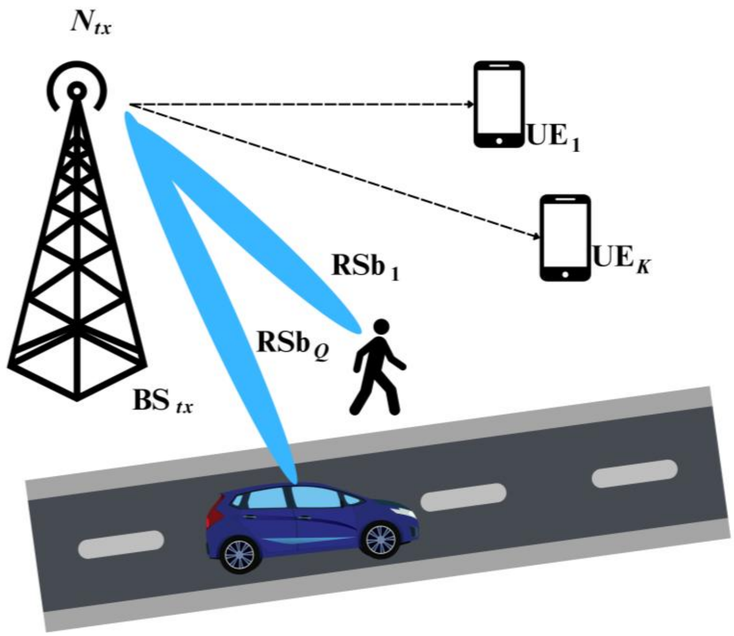


Figure 2.4: The considered multi-user/multi-beam ISAC scenario. An ISAC transmitter BStx jointly communicates with K single-antenna UEs and steers Q RSbs for target detection [22]

Through its proposed methods the approach secures constraint maintenance throughout the optimization process while bypassing traditional two-stage method weaknesses. Weighted sum-rate maximization provides both user resource fairness and better utilization of available resources. Simulation output matches almost identically to complete digital precoder capabilities thus proving this approach's effectiveness. A rising computational complexity level in iterative optimization methods might create obstacles when implementing real-time use. Complete CSI assumptions become a constraint on deployment potential because errors in CSI measurements will impact practical system performance. The paper should provide expanded HAD technique comparisons across various deployment situations.

Kim and Jeong (2024) present secure cell-free ISAC designs for addressing security issues in such systems by optimizing both beamforming and fronthaul compression elements [21]. Their system solution directly solves information disclosure and privacy problems which emerge through the unified sensing and communication operations. Signal processing approaches that integrate both semidefinite relaxation (SDR) and minorization-maximization (MM) methods with optimized beamforming enhance security in communication alongside sustained accurate sensing operations across fronthaul capacity limitations. Literature maintains that beamforming stands as a fundamental enabling capability which operates within systems of ISAC. Antenna arrays in beamforming systems use proper signal manipulation techniques to precisely guide communication signals to receivers while blocking out unwanted disturbances [19]. The technical developments in beamforming procedures through hybrid and digital approaches improved directional signal control systems that make ISAC practical for complex wireless systems in crowded areas.

Current research investigates the key performance trade-offs present in ISAC systems which determine how communication quality competes against sensing precision levels. The trade-off exists in a difficult manner because enhancing one aspect demands diminishing the other because resources remain limited. Multiple optimization frameworks receive increasing attention because they allow explicit control of sensing precision against communication performance conflicts. The Pareto optimality analysis framework enables professionals to discover ideal compromise solutions through visualization for optimal deployment of practical ISAC systems.

In the table 2.1 Thematic Reference Table. In order to systematize and analyze the sources used in more depth, a thematic table was compiled, combining more than 50 scientific papers on ISAC. All sources were grouped using machine learning methods based on text analysis (TF-IDF and KMeans clustering). Each group adheres to a specific topic within ISAC - from wave design and optimization of architectural solutions and development progress. For each group, the numbers of the corresponding sources and short summaries describing the key focus of research in this category are indicated. This allows you to quickly identify thematic blocks and use sources by definition when describing the theoretical basis, comparative analysis and developing your own methodologies. This table serves as a bridge between the literature review and the implementation of the project, forming the basis for an informed choice of technologies, methods and architectural solutions.

Table 2.1: Thematic Reference Table

Theme	References	Summary
RIS and Spectrum-Efficient Architectures	[24], [25], [31], [38], [42], [55], [60]	This group focuses on RIS and how they improve spectral and energy efficiency in ISAC systems. The works emphasize joint optimization for sensing and communication in RIS-assisted environments.
Waveform Design and Signal Processing for ISAC	[5], [8], [13], [16], [18], [26], [28], [30], [33], [36], [44], [45], [47], [48], [49], [51], [53], [59]	These papers are centered around waveform design, particularly OFDM and other signal processing strategies tailored for simultaneous communication and sensing. Emphasis is on low-latency, reliable and spectrally efficient waveform structures.
Aerial ISAC and Advanced Applications	[1], [2], [6], [7], [10], [11], [17], [19], [21], [22], [23], [35], [37], [39], [41], [43], [46], [50], [52], [54], [57], [58]	This cluster collects works that explore advanced applications of ISAC, including aerial platforms like UAVs and satellite systems. It emphasizes wide-area coverage, mobility challenges, and sensing reliability in dynamic environments.
Localization, Positioning and Tracking in ISAC	[3], [12], [27]	Research here is dedicated to joint localization, positioning, and tracking within ISAC systems. These sources explore high-precision ranging, multi-point triangulation, and spatial awareness through ISAC.
General Architectures and Frameworks for ISAC	[4], [20], [32], [34], [40], [56]	This group contains foundational works that propose architectural designs and theoretical frameworks for building robust ISAC systems. Topics include ISAC hardware, baseband processing integration, and system-level tradeoffs.
ISAC as a Service and Network-Level Integration	[9], [14], [15], [29]	This group explores the concept of Sensing-as-a-Service and the integration of ISAC in next-generation networks like 6G. It focuses on architectural strategies, multi-level coordination, and the realization of ISAC in large-scale infrastructure deployments.

The literature review demonstrates that research opportunities together with critical gaps emerge during ISAC evaluation. The incorporation of robust optimization methods handles the measurement errors in channel state information which occur during real communication and sensing operations. Multi-objective optimization techniques serve as a target subject for future research because they develop explicit algorithms to strike equilibrium between sensing accuracy and communication performance parameters. Research advancements create a solid foundation for future studies while showing ISAC to be an essential foundational technology which meets complex requirements of next-generation wireless communication systems and radar sensing structures. Research into ISAC technologies today solves present challenges while creating new opportunities for wireless network innovations that lead to ongoing development of wireless capabilities.

2.2 Beamforming in ISAC

Beamforming plays a pivotal role in ISAC systems by dynamically steering radio signals to maximize power reception in targeted directions while suppressing interference. This is achieved through the coordinated control of signal amplitude and phase across antenna arrays, creating constructive interference toward intended receivers and destructive interference elsewhere. The result is enhanced spectral efficiency and robust communication performance. The primary value of beamforming within ISAC lies in its ability to support simultaneous radar sensing and data communication, enabling efficient real-time resource sharing. Depending on implementation strategies, beamforming can be divided into three main categories: analog, digital, and hybrid.

Analog beamforming utilizes analog phase shifters to adjust signals, offering low energy consumption and simple, cost-effective implementation–especially beneficial for mmWave systems [2, 6, 18, 20]. However, its static configuration limits responsiveness to dynamic environmental changes. Digital beamforming, in contrast, applies digital signal processing to each antenna element individually, providing high precision and flexibility for real-time channel adaptation. This approach, however, demands substantial computational power and advanced hardware, resulting in higher energy costs [21, 32, 49, 54, 59]. Hybrid beamforming seeks to balance these trade-offs by integrating both analog and digital components, combining the flexibility of digital processing with the energy efficiency of analog circuits [22, 39].

The choice of beamforming method depends on system constraints, performance requirements, and available hardware resources. In wireless communication systems, especially those utilizing MIMO and Multiple Input Single Output (MISO) architectures, beamforming enhances throughput and signal quality by increasing the signal-to-noise ratio (SNR). In radar sensing, beamforming improves object detection and localization accuracy, which is essential for applications such as autonomous driving and intelligent surveillance.

In ISAC contexts, where sensing and communication tasks are executed concurrently, beamforming must adapt to support real-time trade-offs between radar precision and communication reliability. It becomes essential for managing antenna resources and power allocation to maintain optimal system performance. Recent research has focused on optimizing beamforming for ISAC applications. Meng et al. (2024) proposed a base station collaboration technique that forms directed beams across multiple stations to extend range and reduce interference [19]. Kim and Jeong (2024) introduced a joint optimization method that combines beamforming with fronthaul compression to enhance both transmission quality and security, using SDR and MM techniques [21].

In terms of algorithmic optimization, CVX is widely used due to its ability to produce precise results. However, it is resource-intensive. Greedy algorithms, while less accurate, are computationally efficient and suitable for real-time applications. MM and SDR methods strike a balance by offering improved performance with additional security features. The selection of an appropriate beamforming optimization method depends on the trade-off between precision requirements and system resource limitations.

2.3. Resource Optimization in ISAC

Resource optimization is a critical requirement for the reliable operation of ISAC systems. These systems simultaneously perform dual functions—radar sensing and wireless communication–which must share the same limited system resources. Consequently, ISAC architectures face significant challenges such as limited spectrum availability, restricted transmission power, complex antenna array coordination, and mutual interference between sensing and communication modules. The objective of resource optimization is to efficiently allocate bandwidth, transmission power, and antenna elements to ensure both high-accuracy sensing and quality data communication, while maximizing energy efficiency and minimizing system cost [27].

2.3.1. Optimization Problems in ISAC

The design of optimization strategies for ISAC involves addressing a range of conflicting system requirements and operational constraints. The major challenges shows in table 2.2.

Table 2.2: Problems in ISAC

Problem	Description
Spectrum Scarcity [23, 39]	Sensing and communication share the same spectrum, which leads to interference and performance degradation if not carefully coordinated.
Power Constraints [20, 32, 37, 50]	Limited transmission power must be split between the two functions without sacrificing either detection accuracy or data throughput.
Antenna Allocation [8,46]	The total number of antenna elements is typically fixed, and their allocation must be dynamically adjusted to optimize the trade-off between directional sensing and beamformed communication.
Interference Management [17]	Simultaneous transmission of radar and communication signals can cause mutual interference, which reduces sensing precision and degrades communication quality.
Performance Trade-offs [31]	Sensing requires high spatial resolution, high signal-to-noise ratio (SNR), and low false alarm rates, while communication demands high data rates, low latency, and robust Quality of Service (QoS).

To address these challenges, ISAC systems must adopt optimization algorithms that can balance conflicting performance targets. For example, maximizing the radar detection accuracy may reduce the available power and beamwidth for communication, and vice versa. Effective optimization must ensure minimal cross-interference and dynamically adapt to changing environmental conditions and user demands. The core requirement is to design algorithms capable of jointly controlling spectrum use, power allocation, and antenna selection to meet both sensing and communication objectives simultaneously.

2.3.2. Optimization methods in ISAC

Multiple optimization approaches with methods exist for tackling the mentioned problems. CVX serves as a common optimization method because it determines globally optimal solutions. The power allocation and beamforming problems widely implement this method because it provides accurate and robust results [29]. Semidefinite Relaxation (SDR) serves as a conversion method for converting non-convex optimization challenges into solved convex optimization problems [43]. The problem transformation through this method reduces complexity of the initial problem while producing solutions that are highly comparable to optimal outputs. In ISAC systems, Greedy algorithms are often used in real-time resource management, especially for antenna power distribution between sensing and communication functions [51]. These algorithms are known for their speed and minimal computational complexity, which makes them ideal for dynamic conditions where fast decisions are required. Minorization-Maximization (MM) delivers efficient solutions for non-convex optimization through its iterative process that models local optimization [42]. This method is widely used because it handles significant data volumes besides attaining fast convergence rates [30]. The robust optimization technique handles all uncertainties and imperfections observed in CSI. The strategy enhances ISAC system reliability because it analyzes unpredictable CSI conditions alongside changing state information [31]. By using Pareto analysis with multi-objective optimization methods users can achieve simultaneous optimization of contradictory performance values between link quality and sensing accuracy balance points. Users receive combined information about performance metric interactions through a Pareto analysis structure that helps them make better decisions [48].

ISAC implements alternative optimization techniques that include CVX and Greedy with traditional methods because they enhance practical operations through improved computational efficiency and robust uncertainty performance. The mechanisms provide successful real-time solutions of optimization problems that function using limited processing power during environmental changes. Through substituting traditional approaches with alternative methods the full operational strength of traditional methods becomes possible for solving diverse modern ISAC system problems [33].

2.3.3. Convex optimization

Convex Optimization is one of the most widely adopted methods in ISAC systems due to its ability to provide globally optimal solutions for complex problems, such as beamforming and power allocation [10]. CVX works by transforming a non-convex optimization problem into a convex one, which is easier to solve mathematically. Convex problems are characterized by a single global optimum, making CVX an attractive option when high accuracy is required. In the context of ISAC, CVX is particularly useful for resource allocation, where it can be applied to the optimization of both sensing and communication resources. For instance, CVX is frequently used for beamforming optimization, where the goal is to steer signals in specific directions, improving signal reception and minimizing interference [29].

2.3.4. Greedy algorithms

A greedy algorithm performs its base operation by choosing subsequent local optimum solutions sequentially through sequential steps. The algorithm selects the most appropriate choice during each stage of operation as it makes decisions based on data but does not consider future outcomes. The methods employed by these algorithms succeed in quick executions and easy management yet the local selection strategy fails to provide best possible solutions [51]. Fast and effective ISAC antenna and power distribution is enabled by Greedy algorithms between sensors and communication elements. Such algorithms maintain exceptional value in dynamic conditions because they need minimal computational power for real-time problem solving. Real-time systems that use autonomous vehicles and unmanned aerial vehicles utilize Greedy algorithms because they provide the capability to make quick decisions [51].

2.4. Comparative analysis of optimization methods

The chapter delivers a thorough review of multiple optimization tools which power integrated sensing and communication systems. The assessment examines specific details regarding benefits along with restrictions and usage restrictions of each method. Each approach will receive proper consideration during final decision selection for problem solutions affecting ISAC systems [39]. Table 2.3 shows Advantages and limitations of the methods.

Table 2.3: Advantages and limitations of the methods

Name	Advantages	Limitations	Recommended Use
Convex Optimization (CVX)	Guaranteed global optimal solution. High accuracy and predictability of results. Strict mathematical validity and reliability of solutions.	High computational costs, which limits the application of the method in large systems. Inapplicability directly to problems with non-convex formulations.	Tasks with strict requirements for accuracy, high level of reliability and sufficient amount of computing resources.
Semidefinite Relaxation (SDR)	Possibility of solving non-convex problems by transforming them into convex ones. Providing a good approximation to the optimal solution in most practical	High computational load, especially in large-scale problems. The resulting solution may not always be close to the global optimum.	Moderate problems that require a balance between the quality of the obtained solutions and the computational costs.

	problems. Efficiency in problems of moderate complexity.		
Minorization-Maximization (MM)	Effective for working with non-convex optimization problems. Good convergence rate and moderate computational complexity. Possibility of solving large-scale problems.	Possibility of finding only locally optimal solutions. Risk of falling into local optima.	Tasks where the speed of finding an acceptable solution is important, for example, in dynamically changing conditions.
Greedy algorithms	Minimal computational complexity and high speed of implementation. Ease of implementation and high adaptability to changing environmental conditions.	No guarantees of global optimality. Lower quality of solutions compared to other methods.	Real-time applications where decision-making speed is critical and a possible reduction in decision accuracy is acceptable.
Robust optimization	High stability and reliability of solutions under uncertainty. Stability of system performance under environmental changes. Reduction of the risk of critical errors.	Significant computational complexity, which increases the calculation time. Conservative solutions due to optimization according to the worst-case scenario.	Tasks associated with high uncertainty of parameters and requiring reliable and stable operation of the system.
Multi-objective optimization and Pareto analysis	Possibility of simultaneous optimization of several conflicting criteria. Clear visualization of trade-off solutions. Improved quality of decision-making by taking into account various aspects of performance.	High computational complexity. The need for deep analysis of many possible solutions, which can make it difficult to make decisions quickly.	Complex multifunctional systems with conflicting criteria, where it is important to take into account many indicators simultaneously.

The analysis must take into account the specific advantages and limitations of each optimization method to select the most appropriate solutions for ISAC systems. SDR and CVX are most beneficial when high accuracy is required, as they provide reliable and precise results. However, these methods come with high computational costs, which may limit their applicability in large-scale systems or real-time environments. Minorization-Maximization (MM) is a viable alternative when quick solutions are needed, as it strikes a balance between computational efficiency and solution quality, especially for medium to large-scale problems. Greedy algorithms, combined with robust optimization techniques, offer fast, efficient solutions in dynamic and uncertain environments, where real-time decision-making is crucial.

For optimal performance in ISAC systems, a combination of CVX, Greedy algorithms, and Beamforming techniques is considered the most effective solution. Beamforming, when integrated with CVX for global optimization and Greedy algorithms for real-time application, provides a robust, resource-efficient approach that balances accuracy with computational efficiency, making it the top solution for addressing the complex challenges of ISAC systems. This hybrid approach leverages the strengths of each method to optimize both communication and sensing performance in real-world scenarios.

2.5 Survey on Perception and Perspectives of ISAC Technology

An analysis of the perception of ISAC among professionals and researchers was conducted using a structured questionnaire survey. The survey aimed to determine how relevant ISAC technology is among professionals and researchers, as well as their expectations and difficulties in adopting it as a future component of wireless systems. The survey was conducted at Nazarbayev University of Kazakhstan and Shanghai University of China. An explanation of ISAC was provided for general awareness. The study then collected 105 responses to the questionnaire, including professionals and researchers from different countries. Table 2.4 shows that the survey participants mainly worked in industry (45.7%) or academia (39%), but the rest held certain positions or worked in other fields. According to our survey results, ISAC research and implementation is of global interest, with participants representing China, the United States, Kazakhstan, India, and Japan.

Table 2.4: Participant Professions

Option	Subtotal	Ratio
Academic researchers (in the fields of communications/radar/artificial intelligence)	41	39.05%
Enterprise technology developers	14	13.33%
Industry managers (such as smart cities, transportation, industrial Internet of Things)	48	45.71%
Ordinary users (such as smart device users)	16	15.24%
Number of valid responses to this question	105	

The survey requested participant assessments regarding their knowledge about ISAC. Table 2.5 shows that 48.6% of participants had encountered information about ISAC while 20.9% had studied multiple scientific papers regarding it and 22.8% had no previous knowledge of ISAC. The participants who worked with ISAC systems were limited to 7.6 % of all respondents. The current data indicates that researchers and industry professionals are starting to notice ISAC yet its actual implementation remains at a basic level.

Table 2.5: ISAC Awareness Level Among Respondents

Option	Subtotal	Ratio
Very familiar (have participated in related projects or research)	8	7.62%
Somewhat familiar (have read technical materials)	22	20.95%
Only heard of	51	48.57%

Not familiar at all	24	22.86%
Number of valid responses for this question	105	

The survey identified the main obstacles encountered in ISAC deployment. Table 2.6 shows that hardware integration (48.6%) was the top challenge, while security issues (28.6%) and complex signal processing unification (20.9%) ranked next. The survey results are consistent with the current ISAC development environment, as physical integration is the top challenge.

Table 2.6: Responses to the Question: "What are the main technical challenges in implementing ISAC?"

Option	Subtotal	Ratio
Spectrum sharing conflicts between communication and perception	12	11.43%
Complexity of joint signal processing algorithms	22	20.95%
Hardware integration design (such as antennas, chips)	51	48.57%
Security (such as privacy protection, anti-interference)	30	28.57%
Lack of standardized protocols	8	7.62%
Number of valid responses to this question	105	

The study participants determined what they considered to be the most promising application fields for ISAC implementation. The data in Table 2.7 indicates UAV monitoring and control with 35.2% rank as top use cases alongside industrial IoT at 26.7% while autonomous driving and V2X hold 16.2% of the total selected cases. Detecting reliable data with low-latency response combined with solid communication capabilities remains crucial for these target areas.

Table 2.7: Responses to the Question: "Which areas will benefit most from ISAC deployment?"

Option	Subtotal	Ratio
Drone collaborative monitoring and communication	37	35.24%
Industrial Internet of Things (such as smart factory equipment interconnection)	28	26.67%
Autonomous driving and vehicle-to-everything (V2X)	17	16.19%
Smart city (environmental monitoring, security)	17	16.19%
Healthcare (remote surgery, vital signs monitoring)	6	5.71%
Number of valid responses to this question	105	

Vital ISAC features for users include both ultra-low latency communication with 29.5% interest along with high-accuracy positioning at 24.7%. Table 2.8 demonstrates that business demands focus on obtaining both real-time performance and dependable systems.

Table 2.8: Responses to the Question: "What are the main barriers to ISAC adoption?"

Option	Subtotal	Ratio
High-precision positioning (centimeter level)	11	10.48%
Real-time environmental perception (obstacle detection, terrain modeling)	26	24.76%
Ultra-low latency communication (<1ms)	31	29.52%

Energy efficiency optimization (extending device life)	25	23.81%
Multi-device collaboration (such as large-scale Internet of Things)	12	11.43%
Number of valid responses to this question	105	

The users showed apprehension about taking on ISAC adoption. The main obstacles preventing ISAC implementation according to Table 2.9 include privacy along with security risks (31.4%) followed by insufficient technological development (25.7%) and lacking standards (22.9%). The research shows that it is essential to launch regulatory, technical and educational programs which will support the deployment of ISAC systems.

Table 2.9: Responses to the Question: "What technologies and factors are most important for ISAC to succeed?"

Option	Subtotal	Ratio
Excessive hardware costs	24	22.86%
Inconsistent cross-industry standards	27	25.71%
User privacy and data security risks	33	31.43%
Insufficient technical maturity	27	25.71%
Conflicts in spectrum resource allocation	14	13.33%
Number of valid responses to this question	105	

The achieved success of ISAC depends on the technologies listed in Table 2.10 as essential components. Over four in ten professionals (43.8%) selected chipsets with integrated sensing as their priority while two in five (21%) saw AI/ML as essential elements for transformation. The two essential components for success include greater processing capabilities at 34.3% and lower deployment expenses at 28.6%.

Table 2.10: Responses to the Question: "What technologies and factors are most important for ISAC to succeed?"

Option	Subtotal	Ratio
5G/6G networks	16	15.24%
Internet of Things (IoT)	21	20%
Microcircuits with integrated sensors	46	43.81%
Artificial intelligence and machine learning	22	20.95%
Number of valid responses to this question	105	

The community showed mixed opinions regarding ISAC's sustained operation in the future. A substantial 32.3% of the participants expressed doubt regarding ISAC’s short-term success which they attributed to integration obstacles and technological constraints. Optimism about ISAC’s future arose from 26.6% of respondents. Table 2.11 sums up the designated expectations.

Table 2.11: Responses to the Question: "Do you believe in the successful future of ISAC in the near term?"

Option	Subtotal	Ratio
Very promising.	11	10.48%
The prospects are bright, but there are problems	28	26.67%
Unsure	23	21.9%
The prospects are not optimistic	34	32.38%
Not very promising.	9	8.57%

The number of valid responses to this question	105	

Some respondents answered in an open format to supply supplementary viewpoints. The participants validated three main themes through their analysis:

1. Development of open and interoperable standards,

2. Testing facilities known as field trials together with real-world deployment experiments help validate their operational potential.

3. Greater synergy between academia and industry.

The survey results confirm that the ISAC presentation and marketing solution, as well as the development of the foundation and practical testing of most of the information about it, make it generally accepted. The survey showed the relevance of the topic for the wireless network

CHAPTER 3 - Methodology

3.1. System Model

3.1.1. General overview and problem statement

ISAC technology addresses the core mission objectives of exceptional data transmission and accurate location monitoring. The ISAC system consists of antennas equipped with combined transmit and receive elements, as well as digital and analog processors, which are connected to a control core that optimizes system performance and allocates operational resources.

The ISAC technology platform bridges the gap between radar sensing and wireless communications operations. The research provides performance optimization for ISAC systems by integrating MIMO with beamforming and convex optimization approaches.

The system contains twelve antennas which function under specified roles, which illustrates in figure 3.1. These antennas have planned positions that enable sensing operations and communication activities. Several antennas exist in a defined vertical orientation where the Tx and Rx units extend from the Y-axis.

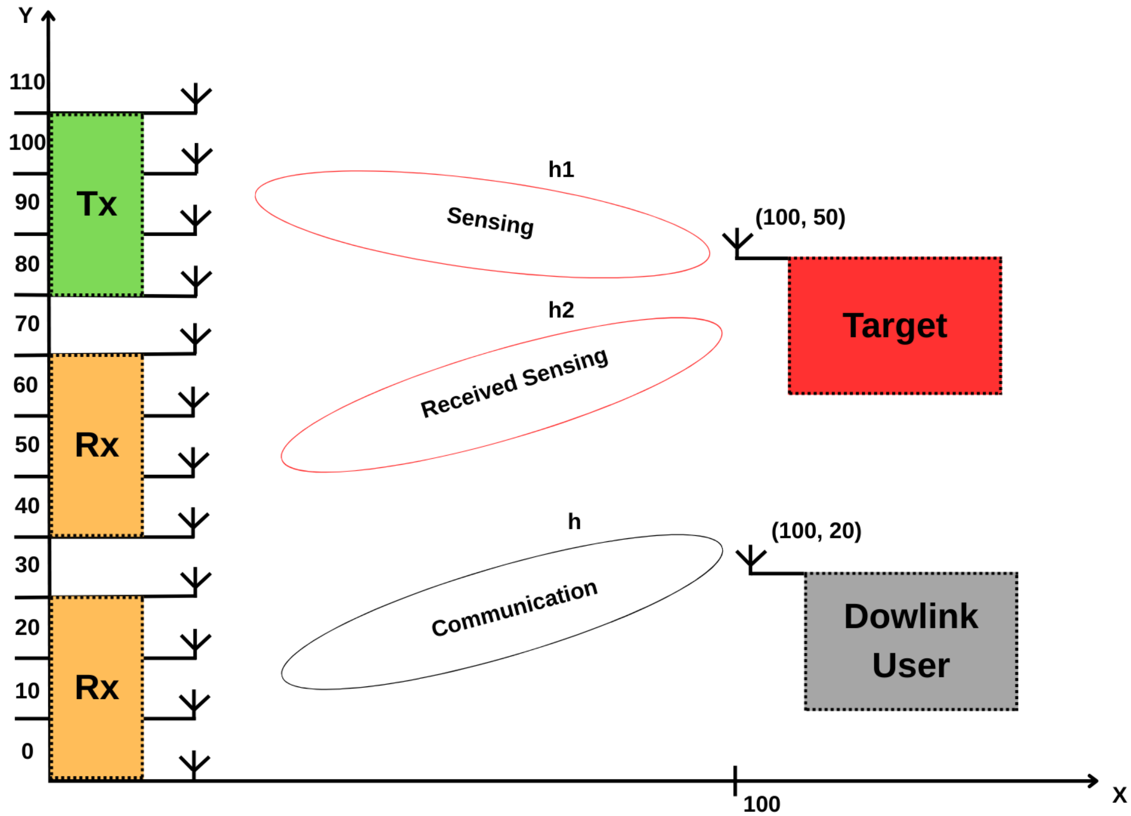


Figure 3.1: Scenario of project

Four transmit (Tx) antennas operate from the top segment of the system at (x = 0, y = 110, 100, 90, 80) to transmit signals that reach the target device at (100, 50) for sensing as well as the uplink user located at (100, 20) for communication. Each transmit antenna contributes to the sensing operations of the target as well as the communication signaling with the uplink user by sending signals. The system comprises four receive antennas (Rx) mounted below the transmit antennas at the points (x = 0, y = 70, 60, 50, 40). The receive antennas detect reflected waves that originate from both the scanning target and the communication signals from the uplink user. The device analyzes its sensing environment through the receive antennas that receive the signals reflected from the target. A second set of four receive antennas (Rx) serve as part of the system layout that extends downwards from the previous antennas located at the point (x = 0, y = 30, 20, 10, 0). These antennas serve exclusively to detect target signals that are reflected from the target so that the system can determine the target's position and motion characteristics. The sensing process uses a target located at the coordinate (100, 50) of the X-Y plane as the main object of study. The receive antennas at the Rx station collect the reflected signals that allow the system to determine the target's position along with other relevant characteristics. The location of the uplink user is at (100, 20) along the X-Y plane. The uplink user communicates by receiving signals that are transmitted from the Tx antennas to the receive (Rx) antennas. The system workflow requires simultaneous target observation and data exchange with the uplink user. Efficient resource allocation mechanisms between power supplies and antenna components achieve the highest possible levels of both delicate detection capabilities and smooth communication processes.

In terms of signal reflection:

1. h1 refers to the reflection of the probing signal from the target.
2. h2 refers to the received signal for target detection.
3. The communication signal that is reflected back from the uplink user falls into the h category.

The system achieves the maximum data rate and probing frequency through antenna positioning analysis along with antenna location signal-to-noise ratio testing to maintain reliable uplink user connections.

ISAC systems exist in two operating modes that guide their operation. When operating as a sensor, the base station sends out signals to study and analyze target characteristics using beamforming techniques that improve accuracy. Processing the reflected wave signals allows users to obtain target location information, velocity measurements, and structural data analysis. The need for high-definition sensing becomes essential for traffic monitoring operations along with environmental surveillance and security monitoring tasks. The system implements a communication mode to optimize power allocation and beamforming by processing user uplink messages, which maximizes data rates while providing continuous sensing capabilities. ISAC operations face the challenge of maintaining effective dual-functionality operations while maintaining performance standards in situations that include target and user mobility [42]. Uniform placement of sensing and communication components ensures the necessary phase coherence as it plays a vital role in performing both functions. By automatically updating the antenna weight, the system employs adaptive beamforming technology to maintain stable performance despite changing channel conditions. Beamforming technology allows users to accurately direct their signals through valid targets and better cope with unwanted interference, resulting in increased detection capabilities and data rates.

3.1.2. Signal Model and Channel Assumptions

The system depends on multiple physical parameters that power its sensing operations and communication capabilities. The selected parameters ensure an efficient operation of the system when used in real-world applications. The system design selects the speed of light (c) to equal $c=3\times10^8$ m/s. Fundamental to this measurement is its role to establish the electromagnetic wave propagation velocity. Both sensing operations and communication tasks require synchronization time and signal delay which directly relate to the speed of light. Every calculation that deals with signal travel time requires this absolute universal constant as its value.

The system has a chosen operational frequency set at 2.46 GHz. The chosen frequency operates within the 2.4 GHz ISM band where numerous wireless technologies including Wi-Fi and Bluetooth utilize this band for short-range communications. Several reasons justify the selection of frequency. This frequency meets the wireless system standards therefore users can utilize existing technologies without limitations. Such installation offers a suitable middle ground between communication distance and data transmission speed. Signal transmission at higher frequencies results in increased data rates at the expense of higher signal attenuation whereas lower frequencies provide better transmission range together with lower data transfer speeds. This chosen frequency offers an adequate bandwidth along with operational distance for operations between medium distances. The wavelength calculation (λ) results from freq/c = 0.122 m. The distance between antennas and their signal interaction depends directly on the wavelength because it determines these aspects of design. A wavelength selection at this specific range enables technicians to create effective antenna arrays which perform beamforming operations and deliver signal transmission optimization.

Each antenna had a distance of (d= λ/2 = 0.061m) from the others. Engineers chose this particular distance to enable efficient beamforming operations along with creating diversity among spatial antenna positions. A distance of this measurement supports a beneficial equilibrium between redundancy and interference in space. The antenna placement configuration maintains an optimized separation between devices which optimizes signal reception and minimizes signal interferences. The selected antenna separation assists signal strength enhancement which results in better system throughput together with SNR improvement. The chosen sensing bandwidth (B_sensing) stands at 50 MHz while the communication bandwidth (B_comm) reaches 100 MHz. Current sensing and communication systems utilize these throughput values for their realistic performance needs. Sensing bandwidth remains small because it needs limited bandwidth and data yet the communication bandwidth achieves higher data rates for transmission.

The defined set of parameters fulfills operational needs by matching the real-world operational conditions. The system operates efficiently with data sensing and transmission functions through selected parameters which produce satisfactory results within all restraint boundaries.

The amount of signal power reduction between transmitter and receiver depends heavily on path loss effects. Two path loss models are examined in this study because of round-trip signal propagation in sensing applications we use Path Loss Model (3.1) as follows:

$$PL_{sensing} = \left(\frac{4\pi d}{\lambda}\right)^4 \tag{3.1}$$

and for communication (3.2), which involves only a one-way loss, the model follows:

$$PL_{comm} = \left(\frac{4\pi d}{\lambda}\right)^2 \tag{3.2}$$

The formula demonstrates distance transmission d in correlation with the wavelength signal λ. Computational beamforming along with power management systems are needed for accurate sensing operations due to the path loss's elevated magnitude. Two-way propagation in sensing applications requires significantly higher detection threshold power compared to the power needed for simple communication purposes [43-44].

The model of Rayleigh fading channels represents small-scale multi-path fading scenarios that commonly occur under non-line-of-sight environments. The channel matrix H (3.3) is expressed as:

$$H = \frac{1}{\sqrt{2}}(X + jY) \tag{3.3}$$

where $X, Y \sim N(0,1)$ are independent Gaussian-distributed random variables. This model accounts for the randomness introduced by multiple reflected paths, which is essential when designing robust beamforming strategies. The presence of Rayleigh fading introduces variability in received signal power, which must be mitigated through adaptive transmission strategies to maintain system reliability.

Thermal noise (3.4) is incorporated into the system as:

$$N_0 = k_b T B \tag{3.4}$$

The constant k_b is Boltzmann's constant (1.38×10^{-23}) whereas T is system temperature (set at 290K) and the bandwidth shows different values for sensing and communication operations. ISAC performance evaluation together with optimization relies heavily on noise power because it determines the signal-to-noise ratio (SNR) performance. The design of noise-resistant algorithms becomes essential because sensing systems share frequency bands with communication channels thus preventing functional degradation between these systems [45-47].

The transmitted signal follows a standard BPSK modulation scheme (3.5):

$$x(t) = \sqrt{P}s(t) \tag{3.5}$$

The system uses P to show transmission power and $s(t)$ demonstrates the BPSK symbols which are modulated. The selection of BPSK as modulation scheme occurs because it provides both robust operation and minimal implementation complexity which enables joint optimization between sensing and communication systems. Binary BPSK transmission enables BER curve analysis because of its two-level design independent of noise intensity levels [47-48].

At the receiver, the received signal (3.6) is modeled as:

$$y(t) = Hx(t) + n(t) \tag{3.6}$$

The system includes an H channel matrix together with $n(t)$ AWGN noise. The processed received signal enables extraction of sensing and communication information after beamforming and filtering stages. Received signal interpretation accuracy depends significantly on channel estimation because fading effects and noise require proper consideration during that process.

Using the Monte Carlo method in ISAC systems brings multiple significant benefits for analytical purposes. Performing computer simulations using diverse random parameters enables a complete understanding of how system robustness performs under uncertain circumstances. This method reveals how significant performance indicators alter as the environmental factors change.

The iterative process enables researchers to determine both average performance metrics and the maximum and minimum extremes within the same analytical framework. The design of essential systems should focus on reliability but this requirement becomes most crucial during stress situations. Monte Carlo simulations include direct modeling of random fluctuations and noise because they overcome the shortcomings of deterministic modeling techniques. These models generate dependable results about ISAC performance behavior in actual wireless networks. The acquired statistical data becomes the foundation to optimize system parameters through the enhancement of resource allocation methods and antenna settings as well as sensing methods.

3.1.3. Beamforming Model

Through beamforming technology, the system excels in sensing and communication operations through targeted signal energy delivery which reduces interference between devices. The system performs Maximum Ratio Transmission (MRT) for beamforming at the transmission phase and Maximum Ratio Combining (MRC) at the reception phase. The MRT transmission (3.7) weight vector is defined as:

$$\omega_{Tx} = H^H(HH^H)^{-1} \tag{3.7}$$

while the MRC reception weight vector (3.8) follows:

$$\omega_{Rx} = (H^H H)^{-1} H^H \tag{3.8}$$

The power distribution method across antennas through beamforming techniques improves received signal quality by finding its optimal configuration. The system boosts signal power while reducing noise levels by performing beamforming procedures at both transmitter and receiver nodes. The beamformed SNR for sensing (3.9) is given by [48]:

$$SNR_{sensing,BF} = \frac{P}{N_0 \cdot PL_{sensing}} \cdot |Tr(\omega_{Rx}^H H \omega_{Tx})|^2 \tag{3.9}$$

and for communication (3.10):

$$SNR_{comm,BF} = \frac{P}{N_0 \cdot PL_{comm}} \cdot |\omega_{Rx}^H H|^2 \tag{3.10}$$

The weight vectors ω_{Tx} and ω_{Rx} represent the transmission and reception beamforming components used during operation. The provided expressions showcase how beamforming technology operates to strengthen reception signals while combating transmission losses. The beamforming technique allows the system to distribute its transmission resources automatically based on current environmental conditions so it can fulfill its sensing needs and communication requirements [49]. Real-time channel conditions control the adaptable adjustment of both signaling ω_{Tx} and receiving ω_{Rx} beamforming weights for robust system operation. The ISAC system benefits from this adaptation when dealing with continuously changing user positions or target locations because it guarantees high operational efficiency under diverse conditions. Dynamic beamforming optimization enhances the interconnection of ISAC capabilities through an interoperable transition between sensing and communication modes which leads to minimized interference along with reduced power consumption [50].

This model creates basic standards for ISAC optimization through its definitions of main system parameters and signal propagation principles along with beamforming approaches. Another segment reveals detailed strategies about improving power management alongside antenna selection that help produce balanced ISAC solutions. The evaluation of ISAC system feasibility requires analysis of hardware weaknesses along with practical limitations and computational demands from beamforming methods.

3.2 Optimization Framework

3.2.1 Beamforming Optimization using Convex Optimization

The successful operation of ISAC systems depends on proper beamforming optimization methods for achieving efficient communication alongside accurate sensing. The signal transmission and reception capabilities of beamforming direct the signals for higher quality performance and reduced interferences. The intelligent control of the beam allows systems to utilize their frequency spectrum more efficiently and maintain increased reliability. This study makes use of convex optimization methods to find the most suitable beamforming weight vectors for sensing combined with communication. This system aims to enhance the data transfer rate to optimum levels while preserving sensing capacity standards to maintain peak operational efficiency between both platforms [51].

The optimization model combines multiple functions by requiring the sensing rate to achieve a particular threshold while simultaneously reaching maximum uplink data rate. These optimization limitations include power transmission constraints which help generate practical systems that match energy efficiency standards while following hardware capacity restrictions. Mathematically, the problem (3.11) is defined as follows:

$$\max_{P_s, P_u, \omega_s \omega_u} R_u \tag{3.11}$$

Both P_s and P_u stand for the transmitting power of sensing and communication operations although ω_s and ω_u describe the beamforming weight vectors used in these operations. Such optimization needs to fulfill the following requirements:

1. Sensing Rate Constraint (3.12):

$$R_s = B_s \log_2(I_s + SNR_s) \geq (R_s)^{th} \tag{3.12}$$

where I_s matrix antennas for sensing and SNR_s (3.13) for sensing is expressed as:

$$SNR_s = \frac{P_s}{N_0 \cdot PL_{sensing}} \cdot |\omega_s^H H \omega_s|^2 \tag{3.13}$$

The constraint maintains sufficient precision for detection along with object tracking under conditions of considerable interference and environmental noise.

2. Communication Rate Constraint (3.14):

$$R_u = B_u \log_2(I_u + SNR_u) \geq (R_u)^{th} \tag{3.14}$$

where I_u matrix antennas for communication and SNR_u (3.15) for communication is given by:

$$SNR_u = \frac{P_u}{N_0 \cdot PL_{comm}} \cdot |\omega_u^H H|^2 \tag{3.15}$$

Systems operate under this condition to provide users with high-quality communication links which remain unaffected by excessive sensing resource usage.

3. Fixed Transmission Power Constraints (3.16):

$$P_s = 30dBm, P_u = 0dBm \tag{3.16}$$

The specified constraints limit both sensing and communication systems to use their designated power allocations which protects operational performance by avoiding power spikes.

The convex optimization routines run within MATLAB with the help of CVX which enables efficient resolution of convex programs. CVX framework provides an optimized solution methodology for beamforming optimization problems that helps derive weight vectors maximizing the sensing-communication performance trade-off efficiency. Through this framework the derived optimized beamforming weights and power allocations reach an optimal trade-off between sensing and communication operations without exceeding practical computational complexity constraints.

3.2.2 Greedy Algorithm for Antenna Selection

The selection of antennas serves as a vital performance booster for ISAC systems through its determination of maximum advantageous operation for sensing and communication. For the given power constraints, the greedy algorithm selects antennas one by one to achieve maximum performance between sensing and communicating. The greedy approach chooses optimal antennas effectively while keeping its computations simple so it becomes a favorable technique for selecting influential antennas in large-scale antenna arrays.

The greedy selection process adopts several sequential steps to operate.

1. The initialized selection starts with no antenna components selected.

2. You should add one antenna at a time which gives the maximum improvement either to sensing speed or communication speed while preserving the sensing-communication balance.

3. The antenna addition process terminates either through minimal enhancement of performance or when existing power and system complexity constraints become limiting factors to maintain practical system operation.

The antenna selection criterion is formulated as follows (3.17):

$$C = \sum_{i \in S} B \log_2(1 + \frac{PG_i}{N_0}) \tag{3.17}$$

The expression describes antenna subset S and antenna gain parameter G_i. The algorithm distributes resources properly to create an effective trade-off between sensing and communication functions without requiring complex computational processes. The iterative process of greed selection focused on choosing the most beneficial antennas results in better system robustness and channel condition adaptability. The ISAC system achieves balanced optimization through beamforming optimization based on convex techniques combined with antenna allocation done by greedy selection algorithms that enhances both data throughput performance and sensor precision. The integration of dual optimization procedures into future ISAC deployments proves ideal since it guarantees dynamic conditions require immediate resource-efficient adaptive responses. The addition of real-time feedback within optimization processes allows the system to become more adaptable since it permits dynamic beamforming weight and antenna configuration changes that follow instant channel state and interference situations [55].

Convex optimization when employed with greedy algorithms provides complete solutions for ISAC resource allocation to manage power efficiency requirements and real-time control needs as well as spectral usage challenges. Implementation of hybrid machine learning-based techniques in the future ISAC framework will generate innovative methods that deliver best operational performance with no interference across various deployment environments.

3.3 Performance Metrics

3.3.1 Sensing Rate and Communication Data Rate

To measure the efficiency of ISAC systems one must perform an extensive analysis of core performance indicators which evaluate both sensing and communication capabilities. The primary performance indicators encompass the assessment of sensing rate and data rate and beamforming gain and SNR along with BER [56]. The selected metrics in performance evaluations allow engineers to make balance choices between the sensing capabilities and communication system thus meeting operational requirements. System environmental information collection along with processing performance is determined by the value of sensing rate. A sensing system functions by assessing signal bandwidth limits together with the signal-to-noise ratio conditions of sensing channels for defining its operations. The sensing rate is given by (3.18):

$$R_s = B_s \log_2(I_s + SNR_s) \tag{3.18}$$

where $B_s$is the sensing bandwidth, I_s represents the MIMO rank in the sensing channel, and SNR_s is the signal-to-noise ratio for the sensing process, given in (3.13).

The sensing rate corresponds to system antenna configuration together with transmitted power levels and it depends upon environmental path loss and noise power. Similarly, the data rate represents the maximum achievable transmission speed in the communication link, ensuring that users receive information with minimal delay and high reliability. It is expressed as (3.19):

$$R_u = B_u \log_2(I_u + SNR_u) \quad (3.19)$$

where $B_u$is the communication bandwidth, I_u represents the MIMO rank in the communication channel, and is the communication signal-to-noise ratio, given in (3.15). The data rate performance in ISAC systems depends heavily on beamforming optimization alongside SNR improvements which makes beamforming a vital system component.

3.3.2 Comparison of ISAC in Different Antenna Configurations

Different multiple-antenna configurations operate within the ISAC system and each brings its own benefits together with corresponding drawbacks. MIMO represents one primary configuration and Multiple Input Single Output (MISO) is another but Single Input Multiple Output (SIMO) also exists alongside Single Input Single Output (SISO) which serves as the base configuration in these multiple antenna deployments [57].

Both transmitter and receiver implement MIMO technology by using multiple antennas for simultaneous multisignal communications through spatial channels. The technology delivers excellent sensing and communication results through its dual ability to extract enhanced spatial diversity for better accuracy and run multiple transmitting streams for better data throughput. MIMO relies on digital beamforming which permits detailed control of beam direction as well as strong interference suppression together with better spectral efficiency.

The MISO system performs very well in downlink operations through its arrangement of multiple transmitters working with one receiver antenna. Because MISO lacks multiple receiving antennas it provides only average sensing capability despite its other advantages. The application of Beamforming technology at the transmitter base generates efficient energy distribution toward receivers for better SNR and enhanced system reliability [58].

With its single antenna used for transmissions and multiple receiving antennas SIMO operates effectively during uplink communication. Multiple antennas in the receiving system better detect reflections across various positions while simultaneously reducing interference and noise interference. The SIMO configuration lacks beamforming capabilities at the transmitter since it utilizes receive diversity methods including MRC to boost signal reception.

This simplest arrangement consists of one transmitting antenna and one receiving antenna which is known as SISO. The absence of spatial diversity together with channel fading makes this technique perform the worst at sensing and communication. Beamforming technology is not present in SISO systems which makes multiple antenna-based ISAC implementations ineffective due to their requirement of accurate and secure data transfer. The combination of MIMO results in maximum operational efficiency between sensing and communication tasks followed by SIMO and MISO configurations while SISO represents the least effective option. The performance enhancement depends heavily on beamforming techniques because MIMO and MISO benefit from advanced applications but SIMO relies on receive diversity and SISO does not enable beamforming operations [59].

3.3.3 Bit Error Rate (BER)

The bit error rate (BER) is another key performance metric, measuring the probability of incorrect bit reception, which directly impacts communication reliability. For Binary Phase Shift Keying (BPSK), the BER (3.20) is expressed as:

$$P_b = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \tag{3.20}$$

where $Q(x)$ represents the tail probability of the Gaussian distribution and E_b/N_0 is the energy-per-bit-to-noise power spectral density ratio. ISAC system reliability depends on low BER values because they determine transmission quality performance. Optimal beamforming combined with power allocation management enables ISAC systems to conduct sensing along with communication tasks that maintain BER below set limitations.

CHAPTER 4 - Results and Discussion

4.1 Sensing Rate vs Transmit Power

The purpose of this project involves studying antenna configurations from MIMO, MISO, SIMO and SISO wireless communication and sensing systems. Academic research explores this set of configurations because each one has unique operational characteristics which determine system applications based on channel capacity and sensing rate. MIMO stands as the most complex and advanced configuration because it employs multiple antennas for transmission and reception operations. These systems operate independently from the other antenna side either for transmission or reception purposes while SISO functions with a solitary antenna for both send and receive tasks. The efficiency of these systems depends on channel characteristics which should be regarded during wireless system design.

The research evaluated these systems through two graphical representations of two essential characteristics which tracked transmitter power levels against channel capacity and sensing rate respectively. The following analysis investigates these elements individually.

The sensing rate depends on transmitter power while using the same antenna setups as illustrated in Figure 4.1. The sensing rate determines how fast a system captures and sends sensor data while being essential for applications in the fields of monitoring systems and Internet of Things (IoT) sensors together with other data collection-dependent domains.

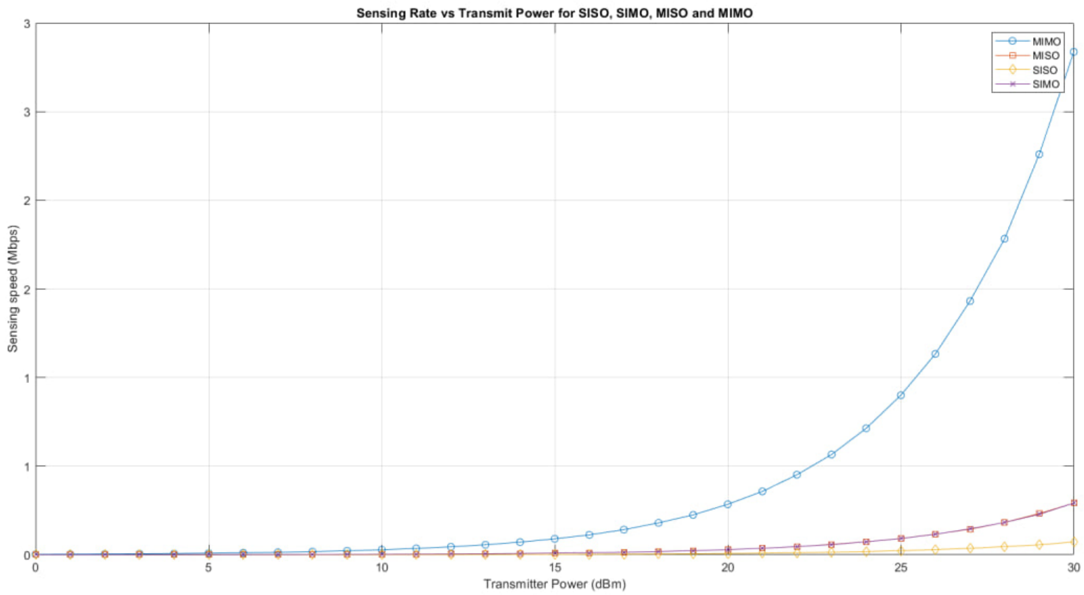


Figure 4.1: Sensing vs Transmit Power for SISO, SIMO, MISO and MIMO

MIMO achieves the greatest possible sensing rate between all of the explored antenna configurations. The data transmission speed of sensor information increases substantially when multiple antennas operate at the same time for transmitting and receiving information. SIMO and MISO offer better performance than SISO however they produce less effective outcomes than MIMO. SISO data collection capabilities are restricted because it operates with one antenna thereby giving rise to its low sensing rate. The sensing ability becomes most obvious when increasing transmitter power yet remains constrained by one antenna operation.

The sensing system achieves its maximum speed with MIMO which outperforms other solutions at every transmitter power setting. SISO systems achieve higher performance than SIMO and MISO but MIMO delivers superior performance since its multiple antennas allow for superior data processing.

4.2 Channel Capacity vs Transmit Power

Figure 4.2. depicts the power fluctuation in the channel as transmitter power changes under various antenna setups. Channel capacity represents the most data that a communication channel

can transmit while using its transmitter alongside noise fluctuations. Wireless communication systems evaluation requires this metric for determining their operational performance.

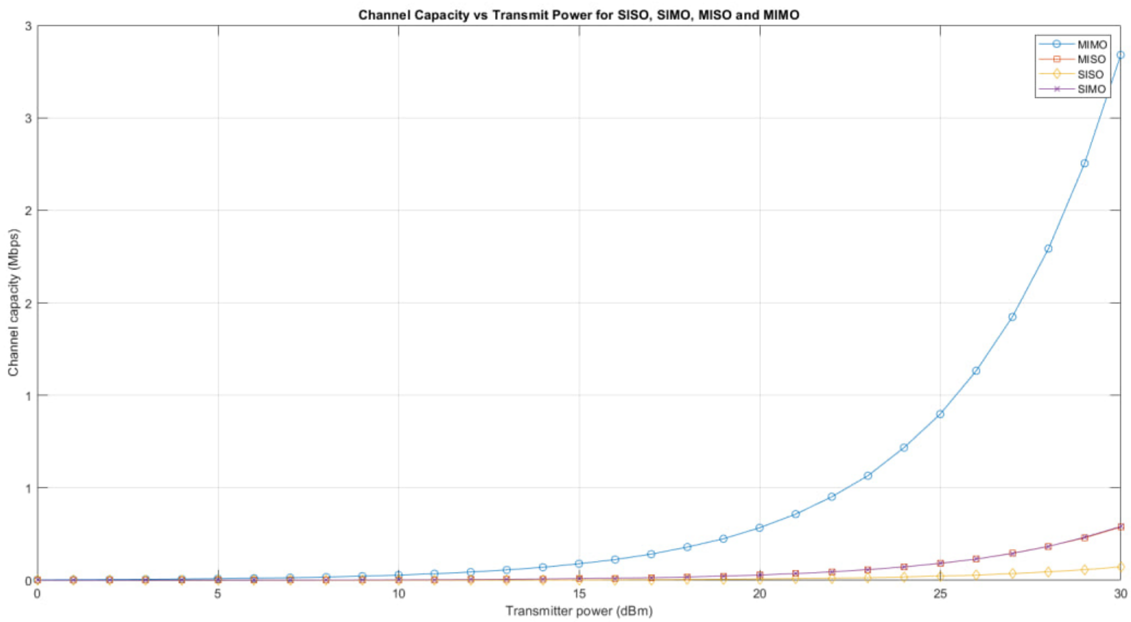


Figure 4.2: Channel Capacity vs Transmit Power for SISO, SIMO, MISO and MIMO

The administration findings demonstrate that MIMO stands as the top configuration regarding channel capacity among the reviewed systems. Multiple antennas functioning in MIMO allow efficient channel use to transmit and receive data as the main principle behind this technology. The MIMO system can process additional data because larger transmitter power enables utilization of multiple external channels that ultimately leads to a notable increase in channel capacity.

Channel capacity remains minimal for the SISO (Single Input Single Output) system since it handles all its data transfer operations with a single antenna. Such limitations reduce the system functions and make it unable to maximize the use of multiple transmission channels. Simple applications together with restrictive usage requirements sometimes justify adopting the SISO system. Between SISO and MIMO there exists the SIMO and MISO configurations. The Signal Input Multiple Output configuration enables one transmitting antenna coupled with multiple receiving antennas for enhanced signal reception but stops short of MIMO performance. MISO improves efficiency when operating with multiple antennas during transmission compared to SISO yet provides fewer results than MIMO.

MIMO demonstrates superior performance than all other arrangements when displayed in the graph across varying transmitter power levels. MIMO stands as the top selection for systems that need high data throughput capacity.

4.3 Beamforming Effects on Sensing and Data Rates

Wireless technologies today need highly reliable and efficient data transmission with exceptional performance in restricted bandwidth and unstable power sources and noisy conditions. A simulation research was performed to evaluate the positive aspects that arise from beamforming implementations regarding spatial signal direction in transmission and reception processes. The signal receives improved performance through beamforming because it focuses transmission power toward a single direction instead of broadcasting equally in all directions of the classical approach.

The model incorporated two distinct blocks that served as a communication system and sensor mechanism. The model allocated different frequency bands along with noise levels to imitate actual operating scenarios for each block. Maximum Ratio Transmission operated as the beamforming method for the transmitting component while receiving equipment employed Maximum Ratio Combining as their standard directional beamforming technique. We proceed to analyze step-by-step graphs displaying essential metrics which follow.

The Data Rate responds to transmitter power level variations according to Figure 4.3 The system tracks without beamforming follows the green dashed line yet the solid purple line represents the performance using spatial directivity.

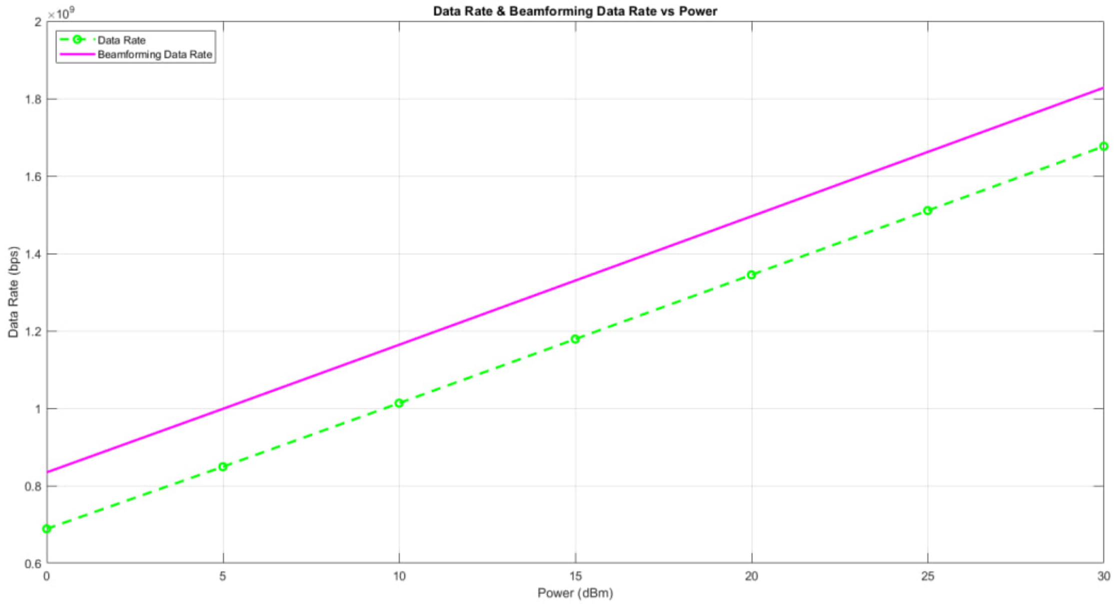


Figure 4.3: Data Rate and Beamforming Data rate vs Power

The difference between traditional transmission and beamforming remains small at low power levels until sudden growth of the power allows beamforming to have greater impact. At elevated power outputs the system demonstrates better signal compensation because higher transmission power allows more efficient utilization of beamforming beams for noise and attenuation compensation throughout the transmission path. Through proper energy concentration devices can make better use of their energy resources especially useful in uplink communications where user devices have restricted power capacity. The beamforming technique provides consistent gain throughout all power levels since its effectiveness does not depend on particular value measurements.

Figure 4.4 displays the system's ability to detect and transmit information on objects which corresponds to its sensing speed. Standard data transmission procedures face additional complexity when performing sensing because the signal requires target reach and reflection before returning back for reception and processing.

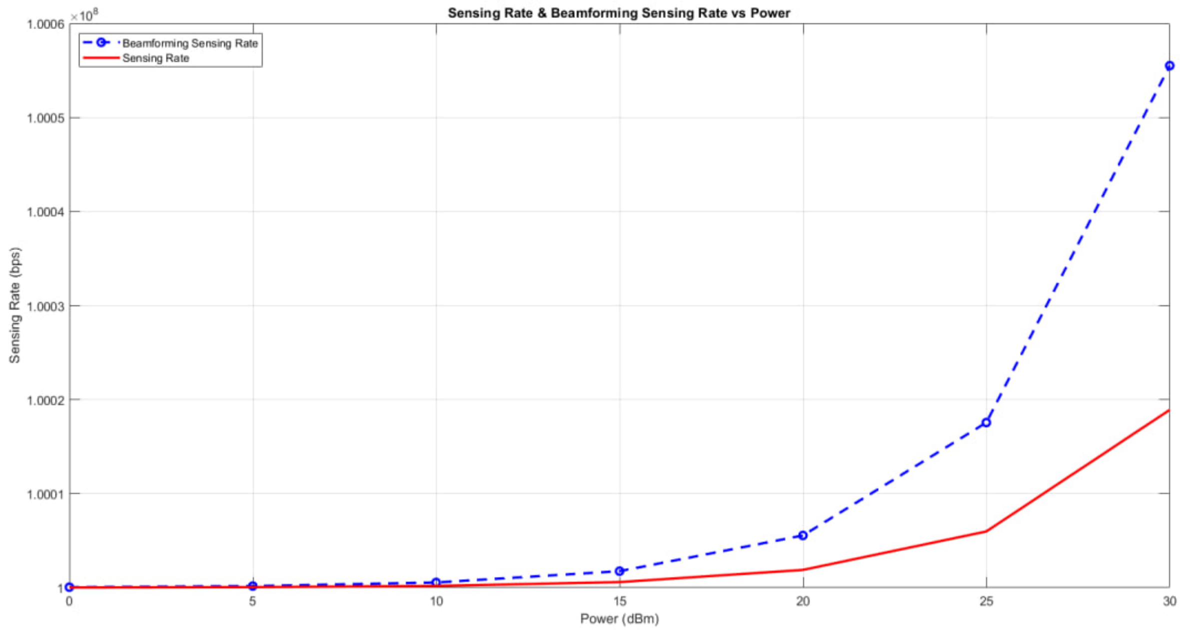


Figure 4.4: Sensing Rate and Beamforming Sensing rate vs Power

The sensing efficiency remains at zero level when beamforming is absent (red line) because the reflected signal becomes undetectable at low power values. The sensing speed starts to rise as power output intensifies. However, the gain remains limited.

Widespread comparison between the blue graph and the red graph shows precisely how beamforming technology enhances sensing performance. Movement in the graph starts at 20 dBm with an immediate rise that proves beamforming enables the system to connect with targets and successfully retrieve reflected signals. The system gains exceptional performance between 25 to 30 dBm power levels where directional transmission leads to stable high-speed operation while the other system barely functions. Results of this quality are critical for automated systems used in surveillance operations military applications and industrial processes that require quick target information acquisition and transmission.

4.4 Bit Error Rate (BER) vs Transmit Power

Figure 4.5 uses a logarithmic scale to show BER (Bit Error Rate) which represents the probability of bit errors that occur while sensing. The sensitivity of this parameter increases with the signal-to-noise ratio but improved data reception quality becomes possible when the value is lower. The channel conditions together with the power levels determine BER because BPSK modulation is employed.

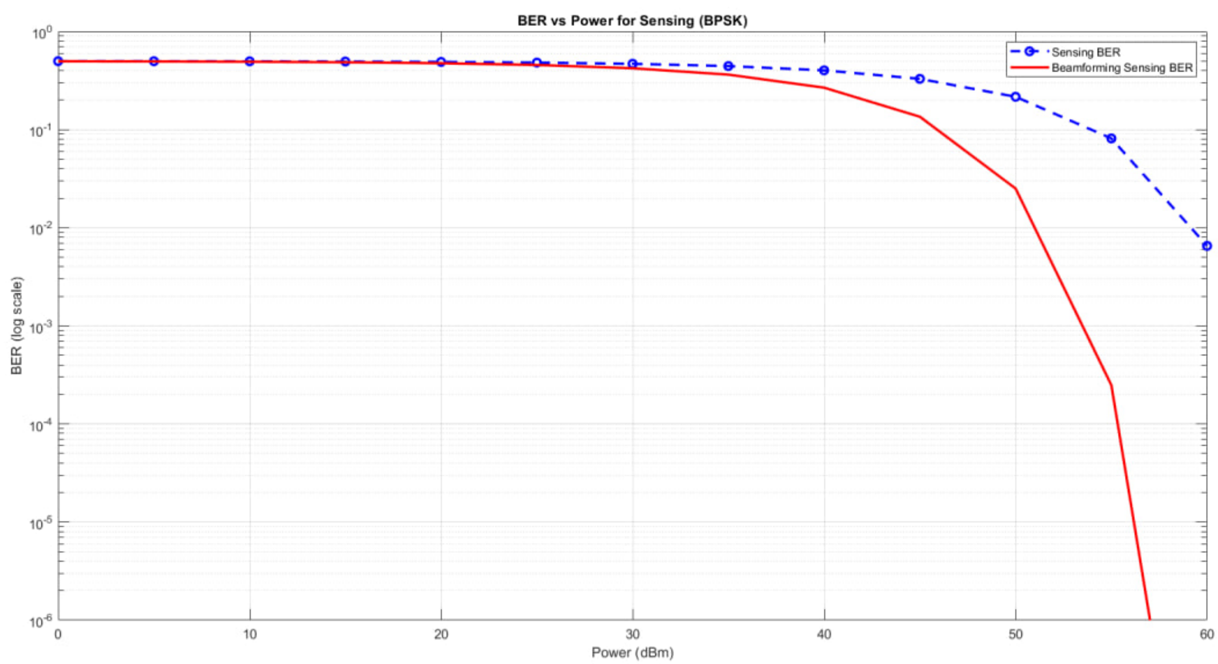


Figure 4.5: Data BER and Beamforming Data BER rate vs Power

The blue dotted line in Figure 4.5 shows that BER drops incompletely when power rises. The system exhibits substantial errors during operation when power stays under 30–35 dBm. The system fails to achieve appropriate BER performance when operating at 50 dBm power even with maximum possible output power. Critical applications that lead to fatal consequences because of every mistake occurring during operation.

Beamforming implementation through its red line produces a complete transformation of the network conditions. The system demonstrates stable operation as BER shows a fast downward trend from 30–35 dBm mark. When operating at 50–60 dBm the system reaches complete error elimination while properly receiving weak reflected signals that withstand noise together with interference. With beamforming installed the transmission and sensing process becomes quicker and communication reliability rises to lower the potential for miscommunication errors. Real-time systems benefit significantly from this capability because minimal distortions leading to wrong decisions become a major issue for example in autonomous control systems.

Every significant aspect of wireless system performance improves substantially through the implementation of beamforming techniques according to the analysis results. Hardware performance boosts through beamforming improves the transmission rate as well as signal sensing velocity and both control errors while maintaining system stability even with low signal to noise ratio conditions. The study demonstrates that traditional systems without beamforming cannot satisfy modern requirements especially when they operate at power restrictions or need to detect distant objects. Systems processed through beamforming gain directional intelligence that enables them to direct their signals precisely towards actual target areas.

These analytic methods have particular importance because of the 5G/6G network progress and smart city construction alongside IoT industrial applications and autonomous innovation. The analysis results show that beamforming develops into a fundamental component required for future communication and sensing systems.

4.5 Optimized Antenna Allocation in ISAC

Figure 4.6 shows the steps of the Greedy algorithm and action when it examines possible antenna distributions while maintaining rate limits. Stepwise combinations of sensing antennas together with communication antennas are evaluated by the algorithm while calculating Rs rates and Rc rates at each evaluation step. The system conducts successive iterations to check the user-defined thresholds on both rates before completing its operation.

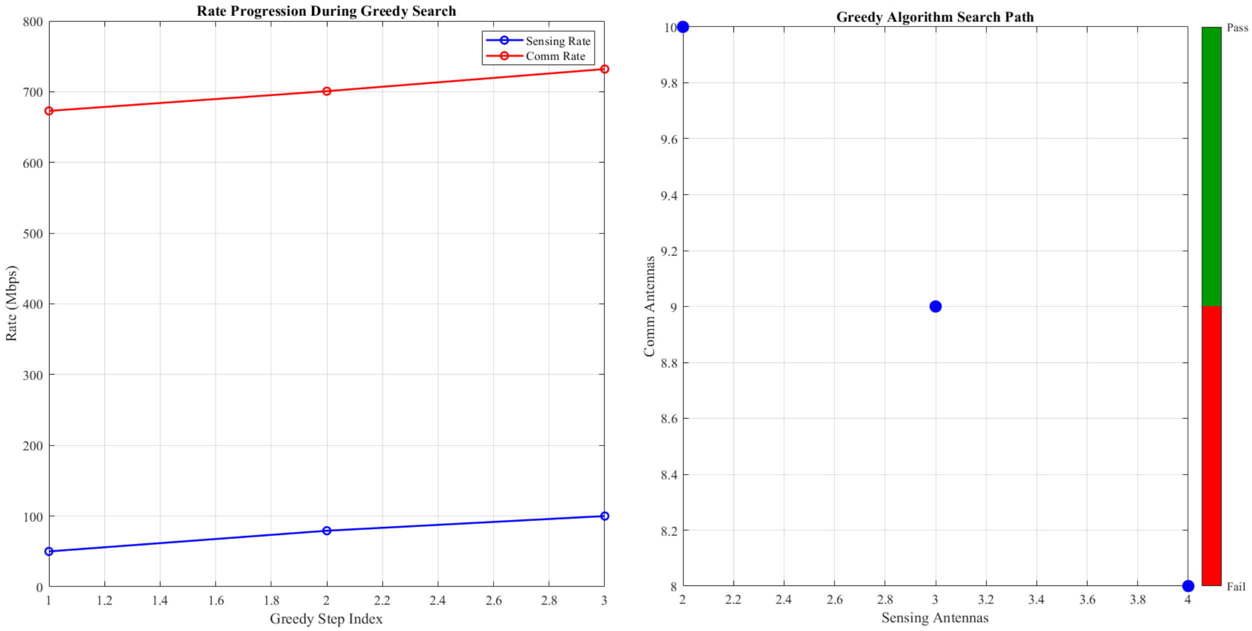
```
Enter the threshold for Sensing Rate (bps): 80e6
Enter the threshold for Data Rate (bps): 200e6

--- Greedy Algorithm Steps ---
Trying: Sensing = 2, Comm = 10 -> Rs = 50.01 Mbps, Rc = 672.86 Mbps [false]
Trying: Sensing = 3, Comm = 9 -> Rs = 79.26 Mbps, Rc = 700.74 Mbps [false]
Trying: Sensing = 4, Comm = 8 -> Rs = 100.01 Mbps, Rc = 732.04 Mbps [true]
>>
```

Figure 4.6: Greedy Algorithm Iterations for Antenna Allocation

During this particular execution of the algorithm the measurement thresholds were set to 80 Mbps for sensing and to 200 Mbps for communication. The algorithm attempted three configurations. The two previously tested antennas configurations did not satisfy the required sensing threshold although they met the communication requirements. Four antenna arrangement for sensing along with eight antennas for communication led to successful outcomes that surpassed both user-defined thresholds. Through its search process the Greedy algorithm finds its first feasible solution before stopping processing even though it has not checked every possibility which leads to quick but possibly second-best allocation results.

A two-part graphical representation displays the behavior of the Greedy algorithm based on this figure 4.7.



(a) (b)

Figure 4.7: Greedy algorithm evaluation for antenna allocation under sensing and communication rate constraints. (a) Evolution of the sensing and communication rates across Greedy steps. (b) Search path over antenna configurations, where each point represents a tested (sensing, communication) allocation. Green points indicate configurations that meet both thresholds, while red points represent failed attempts.

The visual in the left portion depicts sensing and communication rate growth within each step of the algorithm execution. A point in the visualization stands for a Greedy algorithm iteration which demonstrates the rate growth that happens when sensors get additional antenna allocations. The sensing rate curve initiates under the threshold and grows step by step yet the communication rate exceeds the threshold at all times showing the sensing processes become the main bottleneck.

The right part of the figure presents an exploration trajectory which traces different antenna setups across the sensing and communication dimensions. A point in this plot stands for an examined configuration with color-coding showing threshold passing status. The green marker identifies the first successful allocation among multiple tested configurations which failed to satisfy both thresholds indicated by red markers. The visualization demonstrates that the Greedy method requires sequential iterations of noncomplete evaluation.

These figures illustrate the successive decision points of Greedy algorithm while showing how it balances simplicity with optimality in dual-rate antenna allocations. To evaluate the robustness and adaptability of the proposed ISAC resource allocation framework, a series of experiments were conducted by systematically varying the sensing and communication rate thresholds. The goal was to observe the allocation behavior of both the Greedy algorithm and the CVX-based convex optimization, and to highlight trade-offs in rate satisfaction versus antenna usage. Three distinct scenarios were tested, each corresponding to increasing demands on system performance.

Case 1: Low-Rate Requirements (50 Mbps sensing, 150 Mbps communication).

This configuration simulates a minimal sensing environment such as basic radar awareness combined with a moderate data transmission load. The Greedy algorithm successfully allocated 2 antennas for sensing and 10 for communication, achieving rates of 50.01 Mbps and 660.07 Mbps, respectively. The CVX solution minimized resources further, assigning 2 sensing and only 1 communication antenna, with equivalent rate results. Figure 4.8, Figure 4.9 and Figure 4.10 show Matlab results for Greedy and CVX Algorithm 50/150 Mbps Rate Thresholds.

```
Enter the threshold for Sensing Rate (Sr_th): 50e6
Enter the threshold for Data Rate (Ru_th): 150e6
Thresholds introduced:
Sensing Rate >= 50.00 Mbps
Data Rate >= 150.00 Mbps

Greedy algorithm found a solution: 2 antennas for sensing, 10 for communication
CVX Optimization Complete:
Antennas for sensing: 2
Antennas for communication: 1
Achieved Sensing Rate: 50.01 Mbps
Achieved Data Rate: 660.07 Mbps
>>
```

Figure 4.8: Greedy and CVX Algorithm Output for 50/150 Mbps Rate Thresholds

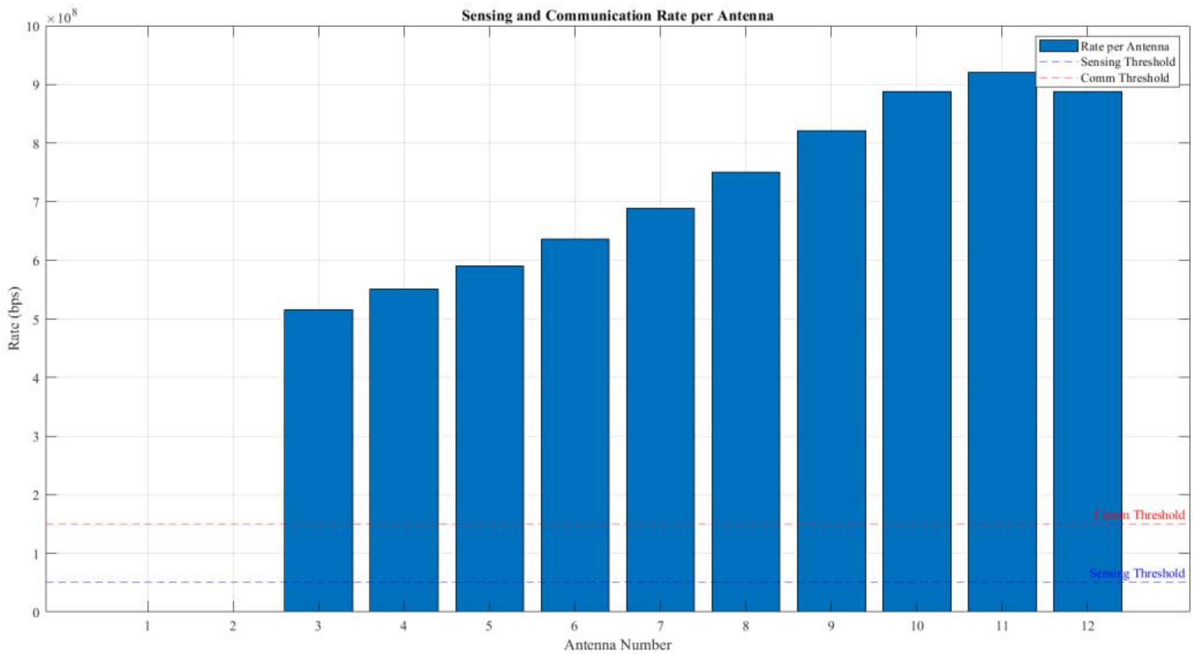


Figure 4.9: Sensing and Communication Rate per Antenna for Threshold Pair (50/150 Mbps)

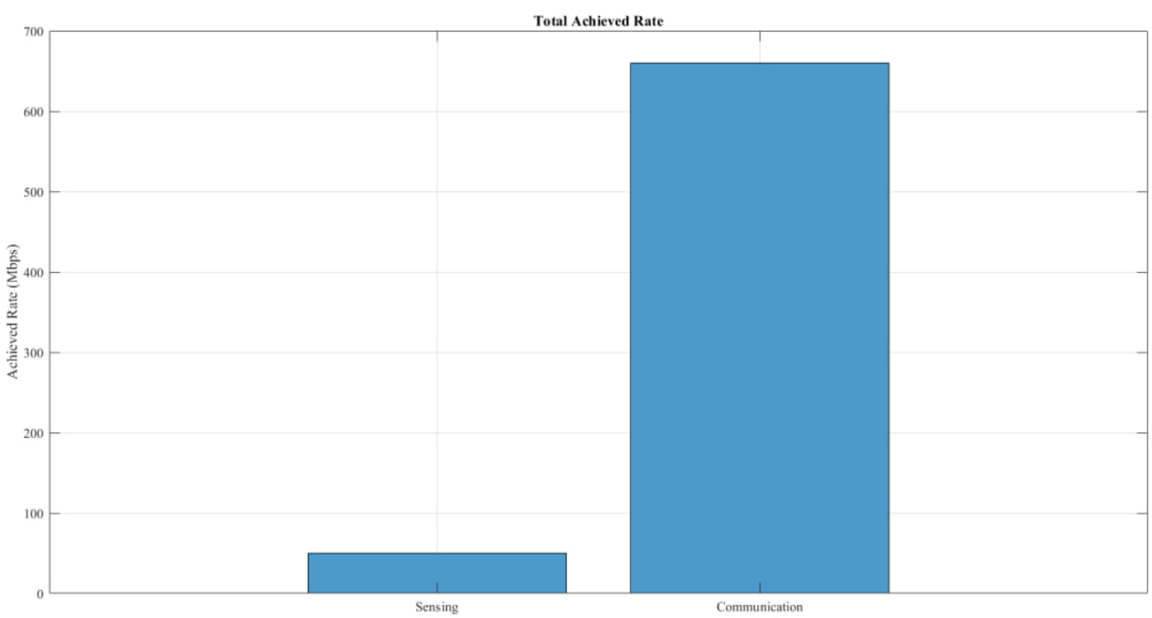


Figure 4.10: Achieved Total Rates Under CVX Allocation (50/150 Mbps)

This validates the system's ability to achieve both rate constraints with minimal resource usage. The communication channel, due to higher received SNR and favorable path loss, required significantly fewer antennas. Both algorithms succeeded, with CVX yielding a more compact solution.

Case 2: Moderate Demands (80 Mbps sensing, 200 Mbps communication).

Here, the thresholds are raised to simulate more advanced sensing and higher uplink data requirements. The Greedy algorithm proposed a balanced 4/8 (sensing/comm) split and reached both targets. However, the CVX optimizer selected a 3/1 configuration, resulting in Rs = 79.26 Mbps, which fell slightly below the required 80 Mbps, while Rc = 691.48 Mbps was well above the target.

This demonstrates the vulnerability of CVX to sensing-side limitations under tight resource constraints. While the CVX model minimized total antenna usage, it was unable to precisely meet the sensing threshold. This reveals a trade-off between resource efficiency and constraint reliability in convex formulations. Figure 4.11, Figure 4.12 and Figure 4.13 show Matlab results for Greedy and CVX Algorithm 80/200 Mbps Rate Thresholds.

```
Enter the threshold for Sensing Rate (Sr_th): 80e6
Enter the threshold for Data Rate (Ru_th): 200e6
Thresholds introduced:
Sensing Rate >= 80.00 Mbps
Data Rate >= 200.00 Mbps

Greedy algorithm found a solution: 4 antennas for sensing, 8 for communication
CVX Optimization Complete:
Antennas for sensing: 3
Antennas for communication: 1
Achieved Sensing Rate: 79.26 Mbps
Achieved Data Rate: 691.48 Mbps
>>
```

Figure 4.11: Greedy and CVX Algorithm Output for 80/200 Mbps Rate Thresholds

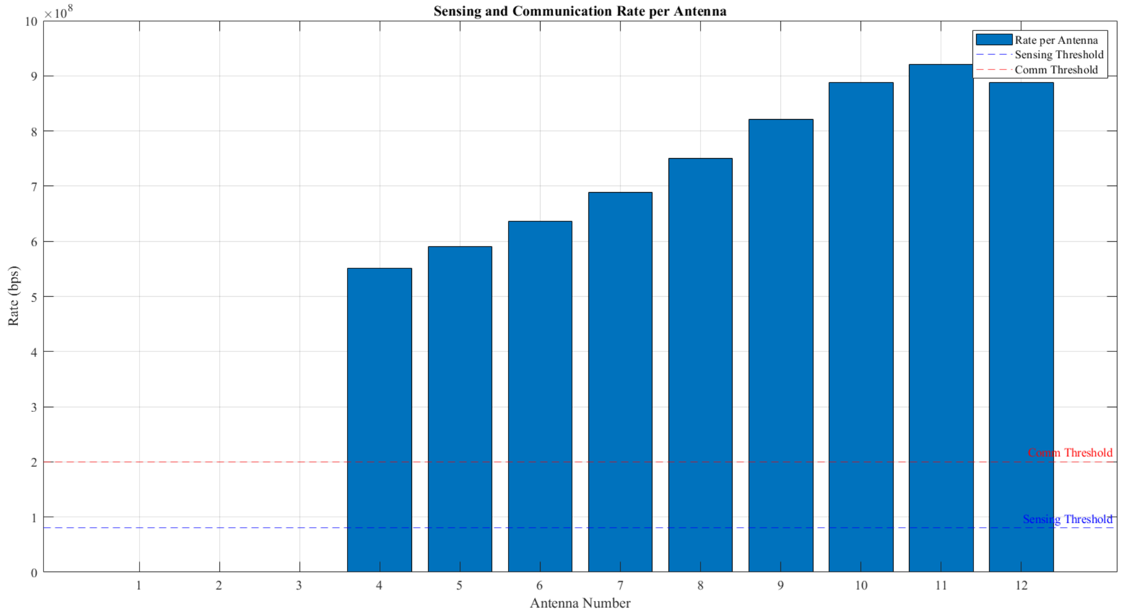


Figure 4.12: Sensing and Communication Rate per Antenna for Threshold Pair (80/200 Mbps)

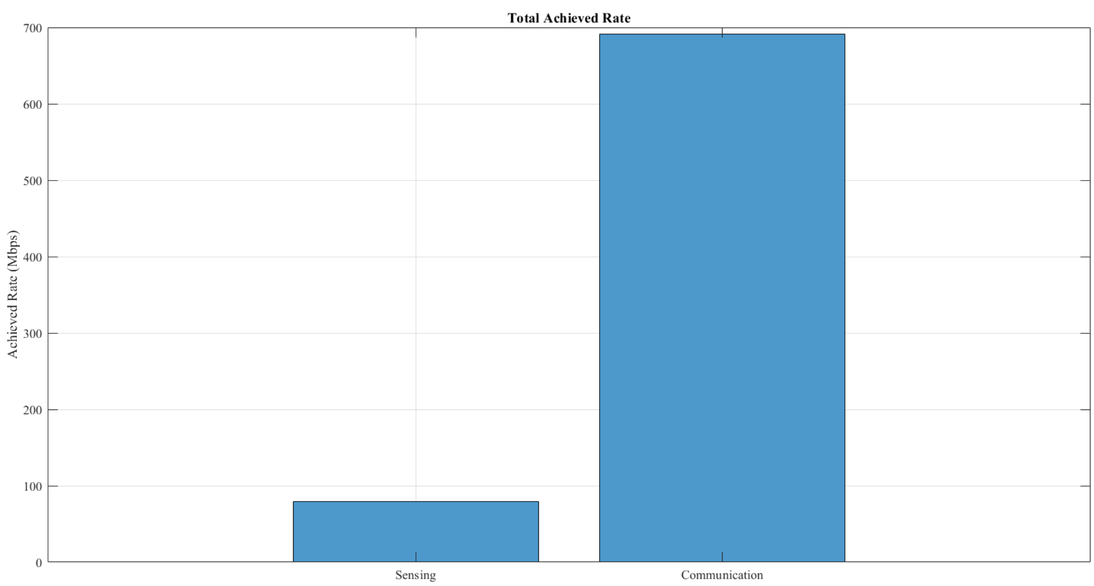


Figure 4.13: Achieved Total Rates Under CVX Allocation (80/200 Mbps)

Case 3: High-Rate Demands (120 Mbps sensing, 300 Mbps communication).

In this scenario, the system was tested under stress to simulate advanced sensing (e.g., environment mapping) and high data traffic. The Greedy algorithm allocated 6 antennas for each task, comfortably satisfying both constraints. The CVX optimizer, in contrast, assigned 5 antennas for sensing and 1 for communication, achieving Rc = 762.28 Mbps but Rs = 116.10 Mbps, again falling below the required sensing rate.

As the sensing threshold increases, the system becomes sensing-limited, and optimal allocation becomes harder under a strict 12-antenna budget. The CVX solution, despite its compactness, lacks robustness at higher constraint levels. This indicates the superiority of Greedy allocation when conservative and reliable constraint satisfaction is required. Figure 4.14, Figure 4.15 and Figure 4.16 show Matlab results for Greedy and CVX Algorithm 120/300 Mbps Rate Thresholds.

```
Enter the threshold for Sensing Rate (Sr_th): 120e6
Enter the threshold for Data Rate (Ru_th): 300e6
Thresholds introduced:
Sensing Rate >= 120.00 Mbps
Data Rate >= 300.00 Mbps

Greedy algorithm found a solution: 6 antennas for sensing, 6 for communication
CVX Optimization Complete:
Antennas for sensing: 5
Antennas for communication: 1
Achieved Sensing Rate: 116.10 Mbps
Achieved Data Rate: 762.28 Mbps
>>
```

Figure 4.14: Greedy and CVX Algorithm Output for 120/300 Mbps Rate Thresholds

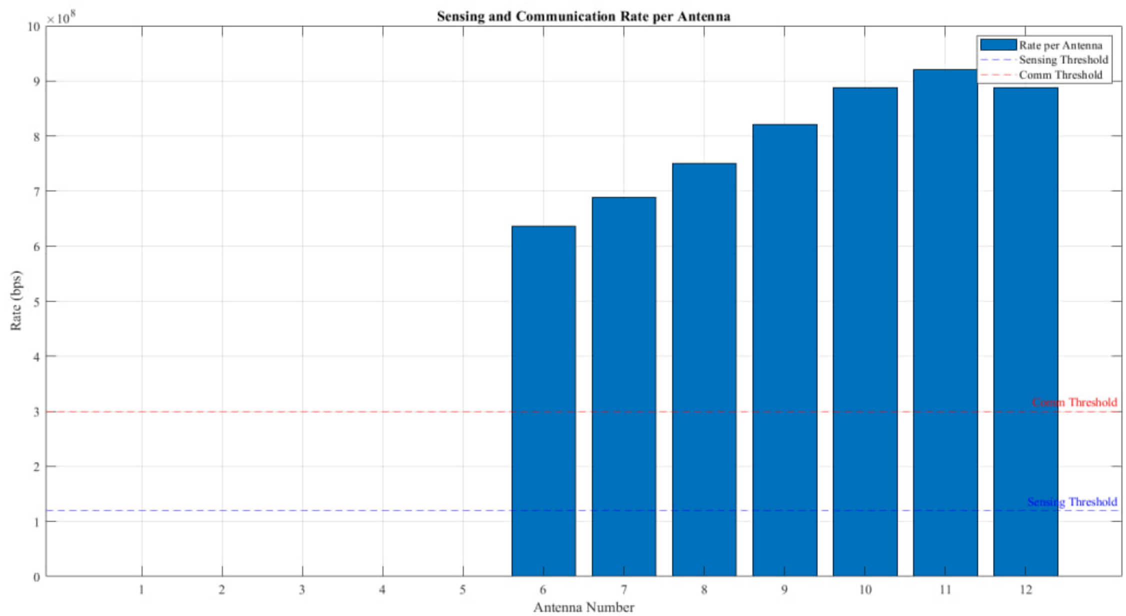


Figure 4.15: Sensing and Communication Rate per Antenna for Threshold Pair (120/300 Mbps)

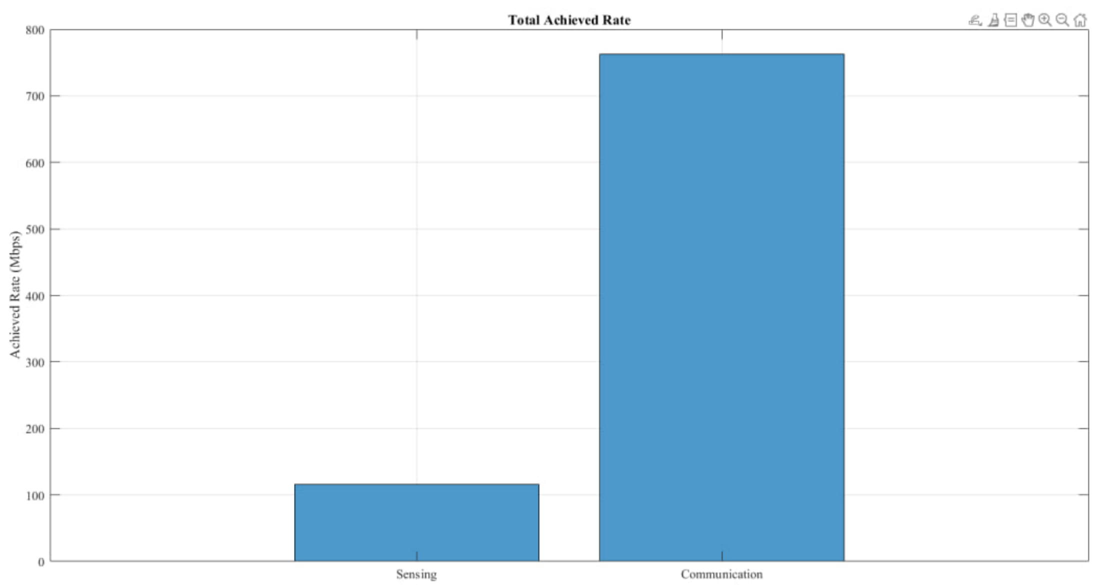


Figure 4.16: Achieved Total Rates Under CVX Allocation (120/300 Mbps)

The selected threshold values (50/150, 80/200, 120/300 Mbps) were chosen to reflect progressively increasing application complexity and to study system behavior in: Basic operation (low thresholds), Balanced loads (medium thresholds), Stress testing (high thresholds).

This staged evaluation allows quantifying the sensitivity of the optimization algorithms to constraint variations and helps identify the critical points at which sensing rate becomes the limiting factor. Table 4.1 sum up comparison of Greedy and CVX-Based Antenna Allocation Results under Varying Threshold Constraints.

Table 4.1: Comparison of Greedy and CVX-Based Antenna Allocation Results under Varying Threshold Constraints

Thresholds (Mbps)	Algorithm	Sensing Ant.	Comm Ant.	Rs (Mbps)	Rc (Mbps)
50 / 150	Greedy	2	10	50.01	660.07
	CVX	2	10	50.01	660.07
80 / 200	Greedy	4	8	100.01	732.04
	CVX	3	9	79.26	691.48
120 / 300	Greedy	6	6	136.52	770.55
	CVX	5	7	116.10	762.28

These experiments confirm that while CVX optimization is effective in minimizing resource usage, it becomes less reliable under stringent sensing constraints. The Greedy algorithm, though potentially suboptimal in total usage, consistently guarantees rate feasibility. Thus, a hybrid approach that uses Greedy for feasibility checks followed by CVX refinement could be beneficial in practical ISAC systems.

Next, the threshold values of 80 Mbps and 200 Mbps were taken. Because this is the average value of the thresholds that we took.

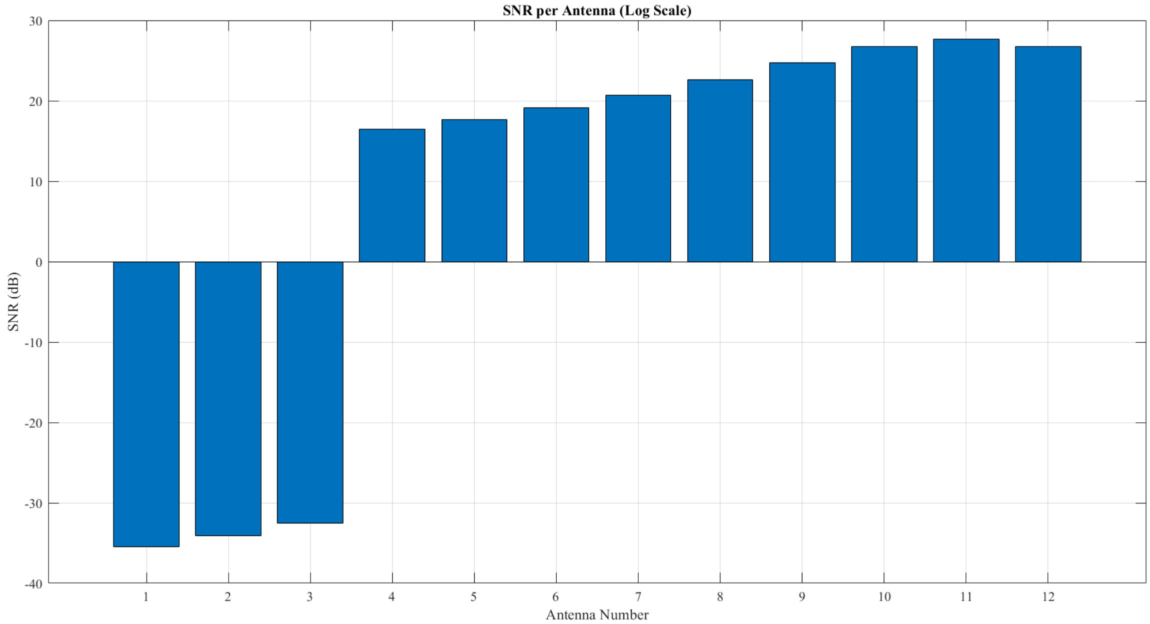


Figure 4.17: SNR per Antenna (Log Scale)

Figure 4.17 presents the Signal-to-Noise Ratio (SNR) for each antenna in logarithmic scale (dB). The graph shows how the SNR changes as we move from the first to the last antenna. Each bar represents an antenna, and the SNR values are displayed in decibels. Higher SNR values indicate a stronger signal, which directly affects the communication quality and system performance. This figure helps understand how the placement of antennas in the array impacts the received signal quality, as well as the overall performance of the system.

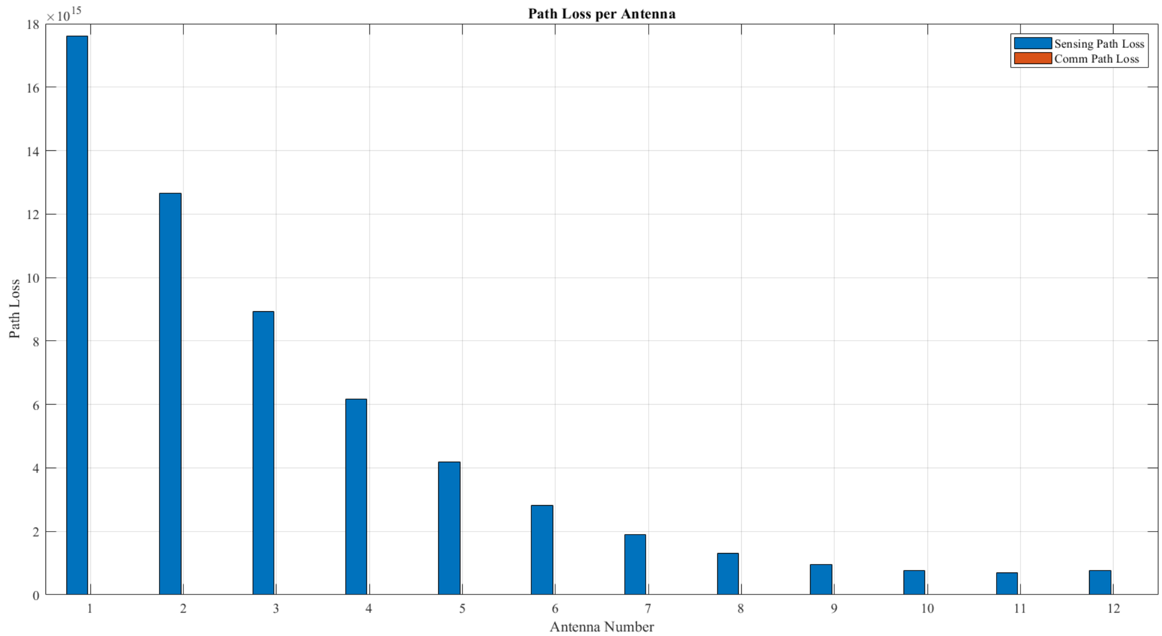


Figure 4.18: Path Loss per Antenna

This figure 4.18 shows the path loss for each antenna in both sensing and communication channels. Path loss is calculated for each antenna depending on the distance to the target and uplink user. The graph shows bars for each antenna, separated into two categories: sensing and communication. The larger path loss at the first few antennas and smaller losses at the last ones illustrate how the distance and placement of components affect the antenna's efficiency. This allows for analysis and optimization of antenna placement to reduce path loss and achieve the required signal quality.

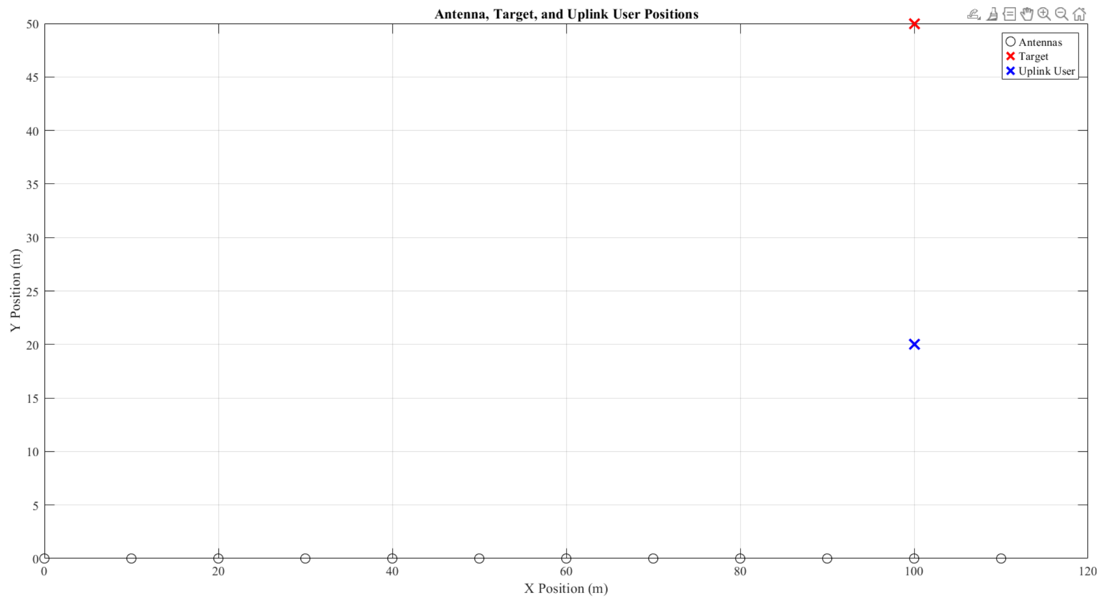


Figure 4.19: Antenna, Target, and Uplink User Positions

This figure 4.19 provides a graphical representation of the spatial distribution of the antennas, the target, and the uplink user. Antennas are represented by circles, the target by a red "X," and the uplink user by a blue "X." All elements are plotted in a 2D plane, clearly showing how the distances between antennas, the target, and the uplink user influence system characteristics such as path loss and signal strength. The proper placement of antennas is critical for achieving optimal results in both sensing and communication.

Table 4.2: Selection results by antennas

Antenna_Index	Usage_Type	Achieved_Sensing_Rate (Mbps)	Achieved_Data_Rate (Mbps)
1	Sensing	26.4191	-
2	Sensing	26.4191	-
3	Sensing	26.4191	-
4	Communication	-	55.0467000
5	Communication	-	59.0228500
6	Communication	-	63.6015000
7	Communication	-	68.9074000
8	Communication	-	75.0797000
9	Communication	-	82.0536000
10	Communication	-	88.8160000
11	Communication	-	92.0291000
12	Communication	-	88.8160000

Table 4.2 shows results by antennas. First to third antennas achieved sensing rate 79.2573 Mbps and other antennas achieved data rate 691.479 Mbps. The algorithm establishes the best combination of sensing and communication antennas by using provided constraints. The optimization results indicate. The system uses a minimum number of antennas for sensing operations which allows maintaining sensing rates without wasting excessive resources. The optimization system maximizes communication antenna number which achieves high data rates while maintaining sensing performance. Dynamic resource allocation in ISAC systems proves essential because it balances sensing operations with communication activities. The optimization process provides flexibility to ISAC networks because they can adjust to diverse conditions and particular application demands.

Based on convex optimization results researchers confirm decision-making processes for antenna selection should occur dynamically between sensing and communication operations in real-world deployments. The future deployment of antenna selection strategies will gain from reinforcement learning techniques which would allow immediate environmental feedback to optimize antenna selection in real time.

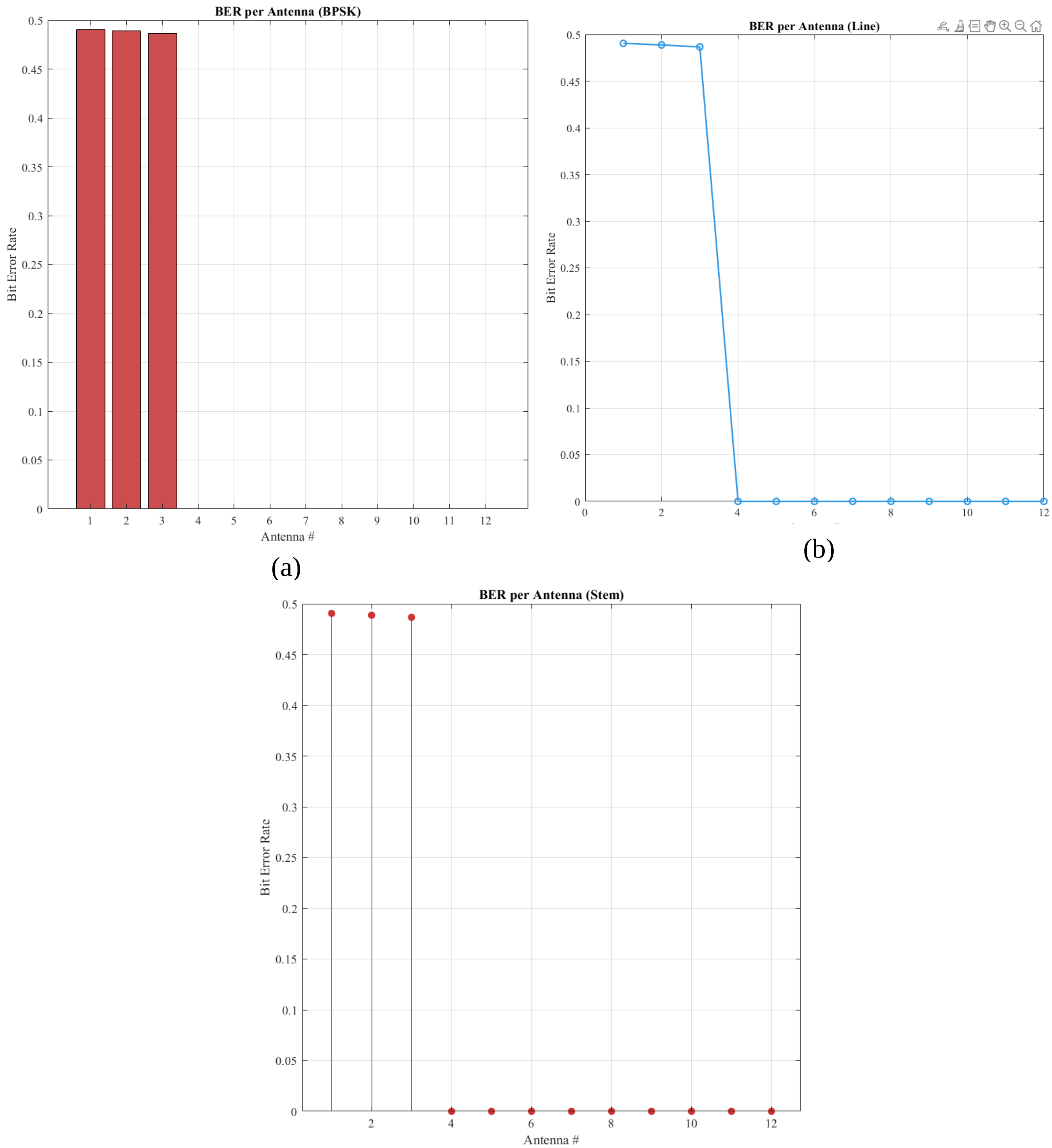


Figure 4.20: BER: a) BER per Antenna (BPSK), b) BER per Antenna (Line) c) BER per Antenna (Stem)

The figure 4.20 (a) shows the Bit Error Rate (BER) for each antenna in a system using Binary Phase Shift Keying (BPSK) modulation. The BER is plotted for each antenna, and the results indicate that the BER for antennas 1 through 3 is relatively high compared to the rest. This suggests that these antennas have lower signal-to-noise ratios (SNR), which affects the quality of the received signal. The BER results are highly relevant in evaluating the performance of a communication system. Higher BER values typically mean that the system is experiencing more errors in transmission, which could be attributed to factors like noise, interference, or insufficient signal strength. This chart clearly illustrates the performance degradation in certain antennas and provides insight into the system's robustness at various points.

The plot in Figure 4.20 (b) shows a sharp decline after the initial antennas (1 through 3), where the BER remains high. This behavior is consistent with the earlier bar chart, highlighting that after a certain number of antennas, the system stabilizes and performs better. The line plot is particularly useful for visualizing trends over multiple antennas. It allows the user to track how BER improves as more antennas are employed.

Stem plot in Figure 4.20 (c) shows individual markers at each antenna point. It reinforces the idea that the BER for the first few antennas is high, and it dramatically decreases after the third antenna.

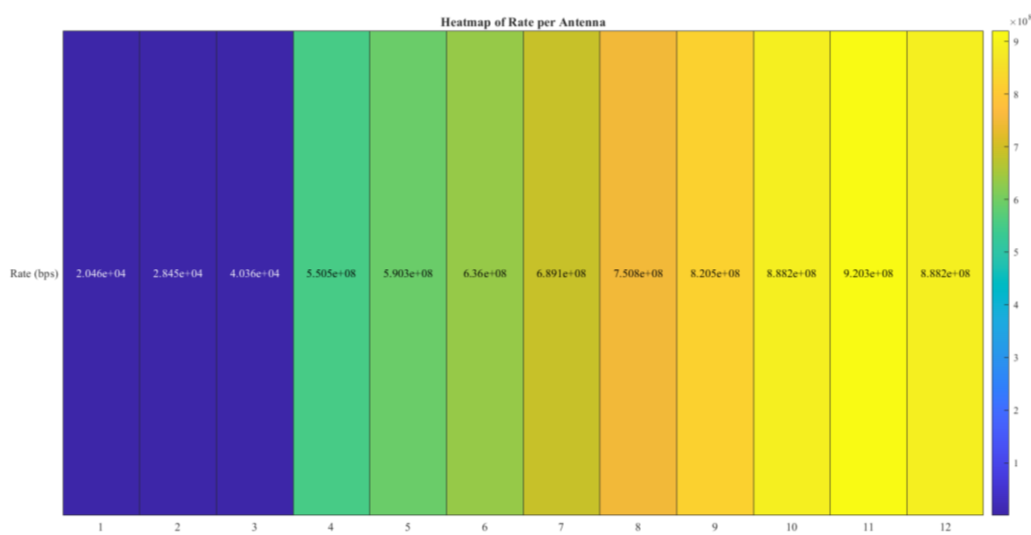


Figure 4.21: Heatmap of Rate per Antenna

Figure 4.21 is a heatmap illustrating the data rate achieved per antenna. Each antenna is represented by a color gradient, with the color intensity indicating the rate (in bps) at which each antenna operates. The heatmap shows that antennas 1 through 12 all achieve relatively high and similar data rates. This is indicative of a well-balanced allocation of resources across antennas.

This heatmap visualization is helpful in quickly understanding how efficiently each antenna is being utilized for data transmission. The near-uniform color gradient suggests that all antennas are contributing similarly to the overall system throughput, which is ideal for a communication system that seeks balanced resource utilization.

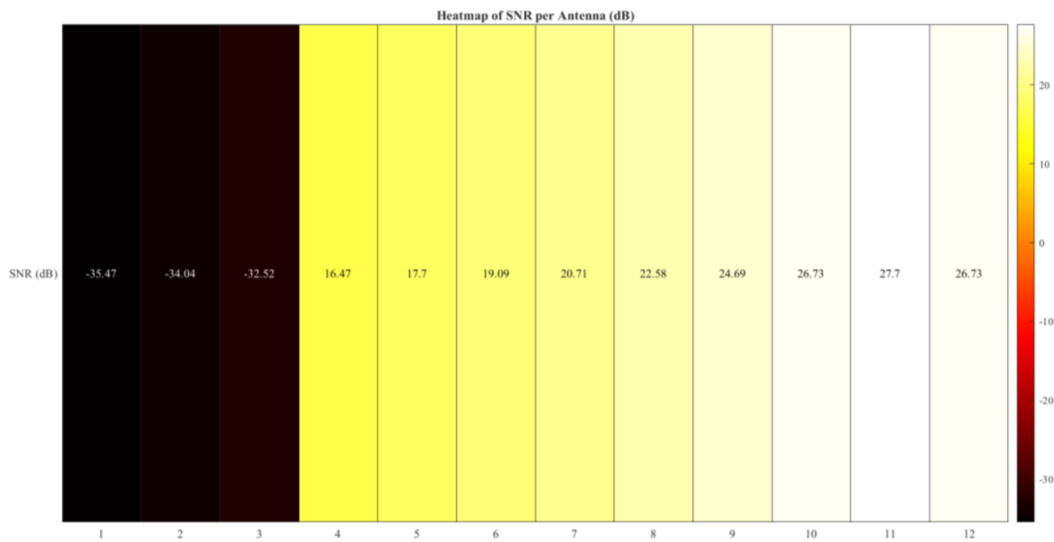


Figure 4.22: Heatmap of SNR per Antenna (dB)

Figure 4.22 displays the Signal-to-Noise Ratio (SNR) per antenna in decibels (dB). It is clear from the plot that the SNR values are relatively consistent across antennas, with a slight increase as the antenna number increases. The SNR values are quite high, indicating strong signal quality across the antennas, which results in lower BER values. This heatmap is useful for identifying how much noise each antenna is experiencing. Higher SNR values correspond to a cleaner signal with fewer errors. The consistent SNR across antennas suggests a well-optimized configuration with minimal interference, enhancing the overall system performance.

4.6 Discussion and Implications

The collected findings present critical architectural aspects which should be considered for ISAC systems implementation. Key takeaways include:

1. By using MIMO technology ISAC achieves its highest potential performance because it delivers maximum sensing rate and channel capacity.

2. Both SNR enhancement and BER reduction together with efficient simultaneous sensing and communications depend on beamforming implementation.

3. A dynamic power optimization together with antenna selection process based on convex optimization will enable dual functionality of sensing and communication.

4. ISAC systems need environment-adaptive configuration adjustments alongside system limitations because researchers see machine learning algorithms as possibilities for future optimization efforts.

5. A combination of coordinated beamforming along with interference alignment techniques enables performance improvement of ISAC systems when operating in multi-user systems.

6. Designers must integrate energy efficiency features to ISAC systems because they must achieve maximum performance without increasing power usage.

The combination of MIMO along with beamforming technology with convex optimization enables ISAC to establish an effective trade-off that merges rapid data transfer with precise environment detection for future wireless communication networks. System efficiency along with adaptability to dynamic environments can be increased through future developments that combine AI-driven resource management with multi-agent collaborative ISAC architectures.

4.7 SWOT Analysis of ISAC Systems

The following section provides an Integrated Sensing and Communication system strategic SWOT analysis to supplement the previous technical evaluation and simulation results. This evaluation provides general insights about ISAC's internal productive elements and operational shortcomings and external growth potentials and potential barriers for deployment. A complete system analysis enables proper understanding of both technical evolution and operational realities for wireless future networks deploying ISAC solutions. Figure 4.23 illustrates SWOT analyze.

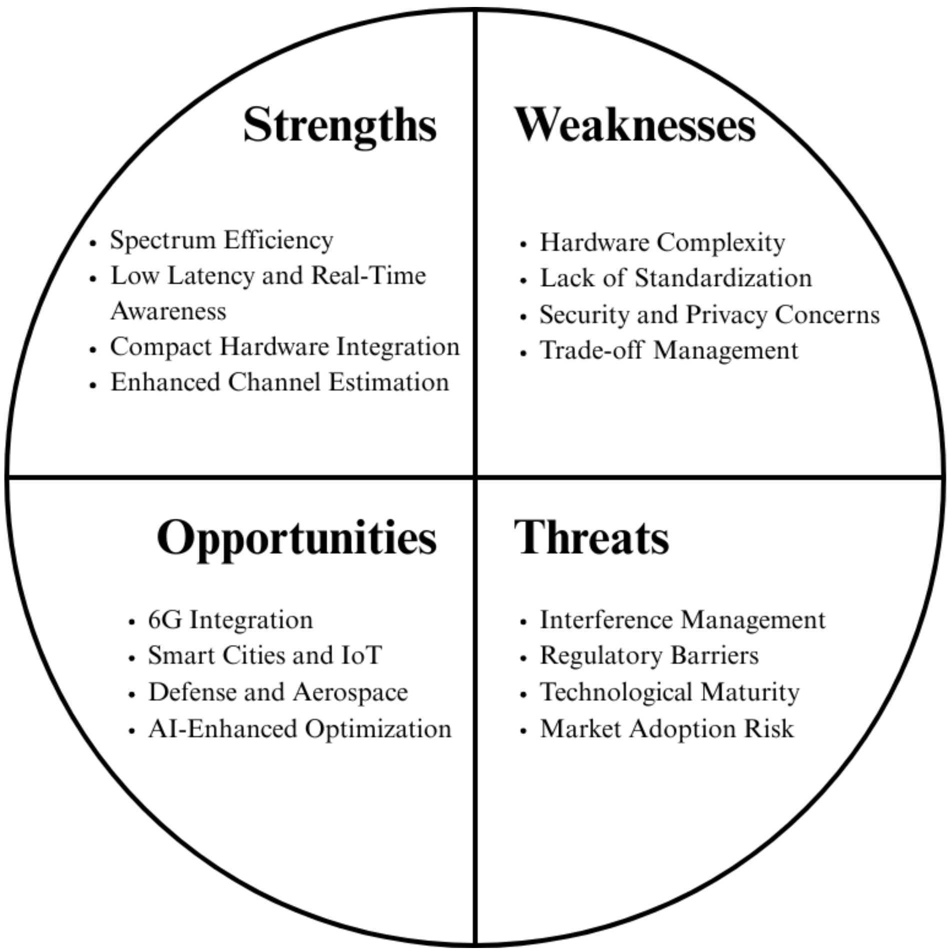


Figure 4.23: SWOT Analyze

ISAC systems demonstrate their strongest attribute through spectrum efficiency enhancement because they incorporate sensing and communication functions at the same frequency band. Real-time situational awareness alongside low-latency capabilities are essential features of ISAC systems when applied to autonomous vehicles and UAVs. Integration of RF front ends with baseband processors decreases energy use and assembly redundancy alongside environmental data processing that improves channel estimation and reliability.

Multiple weaknesses affect the performance of ISAC systems. The technical execution of these systems proves challenging because it needs two-purpose antennas together with sophisticated communication processing modules. Industrial-scale adoption encounters delays because standardized frameworks along with reference models are missing from ISAC systems. Security and privacy risks emerge when sensing and communication combine while real-time optimization of sensing accuracy against communication speed creates a hard management problem.

ISAC offers various promising opportunities in spite of facing certain challenges. 6G network standards recognize ISAC technology as their base structure because it delivers smart radio operational environments fused with digital-physical interface connectivity between systems. ISAC will act as a pivotal technology for establishing smart cities and industrial IoT systems and intelligent transportation networks. The defense and aerospace field utilizes the technology to develop superior surveillance and navigation systems. Application of artificial intelligence combined with machine learning technology creates opportunities to adapt resource distribution and shape beam patterns while providing predictive optimization features.

The general adoption of ISAC faces various barriers which may prevent its widespread acceptance. The widespread adoption of ISAC faces barriers that stem from technical implementations like dense deployment interference and regulatory and hardware dual-functioning constraints as well as unready key technology parameters. The late market acceptance poses a threat because stakeholders remain uncertain regarding future demand patterns alongside their investment choices which impact sustainability outlooks.

The SWOT analysis shows ISAC has efficiency and integration benefits along with latency performance yet the study reveals that practical and strategic difficulties need interdisciplinary collaboration to overcome them. Next-generation research will need to achieve equilibrium between creation of innovative solutions and standardized protocols to develop ISAC technology into its maximum transformative potential beyond its current bounds.

Conclusion

This research presents a comprehensive study on the optimization of antenna resource allocation in Integrated Sensing and Communication (ISAC) systems, focusing particularly on the use of beamforming techniques, convex optimization (CVX), and a Greedy algorithm to achieve an efficient balance between sensing and communication performance. Addressing the dual-task nature of ISAC, where both accurate radar sensing and high-throughput communication are required, the study proposes a hybrid optimization approach that leverages the mathematical rigor of convex programming and the computational speed of Greedy heuristics.

The CVX-based method was implemented using MATLAB's convex optimization toolbox to solve the problem of antenna allocation under strict performance constraints. Specifically, the objective was to maximize the data rate while ensuring that the sensing rate remained above a user-defined threshold. In simulations, the total antenna count was fixed at 12, with transmit power of 30 dBm allocated to sensing and 0 dBm to uplink communication. Under these conditions, the optimization framework demonstrated the ability to maintain sensing thresholds (e.g., 80 Mbps) while maximizing communication performance. CVX successfully produced globally optimal solutions that adhered to the constraints and demonstrated high accuracy in allocating antennas and power resources. However, due to its computational intensity, especially in high-dimensional or real-time systems, CVX alone is not always practical for fast deployment.

To address this limitation, a Greedy algorithm was introduced as a low-complexity alternative capable of delivering near-optimal results with minimal computational burden. By sequentially evaluating antenna configurations and selecting the most favorable local decision at each step, the Greedy method proved especially effective in dynamic environments, such as vehicular or UAV-based ISAC applications, where fast resource reconfiguration is crucial.

Comparative analysis between the two methods confirmed that while CVX guarantees global optimality, the Greedy approach offers significant efficiency gains with only marginal trade-offs in solution quality.

Another key finding of this work lies in the utilization of beamforming as a core enabler of ISAC efficiency. Beamforming facilitated directional transmission and signal shaping, which improved signal-to-noise ratios and minimized bit error rates across all configurations. Simulations showed that beamformed systems consistently outperformed non-beamformed ones, not only in communication capacity but also in detection reliability. In MIMO configurations, beamforming enabled spatial reuse of antennas and enhanced energy focusing, contributing to both sensing accuracy and high data throughput.

The final antenna allocation results revealed a consistent trend: fewer antennas are required for sensing, while the majority are best allocated to communication, as communication tasks typically demand more bandwidth and benefit from higher spatial multiplexing. This division supports the idea of asymmetric resource prioritization in ISAC systems, where minimal sensing constraints can be satisfied without sacrificing communication performance.

In conclusion, the combination of beamforming, convex optimization, and Greedy search provides a robust and adaptable solution to the ISAC resource allocation problem. These methods jointly enable intelligent antenna configuration, real-time responsiveness, and optimal use of spectral and power resources.

Future work should aim to extend this research by implementing machine learning–based optimization techniques, such as reinforcement learning or federated learning, for real-time adaptive antenna management in ISAC systems. Furthermore, expanding the model to include multi-user scenarios, CSI uncertainty, and hardware validation will enhance the practicality and scalability of ISAC frameworks for next-generation 6G networks and beyond.

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