

MACHINE LEARNING DRIVEN ADAPTIVE RIS PARTITIONING AND RESOURCE OPTIMIZATION FOR INTEGRATED SENSING AND COMMUNICATION

A PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
SIGNAL PROCESSING AND DIGITAL DESIGN

Submitted by

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JUNE, 2026

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CANDIDATE'S DECLARATION

I, **Mitali Jawa**, Roll No.-(24/SPD/17), student of M.Tech (Signal Processing and Digital Design), hereby declare that the project dissertation titled “**Machine Learning-Driven Adaptive RIS Partitioning and Resource Optimization for Integrated Sensing and Communication**” which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi, in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, or any other similar title or recognition.

Place: Delhi



Mitali Jawa

Date: **28.05.26**

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CERTIFICATE

I hereby certify that the Project Dissertation titled “**Machine Learning-Driven Adaptive RIS Partitioning and Resource Optimization for Integrated Sensing and Communication**” which is submitted by **Mitali Jawa**, Roll No – **24/SPD/17**, M.Tech (Signal Processing and Digital Design), Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ACKNOWLEDGEMENT

I wish to express my sincerest gratitude to **Dr. Rohit Kumar** for his continuous guidance and mentorship throughout the duration of my project. He consistently provided helpful insights, clarified concepts whenever required, and directed me towards achieving my project objectives. His support and encouragement played a vital role in the successful completion of this work.



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Date: **28.05.2026**

Abstract

Due to the fast evolution of 6G wireless communication networks, the emergence of the Integrated Sensing and Communication (ISAC) technique becomes necessary because communication and sensing can be done simultaneously by sharing a common wireless resource. This paper presents a novel reconfigurable intelligent surface (RIS)-assisted ISAC architecture for the efficient optimization of communication embedded sensing. In the proposed system plan, the allocation of RIS elements for communication and sensing operations are dynamically optimized, as well as communication-sensing priority and power allocation, in order to make the overall performance optimal in non-stationary wireless environments. In addition, Nakagami-m fading channel models are taken to present real-time features of the communication and sensing conditions. A multi-objective reward function is developed using the sensing and communication rates and the communication-sensing tradeoff performance. Various arrangements of the RIS are analyzed to determine the best configuration of division for communications and sensing depending on different scenarios in terms of wireless channel characteristics. An extensive database of simulations is obtained via exhaustive optimization, and an intelligent predicting algorithm of learning of Random Forest is applied to predict the best RIS configuration comparing it with a KNN Classifier which is based on the extracted communications and sensing metrics. The accuracy of predicting the best RIS dividing configuration using the Random Forest method exceeds those achieved using other conventional techniques. This framework provides a reliable and efficient solution for ISAC-RIS systems which supports wireless networks also beyond 6G.

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Chapter 1

Introduction

1.1 Overview of Future 6G Wireless Networks

The explosive rise in the number of intelligent wireless applications and devices has greatly raised the demand for high bandwidth, low latency, and energy-efficient wireless communication systems. While fifth-generation (5G) wireless networks have made it possible to achieve enhanced mobile broadband, ultra-reliable low latency communication, and massive machine type communication, there is still more that future wireless applications will require from wireless systems. Future applications including autonomous transportation, intelligent healthcare, intelligent manufacturing, digital twin, immersive extended reality (XR), Internet of Everything (IoE), unmanned aerial vehicles (UAVs), and smart cities all require intelligent wireless communication capabilities.

To meet these new demands, sixth generation (6G) wireless networks are now seen as intelligent and adaptive communications systems that can seamlessly combine communication, sensing, computing, and machine learning functionalities in an all-wireless environment. Some features that future 6G networks will be able to offer include:

- ultra-high data rates greater than terabits per second,
- ultra-low latency,
- massive connectivity for devices,
- intelligent environmental perception,
- extremely high spectral efficiency,
- enhanced energy efficiency, and

- network autonomy.

While traditional wireless communications systems only consider the performance of the communication process, in future 6G systems, there will be an intelligent interaction with the surrounding environment. Thus, it is necessary to develop new technologies that can do both sensing and communication simultaneously.

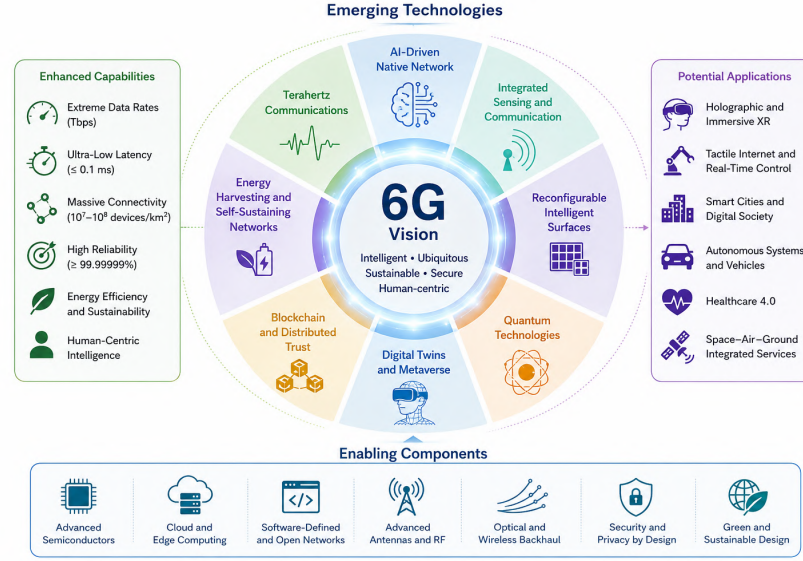


Figure 1.1: New Technologies and Key Components for Future 6G Wireless Networks.

Various technologies have been identified to facilitate the deployment of 6G communications that offer ultra-reliability and intelligent communication channels with extremely high capacity capabilities. Some of the major technologies suggested to enable such a system include integrated sensing and communications, reconfigurable intelligent surfaces, artificial intelligence-based wireless optimization, terahertz communications, large MIMO, edge intelligence, and intelligent reflectors. These technological developments can be leveraged to improve spectrum utilization, network intelligence, sensing, coverage, and power utilization in the next generation of wireless communication systems.

These include RIS-enabled ISAC, which is currently considered one of the most promising areas of study for the wireless networks of the future, mainly because of its potential to optimally utilize spectral resources for simultaneous communications and sensing.

1.2 Integrated Sensing and Communication (ISAC)

The Integrated Sensing and Communication (ISAC) system is one of the recent promising paradigms for next-generation intelligent wireless networks because of its capacity to effectively employ the spectral and hardware resources for communication and sensing simultaneously. Traditional wireless systems usually conduct communication and sensing activities individually utilizing different spectral bands as well as hardware configurations. This results in inefficient use of spectrum, increased cost of installation, and higher power consumption [1–4].

The concept of ISAC resolves these drawbacks by allowing the communication signals to concurrently carry out sensing and target detection operations. The communication signals generated through the process of ISAC find applications in the following domains:

- Target detection,
- Localization,
- Environmental mapping,
- Object tracking,
- Mobility estimation, and
- Radar sensing.

Communication-sensing functionality integration brings the following benefits:

- Increased spectrum efficiency,
- Simplified hardware design,
- Reduced energy consumption,
- Increased situation awareness, and
- Efficient use of resources.

ISAC is becoming increasingly significant for applications in the future like self-driving cars, UAV navigation, intelligent transportation, industrial robotics, and intelligent healthcare.

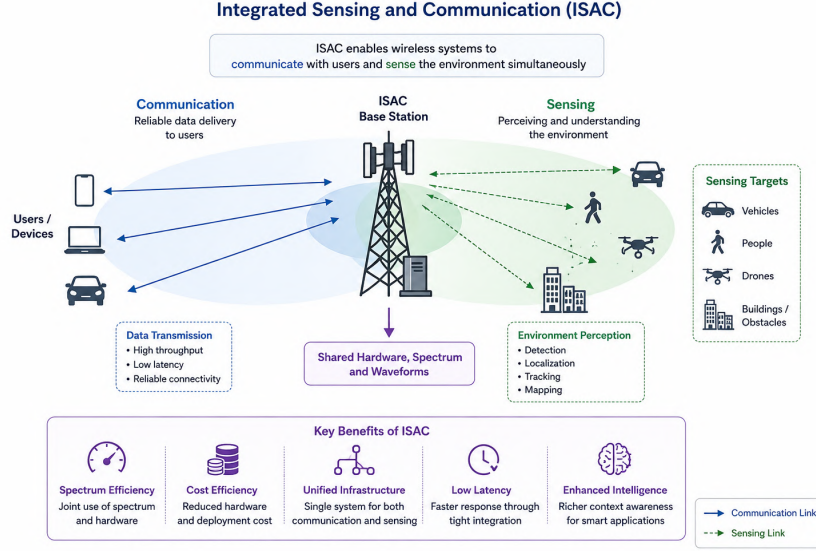


Figure 1.2: Representation of the Concept of Integrated Sensing and Communication (ISAC).

Although ISAC systems are highly beneficial, they pose many practical problems as well. Communication and sensing tend to have contradicting optimization goals. Typically, communications try to optimize for maximum throughput and spectral efficiency, while sensing tries to optimize for precision of target localization and awareness of environment.

1.3 Reconfigurable Intelligent Surfaces (RIS)

Recently, Reconfigurable Intelligent Surface (RIS) technology is introduced in wireless communication systems because it allows the smart control of electromagnetic wave propagation using programmable reflecting elements. An RIS element can independently control the phase shift of incident electromagnetic waves and hence allow intelligent beam steering and shaping of the wireless environment [5–9].

RIS works passively without using any RF chains for transmitting signals unlike other relaying nodes such as conventional relays and active base stations. This makes RIS an energy-efficient system since it consumes less power and simpler hardware [10, 11].

The wireless systems assisted by RIS offer various benefits such as high spectral efficiency, intelligent beamforming, interference cancellation, energy efficiency, wireless coverage improvement, and environment awareness in wireless communications [12, 13].

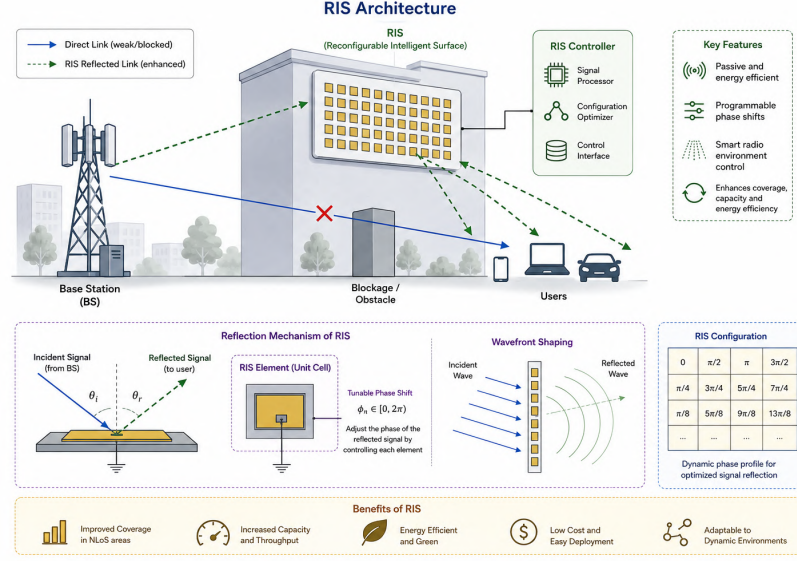


Figure 1.3: Architecture and reflection mechanism of a Reconfigurable Intelligent Surface (RIS).

Wireless systems assisted by RISs can control the properties of the wireless propagation channel for better communication and sensing performance. Thus, RIS is increasingly appealing technology for future generation 6G wireless systems.

1.4 RIS-Assisted Integrated Sensing and Communication

ISAC systems assisted by RIS can leverage the benefits of programmable wireless systems and integrated sensing-communication systems to enhance both communication and sensing performances [4].

For ISAC in RIS-aided systems, the dynamic control of the reflected wireless signals by RIS allows for improvement in both communication and sensing performance. Through proper adjustment of phase shifts of reflected signals, the performance of RIS will lead to an improvement in communication throughput, sensing ability, beamforming gain, performance of target detection, and wireless coverage as well [14, 15].

The ISAC system utilizing RIS technology is able to smartly control signal reflection towards both communication receivers and sensing objects at the same time, which facilitates resource sharing among sensing and communications processes [16, 17].

The proposed method employs a two-hop propagation of communication signals using signal reflection:

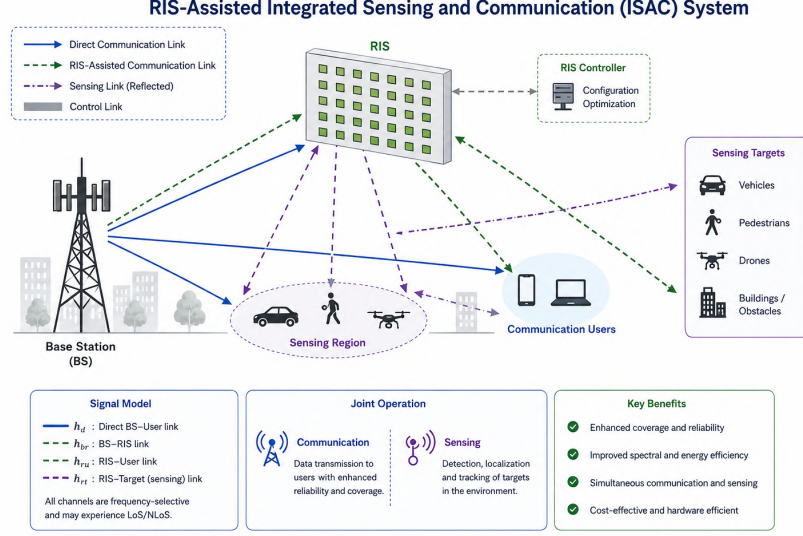


Figure 1.4: RIS-based ISAC System Model.

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{RX} \quad (1.1)$$

while sensing operates under a monostatic four-hop propagation model:

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{Target} \rightarrow \text{RIS} \rightarrow \text{TX} \quad (1.2)$$

The RIS allocates its reflective components for either communications or sensing activities, thus facilitating optimal allocation of wireless resources.

1.5 Problem Statement

Despite the numerous benefits associated with RIS-enhanced ISAC systems, many crucial issues yet need to be addressed through existing literature. The major challenge with existing RIS-enhanced ISAC systems is that most systems use static RIS settings, static resource allocation approaches, perfect CSI knowledge, and complex optimization algorithms. Nevertheless, real-world scenarios for wireless networks are very dynamic due to the presence of various parameters like user mobility, blockages, interferences, varying traffic, and changing sensing requirements. These dynamic scenarios cannot be managed efficiently using static RIS settings and consequently lead to inefficient communication and sensing operations.

The other big problem is related to the conflicting goals of sensing and communication. More use of RIS for communication can be beneficial for communication and

may not be helpful for sensing operations, and vice versa.

Just like that, giving preference to sensing tasks may adversely influence the efficiency of communication. Current approaches to optimization, which include alternating optimization, semidefinite relaxation, convex optimization, and beamforming optimization, have some disadvantages, such as:

- High computational complexity,
- Slow convergence speed,
- Lack of scalability,
- And limited adaptability in real-time wireless environments.

This has led to a great demand for intelligent and adaptive RIS optimization systems that can balance between sensing and communications tasks while reducing computational complexity.

1.6 Motivation and Objectives

There exist a number of drawbacks associated with traditional RIS-based ISAC optimization schemes that necessitate the need to devise a more intelligent approach based on machine learning techniques. Traditionally, most optimization algorithms have relied heavily on iterative beamforming and complex convex optimization schemes that require considerable computational resources.

ML techniques are capable of learning an optimum solution for the problem of optimizing RIS configuration directly using real-world data collected from wireless channels and generated by simulation tools. There exist various benefits of such machine learning techniques for RIS optimization, including fast decision-making, adaptivity in resource allocation, enhanced scalability, and awareness about the surrounding environment. Motivated by these benefits, this research project proposes an adaptive RIS partitioning and resource optimization scheme for RIS-assisted ISAC systems.

The main goals of the proposed thesis are outlined as follows:

- Development of an RIS-enhanced ISAC system able to carry out both communication and sensing tasks simultaneously.
- Proposal of an adaptive RIS partitioning scheme that enables the dynamic assignment of RIS units to communication and sensing tasks.

- Creation of realistic wireless channel models on Nakagami- m fading channels.
- Design of a reward function for optimizing communication and sensing tasks while ensuring fairness.
- Implementation of adaptive transmit power management for communication and sensing processes.
- Development of a Monte Carlo simulation-generated data set in dynamical wireless channels.
- Application of machine learning techniques for optimal RIS tuning and wireless optimization.

1.7 Proposed Framework and Contributions

Description of the proposed framework of ISAC using RIS technology includes Transmitter (TX), Receiver (RX), sensing target, and a reconfigurable intelligent surface (RIS) having 100 configurable reflective elements. The reflective elements of the RIS are divided based on the conditions of the wireless channel.

$$\mathcal{C} \cup \mathcal{S} = \mathcal{N}, \quad \mathcal{C} \cap \mathcal{S} = \emptyset \quad (1.3)$$

The communication channel is given as:

$$h_{comm} = \sum_{n \in \mathcal{C}} h_{TR,n} h_{RR,n} \quad (1.4)$$

The sensing channel can be described as a cascaded reflection-sensing channel:

$$h_{sens} = \sum_{n \in \mathcal{S}} h_{TR,n} h_{RT,n} h'_{RT,n} h'_{TR,n} \quad (1.5)$$

The framework proposed in this study includes adaptive RIS partitioning, reward maximization with consideration for fairness, power control, feature extraction, and prediction of RIS arm using machine learning.

The contributions of this work can be highlighted as follows:

- Introduction of a new approach to designing an intelligent wireless system based on adaptive RIS-ISAC through machine learning.

- Joint optimization of the number of arms of RIS and communication-sensing power.
- Formulation of a reward design that ensures fair distribution of communication and sensing resources.
- Modeling the realistic operation of the wireless environment using Nakagami- m fading channels and variations of the wireless environment.
- Design of the RIS arm prediction approach based on Random Forest and KNN methods.
- Simulation and evaluation of performance of the proposed framework in various wireless conditions.

The proposed design offers several practical benefits such as high communication reliability, accurate sensing performance, adaptive wireless optimization, low computational complexity, flexible RIS configuration, and intelligent resource allocation of wireless systems in the future.

Chapter 2

Theoretical Background

2.1 Introduction

In this chapter, we cover the theory that forms the basis of the adaptive RIS-based ISAC using machine learning. The topics include an overview of the sixth generation wireless communications, ISAC, RIS, channel models in wireless communications, fairness-based optimization algorithms, and machine learning techniques used to optimize RIS adaptively. The theoretical knowledge introduced in this chapter forms the basis of the adaptive RIS partitioning and optimization framework introduced in later chapters.

2.2 Evolution of 6G Wireless Networks

Wireless communication systems have come a long way since their invention from analog communication systems to the current intelligent wireless communication networks. Each generation brought about major improvements in terms of spectral efficiency, communication reliability, data capacity, latency, and mobility. However, due to the ever-increasing demands for intelligent wireless applications such as autonomous driving, industrial automation, smart health, IoT, extended reality, UAVs, etc., there is much more focus on developing the next generation of wireless communication technology, which will be sixth generation (6G) wireless communication systems [1].

Future 6G wireless networks are envisioned to combine communication, sensing, localization, artificial intelligence, and edge computing under one intelligent wireless architecture. In contrast to the previous generations of wireless communication systems, which concentrated only on communication performance metrics, 6G networks will offer intelligent environment-aware wireless service with ultra-reliable low-latency communications (URLLC), massive connectivity, and intelligent decision-making capabilities [12].

Integrated Sensing and Communication (ISAC), Reconfigurable Intelligent Surfaces (RIS), Terahertz communication, Artificial Intelligence (AI), and massive MIMO are some of the technologies deemed critical enablers for future intelligent wireless communication systems. Such technologies are capable of offering adaptive wireless optimization, intelligent processing techniques, spectral efficiency, improved sensing performance, and environment-aware communication performance in next-generation wireless networks [9].

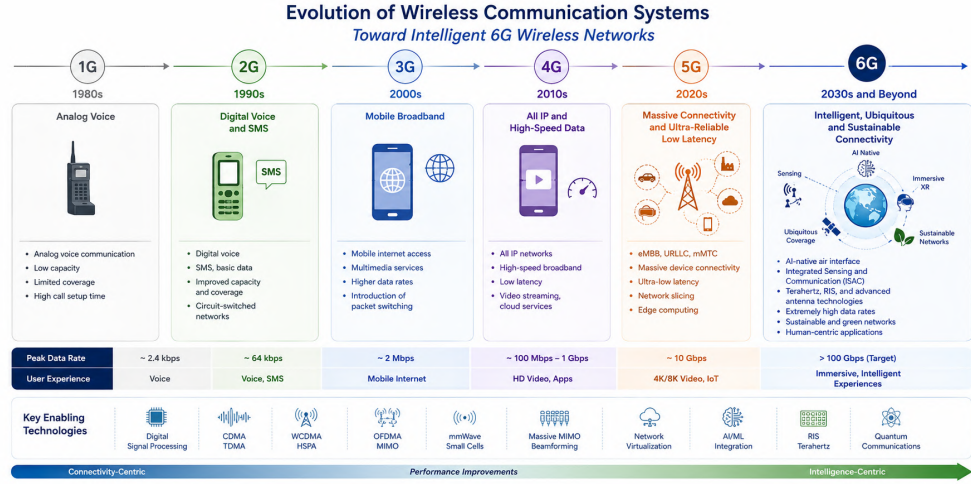


Figure 2.1: Evolution of wireless communications systems to intelligent 6G wireless networks.

The increasing demand for adaptive wireless communication and intelligent sensing capabilities has driven a considerable amount of research into the development of wireless communication systems that can perform both communication and sensing tasks using ISAC techniques [18].

2.3 Integrated Sensing and Communication (ISAC)

One of the most promising techniques in terms of implementing intelligent wireless communication systems is Integrated Sensing and Communications (ISAC), which involves using common spectral resources, hardware infrastructure, transmission waveforms, and signal processing schemes for performing communication and sensing functions [1].

Classical wireless communication systems use separate hardware and spectrum resources to implement communication and sensing functions. This practice results in poor spectral efficiency and higher complexity of implementation. The ISAC concept addresses these issues, enabling integrated communication and sensing operations in the same wireless communication framework [2].

The following applications can be realized at once in the case of ISAC:

- data transmission,
- environmental sensing,
- object detection,
- object localization,
- and situational awareness.

The above joint sensing and communication paradigm is extremely useful for increasing the spectral efficiency, hardware efficiency, energy efficiency, and wireless intelligence because of the sharing of wireless devices and infrastructures for both sensing and communication processes. Hence, ISAC systems can facilitate intelligent communication with environment awareness by using efficient hardware and increased spectrum efficiency [3].

Some examples of future intelligent applications that need ISAC systems include autonomous vehicles, industrial robots, smart transportation, healthcare monitoring, smart surveillance, and UAV-based wireless communication. All these applications require sensing and communication capabilities concurrently for their efficient and reliable functioning.

However, there are some crucial issues with respect to the development of ISAC systems. Some of the most important issues regarding the design of ISAC systems include:

- communication-sensing trade-off,
- interference control,
- resource optimization,
- beamforming techniques,
- and dynamic wireless environment.

Both communication and sensing require the same wireless resources and hence there is the need for efficient intelligent mechanisms for optimizing both communication and sensing tasks. One such mechanism that can be used is that of RIS-assisted ISAC systems.

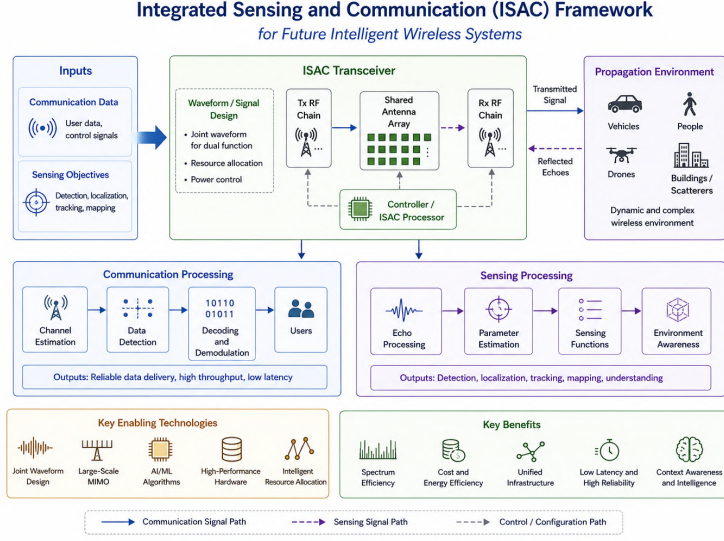


Figure 2.2: ISAC-based intelligent future wireless system framework.

2.4 Reconfigurable Intelligent Surfaces (RIS)

RIS technology has gained considerable prominence of late because of its ability to control the propagation of electromagnetic waves in an intelligent manner through the use of programmable passive reflectors [5].

RIS is made up of many inexpensive programmable reflectors that can independently change the phases and amplitudes of incoming electromagnetic waves. While traditional relay systems use active radio frequency chains, RIS uses passive means for this process, thus promoting efficient wireless networking [6, 7].

The expression for reflected signal from an RIS unit is as follows:

$$y_n = \beta_n e^{j\theta_n} x_n \quad (2.1)$$

where β_n is reflection amplitude, θ_n is phase shift, and x_n is the incident wireless signal.

RIS facilitates through:

- adaptive beamsteering,
- intelligent signal reflections,
 - interference reduction,
 - wireless coverage enhancement,
 - and spectral efficiency gain.

RIS enabled wireless communication networks have a great potential for enhancing the reliability of wireless communications by intelligently steering the wireless signals to intended communication nodes or sensors. Adaptive wireless optimization considering dynamic environment conditions can be achieved using RIS systems [8,9].

Numerous researchers have reported significant gains in:

- communication data rate,
- wireless signal quality,
- energy efficiency, and
- wireless network coverage.

Nevertheless, deployment of RIS technology in wireless systems is still constrained by:

- channel state information,
- phase optimization, and
- other factors.

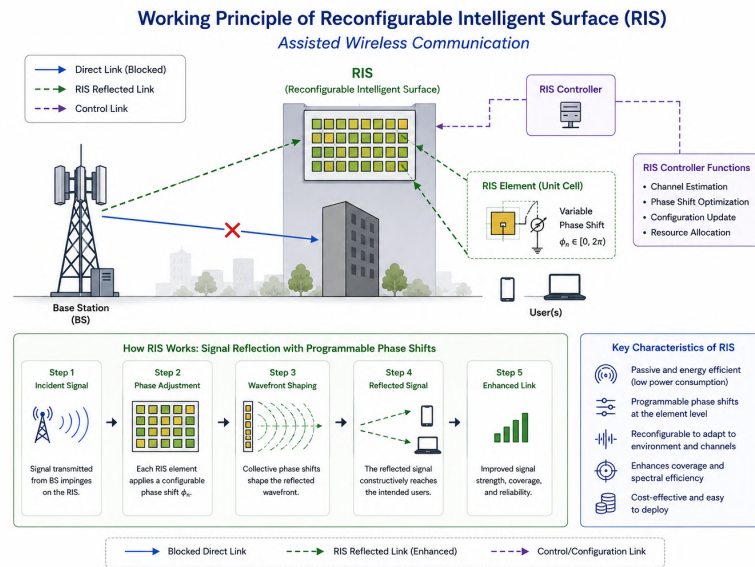


Figure 2.3: Principle of operation of RIS-enabled wireless communication.

The integration of RIS with ISAC enables intelligent wireless systems capable of jointly optimizing communication and sensing operations under dynamic wireless environments.

2.5 RIS-Assisted ISAC Systems

RIS-enabled Integrated Sensing and Communication technology enables programmable wireless propagation manipulation along with integrated sensing and communications features for intelligent future wireless networks [4].

In RIS-enabled ISAC technologies, RIS helps communication users via intelligent reflected beamforming while simultaneously performing sensing functions targeting environment objects [14]. RIS controls the wireless propagation environments intelligently to enhance:

- reliability of communication,
- accuracy of sensing,
- beamforming gain,
- spectrum efficiency, and
- environmental intelligence.

In the case of RIS-enabled ISAC technology, the communication path is

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{RX} \quad (2.2)$$

while sensing path is:

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{Target} \rightarrow \text{RIS} \rightarrow \text{TX} \quad (2.3)$$

In comparison with conventional wireless communication architectures, RIS-based ISAC systems can enjoy the following benefits due to RIS's capability of adjusting signal reflection and optimizing wireless communication with sensing information [3].

Nevertheless, most existing RIS-enabled ISAC systems consider the following settings as given:

- Fixed RIS partitioning,
- Static beamforming scheme, and
- Centralized optimization strategy.

These settings do not suit real-life dynamic wireless environment conditions because of the following reasons:

- User mobility,

- Interference,
- Blockage, and
- Traffic variation.

Hence, adaptivity of RIS partitioning and intelligent resource optimization is crucial for the future.

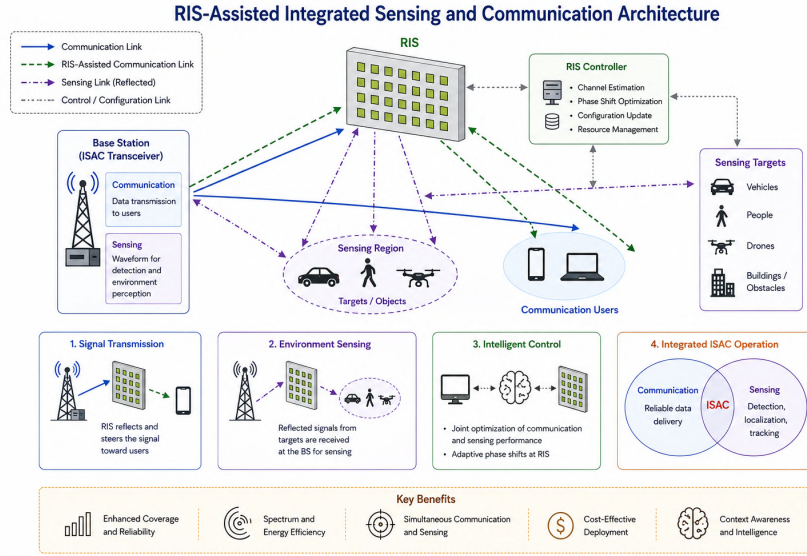


Figure 2.4: Proposed RIS-enabled ISAC communication architecture.

2.6 Wireless Channel Modeling and Performance Metrics

Wireless channels for communication experience multipath fading, path loss, shadowing, interference, and dynamic environmental effects, causing signal attenuation, propagation variations, and uncertainty in communication performance. Hence, proper wireless channel modeling is crucial to evaluate the performance of RIS-enabled ISAC systems.

A proper wireless channel model is thus crucial to evaluate the communication and sensing performance of RIS-enabled ISAC systems.

To generate the wireless channels in the proposed framework, Nakagami- m fading is considered due to its flexibility in modeling channels in both moderate and harsh fading environments [19].

The fading channel coefficient is expressed as:

$$h \sim \text{Nakagami}(m, \Omega) \quad (2.4)$$

where:

- m is fading severity parameter, and
- Ω stands for mean signal power.

As opposed to Rayleigh fading, Nakagami fading offers enhanced flexibility for modeling the RIS-enabled wireless channel environment.

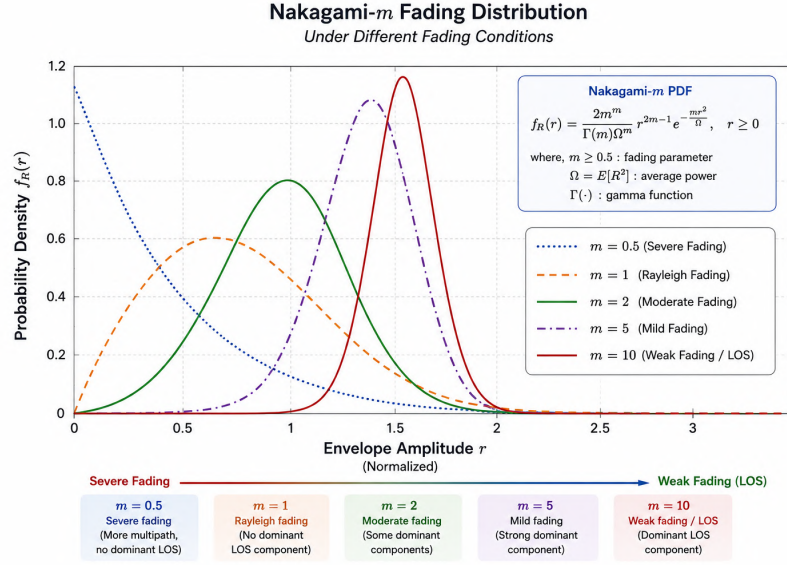


Figure 2.5: Distribution of fading parameters based on the Nakagami- m fading model in various fading environment.

The communication Signal-to-Noise Ratio (SNR) is given by:

$$\text{SNR}_{comm} = \frac{P_{comm} |h_{comm}|^2}{\sigma^2} \quad (2.5)$$

For the sensing SNR expression,

$$\text{SNR}_{sens} = \frac{P_{sens} |h_{sens}|^2}{\sigma^2} \quad (2.6)$$

where:

- P_{comm} and P_{sens} refer to communication and sensing transmission power,
- and σ^2 refers to noise power.

In order to achieve joint sensing and communication, an optimization-based approach is presented using fairness-based optimization metric denoted by:

$$F = \frac{2\text{SNR}_{comm}\text{SNR}_{sens}}{\text{SNR}_{comm}^2 + \text{SNR}_{sens}^2} \quad (2.7)$$

The introduction of fairness-based optimization metric avoids bias towards either communication or sensing.

2.7 Machine Learning for RIS Optimization

Machine learning has become one of the most efficient solutions for solving wireless optimization problems since ML-based methods can find optimal configurations of wireless settings without using iterative optimization algorithms [20].

Machine learning for RIS optimization allows:

- reducing the computational complexity,
- conducting adaptive optimization of wireless systems,
- resource allocation optimization,
- and awareness of environmental decision-making.

Supervised machine learning is employed in the presented framework for predicting RIS arm configuration and optimizing it according to different wireless environment settings. Random Forest (RF) and K-Nearest Neighbour (KNN) classifiers are used for RIS arm prediction and adaptive optimization [21].

Random Forest is an ensemble learning method, which is comprised of many decision trees and makes predictions based on majority voting of all the trees in the model. Random Forest provides powerful non-linear learning capacity and robustness against overfitting in wireless conditions [22].

K-Nearest Neighbour (KNN) is a supervised learning algorithm that predicts labels by finding feature vectors with closest distances [23]. The Euclidean distance of feature vectors is defined as follows:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (2.8)$$

Monte Carlo simulations are used for creating the wireless communication dataset using RIS under different wireless channel environments. The statistical and non-

linear properties of the data set created are extracted for machine learning based RIS optimization and RIS arms prediction [24].

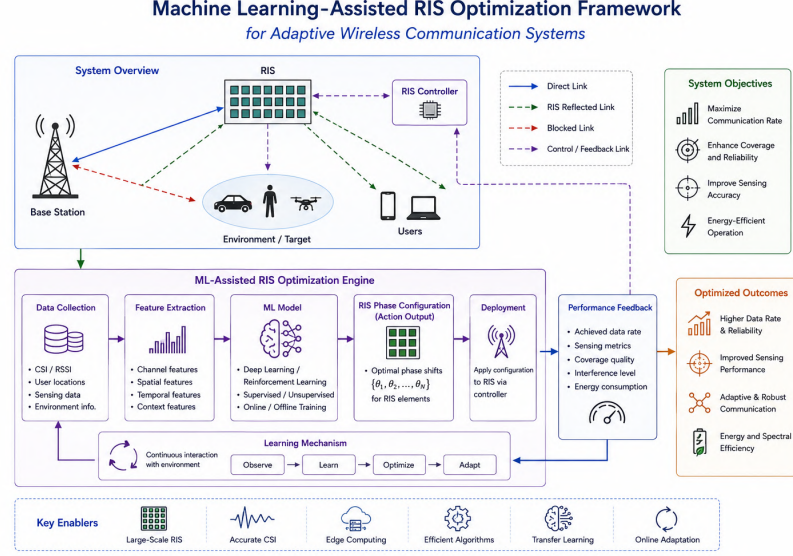


Figure 2.6: Machine learning-based framework for the optimization of RIS for adaptive wireless communication systems.

2.8 Chapter Summary

In this chapter, we have seen the theoretical basis regarding the design of RIS-enabled Integrated Sensing and Communication networks. Fundamental theories on 6G wireless communications, ISAC, RIS, wireless channel modeling, fairness-based optimization, and machine-learning-based RIS optimization were all explained. The theoretical foundations discussed above form the basis of our proposed machine learning-based RIS partitioning and optimization framework in the upcoming chapters.

Chapter 3

Literature Review

3.1 Introduction

The fast development of the next generation of wireless communications, known as the sixth-generation (6G), has led to an increasing need for intelligent wireless environments that enable not only reliable communication but also sensing, localization, and resource management. Emerging wireless communication applications, like autonomous vehicles, industrial automation, smart healthcare, drones, and extended reality, necessitate an ability to provide wireless communication with high throughput and simultaneous environmental awareness. These evolving needs have resulted in many studies dedicated to the integrated wireless sensing and communication, and reconfigurable intelligent surface assisted wireless communications.

Recently, RIS-assisted ISAC has become one of the most promising technologies for future intelligent wireless communication networks due to its ability to control wireless propagation using the programmability principle and combine the abilities of wireless communication and sensing [1, 5]. Studies on RIS-assisted communication systems, sensing-aware wireless network architecture, beamforming algorithms, and wireless communication optimization algorithms based on machine learning techniques are among recent investigations. In this chapter, we consider all existing works dedicated to RIS-assisted wireless communication, ISAC architectures, wireless communication resource allocation, and RIS optimization techniques based on machine learning.

3.2 RIS and RIS-Assisted Wireless Communication Systems

The Reconfigurable Intelligent Surface technology has recently been developed as a disruptive technique in boosting the performance of wireless communication through intelligent manipulation of electromagnetic wave propagation. Specifically, the RIS is made up of many passive reflecting components whose operation allows dynamic adjustment of the phase and amplitude of incoming wireless signals. Differing from traditional relaying systems, RIS works passively, hence offering more energy efficiency due to reduced hardware complexity.

RIS was initially proposed by Wu and Zhang [5], who suggested the idea of intelligent reflecting surfaces for future wireless communication networks and showed how RIS could boost spectral efficiency, signal coverage area, and communication reliability through adaptive management of the wireless channel environment. As such, RIS was recognized as one of the key technologies in future beyond-5G and 6G communication systems. Similarly, Di Renzo *et al.* [6] gave an extensive review on smart radio environment based on RIS technology.

Some other researchers have explored different scenarios associated with RIS-assisted wireless communication systems. Wu and Zhang [25] have proposed an algorithm for joint optimization of active and passive beamforming in RIS-assisted wireless communication networks. In this algorithm, they jointly optimize beamforming at the transmitter side and phase shifts of the RIS to achieve maximum communication throughput. Pan *et al.* [26] have studied multi-cell MIMO wireless communication systems assisted by RIS. They proved that RIS is very effective in suppressing the interference between cells while enhancing coverage and quality of communication in the network.

Tang *et al.* [27] have explored MIMO communication systems enabled by RIS and performed experiments to verify the practicality of such wireless communications. Yu *et al.* [18] have studied multi-RIS-based wireless communication systems and proposed some optimization techniques for configuring phase shifts and allocating powers in wireless transmission through such networks.

Recent works including [8,9] have provided comprehensive reviews on RIS-assisted wireless communication systems, channel estimation methods, beamforming optimizations, hardware restrictions, and deployment issues. It was shown that RIS-based wireless communications can achieve considerable advantages in terms of spectrum efficiency, energy efficiency, and wireless coverage. However, existing RIS-assisted

wireless communication architectures mainly focus on improving communication performance while neglecting the sensing functionality and environment-awareness of these RISs.

Another interesting problem related to RIS-assisted wireless systems is intelligent beamforming and resource allocation optimization. Shen and Yu [28] introduced an effective approach for solving optimization problems using fractional programming in wireless communication systems. Fractional programming was further adopted for RIS-assisted beamforming optimization. You *et al.* [29] studied channel estimation and passive beamforming optimization in RIS-assisted communication systems with discrete phase shifts. They addressed a critical problem in the practical deployment of RISs.

These works show the great potential of existing optimization algorithms in improving communication performance; however, there still exist several limitations. Current solutions usually employ iterative optimization algorithms that require high computation cost and need accurate information about channel states to work effectively. Additionally, dynamic wireless environment adaptation is a crucial issue for practical deployment.

3.3 Integrated Sensing and Communication Systems

ISAC is one of the most recent concepts of intelligent wireless networks research that allows the sharing of spectral resources, hardware, and waveform between the communication and sensing functions. ISAC systems optimize resource utilization and achieve simultaneous spectrum utilization, making these devices more effective both in terms of hardware and software.

In their work, Liu *et al.* [1] provide the most exhaustive analysis of ISAC systems and explore the integration of the communication and sensing functionalities for 6G wireless networks. In this study, the authors show the effectiveness of ISAC in terms of optimizing spectrum usage, increasing resource utilization, and intelligent wireless network operations. Furthermore, some challenges regarding ISAC are mentioned, such as communication-sensing tradeoffs and interference problems.

Ahmed *et al.* [2] provided a comprehensive survey study on intelligent metasurface-assisted ISAC systems along with discussion on RIS-assisted sensing architectures, communication-sensing integration strategies, and open issues for future investigation. In addition, Clerc *et al.* [3] conducted their research on RIS-assisted joint communication and radar sensing systems and analyzed the significance of RIS in increasing

sensing capabilities and radar target detection.

Integrating RIS with ISAC is an interesting research area because RIS is able to provide adaptive wireless signal transmission for both communication and sensing operations. Zhi *et al.* [4] studied RIS-assisted ISAC systems and found that intelligent reflection control through RIS can enhance communication performance as well as sensing performance at the same time. Zhang *et al.* [14] performed further studies on RIS-assisted ISAC.

A number of researchers have explored beamforming optimization and power allocation problems for RIS-assisted ISAC systems. Luo *et al.* [15] designed a joint beamforming and RIS reflection optimization approach for RIS-enabled ISAC systems. The proposed optimization framework optimizes beamforming vectors and RIS phase shifts to optimize sensing and communication performances at the same time. Feng *et al.* [16] focused on joint beamforming and power allocation strategies under communication-sensing tradeoff constraints for RIS-enabled ISAC systems. Li *et al.* [17] introduced resource allocation schemes for RIS-enabled ISAC systems and showed the advantages of adaptive resource allocation schemes for such systems.

Despite all of these studies, the existing work mainly concentrates on fixed RIS configurations or centralized optimization schemes. In real-life wireless systems, communication and sensing requirements keep changing because of mobility, interference, environmental obstructions, traffic conditions, etc. For these reasons, traditional RIS allocation schemes may not be adequate for future intelligent wireless systems.

3.4 Machine Learning-Based RIS Optimization

Recent advancements in the field of machine learning have demonstrated that it is an effective solution for optimizing wireless optimization problems as it enables machine learning solutions to learn optimal wireless configurations through data-driven solutions rather than iterative optimization techniques which are time-consuming processes. Many applications of machine learning in the area of wireless communications include wireless channel estimation, beamforming optimization, interference mitigation, resource allocation, and wireless optimization.

A survey study conducted by Elbir *et al.* [20] on deep learning techniques for future wireless communication systems mentioned the application of machine learning in intelligent wireless optimization.

Many studies related to RIS optimization through machine learning have been conducted recently. First, Taha *et al.* [22] developed a deep learning-based approach

for RIS optimization and showed that optimal RIS settings could be learned by using neural networks from wireless channels alone. Also, Jiang *et al.* [23] used deep reinforcement learning for dynamic RIS optimization in wireless networks.

Secondly, Mei and Zhang [21] considered RIS optimization in the presence of uncertainty within wireless channels and developed a hybrid strategy, combining model-driven and data-driven optimization. Moreover, Wang *et al.* [24] studied machine learning approaches to RIS optimization in wireless communications and illustrated that machine learning enables optimization simplification without sacrificing communication performance.

Despite all the successes achieved by employing machine learning for optimizing the RIS, most of the previous work has centered on optimizing the RIS phase shift and enhancing communication performance. Only a small portion of the literature has explored the possibility of performing adaptive RIS partitioning between communication and sensing tasks. Also, little has been done concerning fairness-based RIS optimization, adaptive RIS power allocation, and environmental awareness of RIS-based resources.

Moreover, previous machine learning algorithms have employed deep learning models which consume much computation and need vast amounts of data to be trained. Alternatively, one could exploit lightweight algorithms like Random Forest and K-Nearest Neighbor which provide optimization capabilities without consuming too much computation.

3.5 Research Gaps and Motivation for the Proposed Work

According to the literature review, there are several key research gaps in current RIS-based ISAC systems. In most cases, current frameworks consider fixed RIS settings and static allocation of sensing and communication resources. This is unrealistic for practical applications because the wireless environment is constantly changing, and its characteristics, such as requirements and interference, vary.

Current optimization strategies utilize either beamforming algorithms, convex optimization algorithms, or semidefinite relaxation techniques, which possess relatively low scalability and computational efficiency. Machine learning-based RIS optimization frameworks concentrate on the optimization of phase shifts in RIS but not on RIS partitioning for sensing and communication tasks.

Moreover, fairness-aware optimization among sensing and communication objec-

tives has been less explored within prior studies. Moreover, dynamic power allocation and resource management in an RIS system based on wireless conditions have also not received due attention. Additionally, most prior RIS-assisted ISAC frameworks lack feature engineering, as well as environment-aware resource optimization mechanisms.

These gaps inspire the need to propose a machine learning-based approach for dynamic partitioning and resource optimization in an RIS-assisted system. The proposed approach includes adaptive RIS partition learning, fairness-aware reward optimization, dynamic power allocation, and supervised machine learning-assisted RIS arm prediction for efficient RIS-assisted ISAC systems. In contrast to the existing frameworks, the proposed approach provides dynamic communication and sensing objective optimization in a real-time wireless scenario through machine learning techniques.

Table 3.1: Comparison of Existing RIS-Assisted ISAC Approaches

Reference	RIS Optimization	ISAC	ML-Based	Major Limitation
Wu et al.	Beamforming	No	No	Static RIS Control
Luo et al.	Joint Optimization	Yes	No	High Complexity
Jiang et al.	RIS Learning	No	Yes	Large Training Cost
Taha et al.	Deep Learning	No	Yes	No ISAC Integration
Zhi et al.	RIS-ISAC Optimization	Yes	No	Fixed RIS Allocation
Proposed Work	Adaptive RIS Partitioning	Yes	Yes	Reduced Complexity

3.6 Chapter Summary

In this chapter, we have performed an extensive literature survey for wireless communication system aided by RIS, ISAC architecture, beamforming optimization, and machine learning-based optimization schemes for RIS. The existing research highlighted the importance of the RIS-assisted ISAC systems for future smart wireless networks. Nevertheless, there are some important aspects which are not yet resolved in the field, including adaptive RIS partitioning, fair optimization, optimization in a dynamic environment, and computationally efficient wireless optimization. Therefore, this motivates us to propose our framework in this thesis.

Chapter 4

System Model and Methodology

4.1 Introduction

This chapter provides the comprehensive system model and methodology adopted for the development of the proposed machine learning based framework for adaptive partitioning of Reconfigurable Intelligent Surface (RIS) and resource optimization for ISAC systems. The proposed approach uses RIS assisted communication, dynamic sensing-communication resource allocation, optimization with fairness, and supervised machine learning techniques to enhance system performance in varying wireless environments.

The proposed scheme differs from traditional RIS based ISAC frameworks due to the use of dynamic RIS partitioning along with dynamic resource optimization and communication-sensing trade-off. Machine learning techniques are also used to predict RIS arm positions.

4.2 System Architecture

In the above proposed ISAC framework based on the RIS, the system includes a TX, RX, target and Reconfigurable Intelligent Surface (RIS) that has $N = 100$ reflectors. These reflectors are arranged between the TX and RX so as to achieve intelligent reflection control of the wireless signals used in both communication and sensing tasks.

For communication purposes, the signals are reflected towards the RX via the RIS, whereas sensing signals are directed towards the target then reflected again back towards the RIS.

In the developed architecture, the communication link is modeled using the two-hop reflected propagation approach:

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{RX} \quad (4.1)$$

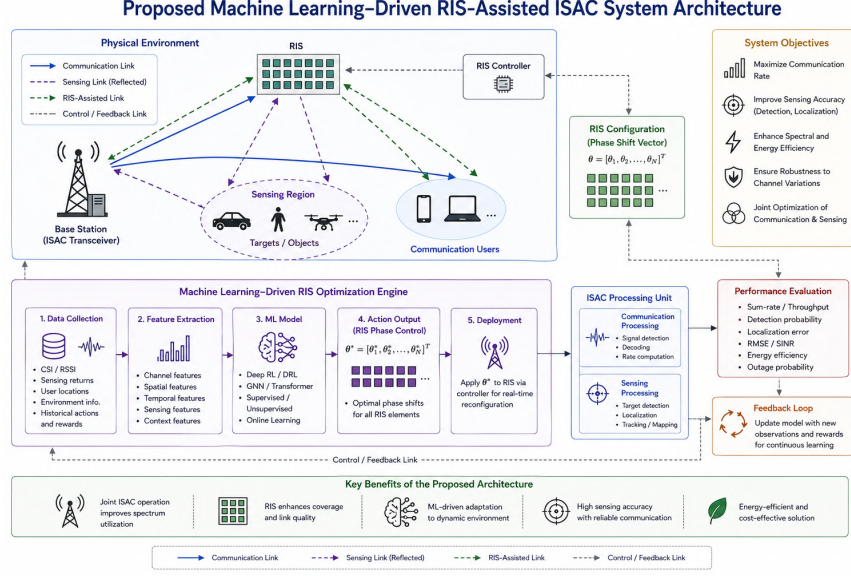


Figure 4.1: RIS-Assisted Intelligent Spectrum Access System Using Machine Learning.

whereas the sensing process is modeled as a monostatic four-hop propagation scenario described by:

$$\text{TX} \rightarrow \text{RIS} \rightarrow \text{Target} \rightarrow \text{RIS} \rightarrow \text{TX} \quad (4.2)$$

The partitioning of RIS reflecting elements for communication and sensing depends on channel characteristics and optimization criteria.

Table 4.1: Geometrical Coordinates of RIS-Assisted ISAC System

Network Entity	Coordinates (x,y)
Transmitter (TX)	(0, 0)
RIS	(50, 20)
Receiver (RX)	(90, 0)
Sensing Target	(25, 10)

The RIS-enabled ISAC system operates based on a two-dimensional Cartesian coordinate geometry. The transmitter, receiver, RIS element, and sensing object occupy specified geographical locations in order to analyze their impact on communication and sensing in realistic radio propagation environments. The distances between entities within the network are measured using the Euclidean distance formula.

4.3 RIS Partitioning Model

The RIS comprises 100 programmable reflectors which are dynamically partitioned between communication and sensing subgroups. Denote by $\mathcal{N}$ the whole group of the RIS elements. The mathematical model for dynamic RIS partitioning may be represented as:

$$\mathcal{C} \cup \mathcal{S} = \mathcal{N} \quad (4.3)$$

$$\mathcal{C} \cap \mathcal{S} = \emptyset \quad (4.4)$$

where $\mathcal{C}$ is the communication RIS arm, $\mathcal{S}$ is the sensing RIS arm, and $\mathcal{N}$ is the total RIS element set.

This framework analyzes nine distinct RIS partitioning arms, wherein each arm corresponds to a distinct allocation of communication and sensing RIS elements. In this regard, the arms partition the RIS reflecting elements for communication and sensing operations based on channel condition and objective optimization.

Each RIS arm consists of a different communication-sensing allocation ratio. As such, this mechanism makes adaptive wireless optimization possible regardless of environmental changes. This partitioning strategy helps achieve an intelligent trade-off between reliable communication and accurate sensing. RIS partitioning arms are dynamically created through Monte Carlo simulations.

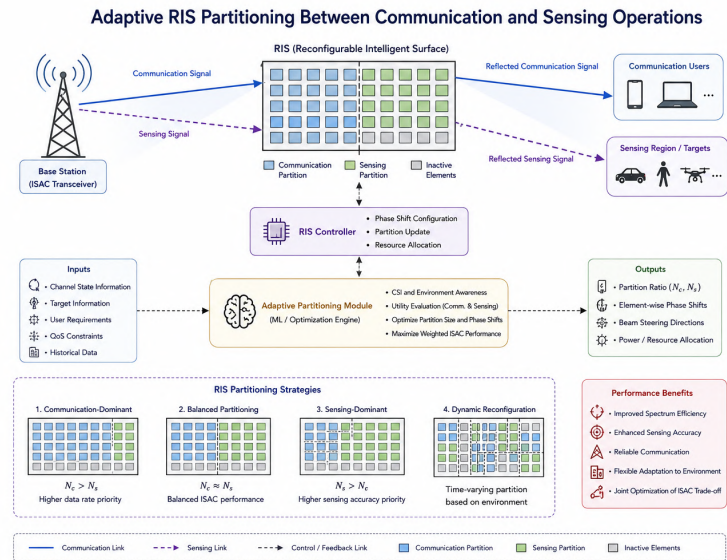


Figure 4.2: Communication vs Sensing Operations Based Adaptation of RIS Arm.

4.4 Wireless Channel Modeling

The wireless propagation channels of RIS-enabled ISAC systems are highly influenced by multipath fading, path loss, blocking, interference, and mobility. In order to consider real-life conditions of the wireless environment, the Nakagami- m fading model is used for channel generation in the proposed framework.

The path loss between communicating nodes is defined as:

$$PL(d) = 10^{-30-20\log_{10}(d)} \quad (4.5)$$

where d represents the distance of propagation.

Distances among various components in the network are derived from Euclidean geometry using:

$$d_{TR} = ||TX - RIS|| \quad (4.6)$$

$$d_{RR} = ||RIS - RX|| \quad (4.7)$$

$$d_{RT} = ||RIS - Target|| \quad (4.8)$$

Nakagami- m fading model is considered here as it allows flexibility in modeling both light and heavy wireless fading conditions. Fading channel parameter is represented by:

$$h \sim \text{Nakagami}(m, \Omega) \quad (4.9)$$

where m is the fading intensity parameter, while Ω represents the average signal strength.

Nakagami fading offers better flexibility than Rayleigh fading when it comes to modeling wireless propagation using the RIS.

4.5 Communication and Sensing Channel Models

In this case, the channel of effective communication is modeled using RIS-assisted reflected communication link. The channel communication performance link will be a two-hop reflected wireless propagation and will be written as

$$H_c = \sum_{n=1}^{N_c} h_n e^{j\theta_n} g_n \quad (4.10)$$

Here, h_n represents the TX-RIS channel gain coefficient, g_n is the RIS-RX channel gain coefficient, and θ_n represents the phase-shift induced by the n^{th} RIS reflecting element.

Coherent Phase Alignment (CPA) is performed by RIS through intelligent manipulation of RIS phase shifts such that there is constructive combining of signals at the receiver end, which enhances the quality of communications signals.

Communication Signal to Noise Ratio (SNR) is given by:

$$\text{SNR}_{comm} = \frac{P_{comm} |H_c|^2}{\sigma^2} \quad (4.11)$$

where P_{comm} stands for communication transmit power and σ^2 denotes noise power.

The data rate is computed based on Shannon capacity and expressed as:

$$R_c = \log_2(1 + \text{SNR}_{comm}) \quad (4.12)$$

Sensing relies on monostatic reflected sensing wherein RIS facilitates sensing of the target through wireless reflections. The sensing channel is modeled as

$$H_s = \sum_{n=1}^{N_s} h_{1,n} h_{2,n} h_{3,n} h_{4,n} e^{j\theta_n} \quad (4.13)$$

Here, $h_{1,n}$, $h_{2,n}$, $h_{3,n}$, and $h_{4,n}$ correspond to the channel gains for TX-RIS, RIS-target, target-RIS, and RIS-TX respectively.

Sensing SNR can be defined as:

$$\text{SNR}_{sens} = \frac{P_{sens} |H_s|^2}{\sigma^2} \quad (4.14)$$

Here, P_{sens} indicates the sensing transmit power.

Sensing rate can be calculated using:

$$R_s = \log_2(1 + \text{SNR}_{sens}) \quad (4.15)$$

4.6 Dynamic Environment Modeling

This method differs from traditional wireless optimization in that it models a dynamic wireless environment. This approach takes into consideration variations in traffic, mobility, interference, and sensing priorities.

The dynamic environmental parameter is modeled as follows:

$$E_{dyn} = 0.4T + 0.3M + 0.3I \quad (4.16)$$

Where T is the traffic intensity, M is mobility variance, and I is interference variance.

Dynamic environment modeling helps in the optimization of the RIS in real-world situations.

4.7 Adaptive Power Allocation

This framework includes an adaptive allocation of transmit power among communications and sensing activities. This transmit power is allocated based on the power allocation parameter β as:

$$P_{comm} = \beta P_{total} \quad (4.17)$$

$$P_{sens} = (1 - \beta)P_{total} \quad (4.18)$$

where β influences the allocation of power for communication, whereas $(1 - \beta)$ influences power allocation for sensing activities. The value of β is adaptively determined to maximize sensing and communication performance under dynamic environments.

4.8 Fairness-Aware Reward Function

In order to simultaneously improve the performance of sensing and communication, a fairness-aware adaptive reward function is developed. The developed reward structure can be mathematically formulated as:

$$\begin{aligned} \mathcal{R} = & \alpha R_c + 1.25(1 - \alpha)R_s \\ & + \lambda F + w_p P_f + w_e E_e \\ & - w_d D - B_p \end{aligned} \quad (4.19)$$

Where:

- R_c and R_s denote the rates for communication and sensing respectively,
- α regulates the communication-sensing trade-off,
- F indicates fairness score,
- P_f stands for proportional fairness,
- E_e denotes energy efficiency,
- D indicates communication-sensing disparity,
- and B_p denotes disparity penalty.

The fairness metric is represented as:

$$F = \frac{2\text{SNR}_{comm}\text{SNR}_{sens}}{\text{SNR}_{comm}^2 + \text{SNR}_{sens}^2} \quad (4.20)$$

The suggested reward formulation provides an optimal balance of communication quality, sensing ability, fairness behavior, and energy consumption performance in dynamic wireless settings.

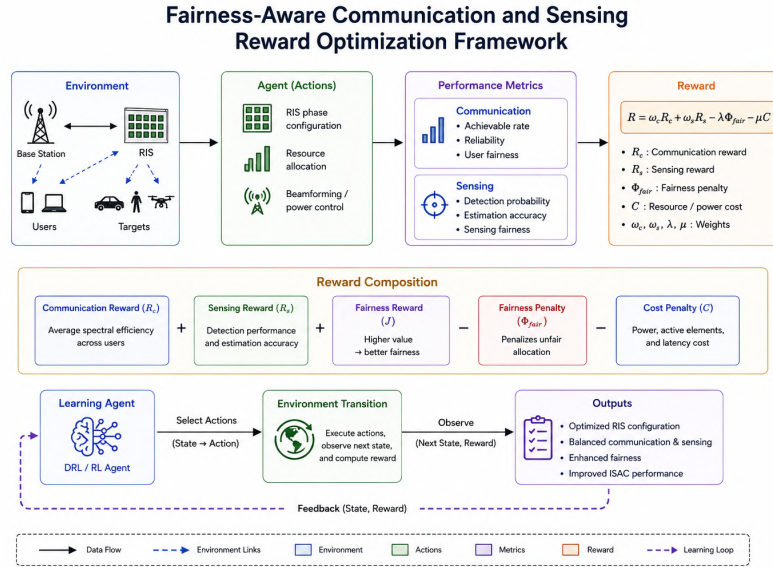


Figure 4.3: Reward Optimization for Communication and Sensing Considering Fairness.

4.9 Simulation Setup

The effectiveness of the proposed ISAC with RIS architecture is assessed by conducting comprehensive MATLAB-based simulations in realistic wireless communication settings. Nakagami- m fading is employed for generating fading conditions for wireless channels.

Simulation analysis is conducted on the basis of communication and sensing quality based on different partitioning schemes, environments, and adaptive power allocation.

Table 4.2 shows the details of some main simulation parameters employed in the proposed framework.

Table 4.2: Simulation Parameters

Parameter	Value
RIS Elements	100
Simulation Trials	5000
Bandwidth	10 MHz
Carrier Frequency	3.5 GHz
Transmit Power	35 dBm
Noise Variance	10^{-9}
Channel Model	Nakagami- m
Machine Learning Models	RF, KNN
Train-Test Split	80:20

4.10 Monte Carlo Simulation and Dataset Generation

Monte Carlo simulations are employed for generating wireless channel realizations and RIS configurations under different wireless environments.

The simulation model performs the following tasks:

- Generation of RIS partitions,
- generation of wireless channel realizations,
- evaluation of sensing and communication SNRs,
- calculation of rewards,
- and generation of the dataset.

At each simulation run, a new assessment of the performance of the RIS-enabled sensing and communication operations is performed, depending on the changes in the wireless environment.

Overall, 15 features related to the communication environment are obtained from simulation-generated data for intelligent RIS configurations and prediction of RIS arm locations using machine learning models.

4.11 Machine Learning-Based RIS Optimization

This RIS-assisted ISAC data is used for prediction and optimization of RIS arms using supervised machine learning-based approach.

Our framework uses the Random Forest (RF) and K-Nearest Neighbour (KNN) classification algorithms to predict optimal RIS arm configuration adaptively. RF uses an ensemble learning technique by using 400 decision trees to enable better nonlinear feature learning, improve generalization capacity, and ensure wireless optimization.

On the other hand, K-Nearest Neighbour uses the concept of classification based on Euclidean distance using 5 neighboring samples to predict the optimal configuration of RIS arm. KNN is also used as a baseline comparison algorithm.

The machine learning models are used to predict the optimum RIS configuration depending on the communication sensing requirement and wireless channel environment.

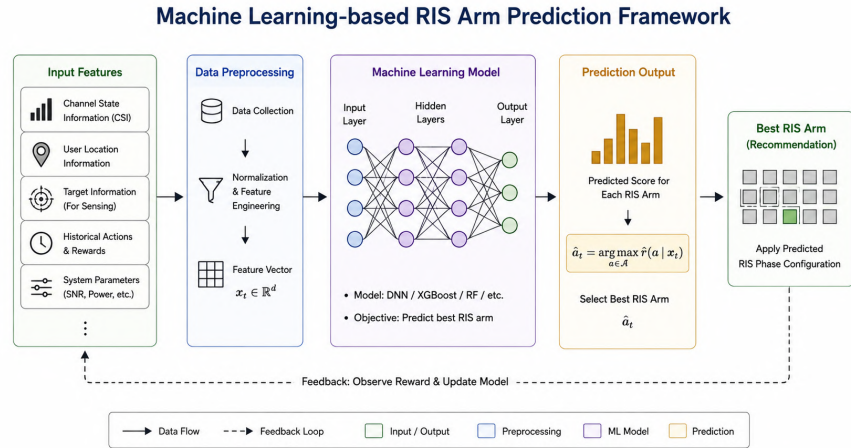


Figure 4.4: Prediction Framework for RIS Arm Using Machine Learning.

4.12 Adaptive RIS Optimization Algorithm

The adaptive RIS-assisted ISAC optimization algorithm is described through the following procedure.

Algorithm 1 Machine Learning-Driven Adaptive RIS Partition Optimization

Input: RIS elements, wireless channel realizations, power allocation parameters, environmental conditions

Output: Optimal RIS partition configuration and adaptive communication-sensing optimization

1. Initialize RIS-assisted ISAC system parameters
 2. Generate Nakagami fading-based wireless channels
 3. Create multiple RIS partitioning arms
 4. Allocate RIS elements between communication and sensing subsets
 5. Compute communication and sensing channel coefficients
 6. Evaluate communication and sensing SNR values
 7. Calculate communication and sensing rates
 8. Compute fairness score and energy efficiency metrics
 9. Evaluate adaptive reward values for all RIS arms
 10. Select RIS arm corresponding to maximum reward
 11. Extract statistical and nonlinear wireless features
 12. Generate machine learning dataset
 13. Train Random Forest and KNN classifiers
 14. Predict optimal RIS partition configurations
 15. Evaluate overall communication and sensing performance
-

4.13 Chapter Summary

In this chapter, we have described the proposed system model and approach to the machine learning-enabled adaptive RIS-assisted ISAC optimization framework. The proposed framework combines the concepts of adaptive RIS partitioning, fairness optimization, dynamic power allocation, Nakagami fading wireless channel model, Monte Carlo simulations, and supervised machine learning for intelligent RIS configuration prediction.

Communication and sensing channel model design, adaptive reward optimization, RIS arms generation, feature engineering, data set creation, and machine learning-enabled RIS optimization approach have been explained in detail. In the next chapter, we present the machine learning-based framework, the training process, performance metric analysis, and classification of the proposed RIS-assisted ISAC optimization framework.

Chapter 5

Machine Learning Framework and Performance Evaluation

5.1 Introduction

This chapter introduces the machine learning algorithm designed for predicting adaptive RIS partition and intelligent optimization of resources in RIS-enabled ISAC systems. The design of the machine learning algorithm involves Monte Carlo based simulation for dataset creation, feature engineering, supervised learning using machine learning algorithms, and wireless optimization to enable intelligent resource optimization in wireless communication-sensing systems.

Contrary to the use of beamforming and optimization-based methods that characterize traditional RIS optimization algorithms, the proposed machine learning approach predicts the optimal configuration of RIS partitions directly from simulations of wireless communication. The algorithms used to predict the RIS arm partition include the Random Forest (RF) and K-Nearest Neighbor (KNN) classifiers.

The chapter covers various issues including dataset creation, feature engineering, learning model development, predictions, performance metrics, analysis of convergence, feature importance analysis, and computational performance assessment.

5.2 Dataset Generation and Feature Engineering

A dataset generator is established by employing Monte Carlo simulations for generating realistic wireless channels assisted by RIS. This simulation framework is capable of testing various partitioning methods based on different wireless channels, communication and sensing compromise criteria, and dynamics within the environment.

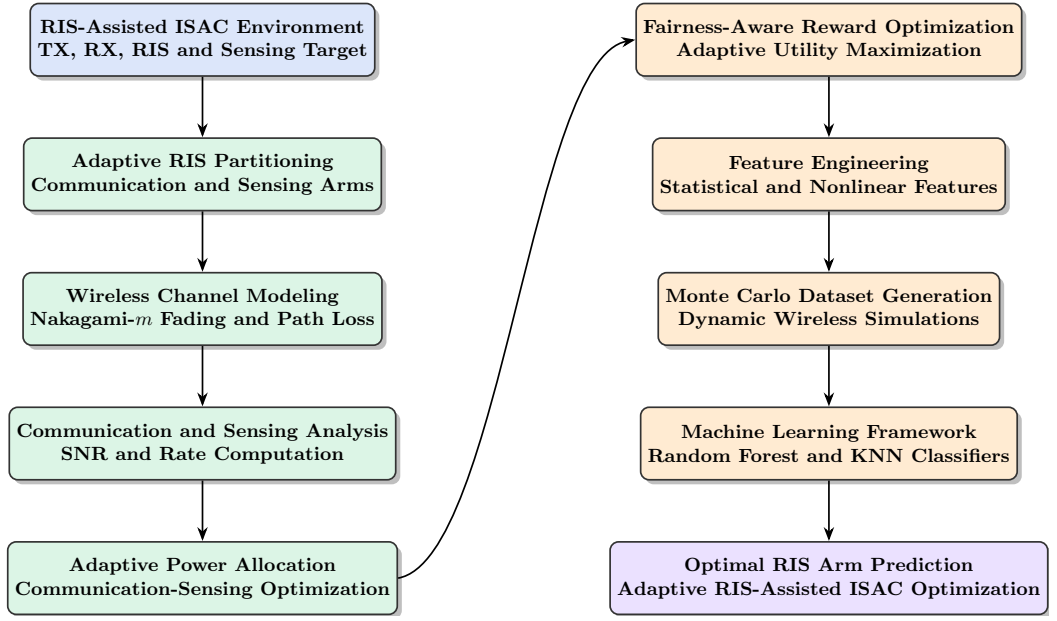


Figure 5.1: Machine learning pipeline for adaptive partitioning of RIS

This dataset contains:

- communication Signal-to-Noise Ratio (SNR),
- sensing Signal-to-Noise Ratio (SNR),
- communication rate,
- sensing rate,
- fairness score,
- energy efficiency,
- environmental interaction parameters,
- and dynamic reward parameters

The communication rate is determined through Shannon capacity:

$$R_c = \log_2(1 + \text{SNR}_{comm}) \quad (5.1)$$

The fairness score is formulated as:

$$F = \frac{2\text{SNR}_{comm}\text{SNR}_{sens}}{\text{SNR}_{comm}^2 + \text{SNR}_{sens}^2} \quad (5.2)$$

Energy efficiency is termed as:

$$\eta = \frac{R_c}{P_{total}} \quad (5.3)$$

Nonlinear interaction features have been developed along with statistical features to enhance machine learning prediction capabilities in dynamic wireless environments.

The created RIS-assisted ISAC data set serves as the basis for RIS arm prediction and adaptive optimization through supervised machine learning techniques.

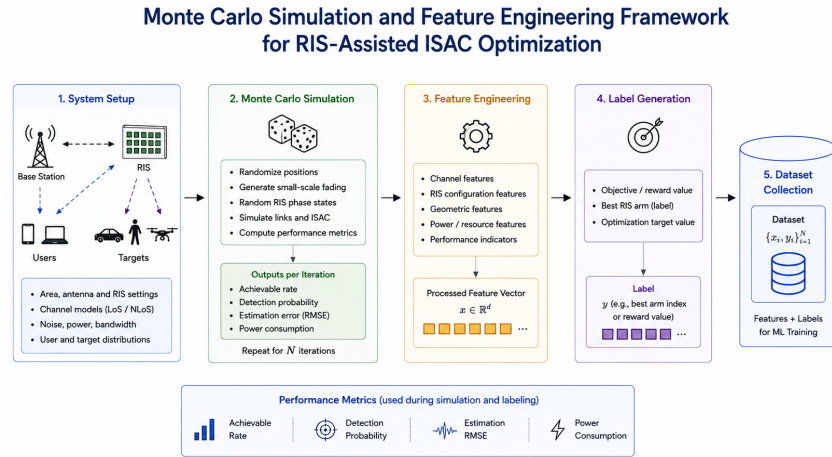


Figure 5.2: Monte Carlo simulation and feature engineering approach to RIS-based ISAC optimization.

5.3 Data Preprocessing and Machine Learning Models

Prior to model training in machine learning, the generated dataset will be subjected to preprocessing to enhance classification accuracy and performance. Preprocessing encompasses the following processes; normalization of the selected wireless features, balance in labeling, standardization of the dataset, and training-testing split.

Normalization enables similar operation ranges of the selected wireless features to ensure stable and accurate training results. An 80:20 ratio has been used in the split ratio of the training and test set.

The proposed approach makes use of two machine learning algorithms; Random Forest (RF) and K-Nearest Neighbor (KNN). The random forest refers to a non-linear ensemble learning method based on the decision trees model. The Random Forest offers better generalization and prevents overfitting hence improves learning performance.

K-Nearest Neighbors (KNN) is a distance-based supervised learning method for

classifying RIS arms. The distance between two feature vectors is determined by the Euclidean distance formula as follows:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (5.4)$$

In the suggested architecture, Random Forest uses 400 decision trees for RIS arm prediction based on adaptive algorithms, whereas KNN is based on $k = 5$ neighboring samples in wireless classification.

5.4 Training and Prediction Framework

The training phase of machine learning consists of extracting relevant features, dataset preprocessing, training classifiers, validation, and RIS arm prediction.

In the training phase, the machine learning classifiers train themselves to identify the relation between:

- Wireless channel state,
- Communication-sensing needs,
- RIS partitioning states,
- And adaptive rewards.

The training procedure includes the following steps:

1. Generating RIS-enabled wireless communication data.
2. Extracting statistical and non-linear features.
3. Preprocessing extracted features.
4. Splitting the dataset into training and testing sets.
5. Training Random Forest and KNN classifiers.
6. Performing RIS partitioning arms prediction.
7. Evaluating prediction performance considering different wireless conditions.

The trained machine learning classifiers make decisions on RIS partitioning arms in accordance with wireless channel conditions and communication-sensing needs.

5.5 Performance Evaluation Metrics

The performance evaluation of the machine learning framework considered includes performance measures for classification and optimization, which include

- classification accuracy,
- precision,
- recall,
- F1-score,
- confusion matrix,
- communication SNR,
- sensing SNR,
- fairness score, and
- reward convergence.

The formula for calculating classification accuracy is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5.5)$$

where TP , TN , FP , and FN are true positive, true negative, false positive, and false negative, respectively.

Formulas for precision and recall are given below:

$$Precision = \frac{TP}{TP + FP} \quad (5.6)$$

$$Recall = \frac{TP}{TP + FN} \quad (5.7)$$

F1 score is obtained using the following equation:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5.8)$$

These measures assess the predictive ability of RIS arms and the machine learning classification algorithm performance under various wireless channel conditions.

5.6 Convergence and Feature Importance Analysis

Convergence analysis is carried out to assess the stability of the model as well as its learning capabilities. The rewards convergence analysis is carried out based on different simulation runs and changing wireless environments.

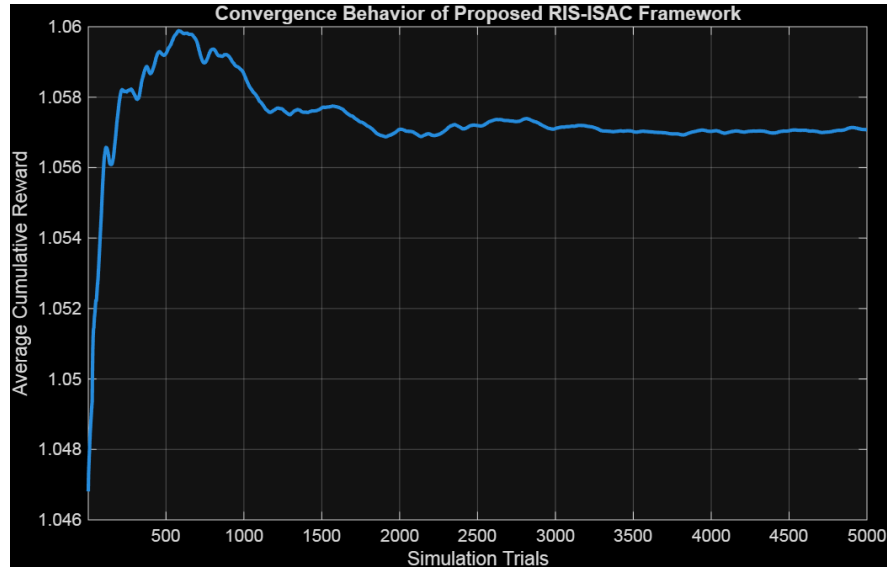


Figure 5.3: Convergence analysis of the proposed RIS-based ISAC optimization approach.

The convergence analysis shows that the model converges in a stable manner, learns adaptively, and optimizes efficiently between communication and sensing.

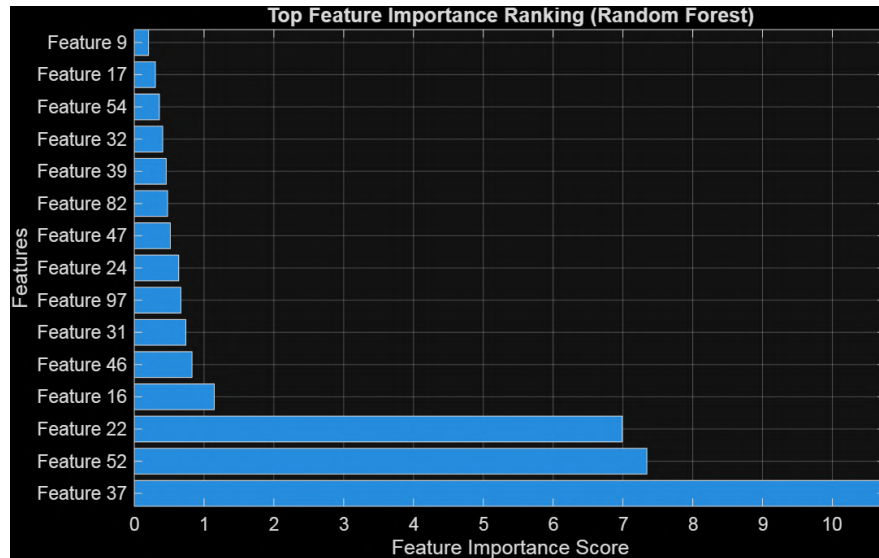


Figure 5.4: Analysis of feature importance using the Random Forest classifier.

Feature importance analysis is done by using the random forest classifier to find the dominant features of wireless communication contributing to the prediction of RIS arms.

This analysis aims at analyzing the importance of communication SNR, sensing SNR, fairness index, energy efficiency, and interaction features, among others, for adaptive RIS optimization. The results confirm the success of the feature engineering methodology for optimizing the performance of intelligent RIS-assisted ISAC.

5.7 Computational Analysis and Discussion

Computational complexity becomes a vital factor when developing any practical RIS-assisted wireless optimization system. The traditional methods of RIS optimization involve iteration-based beamforming and convex optimization, which can be computationally expensive and scale badly.

However, the suggested machine learning approach helps to simplify optimization due to the RIS predictions that can be performed based on the learned models rather than repeated iterative optimization.

Random Forest RIS predictions offer the following benefits:

- fast inference,
- decreased optimization costs,
- better scalability, and
- ability to adjust RIS arms in real-time.

The comparison between the two approaches proves that Random Forest outperforms KNN in predicting the optimal configuration of RIS due to its ensemble learning approach and better non-linear classification capabilities.

Thus, the machine learning-assisted RIS optimization approach allows performing efficient wireless resources management in changing wireless environments.

5.8 Chapter Summary

In this chapter, the machine learning approach designed to predict an optimal RIS partitioning for adaptive wireless optimization through RIS-enabled ISAC systems was introduced. This novel machine learning technique involves generating datasets using Monte Carlo simulation, feature selection, classification using machine learning, convergence analysis, and performance evaluation of adaptive communication sensing optimization.

Random Forest and KNN classifiers have been used to predict the optimal RIS arm based on wireless environments. In the next chapter, simulation results and performance evaluations of the RIS-assisted ISAC optimization framework will be discussed in detail.

Chapter 6

Simulation Setup

6.1 Introduction

This chapter discusses the simulation setup and implementation environment employed in evaluating the proposed machine learning-enabled adaptive RIS partitioning and optimization approach for RIS-enabled ISAC systems.

The simulation environment has been developed based on MATLAB, which performs Monte Carlo simulations in a Nakagami- m fading environment to evaluate the performance of the proposed adaptive RIS-enabled ISAC approach. This environment consists of simulation setup parameters including RIS settings, wireless communication system settings, channel fading properties, geometrical locations of the transmitting node, receiving node, RIS, and the sensing target, machine learning-based settings, adaptive power allocation settings, and different communication and sensing performance metrics.

Through this simulation environment, it becomes possible to analyze adaptive RIS partitioning, fairness-aware optimization, machine learning-based RIS arms estimation, and adaptive communication-sensing trade-off performance under dynamic wireless environments. The proposed simulation environment can be used to assess the performance of adaptive communication-sensing optimization techniques under dynamic wireless propagation conditions.

6.2 RIS Configuration

The structure of the RIS-assisted ISAC system includes one transmitter, one receiver, one sensing target, and one RIS with programmable reflecting components.

The values of the RIS parameters are listed in Table 6.1.

Table 6.1: RIS Configuration Parameters

Parameter	Value
Total RIS Elements (N)	100
RIS Partitioning Strategy	Adaptive Partitioning
Communication RIS Allocation	Dynamic
Sensing RIS Allocation	Dynamic
Number of RIS Arms	9
RIS Reflection Type	Ideal Phase Compensation
RIS Control	Adaptive Machine Learning-Based

The reflection components of the RIS are adaptively assigned to communication and sensing depending on reward maximization and RIS arm prediction using machine learning.

6.3 RIS Partition Arms

The taken RIS partition arms used for adaptive optimization are listed in Table 6.2.

Table 6.2: RIS Partition Arms

Arm Index	Communication RIS Elements	Sensing RIS Elements
1	10	90
2	20	80
3	30	70
4	40	60
5	50	50
6	60	40
7	70	30
8	80	20
9	90	10

Every RIS-based approach corresponds to a specific allocation strategy for communication and sensing.

6.4 Wireless System Parameters

A summary of communication and sensing systems' parameter values in the simulation is shown in Table 6.3.

Table 6.3: Wireless System Parameters

Parameter	Value
Bandwidth	10 MHz
Transmit Power	35 dBm
Noise Figure	10 dB
Communication-Sensing Tradeoff Parameter (α)	0.5
Power Allocation Parameter (β)	Adaptive
Target Reflection Coefficient	5 dB
Monte Carlo Trials	5000

Such parameter values have been chosen so that they reflect realistic scenarios of RIS-assisted ISAC wireless communication systems.

6.5 Geometrical Configuration

The geometrical location of the transmitter, RIS, receiver, and sensing target remains constant throughout the simulation process. Geometrical Deployment Tab.6.4 describes the geometrical deployment scenario considered in our model.

Table 6.4: Node Positions in Simulation Geometry

Node	Symbol	Position (x, y)
Transmitter	TX	(0, 0)
RIS	RIS	(50, 20)
Receiver	RX	(90, 0)
Target	T	(25, 10)

The corresponding Euclidean distances are computed using:

$$d_{TR} = ||p_{TX} - p_{RIS}|| = 53.85m \quad (6.1)$$

$$d_{RR} = ||p_{RIS} - p_{RX}|| = 44.72m \quad (6.2)$$

$$d_{RT} = ||p_{RIS} - p_T|| = 26.93m \quad (6.3)$$

The geometrical deployment facilitates a practical study of RIS-assisted communications and monostatic sensing.

6.6 Machine Learning Configuration

The suggested architecture uses machine learning approaches to learn adaptive RIS arm control as well as optimize communications-sensing.

Table 6.5 depicts the parameters used in the machine learning process.

Table 6.5: Machine Learning Parameters

Parameter	Value
Machine Learning Models	Random Forest, KNN
Dataset Generation Method	Monte Carlo Simulation
Feature Type	Statistical and Nonlinear Features
Dataset Split Ratio	80:20
Random Forest Trees	400
KNN Distance Metric	Euclidean
Classification Objective	RIS Arm Prediction

Machine learning models have been trained with statistics-, fairness-awareness-, nonlinearity-, and interaction-based wireless communication characteristics of the RIS-enabled ISAC simulations.

6.7 Adaptive Reward and Power Optimization

The suggested scheme includes fairness-aware reward optimization, which helps to achieve a balance between communication and sensing capabilities.

Adaptive Reward function can be mathematically stated as follows:

$$R = \alpha \log(1 + \text{SNR}_{comm}) + (1 - \alpha) \log(1 + \text{SNR}_{sens}) + \lambda F \quad (6.4)$$

where:

$$F = \frac{\min(\text{SNR}_{comm}, \text{SNR}_{sens})}{\max(\text{SNR}_{comm}, \text{SNR}_{sens})} \quad (6.5)$$

Adaptive Communication and Sensing Power Allocation is defined as:

$$P_{comm} = \beta P_{total} \quad (6.6)$$

$$P_{sens} = (1 - \beta) P_{total} \quad (6.7)$$

Adaptive tuning of α and β allows achieving intelligence for communication-sensing balancing.

6.8 Simulation Workflow

Simulation flow of the proposed model is given below.

1. Set up RIS-assisted ISAC system parameters.
2. Create Nakagami fading wireless channels.
3. Create RIS partition arms.
4. Partitioning RIS elements among communication and sensing sets.
5. Calculation of communication and sensing channel coefficients.
6. Calculation of communication and sensing SNRs.
7. Calculation of communication and sensing rates.
8. Calculation of fairness-aware rewards.
9. Creation of the wireless communication dataset.
10. Creation of statistical and nonlinear feature sets.
11. Training of the Random Forest and KNN classifier.
12. Prediction of the optimal RIS partition arm.
13. Assessment of the adaptive optimization process.
14. Creation of the communication-sensing performance plot.

The simulation architecture provides intelligent adaptive RIS-assisted optimization of ISAC in various wireless communications environments.

Chapter 7

Results and Discussion

7.1 Introduction

This chapter details the simulation results and performance evaluations for the proposed machine learning driven adaptive RIS partitioning and resource optimization scheme for ISAC systems. The proposed scheme is evaluated based on various channel conditions, RIS partitioning schemes, ISAC scenarios, and dynamic environments.

For the simulations, the MATLAB environment was utilized via Monte Carlo simulations on Nakagami- m fading channels. Performance metrics considered include:

- communication and sensing signal to noise ratio (SNR),
- adaptive RIS partitioning,
- reward optimization with fairness considerations,
- adaptive power control,
- machine learning classification performance,
- convergence behavior,
- feature importance,
- pareto trade-off optimization, and
- RIS arm selection.

In order to make predictions on adaptive RIS partitioning, two machine learning classifiers namely Random Forest (RF) and K-Nearest Neighbour (KNN) classifiers are applied using communication-based statistical, non-linear and fairness aware features.

Simulation results confirm the performance of the proposed system in providing optimized ISAC in dynamic wireless networks.

7.2 Simulation Parameters

The proposed RIS-supported ISAC architecture is implemented using MATLAB simulations considering realistic scenarios for wireless communications. The simulation scenario includes:

- one transmitter,
- one receiver,
- one target object,
- and an RIS comprised of 100 elements.

The elements within the RIS are adaptively divided between communication and sensing tasks through the use of a reward optimization approach along with RIS arm prediction through machine learning methods.

Wireless channels are generated through Nakagami- m fading.

Parameters used for the simulation framework are listed in Table 7.1.

Table 7.1: Simulation Parameters

Parameter	Value
RIS Elements	100
RIS Arms	9
Simulation Trials	5000
Channel Model	Nakagami- m Fading
Transmit Power	35 dBm
Bandwidth	10 MHz
Noise Figure	10 dB
Machine Learning Models	RF, KNN
Train-Test Split	80:20
Power Allocation	Adaptive
Reward Optimization	Fairness-Aware

The presented simulation model enables dynamic assessment of performance metrics for communications and sensing depending on the wireless environment and RIS partitioning settings.

7.3 Communication-Sensing Performance Analysis

The performance metrics adopted for the evaluation of the effectiveness of the proposed RIS-enabled ISAC framework include average Signal-to-Noise Ratio (SNR), achievable communication rate, response of sensing, and adaptive partitioning of RIS.

Average SNR for communication refers to the performance level of communication between the source and the destination with the use of the reflection technique via the RIS channel, whereas sensing SNR stands for the strength of the reflected sensing signal.

The simulation findings indicate that adaptive RIS partitioning enhances both communication reliability and sensing capacity at the same time.

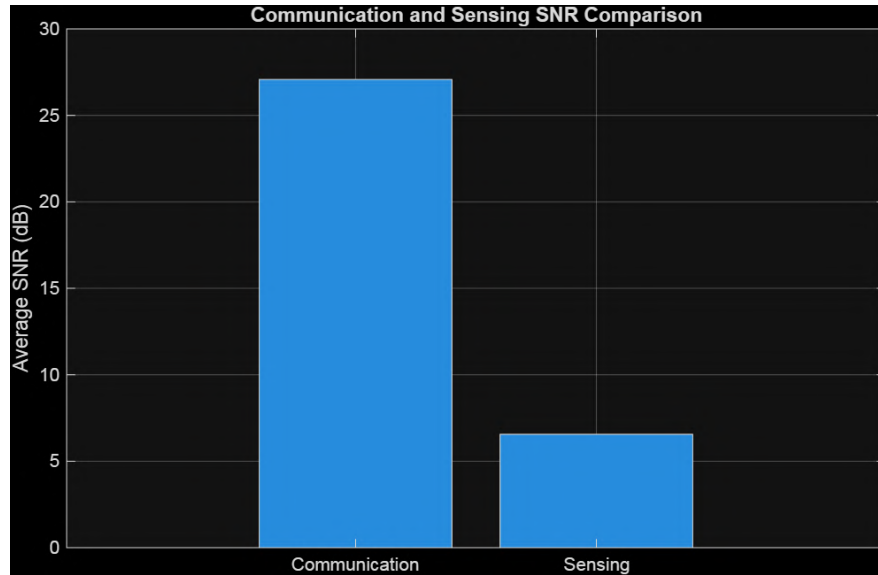


Figure 7.1: Comparison of SNR under adaptive partitioning for communication and sensing.

From the outcomes of the study, it can be observed that allocating more resources towards communications leads to better communication SNR, while allocating more resources towards sensing leads to better sensing SNR. This has been achieved using an adaptive mechanism that optimizes RIS arms intelligently.

On average, the communication SNR obtained from the proposed algorithm is approximately 27.06 dB, while the sensing SNR is approximately 6.57 dB. The high communication SNR can be attributed to phase coherence and constructive RIS-based combining of signals.

7.4 Adaptive Reward and Power Optimization

The new approach uses a fair reward optimization to optimize the trade-off between communication and sensing tasks in a dynamic environment.

The adaptive reward system combines:

- communication rate,
- sensing rate,
- fairness optimization,
- energy efficiency,
- and RIS partition balancing.

Adaptive optimization of the trade-off parameters α and power allocation parameter β allows for efficient use of communication and sensing resources.

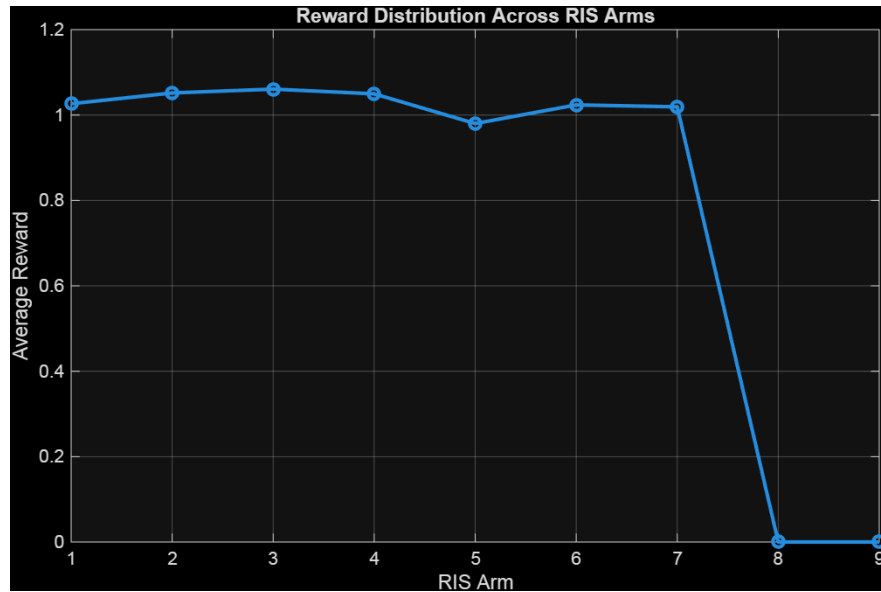


Figure 7.2: Optimization of adaptive rewards under communication-sensing balance.

The findings show that by ensuring fair optimization in the distribution of resources between communication and sensing, the system becomes more stable and efficient in its operation. Additionally, the suggested method also adapts to transmit power control between communication and sensing signals.

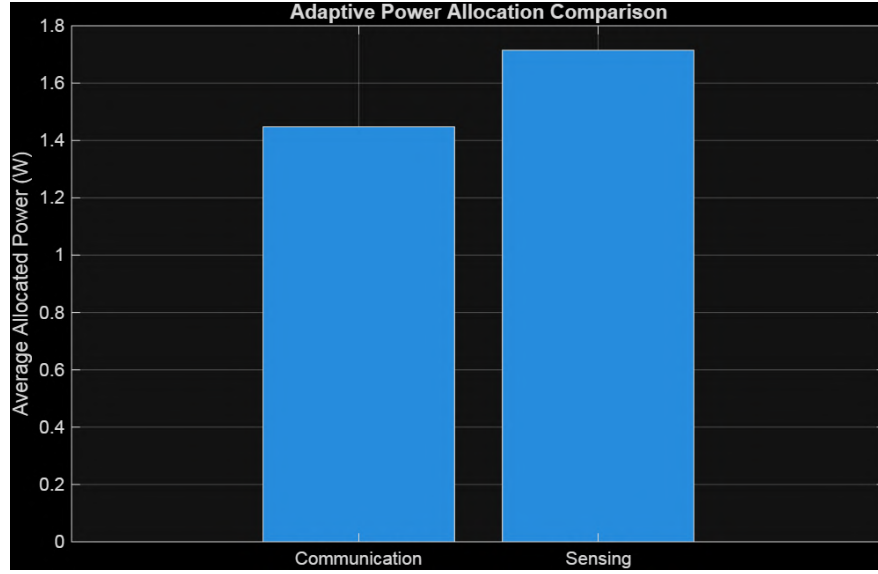


Figure 7.3: Analysis of adaptive power allocation for communication and sensing.

Communication power allocation obtained using the above framework has an average value of 1.4439 W, whereas sensing power allocation is around 1.7184 W. This confirms the effectiveness of adaptive power allocation in enhancing communication-sensing balance and fairness optimization.

7.5 Machine Learning Performance Evaluation

The machine learning performance of the proposed adaptive RIS assisted ISAC system is assessed by using Random Forest (RF) and K-Nearest Neighbor (KNN) classifiers for RIS arm prediction.

Training of the classifiers is done by using wireless communication characteristics including statistics, nonlinearity, interactions, and fairness-awareness generated from the Monte Carlo simulations.

The evaluation of the performance includes the following metrics:

- Classification accuracy,
- Precision,
- Recall,
- and F1-score.

The results of the evaluation are shown in Table 7.2.

Table 7.2: Machine Learning Performance Metrics

Classifier	Accuracy	Precision	Recall	F1-Score
KNN	76.1%	0.73	0.76	0.74
Random Forest	85.3%	0.84	0.85	0.84

Reasons for better prediction ability by Random Forest classifiers include:

- ability to learn ensembles,
- excellent non-linear classification ability, and
- better robustness to changes in wireless channels.

While the KNN classifier offers good classification ability, it shows poor prediction ability compared to the Random Forest due to its dependence on the local neighborhood environment. The results confirm that Random Forest offers more accurate adaptive RIS arm prediction and better optimization consistency in terms of communication-sensing.

7.6 Confusion Matrix Analysis

The performance of RIS arm prediction under different wireless channel environments is analyzed via confusion matrix analysis.

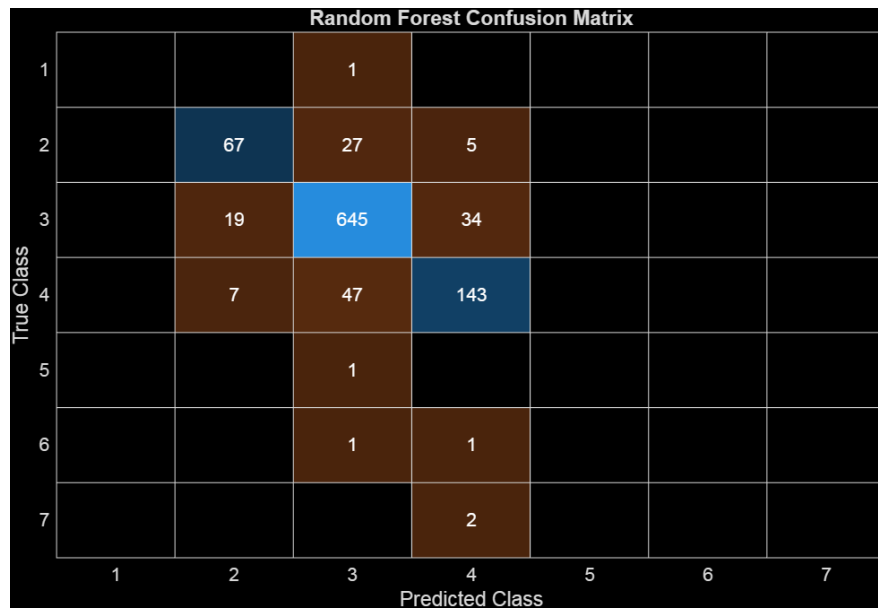


Figure 7.4: Confusion matrix for Random Forest classification model.

The confusion matrices include:

- correct classifications,
- misclassifications,
- and consistency in prediction.

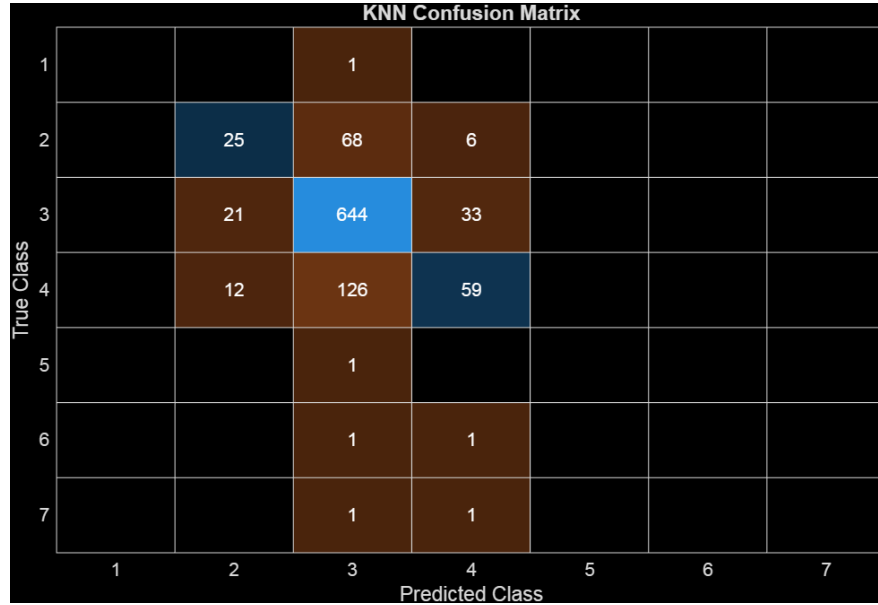


Figure 7.5: Confusion matrix for the KNN classification model.

The Random Forest classifier exhibits better performance with lower rates of misclassification and consistency in RIS arm predictions due to its ensemble learning algorithm.

7.7 Convergence and Feature Importance Analysis

The convergence analysis is done to analyze the performance stability and learning properties of the proposed RIS-enabled ISAC approach. Moving average smoothing technique is used for the visual stability and interpretability of the convergence pattern in cumulative rewards.

The convergence pattern shows that there is stability in the reward optimization process and adaptive RIS learning capability.

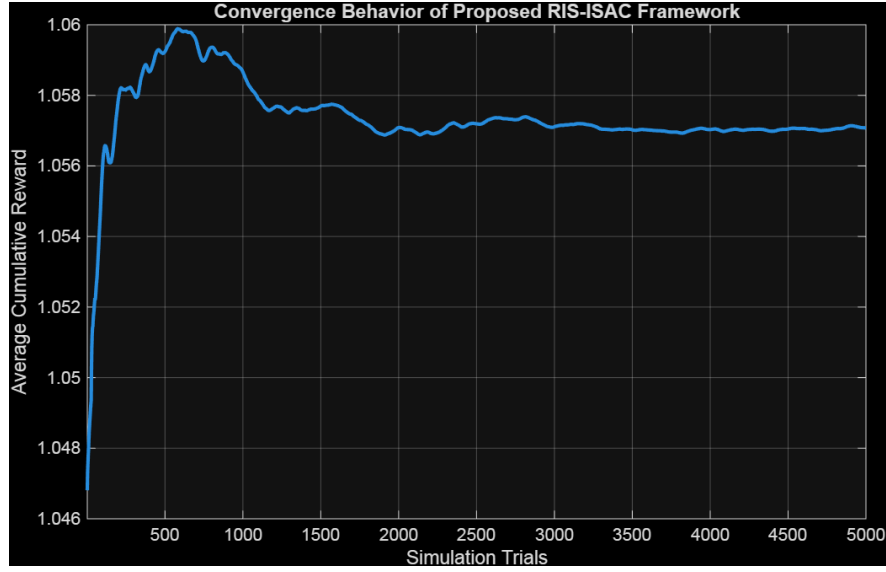


Figure 7.6: Convergence of the proposed adaptive ISAC optimization framework with RIS assistance.

Feature importance analysis is done using the Random Forest classifier to determine the significant factors related to wireless communication that affect RIS arm predictions.

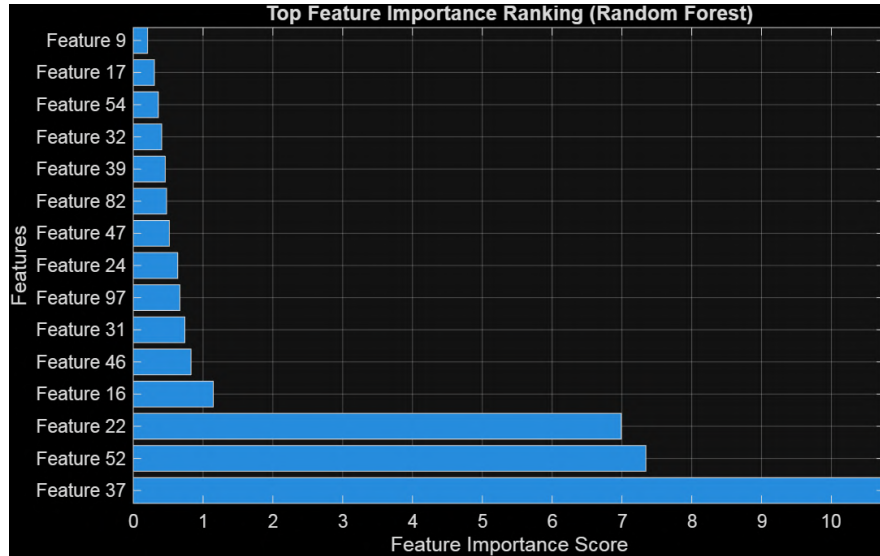


Figure 7.7: Feature importance ranking based on Random Forest for adaptive RIS arm prediction.

The sorted feature importance evaluation shows that communication rate, sensing rate, fairness-based interaction features, and nonlinear optimization coefficients affect adaptive RIS partitioning performance. These findings confirm the usefulness of the suggested feature engineering approach for intelligent RIS-aided ISAC optimization.

7.8 Fairness and Energy Efficiency Analysis

The proposed framework of the RIS-based ISAC system includes a method for fair optimization to ensure balance in communication and sensing under different wireless conditions.

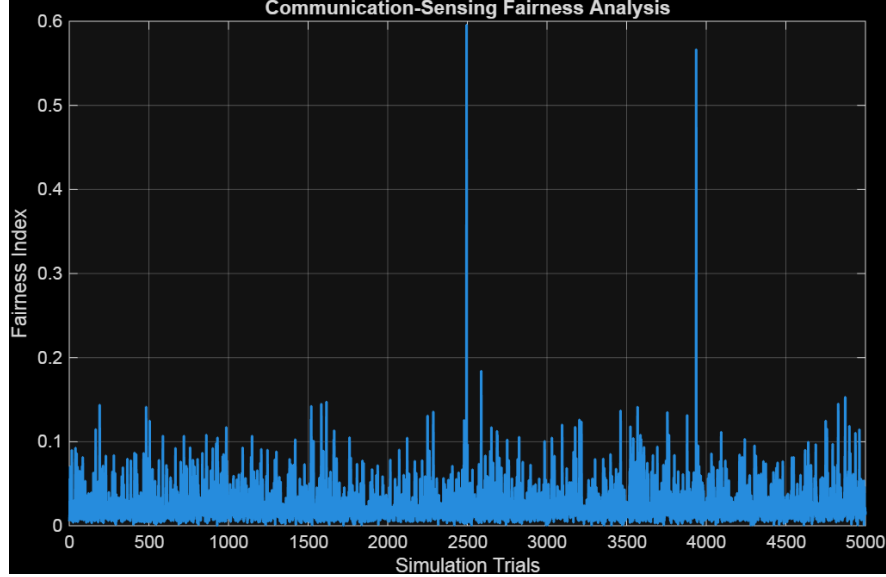


Figure 7.8: Analysis of communication and sensing fairness with adaptive RIS optimization.

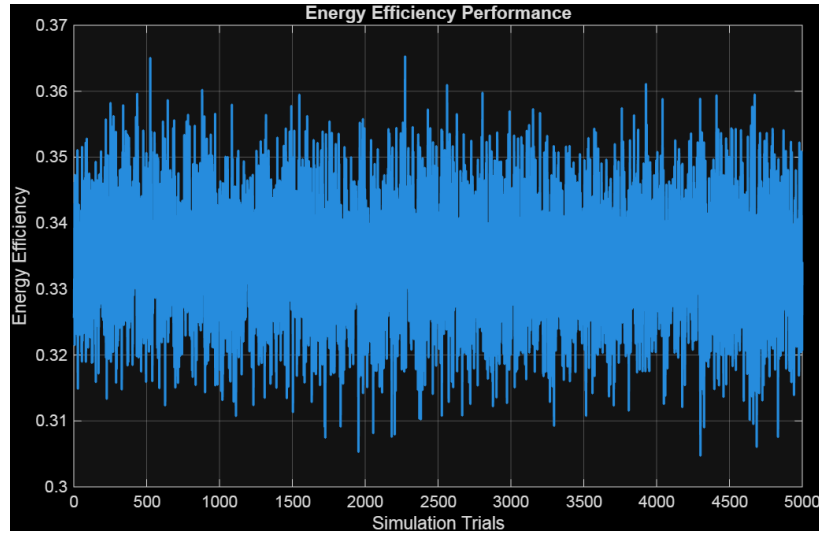


Figure 7.9: Analysis of energy efficiency with RIS-assisted ISAC system.

The fairness measure in Fig 7.8 measures the trade-off between the quality of the communication and sensing signal by utilizing harmonic optimization. The simulation results show that the adaptive RIS partition scheme can achieve balance in the coexistence of communication and sensing without emphasizing one over the other.

Moreover, an analysis of energy efficiency is conducted to investigate the adaptability of wireless resource management in terms of power adaptation and RIS partitioning. The framework in Fig 7.9 will ensure enhanced energy efficiency by ensuring balanced communication-sensing and adaptation of the RIS configuration.

7.9 Pareto Tradeoff and RIS Arm Optimization

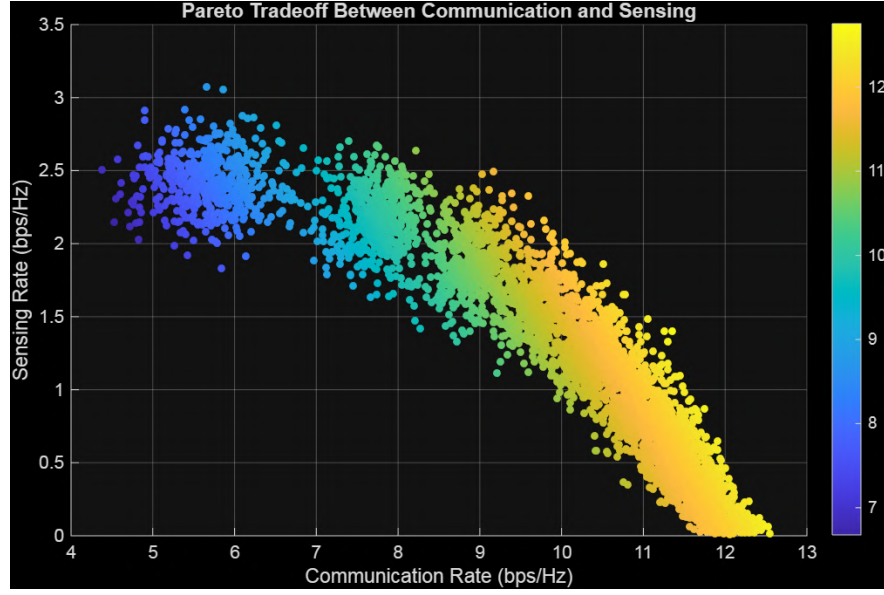


Figure 7.10: Analysis of Pareto optimal communication and sensing trade-offs.

The Pareto analysis in Fig 7.10 of the trade-off between communication and sensing considers the ability of the framework to optimize both aspects concurrently. The Pareto Front illustrates effective communication-sensing trade-offs using adaptive RIS arm partitions and optimization considering fairness.

The study of RIS arm selection is used to validate the effectiveness of adaptive optimization in the proposed scheme. The simulation in Fig 7.11 outcomes show that intermediate RIS partitioning schemes enjoy more selections since they offer a balance between communication and sensing performance.

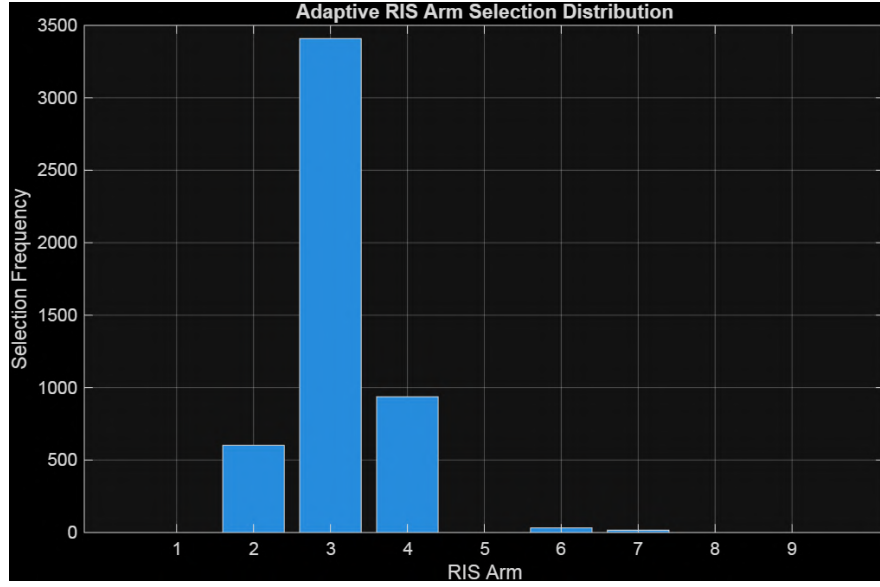


Figure 7.11: Distribution of RIS arms selection with adaptive RIS allocation method under dynamic environments.

7.10 Baseline and Comparative Performance Analysis



Figure 7.12: Comparison of reward for different allocation methods of RIS and adaptive RIS allocation method.

The comparison between the suggested framework and traditional approaches to allocating RISs is made on the basis of the following approaches:

- allocating RISs for communications only,

- allocating RISs for sensing only,
- allocating RISs equally,
- and optimizing RISs using KNN.

The suggested random forest-based adaptive RIS optimization framework demonstrates high performance in reward due to intelligent communication-sensing balancing and adaptive machine learning-assisted prediction

Table 7.3: Comparative Performance Analysis

Method	Adaptivity	Complexity	Performance
Communication-Only RIS	Low	Low	Moderate
Sensing-Only RIS	Low	Low	Moderate
Equal RIS Partitioning	Medium	Low	Good
KNN-Based Optimization	High	Moderate	Very Good
Proposed RF-Based Framework	High	Moderate	Excellent

7.11 Discussion

The simulations prove that an adaptive scheme of RIS partitioning increases the system's performance concerning communication reliability, sensing ability, fairness, and energy efficiency compared with static schemes of RIS partitioning. The developed fairness-aware reward formulation is efficient in balancing the communication and sensing tasks and provides stable convergence of the optimization process in dynamic wireless conditions.

A random forest predictor for RIS arms achieves better classification abilities than the KNN approach due to better nonlinear learning and ensemble classifier ability.

The use of:

- adaptive RIS partitioning,
- fairness-aware optimization,
- adaptive power allocation,
- feature engineering,
- and machine learning-enabled RIS optimization

enhances the capabilities of intelligent wireless resource management.

7.12 Chapter Summary

Simulation results and performance analysis of the proposed intelligent adaptive RIS-assisted ISAC optimization with machine learning have been given in this chapter. Performance analysis for both communication and sensing, rewards optimization based on fairness, adaptive power allocation, machine learning classification performance, convergence analysis, feature importance analysis, Pareto trade-off analysis, and performance of RIS arm selection have been discussed considering different wireless environments.

Simulation results indicate that the proposed framework can enhance communication reliability, sensing capacity, adaptive resource allocation, fairness performance, and intelligent RIS optimization using machine learning-assisted adaptive RIS partitioning.

Chapter 8

Conclusion and Future Scope

8.1 Conclusion

The thesis described an adaptive RIS partitioning and resource optimization technique based on machine learning for use in RIS-assisted Integrated Sensing and Communication (ISAC) techniques. The suggested method involves dynamic partitioning of RIS elements between communication and sensing tasks through adaptive configurations of the RIS arms in Nakagami- m fading channels.

The methods of fairness-aware reward optimization and adaptive power allocation were developed for effective balance of both communication and sensing operations. A dataset was generated and features extracted using a Monte Carlo simulation approach for adaptive optimization of the RIS elements.

Random Forest and K-Nearest Neighbours (KNN) classifiers were used for the prediction of the adaptive configuration of the RIS arms. The simulations indicated that our technique improves communication SNR performance, sensing effectiveness, reward-based and fairness-aware optimization as well as adaptive resource allocation. Random Forest provided better performance due to its superior capability of ensemble learning.

All things considered, the presented framework can serve as a basis for intelligent ISAC optimization in the context of future 6G wireless networks.

8.2 Major Contributions of the Thesis

Key contributions made in this thesis can be briefly highlighted as below:

- Machine learning driven adaptive RIS assisted ISAC optimization framework.
- Adaptive partitioning of RIS among communication and sensing tasks.

- Wireless channel modeling through Nakagami- m fading in RIS aided scenario.
- Fairness based optimization of rewards and power allocation.
- Dataset construction using Monte Carlo simulation and feature extraction.
- Application of random forest and KNN classifier for adaptive RIS arm selection.
- Evaluation through performance measures such as accuracy, precision, recall, F1 score, convergence analysis, feature importance analysis, and Pareto optimization.

8.3 Future Scope

The future development could be directed to:

- optimization of the proposed scheme through deep learning and reinforcement learning,
- multiple user and target RIS-based ISAC systems,
- practical realization of RIS hardware,
- and real-time wireless environment.

The future research could be extended to study practical issues of RIS such as hardware impairments, discrete phase shifts, security issues of RIS-based communications, and low complexity optimization techniques.

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