Optimizing UAV-RIS Integration in Wireless Communication through Genetic Algorithms

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***Abstract*—The rapid advancements in wireless communication technologies have led to the integration of Unmanned Aerial Vehicles (UAVs) with Reconfigurable Intelligent Surfaces (RIS), offering transformative potential for dynamic energy and information transmission. However, optimizing this integration remains a challenge. This paper explores the use of genetic algorithms to optimize the Simultaneous Wireless Information and Power Transfer (SWIPT) mechanism within UAV-RIS systems. The focus is on strategic allocation of RIS elements to enhance both the energy and information transfer efficiency. Our Python-based simulation results affirm the efficiency of the proposed method, marking a significant advancement over traditional centralized approaches. The findings have vast implications for the future of wireless communication technologies, particularly in applications requiring dynamic and energy-efficient connectivity.**

***Index Terms*—UAV, RIS, SWIPT, Genetic Algorithm, Wireless Communication, SNR**

I. INTRODUCTION

Wireless communication has become an indispensable part of our daily lives, connecting not just people but also a myriad of devices that constitute the Internet of Things (IoT) [1]. As the IoT ecosystem continues to expand, traditional communication paradigms are encountering limitations in terms of scalability, energy efficiency, and data throughput [2] [3].

Among the groundbreaking developments in this domain is the incorporation of Unmanned Aerial Vehicles (UAVs) into wireless communication networks [4]. UAVs offer the promise of extended coverage, higher data rates, and improved reliability. Yet, they also introduce challenges, particularly in terms of energy-efficient operation and stable communication [5].

To overcome these challenges, researchers are increasingly focusing on Reconfigurable Intelligent Surfaces (RIS) [3]. These are programmable surfaces capable of directing electromagnetic waves in a controlled manner, thus improving the quality and reliability of wireless communication . The fusion of UAVs with RIS technology offers a transformative approach, especially when supplemented by Simultaneous Wireless Information and Power Transfer (SWIPT) mechanisms [1].

However, the full potential of UAV-RIS systems optimized for SWIPT has yet to be realized. The optimal allocation of RIS elements, for instance, remains a complex problem that can significantly impact system performance [2]. This paper aims to address this very issue through the application of genetic algorithms. Widely recognized for their optimization capabilities, genetic algorithms provide a robust method for solving intricate problems in wireless communication [6].

Our study contributes to the existing body of work by focusing on how genetic algorithms can be systematically applied for the effective grouping of RIS elements, thereby enhancing the SWIPT mechanism in UAV-RIS integrated networks. The ultimate goal is to significantly elevate key performance metrics such as the transmit Signal-to-Noise Ratio (SNR) [3].

The remainder of this paper is organized as follows: Section II elucidates the system model designed for our research, which includes the integration of UAVs with RIS and the SWIPT mechanism. Section III offers an in-depth analysis of the simulation results, and Section IV concludes the paper, outlining the key takeaways and avenues for future research.

II. SYSTEM MODEL

We begin by discussing a UAV-RIS integrated system aimed at enabling SWIPT. This study introduces a genetic algorithm-based optimization of RIS configurations, advancing from previous methods that simply divided RIS elements in half—one for enhancing UT's SNR and the other for energy harvesting. Our focus here is a balanced optimization between SNR at the UT and the energy harvested by the RIS elements.

A. Energy Harvested by RIS Elements

The energy harvested by a single RIS element is represented by [2]:

$$E_h = \eta \times |h_{AP-RIS}|^2 \times P_R$$

Where:

- E_h is the energy harvested by a single RIS element.
- η is the energy harvesting efficiency.
- h_{AP-RIS} is the channel coefficient between the Access Point (AP) and the RIS.
- P_R is the received power at the RIS.

B. Total Energy Harvested

For an RIS array with dimensions $M \times N$, the total energy harvested can be computed as [2]:

$$E_{h_{total}} = \sum_{i=1}^{M}\sum_{j=1}^{N} \eta \times |h_{AP-RIS_{ij}}|^2 \times P_R$$

C. SNR at the User Terminal

The SNR at the UT can be derived as [2]:

$$SNR_k = \frac{\sum_{i,j} A_{ij} \times B_{ij} \times \theta \times P_{BS}}{\sum_{i,j} C_{ij} + \sigma^2} \quad (1)$$

where

$$\begin{aligned} A_{ij} &= |h_{AP-RIS_{ij}}|^2, \\ B_{ij} &= |h_{RIS-UT_{ij}}|^2, \\ C_{ij} &= \sum_k A_{ij} \times B_{ij} \times \theta \times P_{BS}, \\ \theta &= \text{Reflection Coefficient.} \end{aligned}$$

D. Optimization Using Genetic Algorithm

The optimization problem aims to maximize both the harvested energy and the SNR at the UT. To solve this problem, we employ a genetic algorithm, inspired by natural selection processes to evolve potential solutions through generations [6] [7].

1) Genetic Algorithm Workflow: The detailed workflow for the genetic algorithm in optimizing the RIS configurations is as follows:

1) Initialize a population of random RIS configurations.
2) Evaluate each configuration based on a fitness function that considers both SNR and energy harvesting.
3) Select the top-performing configurations for crossover and mutation operations.
4) Evaluate the fitness of the new population.
5) Repeat the steps until a convergence criterion is met.
6) Return the best RIS configuration.

E. Fitness Function

The genetic algorithm evaluates the fitness of each RIS configuration based on a function that balances between the energy harvested and the SNR at the UT. The fitness function ensures that the energy harvested (E_h) is greater than the energy transmitted (E_t) plus a minimum threshold required for the power harvester, as well as maximizing the SNR at the UT.

III. Results

A. Experimental Parameters

The parameters for our simulations are chosen to closely emulate a real-world UAV-RIS system, as summarized in Table I. These settings serve as the foundation for assessing the system's efficacy in energy harvesting and signal-to-noise ratio (SNR) performance.

TABLE I
SUMMARY OF EXPERIMENTAL PARAMETERS

Parameter	Value
RIS Array Dimension	$M \times N$
Energy Harvesting Efficiency	η
Reflection Coefficient	θ
Access Point Transmission Power	$P_{\max}$
Number of UTs	$K = 1$
Channel Model	Rayleigh
Genetic Algorithm Generations	150
Population Size	150
Channel Coefficient ($AP \to RIS$)	$\lvert h_{AP-RIS_{ij}}\rvert$
Channel Coefficient ($RIS \to UT$)	$\lvert h_{RIS-UT_{ij}}\rvert$

B. Distribution of RIS Elements

Figure 1 demonstrates the effectiveness of the genetic algorithm in optimizing the distribution of RIS elements. The optimized layout significantly improves both energy harvesting and SNR at the user terminal (UT).

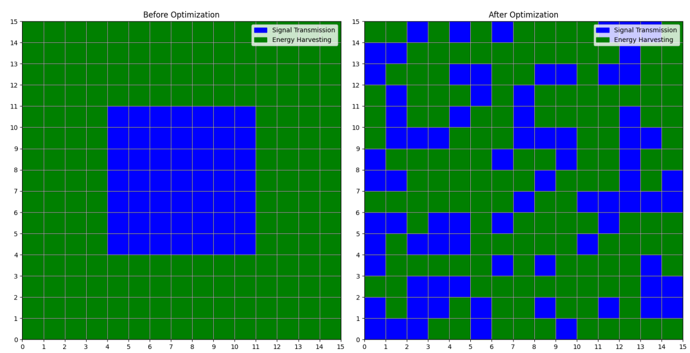

Fig. 1. Before and After Distribution of RIS Elements

C. SNR vs Number of Generations

Figure 2 showcases the gradual improvement of SNR at the UT as the genetic algorithm iterates through generations. It starts from the baseline SNR provided by a traditional RIS element distribution and demonstrates marked improvement.

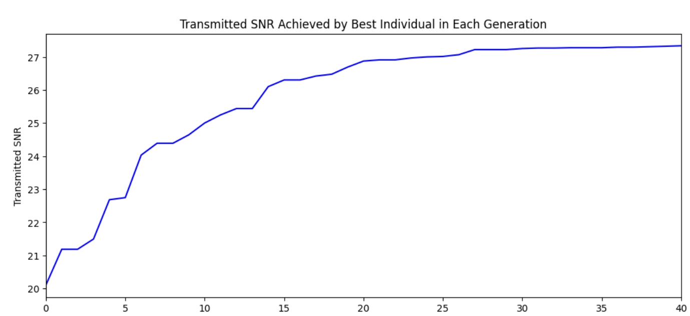

Fig. 2. SNR vs Number of Generations

D. Outage Probability

Outage probability is a crucial metric for the reliability of any communication system. Figure 3 indicates that the optimized RIS element distribution results in a substantially lower outage probability compared to a traditional distribution.

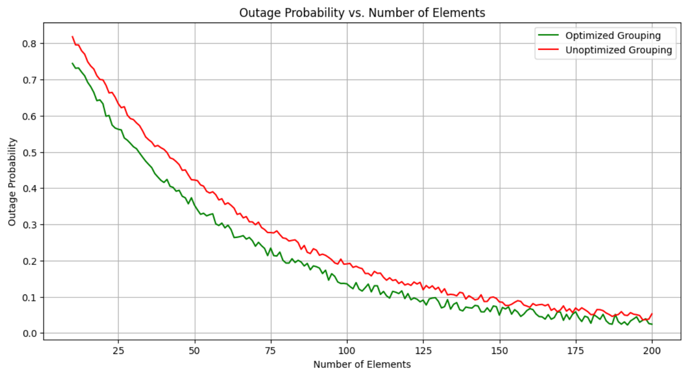

Fig. 3. Outage Probability for Optimized and Traditional Distributions

E. SNR vs Number of RIS Elements

Figure 4 indicates that the optimized distribution of RIS elements is more efficient in achieving the desired SNR. The same level of SNR is attained using fewer elements, highlighting the efficiency of the optimized setup.

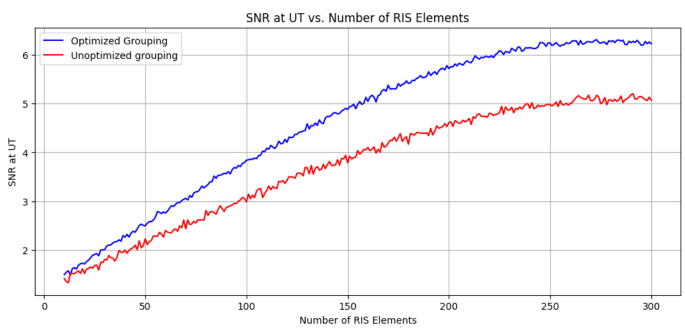

Fig. 4. SNR vs Number of RIS Elements for Optimized and Traditional Distributions

IV. Conclusion

In this research, we introduced a novel approach for enhancing wireless communication systems that utilize both Unmanned Aerial Vehicles (UAVs) and Reconfigurable Intelligent Surfaces (RIS). As we continue to interconnect a myriad of devices—from home gadgets to industrial sensors—the need for robust and energy-efficient wireless systems has never been greater.

Our method employs genetic algorithms to optimize the configurations of the RIS, a technology that holds great promise for future wireless networks. Unlike previous models, which statically divided RIS elements, our dynamic optimization approach aims for a dual benefit: maximized Signal-to-Noise Ratio (SNR) at the User Terminal (UT) and efficient energy harvesting. Experimental results validate the effectiveness of our method, indicating that it not only strengthens the communication link but also achieves this with fewer RIS elements.

The implications are far-reaching. Improved SNR and energy efficiency mean more reliable and sustainable operations, which are crucial for applications ranging from emergency response to large-scale monitoring. With this study, we have taken a significant step toward making next-generation wireless systems more intelligent, adaptable, and resource-efficient.

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