

Placement Optimization and Power Management in a Multiuser Wireless Communication System With Reconfigurable Intelligent Surfaces

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ABSTRACT Employing Reconfigurable Intelligent Surface (RIS) is an advanced strategy to enhance the efficiency of wireless communication systems. However, the number and positions of the RISs elements are still challenging and require a smart optimization framework. This paper aims to optimize the number of RISs subject to the technical limitations of the average achievable data rate with consideration of the practical overlapping between the associated multi-RISs in wireless communication systems. In this regard, the Differential evolution optimizer (DEO) algorithm is created to minimize the number of RIS devices to be installed. Accordingly, the number, positions, and phase shift matrix coefficients of RISs are then jointly optimized using the intended DEO. Also, it is contrasted to several recent algorithms, including Particle swarm optimization (PSO), Gradient-based optimizer (GBO), Growth optimizer (GO), and Seahorse optimization (SHO). The outcomes from the simulation demonstrate the high efficiency of the proposed DEO and GO in obtaining a 100% feasibility rate for finding the minimum number of RISs under different threshold values of the achievable rates. PSO scores a comparable result of 99.09%, while SHO and GBO attain poor rates of 66.36% and 53.94%, respectively. Nevertheless, the excellence of the created DEO becomes evident through having the lowest average number of RISs when compared to the other algorithms. Numerically, the DEO drives improvements by 5.13%, 15.68%, 30.58%, and 51.01% compared to GO, PSO, SHO and GBO, respectively.

INDEX TERMS Reconfigurable intelligent surfaces, wireless communication, differential evolution optimizer, achievable rate limitation.

I. INTRODUCTION

THE GLOBAL employment of the 5th-Generation cellular network (5G) wireless network continues, and both the academic and industrial spheres have turned their attention with great enthusiasm towards envisioning the post-5G future, commonly referred to as Beyond 5G (B5G). The spotlight is now on the prospective Sixth-generation cellular networks (6G) wireless network, designed to fulfill even more rigorous demands than its predecessor [1], [2], [3],

[4], [5], [6]. These demands encompass ultra-high data rates, energy efficiency, seamless global coverage and connectivity, exceptional reliability, and minimal latency. However, achieving these formidable requirements through current technology trends tailored for flexible 5G services, such as enhanced Mobile BroadBand (eMBB), Ultra Reliable Low Latency Communications (URLLC), and massive Machine Type Communications (mMTC), presents challenges that warrant innovative solutions [4], [7], [8], [9]. One of

these innovative solutions is using the RIS in wireless communications [10].

Reconfigurable Intelligent Surface (RIS) is receiving more and more attention as a ground-breaking innovation for managing or modifying wireless communication channels [11], [12], [13]. With respect to the vision of 6G of communications, it is seen to play a crucial part in the realization of the smart radio environment (SRE) [14], [15], [16], [17], [18]. According to the number of RISs participating and the level of cooperation, a fascinating classification of the linked work is provided in [19]. Even in the face of obstacles or in situations when the received power from the direct path is insufficient to establish a reliable connection, RISs can help establish a Line-of-Sight (LOS) link between the transmitter and the receiver using arrays of antenna elements [20]. Through adeptly controlling the reflection of signals by employing an array of economically viable passive reflecting elements, RIS exhibits the capability to modify wireless channels dynamically, thus augmenting the performance of communication systems [7], [21]. Consequently, the prospect emerges of a novel amalgamation, where the hybrid wireless network incorporates active and passive constituents enabled by RIS. This hybridization holds significant promise, offering a pathway to cost-effectively achieve substantial growth in network capacity, ensuring sustainability in the future.

As the deployment of RIS gains momentum, the optimization of RIS placement has become a crucial endeavor [22], [23]. This involves strategically positioning RIS elements to exploit their reflective properties and augment the wireless environment. The fundamental premise of RIS placement optimization revolves around determining the optimal locations for installing RIS elements within a given environment. The goal is to manipulate signal propagation by intelligently reflecting and refracting electromagnetic waves to establish desired communication characteristics. By carefully placing RIS elements, wireless networks can potentially overcome challenges posed by signal blockages, interference, and coverage limitations [24]. To tackle this problem, several optimization techniques have been developed, each of which meets specific goals and conditions [25], [26]. One of these algorithms is the Differential Evolution Optimizer which constitutes a population-based optimization technique within the algorithmic evolutionary class. After summarising the pertinent literature, we move on to a brief discussion of the research motivation, scope of the paper, and challenges before presenting the main contributions.

A. RELATED WORK

Numerous studies have been conducted on the use of optimization algorithms for RIS placement [27]. In the field of RIS replacement optimization, the placement of RIS is examined in [28], a common passive technique for locating non cooperative Radio frequency (RF) transmitters stems from the Time difference of arrival (TDOA) method is introduced in [29]. However, this approach comes with significant

challenges, including the need for precise synchronization between sensors and high-throughput data transmission links. One key consideration in TDOA systems is the configuration of sensor placement. The farther apart the sensors are located, the higher degree of accuracy the localization can be, but this also increases the costs associated with synchronization and data links. The authors introduced an innovative localization system that leverages RIS to enhance accuracy while reducing expenses. The research demonstrates that this new setup, with the use of the beam-scanning capability of RIS sensors, enhances the localization algorithm and surpasses the performance of conventional methods. Furthermore, they provide comparisons with the Cramér-Rao to validate the efficiency of their proposed approach. The study depends on two RISs only with some sensors that can increase the overhead of the network.

The authors in [30] investigated the performance of range estimation for a cellular user in a millimeter-wave (mm-wave) network using Received signal strength indicator (RSSI) measurements with the assistance of RISs. Initially, they introduce an optimal strategy for deploying RISs to minimize the combined probability of obstructing the user's connection to the base station (BS) and the connection to the RIS. Subsequently, the authors presented an approach to range estimation based on certain bounds, where the BS calculates the user's distance directly when there is a LOS connection. In the event that the direct connection is blocked, the BS estimates the user's distance through the reflected path facilitated by the RIS. In existing literature, it is often recommended to position the RIS in close proximity to the BS to enhance path gain. However, their research challenges this notion by revealing that, in scenarios involving obstructions, having the RIS and the BS in close proximity is not the optimal configuration. But they depend on only one RIS in their work.

In [31], the authors presented RIS as a solution to a specific problem and explored localization algorithms based on near-field (NF) resided signal strength (RSS). To provide more details, they utilize a single RIS to create simulated line-of-sight (SLOS) links between an anchor node (AN) and an unidentified node (UN). This is done to address scenarios where a direct line-of-sight path is not available. Also, the authors introduced RIS phase adjustment strategies to maximize the RSS at the UN. Building on this foundation, they establish the correlation between azimuth and phase parameters, leading to precise estimation of the position of an unidentified node (UN) through the application of weighted least squares (WLS) and alternate iteration techniques. Additionally, they tackle the challenge of dealing with both LOS and SLOS paths simultaneously by modifying the reflection coefficients. In conclusion, they suggest a technique to ascertain whether the unidentified node is positioned in the far-field or near-field of the RIS sub-segments, with the objective of minimizing positioning errors. In various applications of location-based Internet of Things (IoT) services, the simultaneous and accurate

localization of numerous energy-constrained devices is a critical requirement.

The authors in [32] addressed this challenge and proposed a positioning method for multiple IoT devices assisted by RIS. In this method, the signals transmitted by users propagate to the BS via both a straightforward path and a reflection path through the RIS. The key factor in their triangulation-based localization approach is the estimation of the propagation delay difference between these two paths, which is accomplished using the cross-correlation function of received signals. They aimed to use one RIS to optimize a BS with multiple antennas to decrease the total transmitted power of the IoT devices, taking advantage of the orthogonality of transmitted signals. In scenarios with orthogonal signals, utilizing the semidefinite relaxation (SDR) method, they recast the non-convex optimization issue for the RIS into a convex problem. In cases involving non-orthogonal signals, they utilize zero-forcing (ZF) combining vectors at the BS to mitigate interference from multiple users. They employ the block coordinate descent (BCD) algorithm to separate the optimization of the combining vectors and the RIS phases.

In [33], a novel joint RIS location and passive beamforming (J-LPB) optimization approach is presented to maximize the secrecy rate while adhering to the RIS placement restriction and the requirement that the modulus of the reflecting coefficient at each RIS unit not exceed 1. They specifically examine the RIS's ideal position and conclude that the sum of the source-to-RIS and RIS-to-destination distances should be kept to a minimum. One of the articles addressing and delving into the optimization challenges for networks assisted by RISs is referenced as [34]. In that research, the authors introduced novel criteria for selecting optimal locations of RISs in wireless networks, enhancing Signal-to-Noise Ratio (SNR) based on a path-loss power model for outdoor communication and an exponential path-loss model for indoor communication. The optimization problem was composed and figured out under the assumption that the coefficients of the channel for multiple RISs were independent and identically distributed (i.i.d.) Rayleigh random variables (RVs).

On the other hand, another significant difficulty in real-world RIS-assisted systems [35], [36], [37], [38], [39], [40], [41], [42] is optimizing the RIS phase shifts. To be able to increase the channel capacity, the RIS setup of point-to-point multiple-input multiple-output (MIMO) systems has recently been improved in [35]. In [43] and [44], the focus was on investigating the URLLC system. This system featured a dedicated RIS assisting the Base Station (BS) in transmitting short packets within a Frequency Blockage Limited (Finite blocklength (FBL)) scenario. The study also explored a Channel blocklength (CBL) allocation and the RIS reflecting phase-shift Operating Point (OP), with user grouping being addressed in [43]. The user grouping challenge presented in [43] was resolved through the application of a greedy algorithm, and the proposed

Operating Points (OPs) were tackled using a semi-definite relaxation technique. To optimize the total achievable rate in the infinite block length regime, considering Shannon capacity, [45] investigated a Multiple-Input Single-Output (MISO) system aided by RISs. This involved adjusting the Base Station (BS) transmit beamforming and the passive beamforming at the RIS using Deep Deterministic Policy Gradients (Deep deterministic policy gradient (DDPG)).

The study in [46] compares half-duplex and full-duplex operation modes for a MISO system with RIS support. Additionally, in cooperative networks, research was conducted on the joint optimization of relay selection and RIS reflection coefficients [47]. For the effective implementation of the metaverse in 6G networks, authors in [48] explored the complementarity of digital twins (DTs) notion. To be more precise, they examine how a DT-assisted RIS-based network design can provide significant advancements in achieving the network latency and dependability required for 6G metaverse realization. A downlink communication system aided by multiple aerial RISs (ARISs) and placed on RISs that is energy-efficient is examined in [49]. The UEs and BS can communicate more easily because of the implementation of several ARISs. After that, the joint optimization issue of the multiple ARISs-assisted communication system's power regulation, phase shift, and ARIS reflecting elements on/off states is developed.

A blockchain-based architecture for information sharing and storage that permits safe knowledge management in intelligent IoT was presented by the authors in [50]. The on-chain encrypted knowledge storage, and an enhanced Delegated Proof of Stake (DPoS) consensus mechanism are two components of their first permissioned blockchain-based decentralized and trustworthy knowledge storage scheme. A unique wirelessly powered edge intelligence (WPEG) architecture was presented in [51], with the goal of using energy harvesting (EH) techniques to produce edge intelligence that is stable, reliable, and sustainable. To protect the peer-to-peer (P2P) energy and knowledge sharing in our system, they first created a permissioned edge blockchain. By taking into account the radiative characteristics of RIS, the authors of [52] derived a general expression of the ergodic capacity for RIS-aided communication systems, where both the LOS and NLOS links are considered. This gives a new degree of freedom in optimizing RIS-aided wireless channels. We investigate the RIS deployment strategy, including RIS rotation and placement optimizations, based on the channel model. In [53], the authors suggested a conjugate gradient and particle swarm optimization (CG-PSO) technique to jointly optimize the RIS phase shifts and Aerial base station (ABS) elevations. The Conjugate gradient (CG) under the fixed ABS altitude and variable transmit power is used to calculate an appropriate RIS phase shift. In the end, they used PSO to determine the ideal ABS altitude, which leads to an enhanced sum rate under the ideal RIS phase shift.

Using numerous RISs to help wireless communication systems, the authors of [54] created a multiple access

strategy for next-generation multiple access (NGMA). They initially looked at the interaction between the efficiency and complexity of the RIS phase setup and the design of NGMA schemes, taking into account the real-world scenario of stationary users working alongside mobile ones. They then created a medium access control (MAC) protocol that incorporates RISs and suggested a multiple access framework for RIS-assisted communication systems based on this framework. Furthermore, a thorough performance study of the RIS-assisted MAC protocol that was created is provided. With a focus on the MAC schemes, the authors of [55] provided four common RIS-aided multi-user situations. Beyond that, they presented and discussed MAC designs for RIS-assisted multi-user communications systems that are centralized, distributed, and hybrid. In conclusion, they discussed about certain RIS-related MAC design problems, viewpoints, and possible uses. In [56], the authors suggested a RIS-assisted transmission technique to solve the coverage and connection performance issues of the aerial-terrestrial communication system. Specifically, they developed an adaptive RIS-assisted transmission protocol, wherein within a frame, the data transfer, transmission strategy, and channel estimate are all conducted separately. Authors examined RIS-assisted MAC layer communications in [57] and suggested a RIS-assisted MAC architecture. Pre-negotiation and the multidimension reservation (MDR) technique are specifically used to accomplish RIS-assisted transmissions. They examined RIS-assisted single-channel multiuser (SCMU) communications in light of this. A single user can reserve the RIS as a whole to facilitate numerous data transmissions, resulting in very efficient RIS-assisted connections at the user's location.

Recent research in [58] examined the use of distributed proximal policy optimization (PPO) for active/passive beamforming at both the Base Station (BS) and RIS in a multiuser scenario. It is important to highlight that the problem addressed in this research was defined within the infinite CBL regime based on the Shannon rate formula, and the primary focus of the discussion did not center around optimizing the CBL. The authors in [41] introduced an innovative approach for grouping elements in centralized RIS, where each group comprises a collection of adjacent RIS elements that share the same reflection coefficient. Using this grouping technique, they recommend an efficient transmission protocol in which it is only necessary to approximate the combined channel for each group. This approach considerably lowers the overhead of training. The authors in [59] aim to reduce the overall transmit power by simultaneously optimizing the transmit beamforming vectors at the BS and the reflection coefficient vector at the RIS using a single RIS. In this regard, an efficient algorithm based on second-order cone programming (SOCP) and alternating direction method of multipliers (ADMM) is introduced to arrive at a locally ideal outcome.

Additionally, to mitigate computational complexity, the authors presented a lower-complexity suboptimal algorithm

based on ZF principles. A practical scenario is investigated in [60] where the BS only requires the large-scale fading gain, and the finite-sized RIS can achieve a limited number of phase shifts. The authors put forward a hybrid beamforming approach to optimize the sum rate. This approach employs continuous digital beamforming at the BS and discrete analog beamforming using the RIS. They develop an iterative algorithm for beamforming and provide theoretical analysis to assess how the RIS size impacts the achievable data rate. An innovative system involving multiple RIS with location information assistance is introduced in [61]. The assumption of imperfect user location information and proceeding to approximate the effective angles from the RIS to the users is addressed. These estimated angles are subsequently employed in the design of the transmit beam and the configuration of the RIS beam. The authors in [62] suggested activating an RIS at the cell boundary of several cells by jointly optimizing the active precoding matrices at the BSs and the phase shifts at the RIS under the power and unit modulus constraints placed on each BS to maximize the weighted sum rate (WSR) of all users. By working together to design the phase shifts and power distribution, the authors of [63] optimized the energy efficiency of a RIS-assisted downlink multi-user system.

The authors of [64] suggested a hybrid beamforming approach to increase the coverage range in the terahertz frequency spectrum for multi-hop RIS-assisted communication systems. The authors of [65] examined how phase noise affected the output power of RIS-assisted communication systems using generalized fading channels. Additionally, the authors of [66] showed that centralized RIS deployments perform worse than uniformly dispersed deployments of the same magnitude. Additionally, [67] investigated the single-RIS and multi-RIS deployment strategies for RIS-aided relay systems and demonstrated that the multi-RIS deployment could achieve a higher system capacity. However, the study in [68] showed that centralized deployment is superior to the spread one by describing the capacity.

The algorithms DEO, PSO, GBO, SHO, and GO have been subjected to a comparative evaluation in order to address the suggested model. Table 1 shows the algorithms' wide applicability. Further refinements have been introduced to facilitate the adoption of these techniques. The fitness function assesses how well a solution performs in reaching the optimization goal. The number of RIS units to be placed and their spatial distribution are the control variables in the context of the model for the RIS-assisted wireless communication system that is being presented. These control variables come in two varieties: the continuous placement of these units and the integer-based count of RIS units. The count of RIS units is handled as a continuous range and rounded to the closest integer since the compared algorithms usually operate within a continuous framework. Furthermore, in this study, adherence to the restrictions is ensured by substituting a randomly picked number within the practical boundaries of the variable when a control

TABLE 1. Adopted algorithms, main features and successful applications.

Algorithm	Ref.	Main features	Main features
DEO	Storn and Price [69] (1995)	DEO fundamentally mirrors the course of biological evolution by gradually advancing a population of potential solutions throughout several iterations. A starting group of randomly produced people, each of which indicates a prospective solution to the optimization issue, forms the basis of the method. It is often represented in a high-dimensional search space as vectors [70], [71]. DEO's efficiency in searching huge, complicated solution areas, which includes ones with nondifferentiable, non-linear, or stochastic objective tasks, forms one of its main benefits. Due to its randomized character and the varied explorations made possible by mutations and crossover procedures, it is also resistant to being caught in local optima [72].	Wireless communication [73], cyberattack of cyber-physical power systems [74], allocation of electric vehicles charging station in electrical networks [75], engineering design [76], unmanned aerial vehicle (UAV) stocktaking task-planning for industrial warehouses [77], reactive power dispatch in power systems [78], parameter estimation [79] and electromagnetic problems [80] are just a few of the areas in which DEO has been effectively used to solve different optimization challenges.
PSO	Kennedy and Eberhart, (1995) [81]	PSO mimics the collective behavior of organisms where individuals adjust their movements based on their own experiences and the experiences of their neighbors to navigate through a solution space efficiently. While each particle's trajectory is shaped by its own locally optimal position, it is also influenced by the global best-known positions within the search space, which evolve as superior solutions are discovered by other particles. This collective movement of particles is designed to guide the swarm towards optimal solutions [82].	Load Frequency Control [83]; Reflux Power Optimization in Triple Active Bridge [84]; maximum power point tracking of fuel cells [85]; Power system Optimization [86].
GBO	I. Ahmadi-anfar <i>et al.</i> [87] (2020)	GBO draws inspiration from Newton's gradient-based methodology. It integrates two key operators. First, the gradient search rule leverages gradient-based techniques to intensify exploration and hasten convergence toward optimal positions. Second, the local escaping operator empowers GBO to navigate away from local optima. The algorithm's efficacy was assessed in [87] on 28 mathematical test functions and six engineering problems. Results from both phases underscored GBO's robust performance, demonstrating its effective mitigation of local optima across various scenarios [88].	Distributed generations integration in electrical feeders [89]; Blockchain-assisted smart home management [90]; Automatic voltage regulator control [91]; Solar-assisted combined heating, cooling and power systems [92]; Energy losses minimization [93].
SHO	S. Zhao <i>et al.</i> [94] (2023)	The SHO is a metaheuristic inspired by sea horses' movement, predation, and breeding behaviors. In the first two stages, SHO mimics the spiral floating and drifting movement patterns and the probabilistic predation mechanisms of sea horses. The third stage leverages the unique male pregnancy characteristic to breed offspring while maintaining the beneficial traits of the male parent, enhancing population diversity. In [94], SHO's performance is evaluated on 23 well-known functions, CEC2014 benchmark functions, and five real-world engineering problems, showing its high effectiveness and adaptability compared to six state-of-the-art metaheuristic algorithms.	DC motor control [95]; DC microgrid islanding detection [96]; Tuning parameter power system stabilizer [97]; Engineering design problems including welded beam design, reducer design, industrial refrigeration system, vessel design, three-bar truss design, and cantilever beam problem [98].
GO	Q. Zhang <i>et al.</i> [99] (2023)	The design of the GO algorithm is primarily inspired by the human capacity for reflection and learning in socially evolving activities. Just as individuals grow by learning from others and reflecting on their own shortcomings to improve, the GO approach embodies these principles. In reference [99], the GO algorithm was tested against various mathematical benchmarks, demonstrating significant advantages over other comparative strategies. It surpassed alternative metaheuristic methods in terms of solution effectiveness and avoiding local optima.	Gesture classification and recognition for visually impaired persons [100]; Intrusion detection systems for IoT [101]; Photovoltaic cells and modules modelling [102]; soft open point allocations in distribution networks [103].

variable is violated. Moreover, penalty terms have been used to include dependent variable limitations in the fitness function. Consequently, solutions failing to meet one or more

restrictions are rewarded with high fitness ratings, reducing the possibility that unworkable solutions will be carried over to further rounds.

B. RESEARCH MOTIVATION

Due to the RIS's location, previous studies have only used it to extend coverage; however, little research has been done on how to deploy the RIS to further disperse cell coverage. Furthermore, most research efforts in the literature focus on solving traditional wireless communication problems under the new assumption of an assisted metasurface solution, ignoring the RIS domain. Finally, there hasn't been enough research done on how to deploy RIS as effectively as possible in a situation where there are several users.

Our study advances the optimization of RIS deployment in wireless communication systems through several novel contributions. Firstly, we extend beyond optimizing the number of RISs by focusing on strategic deployment strategies aimed at enhancing coverage dispersion, particularly in multi-user scenarios, addressing a notable gap in the existing literature. Secondly, we introduce a facility placement problem formulation to systematically determine optimal RIS deployment locations, offering a structured approach that has not been extensively explored before. Thirdly, our proposed robust optimization approach jointly optimizes phase shift coefficients, number, and locations of RISs to minimize the total number revealed to the average permitted data rate, thus enhancing deployment robustness in varying communication environments. Finally, through extensive experimental validation in a multiRIS-assisted wireless communication system set up, we empirically demonstrate the practical applicability and performance improvements of our approach. Collectively, these contributions distinguish our work and significantly advance the understanding and implementation of RIS-assisted wireless communication systems.

C. SCOPE AND RESEARCH QUESTION

In the rapidly evolving landscape of wireless communication systems, the proliferation of IoT devices necessitates robust solutions to overcome challenges posed by interference, signal strength variations, and complex propagation environments. RISs emerge as a promising technology to address these challenges by offering dynamic control over signal propagation, thereby enhancing connectivity and communication quality. However, the optimal deployment of RISs remains a complex optimization problem due to considerations such as the number and positions of RIS elements, technical limitations on achievable data rates, and practical constraints in real-world deployment scenarios. This paper seeks to bridge this gap by introducing a sophisticated optimization framework aimed at determining the optimal placement of RISs in wireless communication systems. By strategically optimizing the number, locations, and phase shift coefficients of RISs, our study aims to maximize communication rates while addressing practical deployment constraints, thus advancing the field of RIS-assisted wireless communication technologies. Through this research, we aim to provide insights into the importance of RIS deployment optimization and contribute to the development of more

efficient and reliable wireless communication systems for IoT applications.

D. CHALLENGES AND LIMITATIONS

While our research aims to advance the understanding and implementation of RISs in wireless communication systems, it is essential to acknowledge the challenges and limitations inherent in the proposed work. One significant challenge lies in the complexity of optimizing RIS deployment, which involves determining the optimal number, locations, and phase shift coefficients of RIS elements. This optimization process entails intricate trade-offs between communication performance metrics such as rate, coverage, and energy efficiency, further compounded by real-world constraints and system requirements. Additionally, the scalability of our proposed optimization framework may pose challenges in adapting to diverse deployment scenarios and accommodating varying user densities, environmental conditions, and system configurations. Furthermore, while our study contributes valuable insights into RIS deployment optimization, it is important to recognize that real-world deployment may encounter practical challenges and limitations such as hardware constraints, regulatory considerations, and deployment costs. Despite these challenges, our research serves as a crucial step towards unlocking the potential of RISs in enhancing wireless communication systems, paving the way for future advancements in this domain.

E. MAIN CONTRIBUTION

This study investigates the RIS deployment position optimization for wireless communication systems supported by several RISs and supporting numerous users in order to close this gap. We define a facility placement problem as an RIS deployment problem, which helps us determine the best location for RIS deployment and maximizes the overall data flow inside the wireless network. Additionally, we examine the impact of different parameters on communications enabled by RIS. In addition, a new robust approach is suggested to jointly determine the phase shift coefficients, number, and locations of RISs with the goal of minimizing the total number of RISs exposed to the average permitted data rate. Using a multiRIS-assisted wireless communication system as a reference, the effectiveness of the suggested method is confirmed.

The main contributions of this paper are as follows:

- 1) Develop DEO algorithm encompassing distinct types of integer-based count of RIS units and their continuous positioning. This proposed methodology seeks to achieve the optimal quantity, locations, and phase shift coefficients of RISs to maximize data rates while minimizing the number of RIS units.
- 2) Demonstrate DEO's superiority over a number of contemporary optimization algorithms, including SHO, PSO, GBO, and GO, in terms of determining the fewest RISs that may be utilized in the network.

TABLE 2. List of the main symbols.

Symbol	Definition
K	Number of single-antenna User Equipments
N	Number of RISs
Θ_n	$\mathbb{C}^{M \times M}$ matrix of phase shift coefficients for the RIS_n
θ_n	$\mathbb{C}^{M \times 1}$ vector of phase shift coefficients for the RIS_n
$\mathbf{h}_{b,r_n}$	$\in \mathbb{C}^{M \times 1}$ the channel vector from RIS n to the AP
$\mathbf{h}_{r_n,u_k}$	$\in \mathbb{C}^{M \times 1}$ the channel vector from UE k to RIS n
h_{b,u_k}	$\in \mathbb{C}^{1 \times 1}$ the channel from UE k to the AP
L_{b,r_n}	The path-loss between RIS n and the AP
ϵ	The Rician factor
$\mathbf{a}_n$	$\in \mathbb{C}^{M \times 1}$ The array response of RIS n
φ_n and ψ_n	The azimuth angle and the elevation angle of departure for the link between RIS n and the AP
$\mathbf{d}_{b,r_n}$	The direct components, and their elements are selected from $\mathcal{CN}(0, 1)$
φ'_n and ψ'_n	The azimuth and elevation angles for the link between RIS n and User Equipment (UE) k
L_{b,u_k}	The path-loss between UE k and the AP
y_{AP}	The received signal at the AP
p_k	The power of transmitted symbol
$\{x_n, y_n\}$	The location of RIS n
L	The size length of each RIS
N_{min}	The minimum number of RISs
N_{max}	The maximum number of RISs
Rd	A vector containing arbitrary continuous numbers that range from 0 to 1.
ND_s	The population size
Dim	The total number of variables for every one of the solutions
fit	fitness function
λ_1 and λ_2	Penalty factors

These optimization algorithms have been utilized for similar optimization problems in previous studies (such as DEO [28], [104], PSO [105], [106], and GBO [107], [108]).

- 3) Use a variety of performance metrics, such as minimum, maximum, average, and feasibility rate of the number of RISs, to compare DEO's effectiveness to that of other optimization methods. This approach comprehensively addresses real-world system constraints, including signal overlap and user distribution.
- 4) Propose a sophisticated model for a wireless communication system leveraging RIS. This model creates optimized reflecting pathways that significantly enhance the received power at user equipment, particularly in multi-user environments.

The remaining sections of the paper are structured as follows: Section II outlines the system model. Section III introduces the development of (DEO) for the optimal

placement of RIS elements. In Section IV, the simulation setup and outcomes from the simulation are presented to validate the performance of the proposed algorithm. Finally, Section V offers conclusions drawn from the study.

Notation: We symbolize column vectors in boldface lowercase as $\mathbf{x}$ and matrices in boldface uppercase as $\mathbf{X}$. For each $\mathbf{X}$, the corresponding pseudo-inverse, transpose, conjugate transpose (Hermitian), and inverse are represented by the symbols $\mathbf{X}^\dagger$, $\mathbf{X}^T$, $\mathbf{X}^H$, and $\mathbf{X}^{-1}$, respectively. The trace function of a matrix $\mathbf{X}$ is denoted as $\text{tr}(\mathbf{X})$. The Euclidean norm is represented by $\|\cdot\|$. $\mathbf{x} \sim \mathcal{CN}(\mu, \varphi)$ is the notation for a circularly symmetric complex Gaussian random vector that is μ for the mean and φ for the covariance matrix. The entire set of complex numbers is symbolized by $\mathbb{C}$. In this notation, $\mathbb{C}^{N \times 1}$ and $\mathbb{C}^{N \times M}$ refer to the generalizations for vectors and matrices, respectively. The identity matrix of size $M \times M$ is symbolized as $\mathbf{I}_M$. Besides, for ease of reference, the main symbols used in this work are listed in Table 2 and the list of abbreviations are listed in Table 3.

TABLE 3. List of abbreviations.

RIS	Reconfigurable Intelligent Surface	UN	unidentified node
DEO	Differential Evolution Optimizer	WLS	weighted least squares
PSO	Particle Swarm Optimization	IoT	Internet of Things
GB0	Gradient-Based Optimizer	SDR	semidefinite relaxation
GO	Growth Optimizer	ZF	zero-forcing
SHO	Seahorse optimization	BCD	block coordinate descent
B5G	Beyond 5G	J-LPB	joint RIS location and passive beamforming
eMBB	Enhanced Mobile Broadband	SNR	Signal-to Noise Ratio
URLLC	Ultra Reliable Low Latency Communications	i.i.d.	Independent and identically distributed
mMTC	Massive Machine Type Communications	FBL	finite blocklength
SRE	Smart radio environment	CBL	channel blocklength
LOS	Line-of-Sight	OP	Operating Point
RF	Radio frequency	MISO	Multiple-Input Single-Output
TDOA	Time difference of arrival	DDPG	Deep Deterministic Policy Gradients
CRLB	Cramer-Rao lower bound	PPO	proximal policy optimization
mm-wave	millimeter-wave	S0CP	second-order cone programming
RSSI	Received signal strength indicator	ADMM	alternating direction method of multipliers
BS	base station	WSR	weighted sum rate
NF	near-field	UE	user equipment
RSS	Received signal strength	AP	Access Point
SLOS	simulated line-of-sight	Mv	mutant vectors
AN	anchor node	fit	fitness function

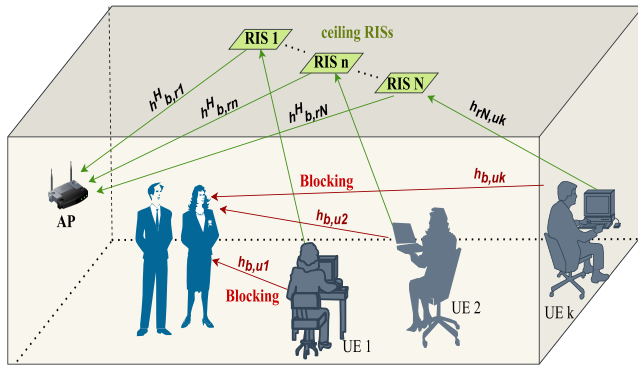


FIGURE 1. System model.

II. SYSTEM MODEL

Our proposed system introduces a multi-RIS-aided wireless communication setup designed for indoor environments such as stadiums and large halls, as depicted in Figure 1. In this configuration, K single-antenna User Equipments (UEs) establish connections with a single-antenna Access Point (AP) in distinct time slots, facilitated by N RISs of uniform size. Each RIS, mounted on the ceiling, comprises a homogeneous planar array featuring M reflecting

elements. The RISs are strategically positioned within the indoor space to optimize signal propagation and coverage, leveraging their ability to dynamically adjust the phase of incident electromagnetic waves. The proposed setup aims to enhance spectral efficiency and mitigate multipath fading and interference typically encountered in indoor wireless environments. By utilizing RISs as passive reflectors, the system enables targeted beamforming and signal steering, improving overall system performance and user experience. The deployment of RISs in this manner provides a cost-effective solution for improving wireless communication in large indoor venues, addressing coverage challenges, and optimizing network capacity.

A. COMMUNICATION CHANNEL MODEL

Let $\Theta_n = \text{diag}\{e^{j\theta_{n,1}}, e^{j\theta_{n,2}}, \dots, e^{j\theta_{n,M}}\}$ is denoted as the matrix of phase shift coefficients for the RIS- n , where $\theta_n = (\theta_{n,1}, \theta_{n,2}, \dots, \theta_{n,M})^T$ is used to represent the phase shift coefficient of RIS- n . Along with that, we also designate $\mathbf{h}_{b,r_n} \in \mathbb{C}^{M \times 1}$ as the channel vector from RIS n to the AP, $\mathbf{h}_{r_n, u_k} \in \mathbb{C}^{M \times 1}$ as the channel vector from UE k to RIS n , and $\mathbf{h}_{b, u_k} \in \mathbb{C}^{1 \times 1}$ as the channel from UE k to the AP. Both UE-RIS and RIS-AP lines employ the Rician fading channel

model. Consequently, $\mathbf{h}_{b,r_n}$ is written as [28]

$$\mathbf{h}_{b,r_n} = L_{b,r_n} \left(\sqrt{\frac{\epsilon}{\epsilon+1}} \mathbf{a}_n(\varphi_n, \psi_n) + \sqrt{\frac{1}{\epsilon+1}} \mathbf{d}_{b,r_n} \right) \quad (1)$$

where L_{b,r_n} represents the path-loss between RIS n and the AP, and ϵ represents the Rician factor. The array response of RIS n is indicated by $\mathbf{a}_n \in \mathbb{C}^{M \times 1}$, where φ_n denotes the azimuth angle and ψ_n signifies the elevation angle of departure for the link between RIS n and the AP. $\mathbf{d}_{b,r_n}$ signifies the direct components, and their elements are selected from $\mathcal{CN}(0, 1)$. Similarly, $\mathbf{h}_{r_n,u_k}$ appears as [28]

$$\mathbf{h}_{r_n,u_k} = L_{r_n,u_k} \left(\sqrt{\frac{\epsilon}{\epsilon+1}} \mathbf{a}_n(\varphi'_n, \psi'_n) + \sqrt{\frac{1}{\epsilon+1}} \mathbf{d}_{r_n,u_k} \right) \quad (2)$$

where φ'_n and ψ'_n represent the azimuth and elevation angles, respectively, for the link between RIS n and User Equipment (UE) k . The direct channel between user k and the Access Point (AP) is symbolized as

$$h_{b,u_k} = L_{b,u_k} d_{b,u_k} \quad (3)$$

where the path-loss between UE k and the AP is denoted by L_{b,u_k} . The received signal at the AP is expressed as

$$y_{AP} = (\mathbf{h}_{b,r_n}^H \Theta_n \mathbf{h}_{r_n,u_k} + h_{b,u_k})x + n \quad (4)$$

where x is the transmitted symbol with power p_k , $\mathbf{h}_{b,r_n}^H \Theta_n \mathbf{h}_{r_n,u_k}$ is the effective channel including RIS phase shift and h_{b,u_k} is the channel gain of the direct path, n represents the noise with $\mathcal{CN}(0, \sigma^2)$. The received SNR is given by

$$SNR = \left(\frac{p_k |t_{b,u_k} h_{b,u_k} + \sum_{n=1}^N t_{b,r_n} \mathbf{h}_{b,r_n}^H \Theta_n \mathbf{h}_{r_n,u_k}|^2}{\sigma^2} \right) \quad (5)$$

The achievable sum rate of user k is shown in (6), shown at the bottom of the page.

where the parameters $t_{a,n}$ and $t_{a,k}$ satisfy

$$t_{b,r_n} = \begin{cases} 0 & \text{if the link between RIS } n \text{ and} \\ & \text{AP is blocked} \\ 1 & \text{otherwise} \end{cases} \quad (7)$$

$$t_{b,u_k} = \begin{cases} 0 & \text{if the link between RIS } n \text{ and} \\ & \text{AP is blocked} \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

B. PROBLEM FORMULATION

In this paper, we introduce a method for concurrently optimizing the quantity, distribution, and RIS reflection patterns in an RIS-aided wireless communication system. The resulting parameters are assessed with the aim of

showing the effectiveness of the proposed approach. The suggested method reduces the quantity of RIS subject to the feasible rate under certain system restrictions, which is represented as

$$\underset{N, \{x_n, y_n\}, \theta_n}{\text{minimize}} \quad N \quad (9)$$

subject to

$$\frac{1}{K} \sum_{k=1}^K R_k \geq \phi \quad (10a)$$

$$x_{\min} \leq x_n \leq x_{\max}, \forall n \in \{1:N\} \quad (10b)$$

$$y_{\min} \leq y_n \leq y_{\max}, \forall n \in \{1:N\} \quad (10c)$$

$$\min\{|x_n - x_c|, |y_n - y_c|\} \geq L, \forall n, c \in \{1:N\} \quad (10d)$$

$$N_{\min} \leq N \leq N_{\max} \quad (10e)$$

where $\{x_n, y_n\}$ is the location of RIS n and L denote the size length of each RIS. The constrain (10a) ensures that the achievable rate for all users is larger than ϕ , (10b) and (10c) illustrate the location restrictions of the RISs. We use (10d) to ensure that RISs are not overlapping, and (10e) ensures that the number of RISs is between $[N_{\min}, N_{\max}]$.

III. DEVELOPED DEO FOR OPTIMAL PLACEMENT OF RIS ELEMENTS

A. DIFFERENTIAL EVOLUTION OPTIMIZER

An evolutionary algorithm known as the DEO is used to address optimization issues, especially those that entail optimizing a function in a continuous space. When dealing with issues where the search space is high-dimensional and the goal function is smooth and continuous, DEO works well. DEO is especially well-liked in a variety of domains, including as computational biology, machine learning, engineering design, and finance, where optimization issues are common and usually display the aforementioned traits.

The population is gradually improved by DEO by combining selection, crossover, and mutation operators. Thus, with each generation that follows, DEO generates new potential solutions. The process of mutation creates trial solutions by upsetting the individuals based on the differences between randomly selected population participants. Using the crossover process, the trial participants are paired with the outcomes of the trial solutions to produce offspring. In order to determine which members of the population are retained based on fitness, the selection process gives preference to solutions that perform better in terms of the optimization goal.

$$R_k = \mathbf{E} \left\{ \log_2 \left(1 + \frac{p_k |t_{b,u_k} h_{b,u_k} + \sum_{n=1}^N t_{b,r_n} \mathbf{h}_{b,r_n}^H \Theta_n \mathbf{h}_{r_n,u_k}|^2}{\sigma^2} \right) \right\} \quad (6)$$

B. ADOPTION OF THE PROPOSED DEO FOR OPTIMAL PLACEMENT OF RIS ELEMENTS

The objective function in the suggested optimization framework, which is the minimization of the number of RISs with N , x , and y as the design variables, is represented by Equation (9). The variables in question are subject to constraints, as indicated by Equations (10b), (10c), and (10e), correspondingly. In contrast, restrictions on inequality resulting from independent variables are managed by Equation (10d) to guarantee that RISs do not overlap and Constraint (10a) to guarantee that the achievable rate for every user is greater than. To solve the given model using the suggested DEO, the following improvements should be put into practice:

1) INITIALIZATION

In DEO, the control variables per population are shown as floating values. To be able to create a population P , they are initially assigned by randomization individuals inside their usage-appropriate computational range. The initial generation might initialize each population member (Ds) as follows:

$$Ds_{i,z}(0) = Ds_z^{min} + Rd \times (Ds_z^{max} - Ds_z^{min}) \quad i = 1 : ND_s \& z = 1 : Dim \quad (11)$$

Rd represents a vector with Dim dimension containing arbitrary continuous numbers that range from 0 to 1. ND_s refers to the population size while Dim denotes the total number of variables for every one of the solutions, and the superscripts min and max indicate the permissible boundaries of the designed system model regarding each variable.

2) MUTATION

At each iteration (It) following population initialization, the mutation phase produces mutant vectors (Ms). The suggested mutation technique chooses a random member and interferes with its solution vector with a variance of two additional vectors chosen at random as follows:

$$MS_{i,z}(It + 1) = Ds_{r_1,z}(It) + F \times (Ds_{r_2,z}(It) - Ds_{r_3,z}(It)) \quad i = 1 : ND_s \& z = 1 : Dim \quad (12)$$

where r_1 , r_2 , and r_3 are three distinct numbers selected at random within the set $[1, ND_s]$. The scaling factor, or F , is a real positive value that regulates how quickly the population changes. F typically has a value in the $[0.4 - 1]$ range.

3) CROSSOVER

The crossover phase follows to be able to broaden the population's variety. By switching out the elements of the mutant (Ms) and target (Ds) vectors, it produces trial vectors (Us) as follows:

$$Us_{i,z}(It + 1) = \begin{cases} Ms_{i,z}(It + 1), & \text{if } Rd^* < C_r \\ Ds_{i,z}(It), & \text{else} \end{cases} \quad (13)$$

where C_r , which is often chosen to fall between $[0, 1]$, represents the crossover factor. Binomial crossover is the type of crossover method used here.

4) FITNESS EVALUATION

A solution's performance with the optimization target is quantified by the fitness function. At first, in the presented model of the RIS-aided wireless communication system, the control variables are the number of RIS to be installed and their distributed positions. Such control variables are two types where the number of RIS is an integer while the installed positions are continuous. The DEO ordinarily operates in the continuous framework, so the number of RIS is treated in a continuous range, and then it is rounded to the nearest integer. Second, a randomly selected number inside the control variable's practicable limits is employed in this research to substitute the violated control variable. Thus, the constraints represented in Equations (10c), (10d) and (10e) are guaranteed.

Additionally, dependent variable restrictions represented in Equations (10b) and (10e) have been incorporated into the fitness function under consideration via penalty terms. The fitness function (fit) is therefore generalized and stated as follows:

$$fit = N + \lambda_1 \Delta GH + \sum_{n=1}^N \sum_{c=1}^N \lambda_2 \Delta GK_{n,c} \quad (14)$$

where λ_1 and λ_2 are penalty factors, ΔGH and ΔGK are defined as shown in equations (15) and (16).

$$\Delta GH = \begin{cases} 0, & \text{if } \frac{1}{K} \sum_{k=1}^K R_k \geq Q \\ |Q - \frac{1}{K} \sum_{k=1}^K R_k|, & \text{else} \end{cases} \quad (15)$$

$$\Delta GK_{n,c} = \begin{cases} 0, & \text{if } \min\{|x_n - x_c|, |y_n - y_c|\} \geq L \\ |L - \min\{|x_n - x_c|, |y_n - y_c|\}|, & \text{else} \end{cases} \quad (16)$$

Based on that model, impractical solutions, that fail to achieve one or more constraints, will have a high fitness score and so there is a slim possibility that the impractical solutions will be passed on to the following iteration.

5) SELECTION

The process of selection contrasts the fitness scores of the original member and its associated newly generated member as shown in equation (17).

$$Ds_i(It + 1) = \begin{cases} Us_i(It + 1) & \text{if } \psi \leq \eta \\ Ds_i(It) & \text{else} \end{cases} \quad (17)$$

where $\psi = fit(Us_i(It + 1))$ and $\eta = fit(Ds_i(It))$. As a result, the population either experiences an improvement in the values of the fitness function or stays the same. Once the maximum number of iterations has been achieved, these phases are then repeated throughout generations. We summarize the developed DEO for optimal placement of RIS elements in the Appendix.

TABLE 4. Parameter settings.

Parameter	Value
The coordinates of the AP	[5, -10, 1] m
Number of RIS elements (M)	100
Length of each RIS element (L)	0.3 m
Rician factor (ϵ)	10
Transmitted power of each user (p_k)	1 mW
SNR (dB)	-23
Minimum number of RISs (N_{min})	1
Maximum number of RISs (N_{max})	10
Number of single-antenna users (K)	20

IV. NUMERICAL RESULTS

To assess the DEO algorithm's superiority over the other algorithms, we run numerous simulations in this section. All these algorithms were created to be able to jointly optimize the quantity and location of RISs. Envision a wireless communication system with multiple RISs, where users are randomly distributed within a square defined by vertices [0, 0, 0], [0, 10, 0], [10, 10, 0], and [10, 0, 0] meters. The RISs are positioned within another square defined by vertices [0, 0, 10], [0, 10, 10], [10, 0, 10], and [10, 10, 10] meters. The wall's location was defined by four vertices at [0, 0, 0], [0, 0, 2.25], [10, 0, 2.25], and [10, 0, 0] m (c.f. Figure 1). The path-loss is modeling as $PL = PL_0 - 10\beta \log(\frac{d}{d_0})$, where $PL_0 = 20dB$ is the path-loss at the reference distance $d_0 = 1m$; d represents the distance between the transmitter and the receiver, and the path-loss exponents for the UE-RIS-AP link and the UE-AP link are assigned as $\beta = 2.2$ and $\beta = 4$, respectively.

A. SIMULATION SETUP

In this subsection, we describe the simulation setup used to evaluate the performance of the proposed optimization framework for RIS deployment in wireless communication systems. The simulations were conducted with the following parameters and methodologies:

- 1) *Software Tool and Platform*: We utilized MATLAB for conducting the simulations. This software tool provides robust capabilities for modeling wireless communication scenarios and optimizing RIS deployment strategies.
- 2) *Simulation Environment*: The simulation environment was configured to mimic realistic wireless communication scenarios, taking into account factors such as signal propagation, interference, and user distribution. We considered an indoor environment to capture diverse deployment scenarios.
- 3) *Parameters*: The parameters used in the simulations shown in Table 4. These parameters were carefully selected to represent typical real-world wireless communication scenarios and enable a

comprehensive evaluation of the proposed optimization framework.

- 4) *Methodology*: The simulation methodology involved the following steps:

- a) *Initialization*: Setting up the simulation environment and configuring the parameters mentioned above.
- b) *Optimization Framework Implementation*: Implementing the proposed optimization framework for determining the optimal number, locations, and phase shift coefficients of RISs.
- c) *Performance Evaluation*: Evaluating the performance of the optimized RIS deployment in terms of communication rate, energy efficiency, and system robustness.
- d) *Comparison*: Comparing the performance of the proposed optimization framework with existing algorithms and methodologies.

- 5) *Assumptions and Constraints*: In conducting our research on optimizing RISs deployment in wireless communication systems, we make several assumptions and acknowledge certain constraints to streamline our investigation and focus on specific aspects of RIS deployment optimization. Firstly, we assume a controlled simulation environment that accurately represents real-world wireless communication scenarios, considering factors such as signal propagation, interference, and user distribution. Additionally, we assume idealized conditions for RIS operation, such as perfect knowledge of channel state information (CSI) and precise control over phase shift coefficients. Moreover, we acknowledge the constraints imposed by practical considerations such as hardware limitations, regulatory requirements, and deployment costs, which may impact the feasibility and scalability of our proposed optimization framework. Furthermore, we recognize the inherent trade-offs between performance metrics such as communication rate, coverage, and energy efficiency, and acknowledge that optimizing one metric may come at the expense of others. By considering these assumptions and constraints, we aim to ensure the rigor and relevance of our research findings while providing a realistic assessment of the potential challenges and limitations associated with RIS deployment optimization in practical wireless communication systems.

In jointly optimizing the number and position of RISs, outcomes from simulation demonstrate the superiority of the DE optimizer algorithm over the other optimization methods (GO, SHO, GBO, and PSO). In this light, we simulate the minimum (best), maximum (worst), and average number of RISs to get a broad sense of the results after thirty cycles of testing these techniques.

Comparative analysis of the DE algorithm with various optimization methods reveals intriguing insights into the

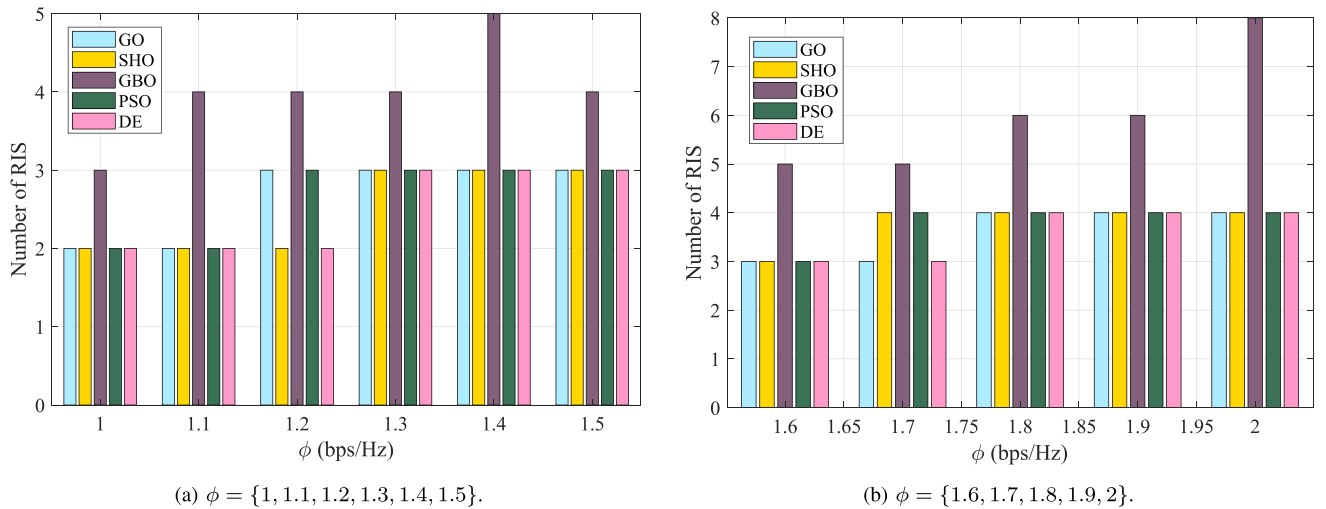


FIGURE 2. Lowest number of RISs found using the baselines over thirty runs and the suggested algorithm.

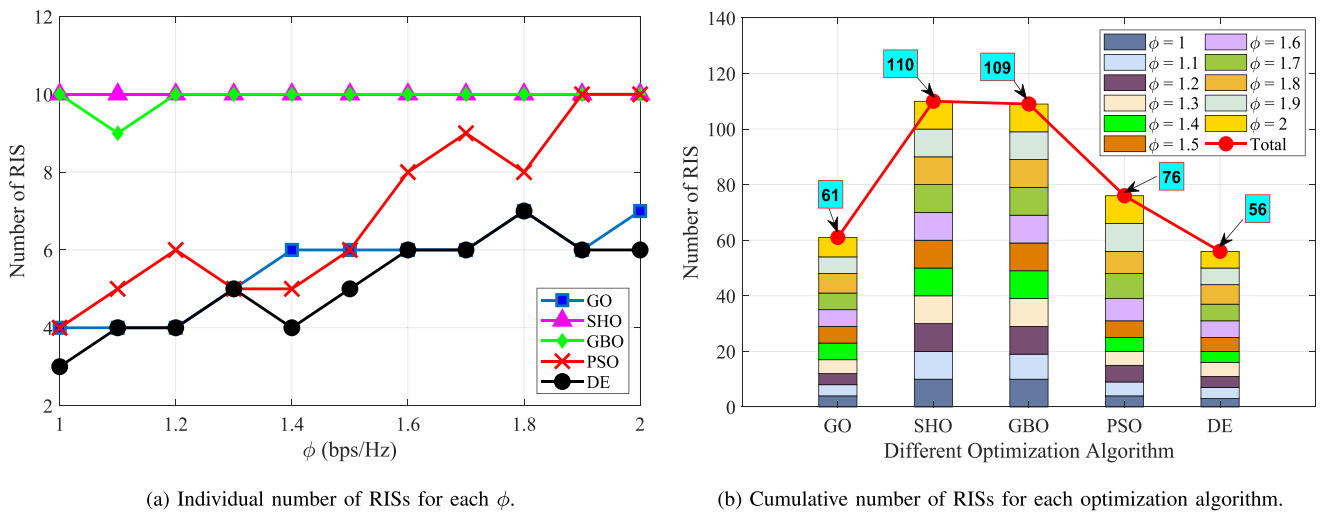
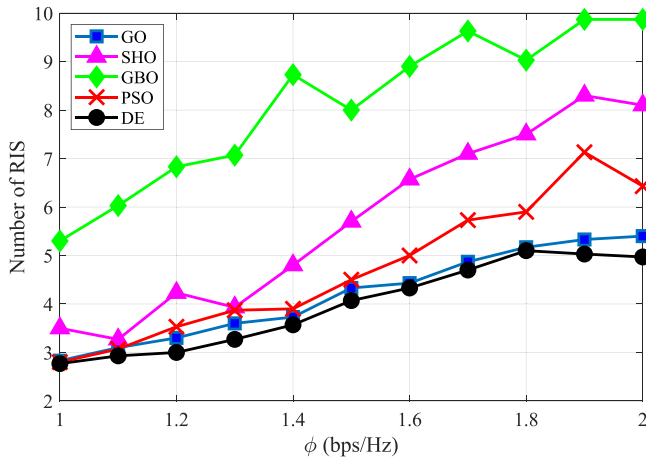
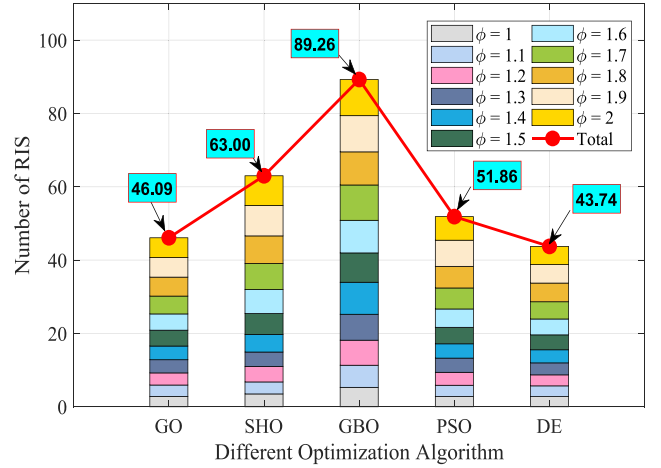


FIGURE 3. The greatest number of RISs that the suggested method and the baselines could produce across thirty runs.

efficacy of different approaches in minimizing the number of RISs required for deployment. As depicted in Figure 2, the DE algorithm consistently yields the lowest number of RISs across a spectrum of scenarios. Specifically, the simulation results illustrate that the DE optimizer algorithm outperforms other optimization techniques, including GO, PSO, SHO, and GBO, across different thresholds of the rate cutoff (ϕ). Notably, at $\phi = 1.2$, the DE algorithm demonstrates superior performance compared to all other methods, achieving the minimum number of RISs necessary for optimal deployment. Similarly, at threshold values of $\phi = 1.2, 1.7$ and $\phi = 1.7$, the DE algorithm consistently outperforms its counterparts, exhibiting a more efficient allocation of RISs to maximize data flow within the wireless network. Furthermore, across all threshold values of ϕ , the DE algorithm maintains its superiority, underscoring its robustness and effectiveness in minimizing the total number of RISs required while ensuring optimal communication performance. These findings

highlight the significant contribution of the DE algorithm in addressing the complex optimization challenges associated with RIS deployment in wireless communication systems.

The examination of the worst-case scenarios, as depicted in Figure 3, sheds light on the maximum number of RISs generated by each optimization approach, providing insights into their performance under challenging conditions. Notably, Figure 3(a) showcases the stark contrast between the optimization techniques, with the DE algorithm demonstrating the fewest RISs, while GBO and SHO yield the highest numbers. This disparity underscores the varying capabilities of different optimization methods in addressing the complexities of RIS deployment. To offer a comprehensive overview, Figure 3(b) illustrates the cumulative maximum number of RISs generated by each method across all rate thresholds (ϕ), providing a holistic perspective on their performance. The results depicted in Figure 3(b) highlight the substantial improvements achieved by the


 (a) Individual number of RISs for each ϕ .


(b) Cumulative number of RISs for each optimization algorithm.

FIGURE 4. The mean number of RISs acquired by the suggested algorithm and the baselines during thirty iterations.

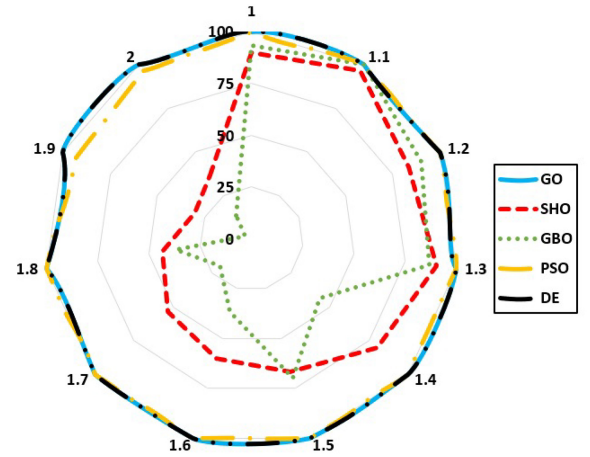
DE optimizer method compared to alternative algorithms. Specifically, the DE algorithm achieves enhancements of 8.19%, 26.32%, 48.62%, and 49.09% when contrasted with GO, PSO, GBO, and SHO algorithms, respectively. These findings underscore the superior performance of the DE algorithm in mitigating the worst-case scenarios and optimizing RIS deployment efficiency, further emphasizing its efficacy in real-world wireless communication systems.

After comprehensively analyzing the minimum and maximum number of RISs generated by diverse optimization algorithms, we further investigate the average number of RISs in Figure 4. In Figure 4(a), we present the average number of RISs produced by each optimization technique across varying rate cutoffs (ϕ). Once again, the DE algorithm stands out by yielding the fewest RISs, while GBO exhibits the highest average number. Notably, our analysis reveals that GO closely follows the performance of the DE algorithm. To provide additional clarity, Figure 4(b) replicates the total number of RISs to underscore the significant benefit of employing the DE algorithm over GO. Comparing the performance of DE with GO, PSO, SHO, and GBO, respectively, reveals remarkable improvements of 5.13%, 15.68%, 30.58%, and 51.0%. These findings highlight the superior performance of the DE algorithm in achieving optimal RIS deployment efficiency across various scenarios, reaffirming its effectiveness in real-world wireless communication systems.

The feasibility rate, which assesses the effectiveness of optimization techniques in achieving the minimum number of RISs under different threshold values of achievable rates, serves as a critical metric for comparative analysis. Mathematically, the feasibility rate is expressed as follows:

$$\text{Feasibility rate} = 100 - \text{failure rate\%} \quad (18)$$

where the failure rate represents the proportion of times the algorithm yields an incorrect number of RISs falling outside the range defined by N_{min} and N_{max} . In essence, a


FIGURE 5. Feasibility Rate of the lowest number of RISs produced over thirty runs using the baselines and the suggested procedure.

higher feasibility rate indicates a more reliable performance of the optimization algorithm in achieving the desired outcome. Figure 5 presents the feasibility rates for various optimization algorithms across different values of the rate threshold (ϕ). The simulation outcomes reveal that both the DE and GO algorithms consistently achieve a 100% feasibility rate across all rate threshold values, indicating their robustness and reliability in minimizing the number of RISs within the specified range. In contrast, GBO emerges as the least viable option, demonstrating lower feasibility rates compared to DE and GO. These findings underscore the importance of considering feasibility rates as a key criterion for evaluating the performance of optimization techniques in RIS deployment optimization.

In summary, our comprehensive analysis demonstrates that across all values of the rate thresholds (ϕ), the DE optimizer method consistently outperforms all other optimization algorithms in several key metrics related to

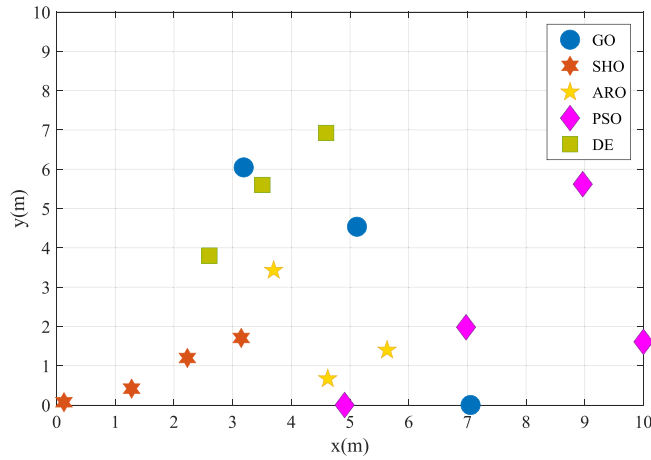


FIGURE 6. Placements obtained by different algorithm for $\phi = 1.7$.

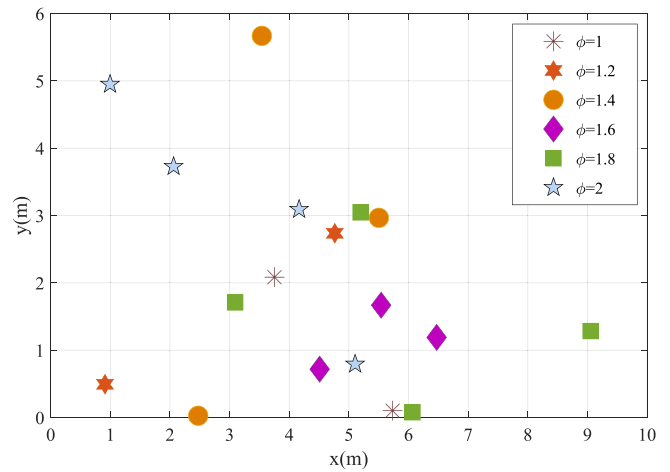


FIGURE 7. Placements obtained by DE algorithm for different ϕ .

the number of RISs. Firstly, the DE algorithm consistently yields the lowest number of RISs required for optimal deployment, indicating its superior efficiency in minimizing infrastructure costs and complexity. Additionally, the DE algorithm excels in mitigating the worst-case scenarios by producing the maximum number of RISs among all optimization techniques. Moreover, our analysis reveals that the DE algorithm exhibits the lowest average number of RISs across various rate thresholds, highlighting its ability to achieve optimal performance under diverse operating conditions. Furthermore, the DE algorithm demonstrates a 100% feasibility rate across all rate threshold values, underscoring its reliability and robustness in achieving the desired outcome. Collectively, these findings underscore the unparalleled effectiveness of the DE optimizer method in optimizing the deployment of RISs in wireless communication systems, reaffirming its status as the superior choice among the evaluated optimization algorithms.

Figure 6 provides a visual comparison of the RIS locations determined using baseline techniques and the DE optimizer algorithm under the condition where $\phi = 1.7$. Notably, our analysis reveals that the RIS positions generated by the DE and SHO algorithms are relatively closer together compared to other methods. This observation suggests that the DE optimizer algorithm offers the additional benefit of practical ease of deployment, as the proximity of RIS positions facilitates more efficient installation and configuration processes. To further investigate this advantage across different values of the rate threshold (ϕ), Figure 7 illustrates the positioning of RISs achieved by the DE optimizer algorithm across various ϕ values. Interestingly, our findings indicate that not all ϕ values equally benefit from this advantage, suggesting that the practical ease of deployment may vary depending on the specific rate threshold. This observation underscores the importance of future research efforts aimed at enhancing the DE optimizer method to ensure consistent and optimized RIS positioning across all ϕ values. By addressing this aspect, we can further optimize the practical deployment

of RISs in wireless communication systems, maximizing their effectiveness and usability across diverse operating conditions.

The convergence properties displayed by different optimization techniques are comprehensively compared in Figure 8. In order to show how close an algorithm is to the ideal answer, the convergence plot shows how many iterations each method needs to reach the lowest fitness value. This contrast is shown in Figures 8(a) to 8(d), discussing algorithmic performance under various optimization situations, for a range of values of ϕ , from 1.0 to 1.7. Figure 8, shows the faster and suitable convergence of the applied DEO in our proposed problem with better performance compared to the other optimization algorithms. Although the GO algorithm converges faster in the beginning, the DEO reaches minimum convergence after several iterations. For example, at $\phi = 1$, the DEO reaches its lowest value after 12 iterations. And at $\phi = 1.4, 1.5$, the DEO algorithm converges after 22 and 25 iterations, respectively.

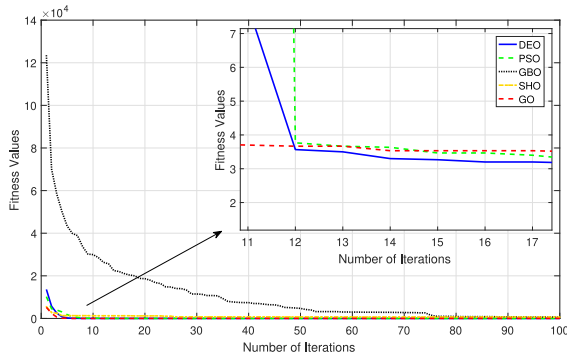
B. COMPLEXITY ANALYSIS

To compare the algorithms (GBO, PSO, DE, GO, SHO) in terms of time and memory complexity based on the provided data, Tables 5 and 6 illustrate their elapsed times and memory usage.

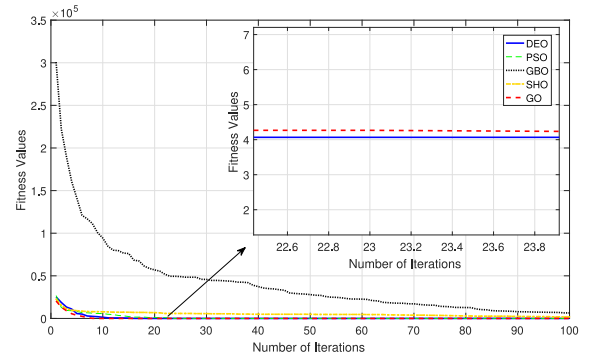
To combine both time and memory complexities into a single metric, we can use a weighted sum or a combined efficiency score. This approach will help in assessing the overall efficiency of each algorithm by considering both elapsed time and memory usage. At first, both the elapsed time and memory usage are normalized to a scale of 0 to 1, where 0 is the best (least time/memory used) and 1 is the worst (most time/memory used) as follows:

$$t_i^{norm} = \frac{t_i - t_{min}}{t_{max} - t_{min}} \quad (19)$$

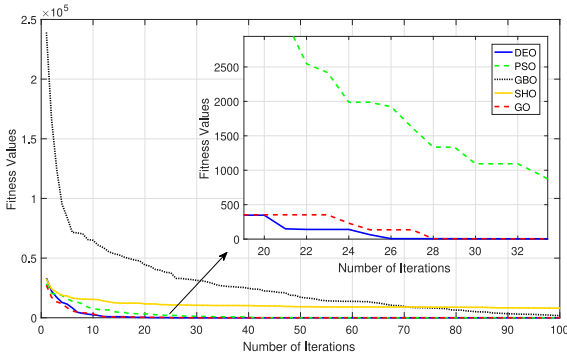
$$m_i^{norm} = \frac{m_i - m_{min}}{m_{max} - m_{min}} \quad (20)$$



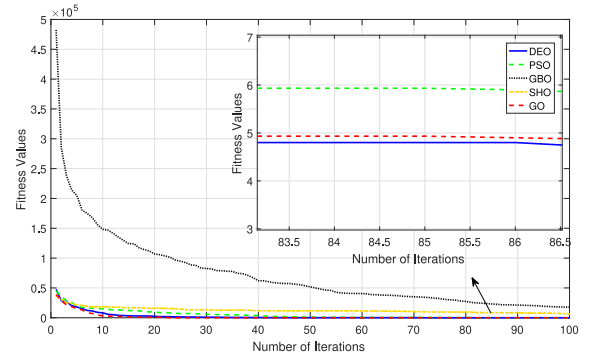
(a) $\phi = \{1\}$.



(b) $\phi = \{1.4\}$.



(c) $\phi = \{1.5\}$.



(d) $\phi = \{1.7\}$.

FIGURE 8. Fitness value versus number of iterations obtained by different optimization algorithms DEO, PSO, GBO, SHO, and GO.

TABLE 5. Time and memory complexity of the compared algorithms (GBO, PSO, DE, GO, SHO).

Algorithm	Elapsed time (t_i)	Maximum possible array	Memory used by MATLAB (m_i)
GBO	141.441329 secs	7723 MB	1711 MB
PSO	141.058207 secs	7624 MB	1746 MB
DEO	116.667113 secs	7699 MB	1706 MB
GO	149.706017 secs	7591 MB	1760 MB
SHO	109.215529 secs	7660 MB	1762 MB

where t_i^{norm} and m_i^{norm} are the normalized elapsed time and memory usage regarding each algorithm (i) while the superscripts min and max are the minimum and maximum values. Then, the combined efficiency score is computed, considering for simplicity equal weights to time and memory. For each algorithm, normalize the elapsed time and memory usage as follows:

$$CombinedScore_i = w_t \times t_i^{norm} + w_m \times m_i^{norm} \quad (21)$$

TABLE 6. Normalized time, memory, and combined scores of the compared algorithms (GBO, PSO, DE, GO, SHO).

Algorithm	t_i^{norm}	m_i^{norm}	Combined Score
GBO	0.800	0.089	0.445
PSO	0.791	0.714	0.753
DEO	0.186	0	0.093
GO	1	0.964	0.982
SHO	0	1	0.5

where, w_t and w_m are the weights for time and memory, respectively. Typically, $w_t + w_m = 1$. For equal weighting, $w_t = 0.5$ and $w_m = 0.5$.

From Table 5, for the elapsed time, the minimum value (t_{min}) is 109.215529 seconds (SHO), and the maximum value (t_{max}) is 149.706017 seconds (GO). For memory usage, the minimum value (m_{min}) is 1706 MB (DE), and the maximum value (m_{max}) is 1762 MB (SHO). Thus, the normalized time and memory can be recorded in Table 6.

In Table 6, the recorded combined efficiency score provides a more holistic perspective of the algorithms' performance by taking into account both time and memory factors, resulting in a more complete evaluation of their efficiency. As shown, the DEO indicates superior performance

TABLE 7. Obtained best, mean, worst, and standard deviation for GO, PSO, GBO, SHO, and DEO for different value of $\phi = \{1, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2\}$.

ϕ	Algorithm (Best/Mean/Worst/Standard Deviation values)				
	GO	SHO	GBO	PSO	DEO
1	2/2.83/4/0.59209	2/3.5/10/2.2552	3/5.3/10/1.822	2/2.8/4/0.664	2/2.77/3/0.4302
1.1	2/3.1/4/0.5477	2/3.27/10/1.337	4/6.03/9/1.671	2/3.07/5/0.6915	2/2.93/4/0.3651
1.2	3/3.3/4/0.4661	2/4.23/10/2.661	4/6.83/10/1.663	3/3.53/6/0.6814	2/3/4/0.2626
1.3	3/3.6/5/0.504	3/3.93/10/2.1324	4/7.07/10/1.892	3/3.87/5/0.6814	3/3.27/5/0.5208
1.4	3/3.73/6/0.9072	3/4.8/10/2.7088	5/8.73/10/1.7604	3/3.9/5/0.6618	3/3.57/4/0.504
1.5	3/4.33/6/0.7581	3/5.7/10/3.142	4/8/10/1.9119	3/4.5/6/0.82001	3/4.07/5/0.4498
1.6	3/4.43/6/0.8172	3/6.57/10/2.9558	5/8.9/10/1.748	3/5/8/1.2317	3/4.33/6/0.6065
1.7	3/4.87/6/0.7761	4/7.1/10/2.832	5/9.63/10/1.033	4/5.73/9/1.1427	3/4.7/6/0.7022
1.8	4/5.17/7/0.8339	4/7.5/10/2.9213	6/9.03/10/1.4259	4/5.9/8/0.9595	4/5.1/7/0.7588
1.9	4/5.33/6/0.6065	4/8.3/10/2.667	6/9.87/10/0.7303	4/7.13/10/1.776	4/5.03/6/0.6687
2	4/5.4/7/0.6746	4/8.1/10/2.617	8/9.87/10/0.9371	4/6.43/10/0.5074	4/4.97/6/0.6149

in both time and memory usage, where it provides the best overall algorithm, possessing a combined efficiency score of 0.093. The GO algorithm, on the other hand, has the lowest overall performance, with a combined score of 0.982, which reflects its longer execution time and increased memory utilization.

Table 7 includes numerical values for different algorithms at varying ϕ values. Analyzing the results, it is evident that increasing ϕ generally leads to better performance in terms of the Best and Mean values obtained by the algorithms. The DEO algorithm consistently achieves the least Best values, with a maximum of 4 at $\phi = 2$ and a minimum of 2 at $\phi = 1$. In terms of Mean values, DEO again performs the best, with a maximum of 5.1 at $\phi = 1.8$ and a minimum of 2.77 at $\phi = 1$. Similarly, the DEO provides the best performance by always achieving the smallest standard deviations for all values of ϕ . This different separate multiple times with different initial conditions offers insights into its robustness. The smallest standard deviation of all scenarios of the DEO proves that it is the most robust algorithm. Therefore, the DEO consistently converges to similar solutions across runs, which derives more likely to find global optima.

C. IMPLICATIONS FOR REAL-WORLD DEPLOYMENT

Our research findings hold significant implications for real-world scenarios in the deployment of RISs within wireless communication systems. Firstly, our optimized deployment framework offers practical insights into enhancing coverage dispersion, particularly in scenarios with multiple users, addressing a critical need in modern wireless networks. By strategically deploying RISs, we can mitigate coverage gaps, improve signal strength, and enhance overall network performance in diverse environments such as urban, indoor,

and outdoor settings. Additionally, our study contributes valuable insights into the scalability and adaptability of RIS deployment strategies, enabling their effective integration into existing wireless communication infrastructure. This scalability is particularly relevant in dynamic network environments where user densities, environmental conditions, and system configurations may vary over time. Moreover, our cost-benefit analysis provides stakeholders with valuable information on the economic implications of deploying RISs, enabling informed decision-making regarding investment in RIS technology. By considering these implications, our research facilitates the practical implementation of RIS-assisted wireless communication systems, paving the way for more efficient, reliable, and cost-effective wireless networks in real-world scenarios.

V. CONCLUSION

This paper looked towards multi-RIS-assisted wireless communications placement optimization. A Differential Evolution Optimizer was introduced to simultaneously optimize the number, positions, and phase shift coefficients of RISs with targeting to minimize the number of RISs while maintaining a feasible rate. Comparisons with various algorithms (including PSO, GBO, Go, and SHO) were used to show the usefulness of the new algorithm. The findings show how effective the proposed DEO is in determining the lowest number of RISs under various threshold values, yielding a 100% feasibility rate. While SHO and GBO get subpar results of 66.36% and 53.94%, respectively, PSO achieves a comparable result of 99.09%. However, the proposed DEO clearly outperforms the other algorithms in terms of having the lowest average number of RISs. When compared to GO, PSO, SHO, and GBO, the DEO achieves

Algorithm 1 DEO

```

1: procedure DEO
2: [Step 1: Define parameters] Insert Population size
   ( $ND_s$ ); Dimension of each individual ( $Dim$ ); Crossover
   probability ( $C_r$ ); Scaling factor ( $F$ ); Maximum number
   of generations ( $G_{max}$ ); Penalty factors ( $\lambda_1, \lambda_2$ ); Problem-
   specific parameters
3:   for  $i = 1 : ND_s$  do ▷ [Step 2: Initialization]
4:     for  $z = 1 : Dim$  do
5:       Randomly initialize each population member
       ( $DS_{i,z}$ ) using Eq. (11)
6:     end for
7:   end for
8:   for  $i = 1 : ND_s$  do ▷ [Step 3: Evaluation]
9:     Fitness[i] = Evaluate(P[i])
10:  end for
11: Function Evaluate(individual) ▷ Extract control
   variables from the individual
12: NumRIS = round(individual[1]) ▷ Number of RIS
   (rounded to nearest integer)
13: Positions = individual[2:Dim] ▷ Positions of RIS
   (continuous)
14:   if NumRIS < MinRIS or NumRIS > MaxRIS then
   ▷ Ensure constraints are met by replacing violated
   variables with random values within limits
15:     NumRIS = Random value within [MinRIS,
   MaxRIS]
16:   end if
17:   for  $j = 1 : \text{length}(\text{Positions})$  do
18:     if Positions[i,j] < PositionLowerBound[j] then
19:       Positions[i,j] = Random value within
       [PositionLowerBound[j], PositionUpperBound[j]]
20:     else if Positions[i,j] > PositionUpperBound[j]
   then
21:       Positions[i,j] = Random value within
       [PositionLowerBound[j], PositionUpperBound[j]]
22:     end if
23:   end for
24: Calculate  $\Delta GH$  using Eq. (15) ▷ Calculate penalty
   terms for dependent variable restrictions
25:   for  $n = 1$  to NumRIS do
26:     for  $c = 1$  to NumRIS do
27:       Calculate  $\Delta GK_{n,c}$  using Eq. (16)
28:     end for
29:   end for
30: Calculate Fitness using Eq. (14)
31: EndFunction
32: generation = 0 ▷ [Step 4: Evolution Loop]
33: while generation <  $G_{max}$  do
34:   for  $i = 1 : ND_s$  do
35:     Select three distinct individuals  $r_1, r_2, r_3$  from
     the population where  $r_1, r_2, r_3$  and  $i$  are not equal ▷
     [Step 5: Mutation]
36:     for  $z = 1$  to  $Dim$  do
37:       Generate mutantVector ( $MS_{i,z}(It + 1)$ )
       using Eq. (12)
38:     end for
39:     for  $z = 1$  to  $Dim$  do ▷ [Step 6: Crossover]
40:       if Random(0, 1) <  $C_r$  or  $j == \text{Random}$ 
       integer in  $[1, Dim]$  then
41:         Generate trialVector ( $US_{i,z}(It + 1) =$ 
          $MS_{i,z}(It + 1)$ ) using Eq. (13)
42:       else
43:         Generate trialVector ( $US_{i,z}(It + 1) =$ 
          $DS_{i,z}(It + 1)$ )
44:       end if
45:     end for
46:     for  $i = 1$  to  $ND_s$  do ▷ [Step 7: Selection]
47:       Evaluate TrialFitness using Steps 11-31
48:       if TrialFitness < Fitness[i] then
49:         ( $DS_{i,z}(It + 1) = \text{trialVector}$ )
50:         Fitness[i] = TrialFitness
51:       end if
52:     end for
53:     generation = generation + 1
54:   end for
55:   end while BestSolution = DS[individual with the
   best fitness] ▷ [Step 8: Result]
56: BestFitness = Fitness[best individual] Return
   BestSolution, BestFitness ▷ Output the best solution
   and its fitness
57: end procedure

```

numerical improvements of 5.13%, 15.68%, 30.58%, and 51.0%, respectively.

For future work, several avenues can be explored to enhance the optimization of RIS deployment in wireless communication systems. Firstly, incorporating real-world constraints and practical considerations such as hardware limitations, environmental factors, and deployment costs into the optimization framework could yield more realistic and applicable results. Additionally, investigating the

dynamic adaptation of RIS configurations in response to varying network conditions, user demands, and channel characteristics could further improve system performance and adaptability. Furthermore, exploring hybrid optimization techniques that integrate the strengths of different algorithms, such as combining DEO with machine learning or reinforcement learning approaches (such as Deep Reinforcement Learning (DRL) algorithms and Self-Organizing Tree Algorithm (SOTA)), may lead to even more efficient and

robust optimization solutions. Moreover, extending the study to consider multi-objective optimization objectives, such as minimizing energy consumption or maximizing network coverage alongside data rate optimization, could provide a more comprehensive understanding of the trade-offs involved in RIS deployment. Also, impressive extensions to this study can be implemented by incorporating the following analyses as future work, including varying the number of reflective elements at each RIS and other benchmark tests.

APPENDIX

See Algorithm 1.

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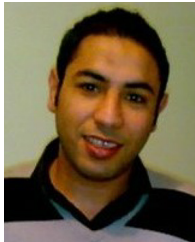
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