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Research Article

Beamforming Efficiency in MIMO-IRS Using Non-Convex Optimization Method

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Abstract: Advances in wireless communication technology face challenges in providing high channel capacity, energy efficiency, and transmitted signal quality in complex channels. Previous studies on Multiple Input Multiple Output (MIMO) with Intelligent Reflecting Surface (IRS) generally discuss theoretical models under ideal channel assumptions using the Semidefinite Relaxation (SDR) method, which exhibits high complexity and limited scalability. A research gap emerges due to the scarcity of studies on MIMO-IRS that address realistic optimization efficiency to maximize the Signal-to-Noise Ratio (SNR) in dynamic environments. This study aims to overcome these limitations through the integrated application of Alternating Optimization (AO) and Manifold Optimization (MO), which can handle non-convex problems more efficiently. The research is grounded in ontological, epistemological, and axiological aspects, employing experimental and simulation methods to optimize active beamforming at the Base Station and passive beamforming at the IRS while maintaining the unit modulus constraint. The results demonstrate that the AO-MO combination in MIMO-IRS increases channel capacity by up to 39.8%, SNR by up to 19.1%, and reduces computational time by more than fivefold compared to conventional methods without AO-MO. The contribution of this study lies in an optimization approach that efficiently enhances channel capacity and SNR without increasing computational complexity, enabling its application in wireless networks requiring high-speed and low-latency communication.

Keywords: Beamforming; Efficiency; Intelligent Reflecting Surface; MIMO; Non-Convex; Optimization.

1. Introduction

The advancement of telecommunications technology, particularly wireless networks, faces significant challenges in meeting demands for high capacity, low latency, and energy efficiency. Meanwhile, conventional wireless communication paradigms rely on a naive realism ontology in engineering, wherein the radio wave propagation environment is regarded as a static entity susceptible to blockage, fading, and path loss, phenomena that frequently constrain wireless system performance. In conventional approaches, these issues are addressed by separately optimizing the transmitter and receiver. This method is rooted in a perspective that views space as a neutral container within which signals propagate passively, while the communication system seeks to compensate for prior channel impairments. However, this conventional approach has reached a point where further performance improvements become increasingly difficult, costly, and reliant on unsustainable computational complexity. From the perspective of the philosophy of science, the conventional paradigm can be examined through an ontological lens, wherein the wireless environment is treated as a passive and fixed entity to which the system must adapt.

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A new paradigm emerges, shifting toward a relational and process-oriented ontology , enabled by the Intelligent Reflecting Surface (IRS). An IRS is an artificially engineered metasurface embedded with a large number of passive reflective elements that can be electronically reconfigured to manipulate the properties of incident electromagnetic waves, including phase, amplitude, and polarization. The IRS consists of a planar surface with electronically controllable passive reflective elements that can be reconfigured to modify the electromagnetic wave environment. By optimizing the phase shifts of these elements, the IRS enhances received signal quality, extends network coverage, and mitigates interference. The Intelligent Reflecting Surface (IRS) intelligently alters the wireless propagation environment through electronic reflection of electromagnetic signals, thereby manipulating the properties of incident waves, such as phase, amplitude, and polarization. Consequently, the IRS transforms the wireless environment from a static, pre-existing entity into a programmable, dynamic process. This represents a fundamental ontological shift: the environment is no longer an obstacle to be overcome but an integral, actively optimizable component of the communication system. By manipulating the propagation environment, the IRS creates highly favorable virtual channels, offering new pathways to circumvent blockages and interference.

The introduction of the IRS represents not merely a technical innovation but a fundamental ontological shift in conceptualizing the reality of the wireless environment. Whereas a substantial realist ontology regards space and the objects within it as fixed and independent entities, the IRS approach adopts a relational ontology that emphasizes how the properties and behavior of an entity, in this case, the propagation environment, are shaped by its relations and interactions with other systems. In a process ontology, reality is understood as a state of becoming rather than static being. In other words, IRS transforms the environment from a static given into a dynamic, programmable process. Thus, IRS does not merely manipulate electromagnetic waves; it reconfigures the ontological relations among transmitter, receiver, and environment, wherein all three now participate in a communicative process that mutually influences and actively co-constitutes one another's reality and existence.

The potential of the IRS to enhance system performance, particularly Signal-to-Noise Ratio (SNR), has garnered significant attention in recent years. SNR is a fundamental metric that directly impacts channel capacity and bit error rate. In IRS-aided Multiple Input Multiple Output (MIMO) systems, SNR improvement is achieved through intelligent phase alignment of all IRS elements, ensuring that reflected signal components arrive coherently at the receiver and constructively reinforce one another. The subsequent challenge lies in determining the optimal phase configuration for passive IRS elements (passive beamforming) in conjunction with active beamforming at the Base Station (BS), which gives rise to a highly complex optimization problem characterized as non-convex and NP-hard, a major challenge in wireless communication systems.

Various approaches have been proposed to address this optimization problem. Semidefinite relaxation (SDR)-based solutions are widely adopted but often incur high computational complexity. Alternating Optimization (AO) has emerged as a promising method to simplify the problem by alternately optimizing the BS and IRS variables. However, within the AO framework, the IRS phase optimization subproblem remains challenging due to the inherent unit modulus constraint on passive elements. This is where Manifold Optimization provides an elegant solution. By reframing the set of IRS phase elements as a

Riemannian manifold, a geometric space with a specialized structure. Optimization can be performed directly and efficiently. The Riemannian conjugate gradient method inherently satisfies the unit modulus constraint, often yielding faster convergence and superior performance compared to SDR-based methods.

Therefore, this study aims to optimize beamforming efficiency in IRS-aided MIMO systems through the on-convex optimization. The primary contribution of this research lies in the efficient formulation and solution of the joint active and passive beamforming optimization problem, leveraging the problem-decomposition strength of AO and the non-convex subproblem-handling capability of Manifold Optimization. Through comprehensive simulations, this work demonstrates that the proposed approach not only achieves significant SNR gains over conventional baseline schemes but also bridges the gap between theoretical complexity and practical, efficient implementation in intelligent, reconfigurable wireless communication systems.

2. Method

This study adopts an empirical epistemological approach, wherein knowledge regarding optimization in MIMO-IRS systems is derived through experimental and simulation methods. Such knowledge is not obtained solely from theory but also through practical testing and numerical verification based on the mathematical formulations of the optimization methods, which are processed and applied. Simulations are employed to evaluate the effectiveness of Alternating Optimization and Manifold Optimization in maximizing channel capacity, Signal-to-Noise Ratio (SNR), and computational time efficiency. Accordingly, the epistemology of this research lies in the development of MIMO-IRS technology through experimentally obtained data and the validation of simulation results concerning the real-world impact of applying AO and MO in MIMO-IRS systems.

This study commences with a theoretical understanding of the MIMO-IRS model, wherein the phases of IRS elements are programmed to enhance the quality of the received signal. The SNR is maximized by optimizing the phase configuration of the passive IRS elements and the active beamforming configuration at the Base Station (BS). Mathematically, the research involves the optimization of IRS element phases and active beamforming to maximize SNR, as formulated as:

$$SNR\ (dB) = 10 \cdot log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (1)$$

Where, P_{signal} is Received Signal Power, and P_{noise} is Noise Power in the System. Signal power represents the average power of the desired signal received at the receiver. In contrast, noise power denotes the average power of noise present in the system, which may originate from various sources such as interference, distortion, and thermal fluctuations. Subsequently, optimization is performed using Alternating Optimization (AO) for the MIMO system with Intelligent Reflecting Surface (IRS), encompassing active beamforming at the Base Station (BS) and passive beamforming at the IRS. AO enables the decomposition of the optimization problem into two primary subproblems, which are solved alternately through iterations, namely:

1. Optimization of active beamforming at the Base Station (BS), where the IRS phases are considered fixed. The system optimizes the active beamforming at the Base Station (BS) while treating the IRS phases as constant. This active beamforming optimization aims to maximize the received signal power at the receiver, accounting for the channel from the Base Station (BS) to the IRS and from the IRS to the user.

   Mathematically, the active beamforming at the Base Station (BS) can be optimized using the Maximum Ratio Transmission (MRT) approach. This technique optimizes signal transmission by directing the signal along the direction of the strongest channel, where the beamforming vector at the Base Station is expressed as:

$$\boldsymbol{W}_{BS} = \boldsymbol{H}^{\dagger}{}_{BS} \quad \textbf{(2)}$$

   Where, W_{BS} is beamforming vector for BS, the channel matrix from BS to IRS is H_{BS} and the conjugate transpose of a matrix H_{BS} is defined as $H^{\dagger}{}_{BS}$.

   In this step, the BS sends a signal in Line-of-Sight to the IRS, so that the signal can be received optimally.
2. Optimization of IRS phases, where the BS beamforming is considered fixed, and optimization is performed on the phases of the IRS elements. Subsequently, in the IRS phase optimization, the BS beamforming is treated as fixed, and optimization is applied to the IRS elements to adjust the reflection phases of the signals transmitted by the BS.

   In phase optimization, a unit modulus constraint is frequently encountered, wherein each IRS element can only assume phase values on the complex unit circle ($\left|e^{j\theta} = 1\right|$). Thus, resulting in a non-convex problem, where mathematically, the optimization of the IRS phase on the n-th element can be calculated using the formula:

$$\theta_n = arg\left(\sum_{k=1}^{K} \boldsymbol{h}_{k,IRS}^{H}\ \boldsymbol{W}_{BS}\right) \quad \textbf{(3)}$$

   With θ_n as the phase element n in the IRS. The channel between the IRS and the-k recipient is $h_{k,IRS}^{H}$ and W_{BS} as pre-calculated beamforming vectors. This optimization ensures that the phases of the IRS elements are adjusted such that the reflected waves constructively interfere, thereby enhancing the quality of the received signal. The Alternating Optimization process is performed iteratively by optimizing one variable, then updating the other alternately until an optimal solution is achieved.

   By employing this method, each step becomes more tractable and enables progressive optimization, resulting in greater efficiency in achieving maximum SNR (this approach reduces the computational complexity often associated with semidefinite relaxation (SDR)-based methods).

Following the optimization of BS beamforming using AO, the next step involves optimizing the phases of the IRS elements subject to the unit modulus constraint. This study employs Manifold Optimization, which enables more efficient handling of highly complex optimization problems. Manifold Optimization transforms the search space into a Riemannian manifold, a geometric space with specialized structure, allowing the problem to be solved while naturally accommodating the unit modulus constraint on the passive IRS elements

Manifold Optimization treats the elements to be optimized as points on a Riemannian manifold and applies optimization methods tailored to the structure of that space. The steps involved in implementing Manifold Optimization are as follows:

1. In MIMO-IRS system, the phases of the IRS elements are optimized to ensure that the reflected signals constructively interfere, thereby enhancing the Signal-to-Noise Ratio (SNR). This step simultaneously optimizes the IRS element phases under the unit modulus constraint, as previously described. Mathematically, the IRS phase optimization can be formulated as follows:

$$\boldsymbol{W}_{IRS}^{*} = \arg\max_{\boldsymbol{W}_{IRS} \in \mathcal{M}} SNR_{(\boldsymbol{W}_{IRS})} \quad \textbf{(4)}$$

   Where the phase vector of the IRS element is defined by W_{IRS}, $\mathcal{M}$ as a Riemannian manifold that includes all the problematic phase elements in $\left|e^{j\theta} = 1\right|$ and SNR as Signal-to-Noise Ratio. The subsequent step involves applying the Riemannian gradient method to optimize the phases of the IRS elements. In this approach, the gradient is computed within the manifold space rather than the conventional Euclidean space. Optimization is performed using the Riemannian conjugate gradient, which is specifically designed to optimize functions on manifold spaces. This method adjusts the IRS element phases by following the gradient direction aligned with the manifold structure. Mathematically, the gradient of the function $SNR_{(W_{IRS})}$ on a Riemannian manifold can be computed using the formula:

$$\nabla_{\boldsymbol{W}_{IRS}} SNR_{(\boldsymbol{W}_{IRS})} \quad \textbf{(5)}$$

   This gradient indicates the optimal direction for updating the parameter W_{IRS} to increase SNR. Using the conjugate gradient method, parameter updates are performed more efficiently, avoiding unproductive steps in the solution search.

2. The next step involves updating the parameter (IRS phase) along the gradient direction on the Riemannian manifold. This process is performed iteratively until convergence is achieved. The W_{IRS} parameter update at k iteration can be computed using the following formula:

$$\boldsymbol{W}_{IRS}^{k+1} = exp_{\boldsymbol{W}_{IRS}^{k}}(-\alpha_k \nabla_{\boldsymbol{W}_{IRS}} SNR_{(\boldsymbol{W}_{IRS}^{k})}) \quad \textbf{(6)}$$

   Where, W_{IRS}^{k} as IRS element phase value at k-iteration, $exp_{W_{IRS}^{k}}$ as the exponential map on manifolds, which transforms gradients on Euclidean space to manifold space, and α_k is the learning step at k-element that controls the size of the update. This update step continues until convergence is reached, namely when the change in SNR in the next iteration is very small, or there is no longer any significant change.

Conduct simulations and evaluations to assess the effectiveness of the proposed approach, namely the combination of Alternating Optimization (AO) and Manifold Optimization (MO), in maximizing the Signal-to-Noise Ratio (SNR) in an Intelligent Reflecting Surface (IRS)-aided MIMO system. The simulations aim to demonstrate the performance gains achieved by the proposed method compared to baseline schemes. The initial step involves designing the simulation by constructing a system model that incorporates the following elements:

1. A MIMO-IRS communication system comprising a Base Station (BS), an Intelligent Reflecting Surface (IRS), and receivers (users). The BS transmits signals that are reflected by the IRS and subsequently received by the users.
2. The channel model between the BS, IRS, and receivers, accounting for path loss, fading, and potential interference.
3. The unit modulus constraint on IRS elements, ($\left|e^{j\theta} = 1\right|$), must be enforced in the simulation to ensure that the computed phases satisfy this constraint.
4. Beamforming schemes for optimization at the Base Station (BS) and IRS, implemented using Maximum Ratio Transmission (MRT) for the BS, and Alternating Optimization (AO) combined with Manifold Optimization (MO) for IRS optimization.

Subsequently, prior to initiating the simulation, the experimental parameters must be carefully prepared, including the number of IRS elements (N), the IRS size, and the number of reflective elements employed in the system; channel conditions simulated, encompassing Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS), along with fading characteristics such as Rayleigh and Nakagami fading; the transmit signal power from the BS, utilized in SNR computation; IRS parameters, including the optimized phases and the unit modulus constraint on IRS elements. The next step involves implementing Alternating Optimization (AO) to optimize active beamforming at the BS and the phases of the IRS elements. The iterative process is as follows:

1. Base Station beamforming Optimization, where in each iteration, the BS beamforming is first optimized under the assumption of fixed IRS phases, employing the Maximum Ratio Transmission (MRT) method to adjust the beamforming vectors at the BS.
2. IRS phases Optimization, where, following the optimization of BS beamforming, the IRS phases are subsequently optimized assuming fixed BS beamforming, utilizing an appropriate IRS phase optimization technique, such as gradient descent or Riemannian conjugate gradient on the manifold space.

Subsequently, Manifold Optimization (MO) is performed to address the phase optimization problem of the IRS under the unit modulus constraint. The Riemannian conjugate gradient method is applied on the Riemannian manifold space to efficiently optimize the phases of the IRS elements. In this stage, each iteration involves computing the gradient and updating the IRS phase parameters in a manner consistent with the manifold structure, thereby ensuring that the unit modulus constraint is satisfied.

Next, as a comparison, baseline schemes will be employed in the simulation. These schemes may include a MIMO system without an IRS or a MIMO system utilizing conventional optimization techniques such as semidefinite relaxation (SDR). This is essential for assessing whether the combination of AO and MO yields significant performance improvements over traditional methods. Following the execution of the simulations, the obtained results must be analyzed to evaluate the effectiveness of the proposed approach. Several key performance metrics that will be evaluated include:

1. Signal-to-Noise Ratio (SNR). A primary metric employed to evaluate system performance is the SNR, which is computed based on the received signal power at the receiver relative to the noise power in the channel. In this simulation, the SNR calculated for each system configuration will be compared against the baseline schemes to demonstrate the performance gains achieved through IRS optimization.
2. Channel capacity. The channel capacity attained by the system represents another critical parameter that will be computed in the simulation. The channel capacity can be determined using the following formula:

$$C = \log_2(1 + SNR)$$

Where capacity C is measured in bits per second (bps). A higher channel capacity indicates better channel quality, and more data can be transmitted.

3. The computation time for each optimization iteration will also be measured to compare the efficiency of Alternating Optimization and Manifold Optimization compared to the conditions. Lower computation time indicates a more efficient approach in terms of resource usage.

3. Results and Discussion

Channel Capacity

The channel capacity indicates the maximum amount of data that can be transmitted through a channel per unit time. An increase in channel capacity is directly proportional to the improvement in SNR, as a higher SNR enables data transmission at higher rates with lower error probabilities.

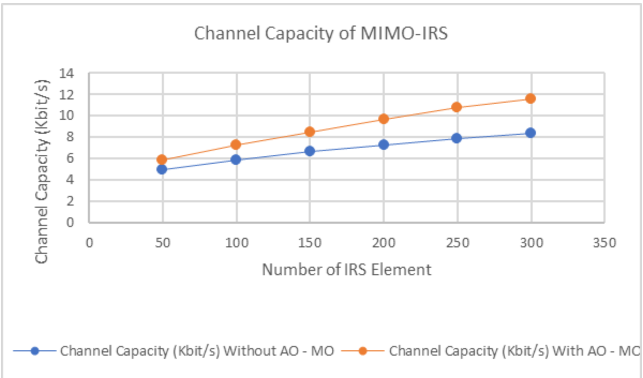

Figure 1. MIMO-IRS System Channel Capacity.

Figure 1 illustrates the comparison of channel capacity in a MIMO-IRS wireless communication system with and without the application of Alternating Optimization and Manifold Optimization. The figure clearly demonstrates that the combined implementation of AO and MO significantly enhances the channel capacity in the MIMO-IRS wireless network. Furthermore, Figure 1 reveals that as the number of IRS elements increases, the resulting channel capacity also rises, particularly in the MIMO-IRS system employing the joint AO and MO approach.

Table 1. Channel Capacity Improvement Achieved through the Combined Application of Alternating Optimization and Manifold Optimization.

Number of IRS Elements	Channel Capacity (Kbit/s)		Increasing (%)
	Without AO - MO	With AO-MO	
50	4,9	5,8	18,4
100	5,8	7,2	24,1
150	6,6	8,5	28,8
200	7,2	9,7	34,7
250	7,8	10,8	38,5
300	8,3	11,6	39,8

Based on the simulation results as described in Table 1, the MIMO-IRS wireless communication system employing the combined Alternating Optimization (AO) and Manifold Optimization (MO) achieves a channel capacity improvement of up to 18.4% when using 50 IRS elements. Although increasing the number of IRS elements in the MIMO-IRS system significantly enhances channel capacity, the application of the joint AO and MO framework yields substantially greater gains. For instance, in a MIMO-IRS system with 300 IRS elements utilizing this combined optimization, the channel capacity increases by up to 39.8%.

These results demonstrate that the integration of AO and MO in the MIMO-IRS system effectively optimizes active beamforming at the Base Station and passive beamforming at the IRS, thereby enabling significantly higher SNR through more constructive interference alignment. In the IRS framework, phase optimization of the reflective elements ensures that the reflected waves are coherently aligned with the direct signal, generating constructive interference at the receiver, wherein multiple electromagnetic waves reflected by the IRS elements reinforce rather than cancel each other. This phenomenon enhances the SNR and improves the quality of the received signal.

Analysis of the simulation results, which indicate substantial channel capacity improvements, confirms the established finding that a larger number of well-configured IRS elements leads to significant capacity gains [3]. The application of AO and MO strengthens constructive interference alignment, ultimately enhancing overall system capacity.

Signal Quality Improvement (SNR)

A primary metric for evaluating the performance of a communication system is the Signal-to-Noise Ratio (SNR), defined as the ratio of the received signal power to the noise power in the system. A higher SNR indicates superior channel quality, which in turn positively influences data rate and bit error rate.

Figure 2. SNR on MIMO-IRS.

Figure 2 presents the simulation results for the MIMO-IRS system optimized using Alternating Optimization (AO) and Manifold Optimization (MO), demonstrating a significant SNR improvement compared to the baseline scheme (without optimization). The SNR values are computed for each tested configuration and compared against the baseline scheme that does not employ AO and MO.

Table 2. SNR Comparison in the MIMO-IRS Wireless Communication System.

Number of IRS Elements	SNR (dB)		Peningkatan (%)
	Without AO - MO	With AO-MO	
50	16,5	18,2	10,3
100	17,3	19,5	12,7
150	18	20,7	15
200	18,5	21,8	17,8
250	19	22,5	18,4
300	19,3	23	19,1

Based on the simulation results as shown in Table 1, it can be seen that the application of Alternating Optimization and Manifold Optimization in the MIMO-IRS system can significantly improve the Signal-to-Noise ratio compared to the MIMO-IRS system without optimization. The significant SNR improvement in the MIMO-IRS system through the application of AO and MO optimization can accommodate more data and more users without experiencing a decrease in signal quality. This means that the system is more resistant to interference and fading and has better transmission reliability. With the much better increase in signal quality or SNR, it shows that the system has low latency and Bit Error Rate (BER), so that it can improve communication quality and user experience in various applications, especially in high-speed data communications.

This finding is in accordance with research, which suggests that manifold optimization is effective in improving the reliability of wireless communication systems with IRS [10]. This is relevant to research results, which emphasize that the implementation of MIMO-IRS with appropriate optimization is the key to realizing efficient and energy-saving wireless networks.

Computation time, which is the efficiency of resource utilization.

Computation time is the time required to complete the optimization for each method, compared to measuring computational efficiency. In wireless communication systems, computation time is a major concern because it is closely related to real-time message delivery.

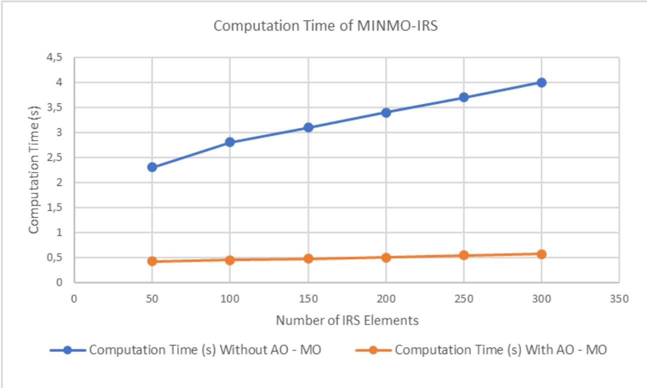

Figure 3. Computation Time in MIMO-IRS.

Figure 3 shows the simulation results of the computation time in a MIMO-IRS system without optimization and with a combined application of Alternating Optimization and Manifold Optimization. The MIMO-IRS system using the combined application of AO and MO shows significantly faster computation times as the number of IRS elements increases. This means that the combined application of AO and MO can decompose non-convex optimization problems while addressing the unit modulus constraint without requiring computationally demanding relaxation.

Table 3. Comparison of Computation Time on MIMO-IRS System.

Number of IRS Elements	Computation Time (s)		Incrising Computation Time Speedup (times)
	Without AO - MO	With AO-MO	
50	2,3	0,42	4,47
100	2,8	0,45	5,22
150	3,1	0,47	5,6
200	3,4	0,5	5,8
250	3,7	0,54	5,85
300	4	0,57	6

Table 3 presents a comparison of computational time for the MIMO-IRS system without optimization and with the combined application of Alternating Optimization (AO) and Manifold Optimization (MO). In the implementation of AO and MO, the increase in computational time with a growing number of IRS elements remains relatively stable. This indicates that the optimization using AO and MO in the MIMO-IRS system does not experience exponential growth in computational time due to numerical iterations, thereby demonstrating significantly higher efficiency in terms of computational duration. In other words, the combined AO and MO approach enables the MIMO-IRS system to support real-time communication.

The results and discussion in this study are conducted through an empirical epistemological approach to construct knowledge derived from experiments and simulations. Consequently, the generated knowledge is not merely theoretical but can also be empirically verified through simulation outcomes. This research demonstrates that practical testing via simulations provides evidence that optimization in MIMO-IRS networks through the combined AO and MO framework enhances channel capacity and SNR while reducing computational time. As a result, the AO and MO optimization in the MIMO-IRS system is validated not only mathematically but also as a practical solution tested and confirmed through experiments and simulations.

From an axiological perspective, this research contributes not only technically to the advancement of MIMO-IRS technology but also provides practical value in the application of Alternating Optimization and Manifold Optimization. In this study, the axiological aspect resides in the technological utility, particularly in terms of improved channel capacity, enhanced SNR, and resource efficiency with respect to computational time.

4. Conclusions

This research successfully optimizes the SNR in a MIMO system using an Intelligent Reflecting Surface (IRS) with a more efficient approach in terms of computation. By applying the combined Alternating Optimization (AO) and Manifold Optimization (MO) methods, this study demonstrates that both methods can significantly enhance the channel capacity and optimize beamforming efficiency in the MIMO-IRS system.

The simulation results demonstrate that the combined application of Alternating Optimization (AO) and Manifold Optimization (MO) in the MIMO-IRS system effectively enhances several critical aspects of wireless communication, namely channel capacity, SNR, beamforming, and computational efficiency.

The integration of AO and MO in the MIMO-IRS system yields a significant increase in channel capacity compared to systems without optimization. Channel capacity determines the maximum amount of information and data that can be transmitted. By leveraging the combined AO and MO framework, the system maximizes the utilization of IRS reflective elements, thereby enabling more efficient signal transmission.

Similarly, in terms of beamforming efficiency, the system employing the joint AO and MO optimization ensures superior signal quality, minimizing interference and fading, reducing bit error rates, and supporting higher data transmission speeds. From the perspective of computational time, the AO and MO optimization substantially reduces processing duration. Lower computational time indicates a more adaptive and responsive system capable of handling rapid channel variations without compromising transmission quality.

The simulation outcomes confirm that the combined AO and MO approach is highly beneficial for wireless networks requiring low latency, high channel capacity, and robust reliability, particularly in supporting real-time communication.

Alternating Optimization and Manifold Optimization have proven effective in optimizing MIMO-IRS wireless channels. However, certain considerations must be addressed in their implementation. Specifically, proper initialization of beamforming phases is essential to prevent delays in the convergence of the optimization algorithm and to minimize the number of iterations required to achieve the optimal solution. In MIMO-IRS systems, excessively prolonged optimization processes can pose challenges, especially in real-time communication networks that demand rapid processing to adapt to dynamic channel conditions.

From an axiological perspective, this research makes a technical contribution to the advancement of MIMO-IRS technology, while also offering social and practical value. Furthermore, it promotes sustainability by reducing computational complexity and resource consumption, aligning with the efficiency requirements of future wireless networks.

Thus, this research has successfully addressed the challenges of efficiently improving SNR in MIMO-IRS systems, addressing non-covex optimization problems, and providing practical solutions for wireless network applications requiring high capacity and low latency.

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Author Contributions

Conceptualization, Devi Rahmayanti and Syaad Padmanthara; methodology, Syaad Padmanthara; software, Devi Rahmayanti; validation, Syaad Padmanthara; formal analysis, Devi Rahmayanti; investigation, Devi Rahmayanti; resources, Devi Rahmayanti; data curation, Devi Rahmayanti; writing—original draft preparation, Devi Rahmayanti; writing—review and editing, Devi Rahmayanti and Syaad Padmanthara; visualization, Devi Rahmayanti; supervision, Syaad Padmanthara; project administration, Devi Rahmayanti and Syaad Padmanthara; funding acquisition, Syaad Padmanthara.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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