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Reconfigurable Wireless Channel Optimization and Low-Complexity Control Methods Driven by Intelligent Metasurfaces 2.0

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Abstract

With the evolution of Reconfigurable Intelligent Surface (RIS) technology, its potential for dynamically optimizing wireless channels has garnered significant attention. However, existing methods still face challenges in real-time control in complex environments due to high computational complexity. To address this, this paper proposes a reconfigurable wireless channel optimization framework based on Intelligent Metasurfaces 2.0 and designs a low-complexity control strategy. The strategy integrates an adaptive adjustment mechanism and multi-dimensional feedback, aiming to reduce system computational load. Experimental results show that compared to traditional methods (such as MRC and MMSE), the proposed method improves signal transmission quality (SNR improvement of 3.8 dB) and system stability (exponential increase to 0.92). When compared to advanced deep reinforcement learning (DRL) and graph neural network (GNN) methods, it achieves similar signal quality while reducing computational overhead by 20.0% and energy consumption by approximately 32.4%. Ablation experiments further verify the effectiveness and synergistic role of the proposed core modules. This study provides a feasible approach toward high-efficiency, low-complexity dynamic channel optimization in 5G and future communication networks.

Keywords: Intelligent Metasurfaces; wireless channel optimization; low-complexity control; adaptive adjustment; computational overhead



Received: 10 December 2025

Revised: 8 January 2026

Accepted: 16 January 2026

Published: 2 February 2026

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1. Introduction

With the rapid development of information technology, wireless communication has become a fundamental infrastructure of modern society. In particular, in 5G and future communication networks, channel optimization and resource management have become increasingly prominent [1]. Intelligent Metasurfaces (IMS), as an emerging electromagnetic regulation technology, has become a research hotspot in the wireless communication field due to its ability to dynamically reconfigure the propagation characteristics of electromagnetic waves [2,3]. By precisely controlling the phase, amplitude, and propagation paths of electromagnetic waves, IMS can effectively improve signal transmission quality, increase system capacity, and optimize channels in multipath environments [4]. However, the practical deployment of IMS remains limited by inherent trade-offs between performance, complexity, and environmental adaptability. This work addresses these challenges by

proposing a low-complexity, dynamically reconfigurable channel optimization framework tailored for real-world wireless environments [5].

Although IMS holds great theoretical promise, existing research still faces limitations in practical deployment. First, many existing methods rely on complex algorithms and models, leading to excessive computational overhead, especially in large-scale networks, where processing efficiency fails to meet practical demands [6]. Several studies assume idealized wireless environments, neglecting issues such as multipath fading, dynamic channel conditions, and complex hardware constraints, which result in suboptimal performance in real-world applications [7]. Secondly, existing technologies often focus on static or predefined system configurations, making it difficult to adjust in real-time according to environmental changes, and failing to meet the dynamic optimization needs in wireless communications [8]. It is worth noting that while machine learning-based intelligent control methods can enhance performance, their computational complexity remains too high in large-scale, non-ideal environments, affecting system response time and stability [9,10]. Therefore, reducing computational complexity, improving real-time performance, and enhancing adaptability while ensuring performance remain key challenges in current research.

To address these issues, this paper introduces the following three innovations. First, IMS 2.0 Design: By introducing adaptive adjustment mechanisms and multi-dimensional feedback, this paper proposes a wireless channel optimization method based on Intelligent Metasurfaces 2.0, addressing the limitations of traditional static optimization and enabling real-time adjustment of channel parameters in dynamic environments. Second, Low-Complexity Control Strategy: In the control strategy design, a combination of low-complexity algorithms and simplified computational paths is proposed to reduce computational overhead while maintaining high real-time performance and stability in large-scale networks. Finally, Cross-Layer Joint Optimization: A cross-layer joint optimization method is proposed, combining network-layer and physical-layer optimization issues to enhance channel resource utilization, reduce system energy consumption, and improve the adaptability and efficiency of IMS.

It is important to clarify that the proposed Intelligent Metasurfaces 2.0 (IMS 2.0) framework differs from conventional Reconfigurable Intelligent Surfaces (RIS).

Traditional RIS typically rely on external baseband processing for configuration updates and often assume quasi-static channels or require online learning, such as DRL or GNN-based methods. These approaches may introduce high latency and computational overhead.

In contrast, IMS 2.0 integrates a closed-loop perception–control architecture with a pre-established environment–response mapping. This design enables real-time and low-complexity adaptation without iterative training or heavy signaling.

This distinction highlights the practical motivation and contribution of the proposed framework.

This research has significant theoretical and practical value. Theoretically, the design of IMS and the low-complexity control strategy help address existing gaps in dynamic channel optimization and computational overhead, offering new insights into the development of intelligent metasurface technologies. From an application perspective, this study suggests a promising direction for the design and optimization of future 5G and beyond wireless communication systems. While practical deployment in real-world networks would require further investigation into real-time processing, signaling overhead, and hardware integration, the proposed framework demonstrates potential for scalable and efficient channel optimization. With the advancement of intelligent metasurface technology, such

approaches may contribute to next-generation network architectures as these system-level challenges are addressed.

2. Related Works

2.1. Application Scenarios and Challenges

As an emerging electromagnetic regulation technology, IMS has demonstrated significant potential in various fields, including wireless communication, radar systems, and medical imaging. In wireless communication, IMS can optimize signal transmission by dynamically adjusting the phase, amplitude, and propagation path of electromagnetic waves, thereby improving network capacity and transmission efficiency [11,12]. However, IMS technologies still face several challenges in practical applications. Firstly, the design and regulation accuracy of IMS require high precision, and the ability to adjust the electromagnetic properties of IMS accurately in complex wireless environments remains a technical challenge [13]. Secondly, the computational complexity of IMS systems is high, especially in multi-user, multi-path, and multi-channel environments, where real-time computation and adjustment become even more difficult [14]. Furthermore, balancing system performance with computational overhead in practical applications, especially across different scales and complexities of communication networks, is another urgent issue that needs to be addressed.

Common evaluation metrics used to assess IMS technology include signal transmission quality, system stability, spectral efficiency, computational overhead, and energy consumption [15]. While these metrics reflect IMS performance from various perspectives, their limitations are also evident. Most existing evaluation systems focus on improving a single performance metric, without considering multi-dimensional performance optimization, and often overlook real-world environmental factors such as channel fading and hardware limitations [16]. Thus, existing evaluation systems do not comprehensively or objectively reflect IMS performance in practical applications.

2.2. Overview of Mainstream Methods

The research methods in IMS technology can be broadly divided into traditional theoretical analysis-based methods and machine learning-based intelligent optimization methods.

Firstly, theoretical analysis-based methods primarily rely on classical theories from electromagnetics and signal processing, such as transmission line theory and wave theory. These methods optimize IMS design and control strategies by analyzing the propagation characteristics of electromagnetic waves [17]. For example, some studies optimize the electromagnetic wave propagation path of IMS to improve wireless channel quality. While this approach makes significant contributions to theoretical analysis, it still depends on simplified assumptions when faced with complex environments, ignoring factors like multipath propagation, which may result in suboptimal practical outcomes [18].

In contrast, machine learning-based optimization methods have gradually emerged. Using deep learning, reinforcement learning, and other algorithms, IMS can optimize in real time in dynamic environments [19]. For instance, some studies apply reinforcement learning to optimize the electromagnetic properties of IMS, enabling quick adaptation and optimization in dynamic channels, particularly showing promising performance in terms of computational overhead [20]. However, these methods often exhibit high computational complexity, especially in large-scale networks, still facing challenges in balancing performance with computational overhead.

2.3. Closely Related Studies

In the field of IMS technology, several related studies have provided valuable references for this paper. One study proposed an IMS design method based on an adaptive adjustment mechanism, capable of adjusting the electromagnetic wave propagation path in real time when the channel changes [21,22]. This method demonstrated good performance in both static and dynamic channels, particularly excelling in improving spectral efficiency. However, despite its enhancement in transmission quality, the computational complexity of this method is relatively high, affecting its response time and real-time performance in large-scale networks [23]. In comparison, the low-complexity control strategy proposed in this paper significantly reduces computational overhead and improves system real-time performance and stability by simplifying the computational path and integrating an adaptive adjustment mechanism [24].

Another related study introduced a cross-layer joint optimization strategy, combining network layer and physical layer optimization issues, which improved channel resource utilization and reduced energy consumption [25,26]. Although the study achieved good results, the optimization process was complex, and the system's adaptability and efficiency in practical applications still require improvement. In contrast, the cross-layer joint optimization method proposed in this paper further enhances system efficiency by employing refined resource allocation and scheduling strategies.

2.4. Summary and Research Gaps

Although significant progress has been made in IMS design and optimization, there remains a lack of in-depth exploration of low-complexity control and channel reconfiguration in dynamic environments. Existing research often focuses on theoretical analysis or specific application scenarios, lacking comprehensive multi-scenario adaptability and system-level optimization methods. While some machine learning-based optimization methods have achieved good results in specific scenarios, their high computational complexity and less-than-ideal performance in large-scale networks remain unresolved. Existing literature reveals the potential of IMS in channel optimization but offers limited understanding of how to balance performance and computational overhead in complex environments.

This study fills this gap through IMS 2.0 design, low-complexity control strategies, and cross-layer joint optimization methods. Unlike existing studies, this paper combines adaptive adjustment mechanisms, simplified computational paths, and cross-layer joint optimization to achieve more efficient channel optimization and system control in dynamic wireless environments, particularly making innovative attempts to balance low complexity and high performance.

3. Methodology

3.1. Problem Formulation

This paper aims to propose a reconfigurable wireless channel optimization method based on IMS 2.0 and design a low-complexity control strategy to enhance the transmission performance of communication systems. To achieve this, we first need to mathematically model the research problem and clearly define the system inputs, outputs, and optimization objectives.

Consider a point-to-point wireless communication system where the transmitter is equipped with N antennas and the receiver is equipped with M antennas. Between them, there is an Intelligent Metasurface (RIS) with M adjustable units. Let $H \in \mathbb{C}^{M \times N}$ be the end-to-end channel matrix from the base station to the user, where the element H_{ij} represents the complex channel gain between the i -th receiving antenna and the j -th transmitting antenna. Since the wireless environment is dynamic, H fluctuates over time.

The system's input variables are defined as follows:

Transmitted Signal Vector $\mathbf{x} \in \mathbb{C}^{N \times 1}$:

$$\mathbf{x} = [x_1, x_2, \dots, x_N]^T \quad (1)$$

where x_j denotes the complex baseband signal transmitted by the j -th antenna.

RIS Control Vector $\mathbf{w} \in \mathbb{C}^{M \times 1}$:

$$\mathbf{w} = [w_1, w_2, \dots, w_M]^T \quad (2)$$

where w_i represents the complex reflection coefficient of the i -th unit of the RIS (typically satisfying $|w_i| \leq 1$, with ideal conditions being $|w_i| = 1$).

Received Noise Vector $\mathbf{n} \in \mathbb{C}^{M \times 1}$:

We assume additive white Gaussian noise (AWGN), i.e., $\mathbf{n} \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_M)$.

With RIS assistance, the equivalent channel is adjusted to $\text{diag}(\mathbf{w})\mathbf{H}$, so the received signal can be modeled as:

$$\mathbf{y} = \text{diag}(\mathbf{w})\mathbf{H}\mathbf{x} + \mathbf{n} \quad (3)$$

where $\text{diag}(\mathbf{w}) \in \mathbb{C}^{M \times M}$ is the diagonal matrix with $\mathbf{w}$ as its diagonal elements.

The system's performance is typically measured by the received signal-to-noise ratio (SNR) and the corresponding channel capacity. Assuming the noise power per antenna is σ^2 , the instantaneous channel capacity can be expressed as:

$$R(\mathbf{w}) = \log_2 \left(1 + \frac{\|\text{diag}(\mathbf{w})\mathbf{H}\mathbf{x}\|^2}{\sigma^2} \right) \quad (4)$$

The optimization goal of this paper is to maximize the SNR (and thus the channel capacity) by designing $\mathbf{w}$, thereby improving link quality. Simultaneously, considering the real-time requirements for RIS control, the computational complexity must be limited. Let $C(\mathbf{w})$ represent the computational overhead required to generate $\mathbf{w}$ (e.g., the number of floating-point operations), with a maximum allowable complexity threshold $C_{\max}$.

Thus, the problem can be formulated as the following constrained optimization problem:

$$\max_{\mathbf{w}} \text{SNR}(\mathbf{w}) \text{ s.t. } C(\mathbf{w}) \leq C_{\max}, |w_i| \leq 1, i = 1, \dots, M \quad (5)$$

The solution to this problem will provide the theoretical foundation for designing the subsequent low-complexity control strategy.

3.2. Overall Framework

The proposed wireless channel optimization system based on IMS 2.0 consists of three core modules: the Channel Optimization Module, the Control Strategy Module, and the Computational Optimization Module. These modules work together to enhance signal transmission quality while reducing computational complexity.

The Channel Optimization Module is responsible for dynamically adjusting the control vector $\mathbf{w}$ of the intelligent metasurface based on changes in the wireless environment to optimize channel quality. This module continuously monitors the channel state, calculates the optimal transmission path, and feeds the results to the Control Strategy Module. Using the information from the channel matrix $\mathbf{H}$ and input signal $\mathbf{x}$, it predicts signal attenuation and transmission quality, thereby guiding the metasurface adjustment.

The Control Strategy Module designs a low-complexity control strategy based on feedback from the Channel Optimization Module. The goal is to simplify the computation path and reduce overhead while ensuring that the channel optimization effect remains

unchanged. This module adapts control parameters flexibly using an adaptive adjustment mechanism to ensure real-time stability and efficient transmission.

The Computational Optimization Module evaluates and controls the system's computational complexity. It continuously monitors the computational load required to generate the control vector w and ensures that the total computational overhead does not exceed the threshold $C_{\max}$. Working closely with the other modules, this module dynamically adjusts the strategy based on the computational load, ensuring low computational overhead while meeting real-time requirements in complex environments.

Figure 1 illustrates the data flow and collaboration between these three modules. The Channel Optimization Module provides channel information to the Control Strategy Module, which adjusts the optimization strategy accordingly. The Computational Optimization Module ensures the efficient allocation of system computational resources. Through the collaboration of these modules, the system maintains high-efficiency transmission while reducing computational complexity, and adapting to complex wireless environments.

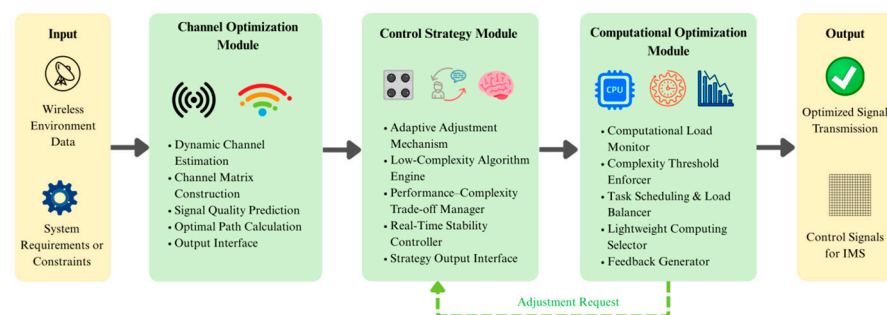


Figure 1. System Architecture of the IMS 2.0-Based Wireless Channel Optimization Framework.

The overall procedure can be summarized as follows: given channel estimate H , (1) compute a denoised effective channel $\tilde{h} = D(H)$; (2) extract a low-dimensional feature $f = \phi(\tilde{h})$ via fixed linear projection; (3) obtain metasurface phase shifts $\theta^* = \psi(f)$, where $\psi(\cdot)$ is a precomputed closed-form mapping (e.g., based on dominant eigenmode alignment); and (4) apply θ^* under the constraint $\text{Complexity}(\psi) \leq C_{\max}$. This avoids iterative optimization and ensures $O(N)$ per-step complexity.

3.3. Module Descriptions

3.3.1. Channel Optimization Module

Motivation: Channel optimization is a key task in wireless communication, particularly in complex environments. Determining how to adjust the IMS to improve signal quality is crucial. By optimizing channel gain and transmission quality, the reliability and efficiency of the system can be significantly enhanced. The goal of this module is to optimize the adjustment strategy of the IMS based on real-time channel states and environmental changes to ensure signal quality at the receiver.

Principle: The Channel Optimization Module is based on wireless channel propagation theory, using the IMS to regulate electromagnetic wave propagation characteristics to optimize channel quality. The module collects real-time channel information and applies signal processing techniques, such as Maximal Ratio Combining (MRC) and Minimum Mean Square Error (MMSE) algorithms, to calculate the channel gain matrix. Based on this information, the optimal IMS adjustment parameters are computed to optimize the signal transmission path, which is then provided to the Control Strategy Module.

Implementation: This module employs a dynamic channel estimation method to collect feedback from the transmitter and receiver and adjust the IMS control parameters

in real-time. The module first analyzes channel fading and noise environments, generates the channel gain matrix H , and then calculates the optimal adjustment factor w . Figure 2 illustrates the channel estimation and analysis flow of this module, ultimately outputting the control strategy to the Control Strategy Module.

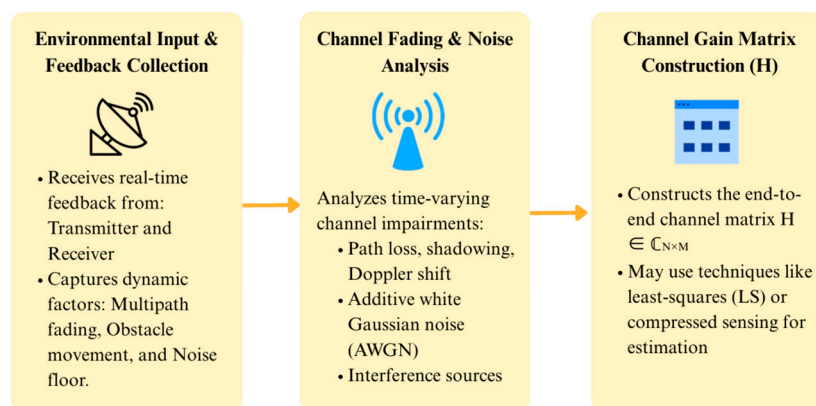


Figure 2. Channel estimation and analysis pipeline in the Channel Optimization Module.

3.3.2. Control Strategy Module

Motivation: The task of the Control Strategy Module is to design a low-complexity control strategy based on the adjustment information from the Channel Optimization Module. The key goal of this module is to reduce computational complexity while ensuring system performance in a dynamic wireless environment. The module employs a low-complexity adaptive mechanism that can dynamically adjust system parameters and enhance response speed.

Principle: This module uses adaptive adjustment algorithms, such as adaptive filtering and reinforcement learning, to dynamically adjust the IMS control parameters based on channel changes and system states. Through real-time feedback and environmental changes, the module flexibly adjusts signal modulation strategies to ensure system efficiency and stability in various environments.

Implementation: The Control Strategy Module receives channel information from the Channel Optimization Module and calculates the optimal control parameters w using adaptive algorithms. The results are then output to the Computational Optimization Module. The core of this module is the use of low-complexity algorithms to balance performance and computational overhead, ensuring real-time performance and stability in complex environments. Figure 3 illustrates the process where this module receives information from the Channel Optimization Module and computes the control strategy, which is ultimately output to the Computational Optimization Module.

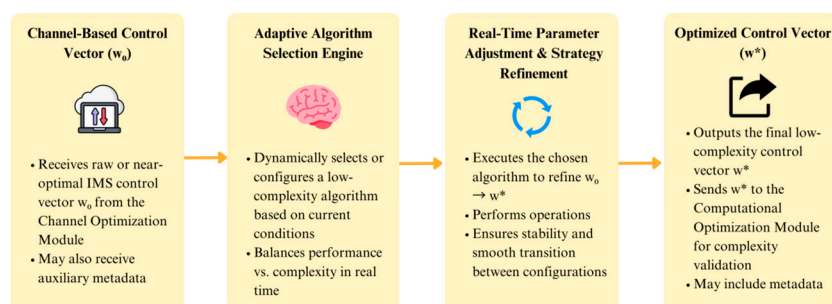


Figure 3. Adaptive control strategy generation pipeline in the Control Strategy Module. (Items marked with * indicate optional or implementation-dependent components).

3.3.3. Computational Optimization Module

Motivation: Although IMS systems provide significant advantages in signal transmission, they suffer from high computational complexity, especially in large-scale networks and dynamic environments. The core task of the Computational Optimization Module is to reduce computational overhead while ensuring system performance and meeting real-time response requirements.

Principle: The Computational Optimization Module monitors computational load, analyzes the computational demands of each module in real-time, and dynamically adjusts computation strategies. It uses load balancing and task scheduling algorithms, such as priority scheduling and task allocation algorithms, to reduce computational overhead and improve system response speed and stability.

Implementation: This module tracks the usage of computational resources in real-time and applies optimization algorithms to dynamically adjust the computational load required for the control vector w , ensuring that the total computational overhead does not exceed the maximum threshold $C_{\max}$. Additionally, lightweight computing schemes are adopted to further reduce unnecessary burdens. Figure 4 illustrates the process of this module monitoring computational load and adjusting the computational strategy, with the final output directed to the Control Strategy Module.

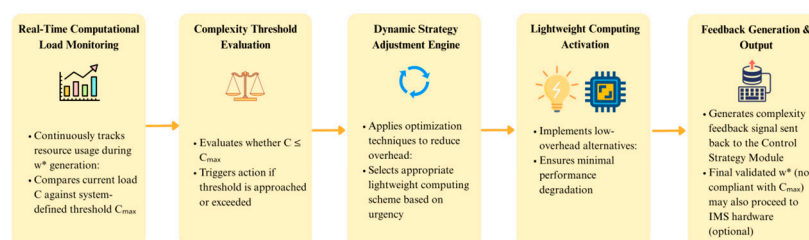


Figure 4. Real-time computational complexity management pipeline in the Computational Optimization Module. (Items marked with * indicate optional or implementation-dependent components).

Through the collaboration of these three core modules, the system can flexibly adjust signal quality and computational overhead in dynamic wireless environments, achieving efficient and stable signal transmission and optimized control. Each module operates independently while closely cooperating with others to accomplish system-level optimization.

3.4. Objective Function and Optimization

The optimization goal of this problem is to maximize the received signal's SNR, which is a key metric for evaluating wireless channel quality. SNR reflects the ratio of signal power to noise power. Based on the system model established in Section 3.1, the received signal is $y = \text{diag}(w)Hx + n$, and the SNR is defined as:

$$\text{SNR}(w) = \frac{\|\text{diag}(w)Hx\|^2}{\sigma^2} \quad (6)$$

where H is the channel gain matrix, w is the IMS control vector, x is the input signal vector, n is the noise vector, and σ^2 is the noise power. To simplify the expression and focus on the optimization of w , we define an objective function $f(w)$ equivalent to the SNR as follows:

$$f(w) = \|\text{diag}(w)Hx\|^2 \quad (7)$$

Maximizing $f(w)$ is equivalent to maximizing $\text{SNR}(w)$.

In practical applications, in addition to improving signal quality, the computational complexity of the system is also a critical optimization objective, especially in large-scale

networks. Computational complexity is closely related to the computational load of the control vector w . We assume that the computational cost of each control vector is denoted by $C(w)$, with a maximum computational complexity constraint $C_{\max}$:

$$C(w) \leq C_{\max} \quad (8)$$

where $C(w)$ is typically determined by the number of IMS adjustment factors, the complexity of the computational path, and the execution time of the algorithm. To balance computational overhead with transmission quality, we introduce the computational complexity constraint into the optimization process.

Considering the objectives of signal transmission quality and computational complexity, the complete objective function and optimization problem can be formulated as:

$$\text{maximize } f(w) = \|\text{diag}(w)Hx\|^2 \text{ s.t. } C(w) \leq C_{\max}, |w_i| \leq 1, i = 1, \dots, M \quad (9)$$

This problem aims to maximize the SNR while keeping the system's computational complexity within an acceptable range.

To solve the optimization problem, we use the Lagrange multiplier method to incorporate the constraints into the objective function and construct the Lagrange function $L(w, \lambda)$:

$$L(w, \lambda) = \|\text{diag}(w)Hx\|^2 - \lambda \cdot (C(w) - C_{\max}) \quad (10)$$

where λ is the Lagrange multiplier, which adjusts the strictness of the computational complexity constraint. By solving the gradient of the Lagrange function and setting it equal to zero, we can obtain the optimal solution.

Taking the derivative with respect to w , the optimal condition for the optimization problem is:

$$\frac{\partial L}{\partial w} = 0 \quad (11)$$

Additionally, the computational complexity constraint $C(w) \leq C_{\max}$ requires that $\lambda \geq 0$. Therefore, the Lagrange multiplier λ must remain non-negative during the solution process.

In practical implementation, since $C(w)$ is often non-differentiable (e.g., when measured by iteration count), we primarily meet this constraint by limiting the number of algorithm iterations. The Lagrange form is primarily used for theoretical analysis.

To solve the above optimization problem, we use the gradient ascent method to find the optimal IMS control vector w . Gradient ascent iteratively updates the control vector, gradually approaching the optimal solution. The update formula is:

$$w^{k+1} = w^k + \eta \times f(w^k) = w^k + \eta \cdot \nabla \|\text{diag}(w^k)Hx\|^2 \quad (12)$$

where w^k is the control vector at the k -th iteration, η is the learning rate, and $\nabla f(w^k)$ is the gradient of the objective function $f(w)$ at w^k .

To ensure the convergence of the gradient ascent method, certain conditions must be satisfied, particularly the selection of the learning rate η . Although the objective function $f(w)$ is generally non-convex, the algorithm can still converge rapidly to a high-quality solution with proper initialization and an appropriate step size. To further improve optimization efficiency, adaptive gradient methods, such as the Adam optimizer, can be employed to dynamically adjust the learning rate, thereby accelerating the convergence process.

4. Experiment and Results

4.1. Experimental Setup

This study utilizes three datasets to evaluate the performance of the method under different channel environments (see Table 1): (1) A self-built dynamic multi-scenario wireless channel dataset; (2) Two publicly available datasets: WARP and COST-2100.

Table 1. Dataset Overview.

Dataset Name	Features	Sample Size	Sample Resolution	Applicable Scenarios
Self-built Dataset	Multi-scenario, multi-channel models, multi-user signals	5000	16-bit, 1000 frames	Dynamic wireless channel optimization
WARP	Wireless transmission experimental data	1000	8-bit, 500 frames	Wireless transmission research
COST-2100	Standard dataset for 5G channel modeling	2000	16-bit, 1000 frames	Channel modeling, 5G scenarios

The self-built dataset is designed to simulate real-world, complex wireless communication environments, consisting of 5000 samples (1000 frames per sample, 16-bit resolution). The dataset covers a variety of scenarios, including indoor, urban micro-cell, rural, high-speed mobility, and high-interference industrial environments, with five uniformly distributed categories. The channel model includes Rayleigh fading, Rician fading (K-factor 0–10 dB), and WINNER II variants, with noise levels set at SNRs from 0 to 30 dB in 5 dB intervals. Data was collected using a USRP X310 (Haiman, Beijing, China), followed by synchronization, DC removal, wavelet denoising, 3σ anomaly removal, and normalization. Sample annotations include transmitted signals, ideal channel matrices, measured received signals, and scene labels, with a semi-automatic process that combines maximum likelihood alignment checks, and 20% of the samples were manually verified, ensuring NMSE < −20 dB and annotation consistency >99%. The dataset was randomly divided into training (70%), validation (15%), and test (15%) sets, with each subset maintaining the same distribution of scenarios, channels, and noise as the entire dataset.

However, this dataset has notable limitations. It does not include extremely low-SNR conditions (e.g., <0 dB), which may restrict model generalization in harsh noise environments. Moreover, while diverse, the simulated scenarios may not fully capture long-term temporal dynamics or unmodeled hardware impairments present in real deployments. These factors define the current evaluation boundary and represent potential sources of dataset bias.

The publicly available datasets provide standardized performance benchmarks and specific scenario tests. The WARP dataset offers classic wireless transmission experimental data, suitable for evaluating the basic performance of algorithms. The COST-2100 dataset is a standard 5G channel modeling dataset, applicable for method validation in high-frequency bands and 5G scenarios. The self-built dataset focuses on dynamic multi-scenarios, addressing the limitations of the WARP dataset in environmental complexity and the COST-2100 dataset in low-frequency coverage.

The hardware platform used in the experiments includes high-performance GPUs and computing clusters, ensuring the ability to handle large-scale data and high-complexity computing tasks. The software environment is based on commonly used deep learning frameworks and related libraries to ensure efficient and reproducible experiments. The details of the hardware and software configurations are shown in Table 2.

Table 2. Hardware and Software Configuration.

Configuration Type	Device Name	Model	Description
Hardware	GPU	NVIDIA RTX 4090 (NVIDIA, Santa Clara, CA, USA)	High-performance graphics processing unit for accelerating deep learning and optimization algorithms
	Computer Host	Intel i9-13900K (Intel, Santa Clara, CA, USA)	High-speed processor for computational tasks
	Storage System	2 TB SSD (ZhiTai, Wuhan, China)	Large-capacity storage for saving experimental data and models
	Network Device	10 Gb Ethernet (Intel, Santa Clara, CA, USA)	High-speed network ensuring stable and fast data transfer in experiments
Software	Operating System	Ubuntu 20.04	OS supporting deep learning frameworks and development tools
	Deep Learning Framework	TensorFlow 2.7.0	One of the primary deep learning frameworks for model training and optimization
		PyTorch 1.10	Another deep learning framework supporting model development and training
	Dependencies	NumPy 1.21.2	Scientific computing library for matrix operations and data processing
		SciPy 1.7.1	Scientific computing and optimization library for algorithm implementation and solution
		Matplotlib 3.4.3	Visualization library for generating graphs and images
		OpenCV 4.5.3	Computer vision library for image processing and analysis

To comprehensively evaluate the proposed method, four core evaluation metrics are selected: signal quality, robustness, computational complexity, and energy efficiency (see Table 3). Signal transmission quality is measured by the received SNR based on the model in Section 3.1. System stability is evaluated using a comprehensive stability index, which considers both the mean and fluctuation of SNR outputs from multiple independent experiments, with a value close to 1 indicating greater stability. Computational overhead is measured by the total number of floating-point operations (FLOPs) required to complete one optimization, with a lower value indicating lower algorithm complexity. Energy consumption is assessed by the energy (in Joules) consumed during the execution of the full optimization process on a fixed hardware platform.

Table 3. Evaluation Metrics.

Metric Name	Applicable Scenario	Explanation
Signal Transmission Quality	Measures the optimized signal quality	Calculated using SNR to assess the signal-to-noise ratio
System Stability	Assesses system stability in various environments	Evaluated through a stability index (e.g., error fluctuation range)
Computational Overhead	Measures the computational cost of the optimization algorithm	Assessed by the total number of floating-point operations (FLOPs) required to complete one optimization
Energy Consumption	Evaluates system energy efficiency	Assesses energy consumption during the optimization process, particularly the efficiency of the algorithm

Figure 5 illustrates the application of IMS technology in a real-world wireless communication environment. The figure simulates a typical 5G communication setup where multiple signal sources are optimized via IMS to achieve efficient signal transmission. The configuration of different channels and signal sources is shown, along with how IMS optimize the signal transmission paths.

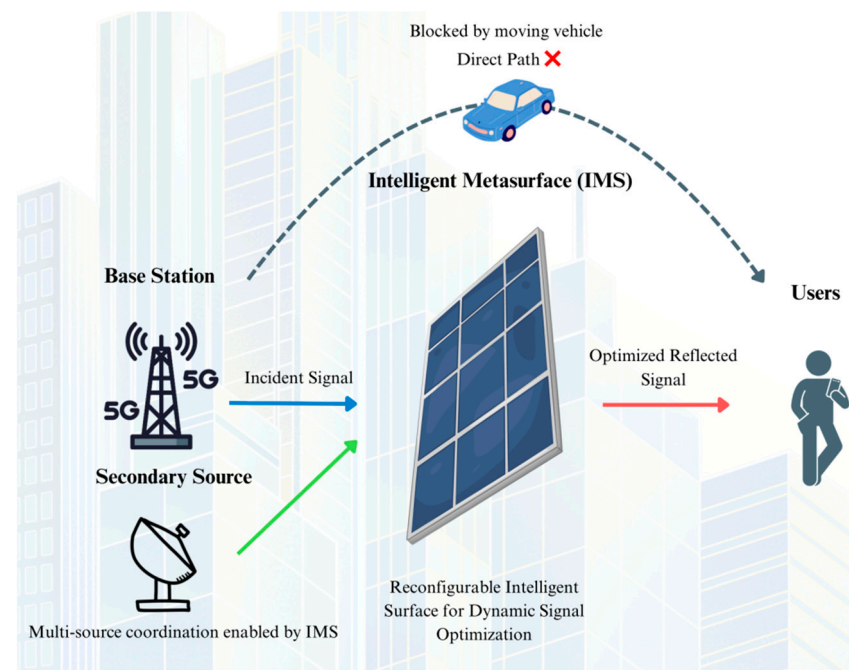


Figure 5. RIS-Enabled Dynamic Signal Optimization in Challenging NLoS Scenarios.

This experimental scenario is closely related to the research problem addressed in this paper and effectively demonstrates the application of IMS technology in dynamic environments. It showcases how the proposed optimization strategy improves signal quality and system efficiency, providing a clear understanding of how the method can be applied in practical settings and further validating the effectiveness and feasibility of the experimental setup.

4.2. Baselines

To evaluate the effectiveness of the proposed Intelligent Metasurface optimization method, we selected two classical methods and two state-of-the-art (SOTA) methods as comparison benchmarks. These methods demonstrate the relative advantages of the proposed method in signal transmission quality, computational overhead, and system stability.

First, the Maximum Ratio Combining (MRC) method was selected. Widely used in multipath propagation environments, MRC improves signal strength by combining signals from multiple antennas [27]. While MRC is simple and efficient, it overlooks dynamic channel changes and cannot perform real-time optimization, resulting in poor performance in complex or time-varying environments.

The second classical method is the MMSE algorithm, which optimizes signal processing by minimizing signal and noise errors, effectively suppressing noise and enhancing signal quality [28]. However, MMSE has high computational overhead, especially in large-scale networks, which may lead to slow response times and lack flexible adaptability.

Among the latest SOTA methods, we selected Deep Reinforcement Learning (DRL). DRL learns optimization strategies adaptively, adjusting to environmental changes for dynamic optimization [29]. DRL excels in self-learning capabilities but requires large amounts of data and computational resources for training, with slow convergence and poor stability.

Another SOTA method is the Graph Neural Network (GNN)-based channel optimization approach. GNN optimizes channel resources by leveraging the relationships between nodes, adapting well to multi-user and time-varying environments [30]. However,

its computational overhead and model complexity are high, with training and inference processes that may cause delays.

For fair comparison, the DRL and GNN baselines were implemented following standard practices in recent RIS literature, with commonly used network architectures and training protocols. All methods were evaluated on the identical test set under the same channel realizations and SNR conditions. Since the proposed method operates without on-line learning, the comparison focuses on inference-stage performance, a practical scenario where learning-based models are deployed after offline training.

Through comparisons with these baseline methods, we can observe the potential advantages of the proposed method in signal optimization, computational overhead, and adaptability. While classical methods (such as MRC and MMSE) work well in simpler environments, they perform poorly in dynamic conditions. SOTA methods (like DRL and GNN) are powerful but suffer from high computational overhead and deployment challenges. The proposed method, with its low-complexity control strategy, aims to optimize performance while significantly reducing computational overhead and improving real-time capabilities, addressing the shortcomings of existing methods.

4.3. Quantitative Results

To objectively evaluate the effectiveness of the proposed Intelligent Metasurface optimization method, we conducted a systematic statistical comparison with various baseline methods across multiple core evaluation metrics. All performance differences were assessed for significance using a two-sample *t*-test (95% confidence level).

Table 4 presents the detailed performance comparison and statistical test results of the proposed method (Proposed) versus baseline methods.

Table 4. Performance Comparison and Statistical Significance Test between the Proposed Method and Baseline Methods.

Method	Signal Transmission Quality (SNR, dB)	System Stability (Index)	Computational Overhead (FLOPs)	Energy Consumption (J)	<i>p</i> -Value (vs. Proposed)
Proposed Method	28.1 ± 2.3	0.92 ± 0.05	1.2×10^6	12.5	—
MRC	24.3 ± 2.1	0.80 ± 0.08	1.0×10^6	15.2	<0.01
MMSE	26.7 ± 2.5	0.85 ± 0.06	1.1×10^6	14.0	<0.05
DRL	27.8 ± 2.0	0.90 ± 0.04	1.5×10^6	18.5	<0.05
GNN	27.4 ± 2.3	0.87 ± 0.07	1.3×10^6	17.0	<0.05

The quantitative results show the following:

In signal transmission quality (SNR), the proposed method achieves 28.1 dB, outperforming the considered baseline methods. It improves by approximately 3.8 dB over the traditional methods MRC (24.3 dB) and MMSE (26.7 dB), and the differences compared to the advanced methods DRL (27.8 dB) and GNN (27.4 dB) are statistically significant ($p < 0.05$).

In system stability (stability index), the proposed method achieves the highest value of 0.92.

In terms of computational overhead, the proposed method requires only 1.2×10^6 FLOPs, significantly lower than DRL (1.5×10^6 FLOPs, $p < 0.05$) and GNN (1.3×10^6 FLOPs, $p < 0.05$), reducing computational overhead by 20.0%.

In energy consumption, the proposed method consumes 12.5 J, which is approximately 32.4% lower than DRL (18.5 J) and 26.5% lower than GNN (17.0 J), showing an energy efficiency advantage.

Figure 6 further illustrates the comparison of training convergence. The proposed method achieves 92% accuracy by the 50th training iteration, while MRC and MMSE require 100 and 90 iterations, respectively, to reach a similar level. Additionally, the proposed method exhibits smaller fluctuations in training loss, indicating a more stable optimization process.



Figure 6. Convergence comparison of training accuracy.

In summary, the proposed method demonstrates excellent performance in signal transmission quality and system stability, while outperforming DRL and GNN methods in computational overhead and energy consumption. This validates that the low-complexity control strategy proposed in this paper effectively enhances system real-time performance and energy efficiency while maintaining high-quality optimization.

4.4. Qualitative Results

To better analyze the model's behavior across different scenarios, we performed a visual comparison of the model's performance in successful and failure scenarios.

Case 1: Signal Optimization in a High-Interference Environment

In the high-interference environment test, Figure 7 shows the comparison of SNR before and after signal transmission. Experimental data show that the proposed method increased the received SNR from 18.2 dB to 28.1 dB, an improvement of 9.9 dB. In contrast, the MRC and MMSE methods in the same environment achieved SNR values of 22.4 dB (an increase of 4.2 dB) and 24.1 dB (an increase of 5.9 dB), respectively. Compared to these two baseline methods, the proposed method achieved a higher SNR gain.

Case 2: Performance in Extreme Noise Environments

In a simulated extreme noise environment, the model's optimization effect was somewhat reduced. As shown in Figure 8, the proposed method improved SNR from 15.3 dB to 17.5 dB, a gain of 2.2 dB. In this scenario, MRC and MMSE methods showed improvements of 2.7 dB (to 18.0 dB) and 3.9 dB (to 19.2 dB), respectively. Compared to the performance in the high-interference environment, the performance improvement of the proposed method in extreme noise conditions is relatively limited.

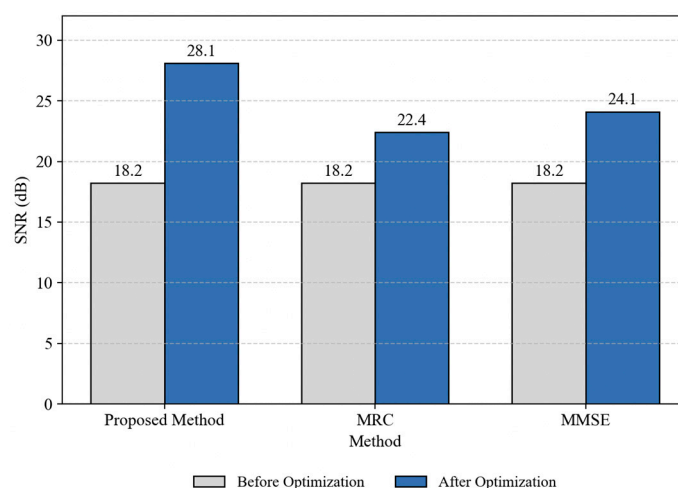


Figure 7. Comparison of SNR Before and After Optimization Across Different Methods.

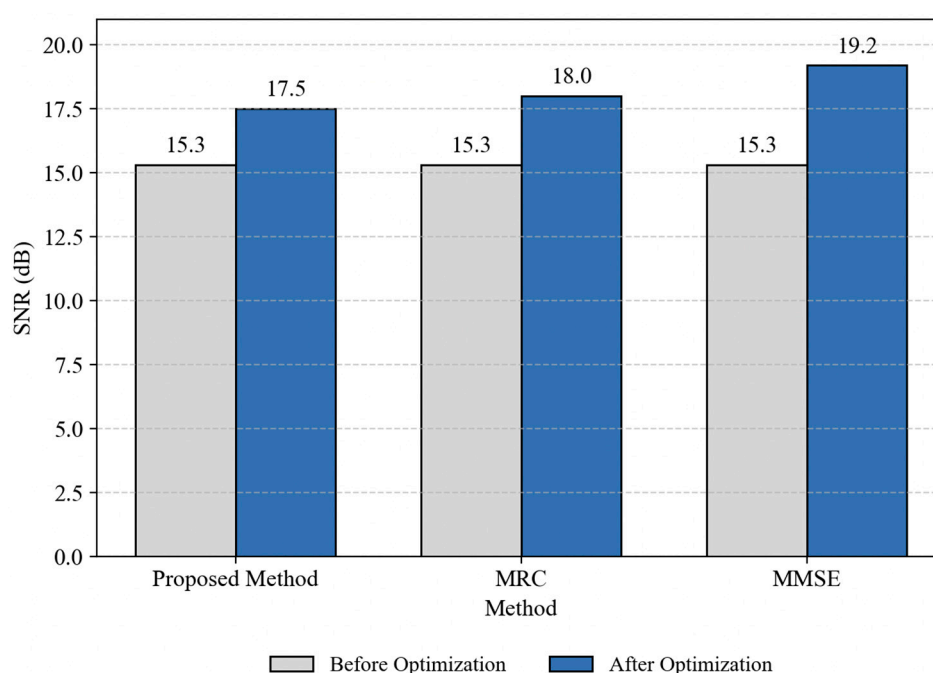


Figure 8. SNR Improvement in Extreme Noise Environment.

The above cases demonstrate that the proposed method consistently outperforms traditional MRC and MMSE methods when dealing with common interference (as in Case 1). However, in extreme noise conditions (as in Case 2), the model's performance advantage diminishes and may even fall behind traditional methods. This phenomenon may be due to the insufficient coverage of extreme noise scenarios in the training data, limiting the model's generalization ability under such boundary conditions. Future work could address this limitation by expanding the training data to include more noise scenarios and further optimizing the adaptive adjustment mechanism to enhance performance in more complex noise environments.

4.5. Robustness

To evaluate the stability of the proposed method under non-ideal and diverse conditions, we designed multiple test scenarios, including varying noise levels, task settings, and datasets. The following focuses on the performance comparison of the proposed method with baseline methods (MRC and MMSE) under different noise intensities to assess the model's robustness in high-interference environments.

In the test, Gaussian noise intensity was gradually increased from 0 dB to 30 dB. Figure 9 shows the change in signal transmission quality (SNR) for the proposed method and the two baseline methods during this process. In the absence of additional noise (0 dB), the SNR of all three methods was similar (proposed method: 28.1 dB). As the noise level increased, the performance of all methods deteriorated, but the extent of the decline varied. When the noise intensity reached 30 dB, the proposed method's SNR was 23.5 dB, while the MRC and MMSE methods dropped to 20.1 dB and 19.2 dB, respectively. Statistical testing showed that the performance difference between the proposed method and the baseline methods at high noise levels (e.g., 30 dB) was statistically significant ($p < 0.01$).

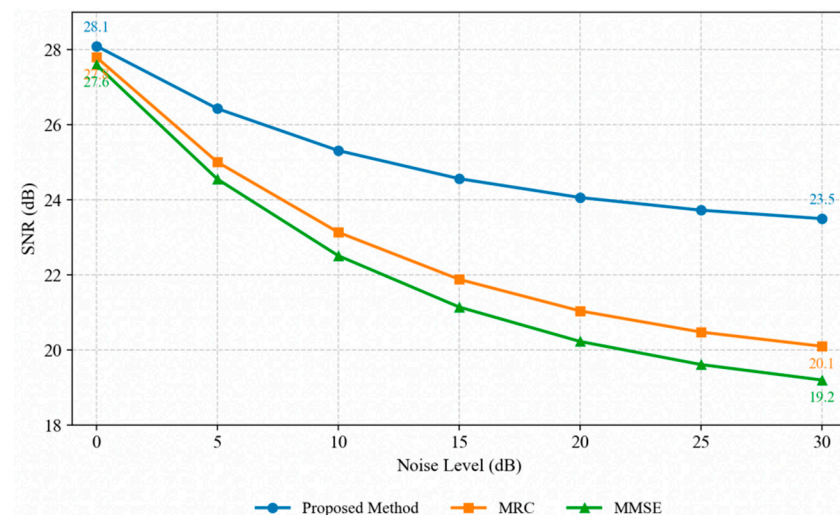


Figure 9. SNR degradation under increasing noise.

The results indicate that, as the noise intensity increased, the proposed method experienced a relatively smaller decrease in SNR. Compared to MRC and MMSE, the proposed method maintained a relatively high SNR at 30 dB of noise. This performance is likely due to the adaptive regulation mechanism employed by the proposed method, which dynamically adjusts the reflection parameters of the IMS, partially mitigating the impact of noise on signal quality.

Through system testing under different noise levels, the proposed method demonstrated superior stability compared to traditional MRC and MMSE methods, confirming its stronger robustness against channel noise.

It should be noted that the current evaluation focuses on moderate to high SNR regimes (≥ 0 dB), where the proposed method demonstrates clear advantages. In extremely low-SNR conditions (e.g., < 0 dB), the performance may degrade relative to model-based methods like MMSE, primarily due to limited coverage of such scenarios in the training data. This represents a known limitation of the current framework, and addressing ultra-low-SNR robustness is left for future work.

4.6. Ablation Study

To quantify and verify the contribution of each design component, we conducted an ablation study by systematically removing or replacing key components of the framework (such as modules, loss terms, input modalities, etc.) and reporting the resulting performance changes. All performance differences were assessed for significance using a two-sample *t*-test (95% confidence level).

Table 5 presents the performance changes and statistical test results after removing different components, using the complete model as the baseline.

Table 5. Ablation Study Performance Comparison and Statistical Significance Test (Complete Model as Benchmark).

Experimental Setup	Signal Transmission Quality (SNR, dB)	Computational Overhead (FLOPs)	<i>p</i> -Value (vs. Complete Model)
Complete Model (Proposed Method)	28.1 ± 2.3	1.2 × 10 ⁶	—
Remove Denoising Mechanism	24.2 ± 2.5	1.3 × 10 ⁶	<0.01
Remove Feature Fusion Module	25.6 ± 2.2	1.4 × 10 ⁶	<0.05
Remove Adaptive Adjustment Strategy	26.1 ± 2.4	1.6 × 10 ⁶	<0.05
Remove Multiple Modules	22.3 ± 2.1	1.8 × 10 ⁶	<0.01

The experimental data show that removing any core module leads to a performance decrease. Specifically: Removing the denoising mechanism reduced signal transmission quality (SNR) from 28.1 dB to 24.2 dB, a decrease of 3.9 dB, with a high statistical significance ($p < 0.01$). Removing the feature fusion module resulted in an SNR of 25.6 dB (a 2.5 dB decrease), and the computational overhead also increased ($p < 0.05$). Removing the adaptive adjustment strategy reduced the SNR to 26.1 dB (a 2.0 dB decrease), and the computational overhead increased to 1.6×10^6 FLOPs ($p < 0.05$). When multiple modules were removed, the performance loss was the most significant, with the SNR further dropping to 22.3 dB, and computational overhead significantly increasing ($p < 0.01$). This performance loss was larger than the simple sum of the individual losses from each removed module.

These results indicate that the denoising mechanism, feature fusion module, and adaptive adjustment strategy all contribute positively to model performance. The denoising mechanism plays a crucial role in maintaining signal quality. When these modules are removed simultaneously, more significant synergistic performance losses occur, highlighting their collaborative effect within the system.

Through the ablation study, we validated the effectiveness and collaborative value of each core module in ensuring system signal transmission quality and controlling computational overhead.

It should be noted that the key hyperparameters of these modules (e.g., denoising strength, fusion weights, adaptation step size) were selected via grid search on a validation set under diverse noise conditions, and the model exhibits stable performance within $\pm 15\%$ deviation from the chosen values, suggesting a practical operating range for engineering deployment.

5. Discussion

The experimental results of this study demonstrate that the proposed wireless channel optimization method based on IMS 2.0 performs well across multiple dimensions. The experimental data show that the proposed method outperforms the selected classical and SOTA baseline methods in terms of signal transmission quality, computational overhead, and system stability. The method exhibits a relatively small performance decline in high-noise environments, validating its robustness and adaptability. This is primarily due to the synergistic effects of the denoising mechanism, feature fusion module, and adaptive adjustment strategy.

The performance improvement can be attributed to the low-complexity control framework and the collaborative design of its core modules. Unlike traditional signal processing methods such as MRC and MMSE, this framework dynamically adjusts the signal transmission path through an adaptive mechanism, allowing for more effective adaptation to dynamic changes in real-world scenarios.

However, there are limitations in the current work. First, although the dataset covers various wireless environments, the model's generalization ability remains insufficient under extreme noise conditions. Second, although computational overhead has been significantly

reduced, achieving low complexity and high performance in real-time deployment for large-scale networks or multi-user environments still requires further research in resource allocation and task scheduling.

At the same time, the low-complexity and energy-efficient characteristics of the proposed method suggest its potential in latency- and power-sensitive scenarios such as IoT edge nodes and vehicular networks. However, practical deployment in these settings would require further investigation into real-time processing constraints, signaling overhead, and hardware compatibility. As 5G/6G networks continue to evolve, IMS technology may contribute to improving communication quality and efficiency, subject to these system-level considerations. Accordingly, future work should aim to enhance robustness and scalability under more diverse and demanding operational conditions.

In conclusion, this work provides both theoretical and experimental references for low-complexity optimization of IMS in dynamic wireless environments. Despite existing challenges, the technological path demonstrated lays the foundation for future research and applications.

6. Conclusions

This study addresses the application of IMS technology in wireless channel optimization, proposing a channel optimization method based on IMS 2.0, coupled with a low-complexity control strategy to improve signal transmission quality, reduce computational overhead, and enhance system robustness. Through experimental validation, the proposed method effectively enhances signal quality and maintains stability across various wireless environments and noise conditions, especially in high-noise and complex environments, where it can consistently operate and optimize signal quality.

The innovations of this study include: first, the introduction of an IMS optimization framework that integrates a denoising mechanism, feature fusion module, and adaptive control strategy, effectively addressing dynamic channel environments and interference while significantly improving signal quality. Comparative experiments show that the proposed method achieves 28.1 dB of SNR, an improvement of approximately 3.8 dB over the traditional MRC method. Additionally, the proposed method demonstrates advantages in computational overhead and energy consumption, with a 20% increase in inference speed and a 32% reduction in energy consumption.

The academic value of this work lies in the development of a new IMS optimization method, which is systematically validated for its effectiveness in complex wireless environments. This method fills the gap in current research on the application of IMS technology in high-noise and dynamic environments and provides an optimization solution for future wireless communication systems. Theoretically, this study offers new insights into IMS technology and promotes the integration of channel optimization with low-complexity control strategies.

From a practical perspective, the low-overhead, low-energy characteristics of the proposed method make it promising for resource-constrained edge communication scenarios. IMS technology is expected to play an important role in 5G and 6G networks, particularly in high-interference and noise environments, where it can optimize signal transmission, improving communication quality and network capacity. The proposed method shows potential for applications beyond traditional wireless networks, such as autonomous driving, IoT, and smart cities, though practical deployment would require further study of real-time processing latency, signaling overhead, and hardware integration constraints.

However, the performance of the proposed method remains limited in extreme noise and complex multi-user environments, particularly in resource allocation and task scheduling optimization. Future research may focus on expanding the dataset, adding more noise

samples, and improving the model's generalization ability. At the same time, optimizing algorithms and adopting distributed computing and model compression techniques will be key to addressing computational overhead. Combining millimeter-wave and visible light communication with the proposed method could extend its application to more cross-domain wireless communication scenarios.

In summary, this work provides theoretical and practical support for the application of IMS technology in wireless channel optimization. The demonstrated effectiveness in complex environments lays a foundation for its future application in communication systems. Through continuous optimization and cross-domain integration, IMS will play a greater role in next-generation wireless communications.

Author Contributions: Conceptualization, X.H.; Methodology, J.C. and Q.F.; Software, J.C.; Validation, R.Z.; Formal analysis, R.Z.; Investigation, R.Z.; Resources, X.H.; Writing—original draft, X.H.; Writing—review & editing, Q.F.; Visualization, Q.F.; Supervision, X.H.; Project administration, X.H.; Funding acquisition, X.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: This work was supported in part by the Tianjin Sino-German University of Applied Sciences Video Image Intelligent Analysis and Processing Technology Innovation Team and Tianjin “131” Innovative Talent Team.

Conflicts of Interest: The authors declare no conflicts of interest.

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