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Research Article

Improvement of Internet of Things (IoT) Interference Based on Pre-Coding Techniques over 5G Networks

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ABSTRACT

The advent of 5G technology has revolutionized wireless communication, offering unprecedented data rates, reduced latency, and enhanced connectivity. A critical component driving these advancements is Multiple-Input Multiple-Output (MIMO) technology. MIMO utilizes multiple antennas at both the transmitter and receiver ends to improve communication performance. In the context of the Internet of Things (IoT), MIMO plays a pivotal role in enhancing network efficiency, reliability, and capacity and can improve system capacity and reduce interference between different users. By leveraging MIMO, IoT devices can achieve higher data throughput and better signal quality, even in challenging environments. This is particularly important for IoT applications that require real-time data transmission and low latency, such as smart cities, autonomous vehicles, and industrial automation. Additionally, MIMO technology helps in mitigating interference and improving spectrum utilization, making it an essential enabler for the massive connectivity demands of IoT networks in the 5G era. However, due to the high channel dimension, complex channel estimation and precoding algorithms in the system, the system hardware and software overhead will increase. The precoding algorithms of massive MIMO systems are divided into three types: digital, analog and hybrid. The three types of precoding algorithms are summarized and compared, and the advantages and disadvantages of different precoding algorithms and applicable scenarios are summarized. The channel estimation schemes are divided into training estimation and blind estimation, and the advantages and disadvantages of the two types of schemes are summarized. It is pointed out that the reasonable use of the channel sparsity of massive MIMO can improve the quality of channel estimation and reduce the estimation overhead.

1. INTRODUCTION

The Internet of Things (IoT) represents a massive network of interconnected devices, ranging from everyday household items to advanced industrial machinery. By enabling these devices to communicate and share data, IoT has the potential to significantly enhance network performance and reliability. One of the key benefits of IoT in networking is its ability to provide real-time data collection and analysis. This allows for proactive monitoring and management of network resources, leading to more efficient and effective operation [1]. It has been expected to play an important role in human communication and enable machine connectivity to devices[2]. As the number of these devices steadily increases, reliable and efficient wireless connectivity delivering high-speed data and low latency is essential, which necessitates more coverage and more reliable data [3]. This technology includes these devices that extract data together and enable exchanges, where each item is uniquely identified by embedded computer systems, as well as working with existing internet systems. Although current 4G networks have been widely used in the IoT and 4G continues to mature to meet the needs of future IoT applications, existing IoT solutions face many challenges, such as the number of nodes, security, and new standards possibly integrated with the IoT. Thus, 5G networks will greatly enhance modern IoT, enhance cellular performance, IoT security, and connectivity challenges, and put the future of the internet in their hands [4]. It is easy to predict that, in the coming years, billions of users in metropolitan areas will need to send and receive holographic video continuously, which will require increasing the data rates and spectral efficiency of radio transmissions, increasing dramatically, approximately 100 Mbps per user in each passing [5]. New requirements for future applications in the IoT, such as an estimated 7620 new devices connected to the internet every minute and the growth of 5G wireless technologies, are two of the key developments enabling 5G-enabled IoT [6].

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The advent of 5G technology has brought about significant advancements in wireless communication, particularly in the realm of the Internet of Things (IoT). Precoding technology uses CSI to pre-process the transmitted signal at the transmitter of the downlink to minimize the interference between different users and antennas, and concentrate the signal energy near the target user, so that the receiver can obtain a better signal-to-noise ratio (SNR) and enhance the channel capacity of the system. The two primary issues of precoding are acquiring Channel State Information (CSI) and determining the precoding matrix. The utilization of large-scale antennas results in an increase in the dimensions of both the channel matrix and the precoding matrix, the algorithm complexity, system hardware cost and implementation difficulty will increase. Many research works have been carried out to minimise the computational complexity and overhead of the system: in [7], the authors proposed to use Newton and Chebyshev iteration to estimate the channel matrix inverse to minimize the computational complexity of the zero-forcing (ZF) inverse in it is precoding scheme; in [8], the authors used signal-to-leakage-to-noise ratio (SLNR) instead of the signal-to-interference-to-noise ratio (SINR) as the optimization target for solving the precoding matrix in the Multiple Input and Multiple Output (MIMO) scenario, effectively avoiding the related problems of non-deterministic polynomial difficulty. Hence, the (MIMO) being a one of the main technologies enabling these improvements. MIMO platforms utilize several antennas at the receiving and transmitting ends to improve communication efficacy. This technique is crucial for meeting the ever-increasing demands for higher data rates, improved reliability, and efficient spectrum utilization in IoT networks. By increasing spectral efficiency, data rates, reliability, coverage, and energy efficiency, MIMO enables more robust and efficient communication for the ever-expanding IoT ecosystem[8][31]. The precoding system can be categorized under digital baseband precoding of signals, analog radio frequency precoding, and hybrid precoding, depending on how the precoding matrix operates at the baseband or radio frequency (RF). For digital baseband precoding, conventional nonlinear as well as linear precoding are capable of being directly implemented in large-scale MIMO platforms; however, the computational complexity for nonlinear precoding is significantly high, making the linear approach more favourable. Analog precoding can substantially diminish system hardware overhead, however at the expense of certain performance metrics. Hybrid precoding, a recently developed approach, integrates the benefits of digital and analog precoding, balancing hardware overhead with system speed [9]. Channel estimation can be divided into training estimation and blind estimation according to whether it introduces training signals. Training estimation requires designing different pilot sequences for each user. Due to the large number of users in the cell, large-scale MIMO has serious pilot pollution. Blind estimation estimates the channel and transmitted signal directly based on the received data. Since large-scale antennas are deployed at the base station, the complexity and computational complexity for estimation algorithm are very high[10]. This paper aim of to improve and reduce the interference between the waves of devices connected to each other through the IoT.

2. RELATED WORKS

Many previous studies dealt with the issue of data mining through the use of clustering techniques and compared the results of each technique by evaluating those results. In this part of the paper, we discuss the most important previous studies, which are similar to our current study. The study by Mario Pons et al. [11], introduces 5G and IoT technology and describes typical IoT applications, common topologies, and recurrent issues. Furthermore, in their study, they discussed interference in all wireless applications, special interference in 5G networks, The Internet of Things and potential optimization techniques. to overcome these challenges. In their study, they used 5G networks to ensure reliable and efficient connectivity for IoT devices, and stress was placed on the importance of reducing and optimizing network infrastructure, which is critical for successful business systems. Companies that use this technology to increase productivity, reduce downtime, and increase customer satisfaction have benefited from this knowledge. They also highlighted the possibility of integrating web services to improve internet access and speed, opening the door to new and innovative applications and applications.

There is a great deal of research on network design for higher costs, and the advantages of the widespread use of high-output MIMO for broadband communications are well known. However, how the IoT, in terms of significantly different requirements and constraints for broadband communication and the widespread adoption of MIMO for the IoT, is still a growing issue. In their study, Alexandru-Sabin Bana et al. [12] investigated the feasibility of large-scale MIMO in IoT communication. They specifically addressed the ultra-reliable low-latency connections (URLLC) and massive device-type connections and that make up the two broad categories of IoT connections envisioned for a 5G network. By describing the potential and difficulties in utilizing the enormous MIMO of IoT connections, this article closes this significant gap. They offered many acceptable connection strategies and provided insights into the trade-offs that occur when massive MIMO is applied to mMTC or URLLC. Network slicing of wireless resources and concurrent large MIMO utilization to enable IoT connections are still being discussed, with extremely diverse requirements. The major finding is that mass MIMO technology can be advantageous in IoT connection scenarios, but doing so necessitates good coordination between physical layer technologies and protocol design.

Abed et al. [13], used resources effectively to build an IoT network system that performs better and is more dependable. By combining two different types of algorithms, such as the dynamic method (adaptive firefly) and the static technique (weighted round robin), load balancing has been used in cloud computing for dynamically spread the workload between nodes to prevent overloading of any one resource. The results show increased throughput, higher throughput, and shorter response times.

3. PRECODING IN 5G

Precoding is the process of transmitting signal processing necessary to optimize the signal received for specific receivers and antennas while reducing interference for all other receivers and antennas. Precoding is the procedure of configuring a radio frequency system's transmission signal. Precoding utilizes transmitter channel state information to enhance performance and improve spectral efficiency. Spatial multiplexing is employed to achieve the superposition of multiple beams, consisting of various distinct data streams.[14].

Precoding and beam shaping are frequently used interchangeably in WiFi, 4G networks, and 5G networks, however they are not the same. Precoding describes a software application related to communication theory, while beam shaping explains hardware implementation along with system antennas. Furthermore, beam shaping can be utilized on both receivers and transmitters, while precoding usually refers to the transmitter side.[15][16].

The amplitudes and signals transmitted phases from the various transmitting antennas are individually controlled during precoding. Beam forming can better direct energy toward the target receiver when precoding is used. In later publications, many facets of beam forming and second-generation beam forming will be covered[17][37].

For several communication technologies, including WiFi, 4G, and 5G, precoding is employed. Precoding assumes that the transmitter has been cognizant of the channel's state information (CSI). Precoding begins with channel sounding, which includes transmitting a coded message to the receiver (also known as a sounding packet or a pilot signal). Every user replies to the transmitter with it is unique CSI. The precoding (spatial mapping) matrix for subsequent data transfer is set using the consumers' CSIs[14].

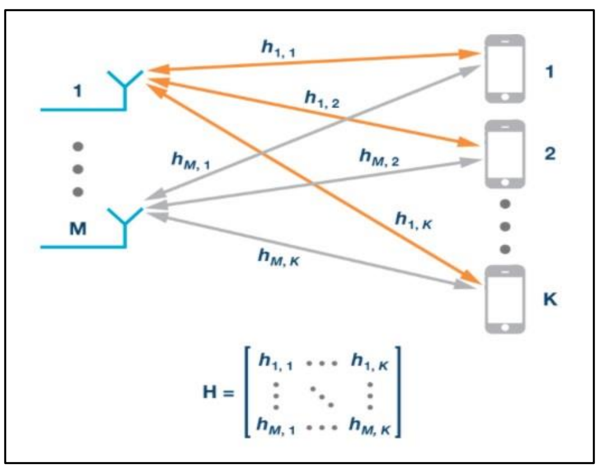

Fig. 1. Channel state information is required to characterize a massive MIMO system[16].

4. PRECODING SCHEMES

4.1 Digital Precoding Scheme

Digital baseband precoding serves as the process used to process the modulated signal stream with a matrix prior to the digital-to-analog conversion. This approach necessitates that the quantity of RF chains be equivalent to the quantity of antennas in order to achieve optimal system performance. In traditional MIMO platforms, both nonlinear and linear precoding schemes can be effectively utilized in large-scale MIMO platforms as a digital baseband precoding scheme, but nonlinear precoding such as dirty paper (DPC) has high algorithm complexity, and the computational complexity can be increase sharply as the number of antennas increases. In addition, GAO X et al. [18] conducted actual measurements and found that in large-scale MIMO platforms, low-complexity linear precoding can achieve 98% of the performance of DPC precoding. Therefore, linear precoding is the standard method used for millimeter-wave large-scale MIMO. The most frequently used linear precoding methods are truncated polynomial expansion (TPE), minimum mean square error (MMSE), Zero Forcing (ZF), and maximum ratio transmission (MRT).

MRT is also called matched filter scheme (MF) in many literatures [19], [20]. The precoding matrix and the signal received by the user can be defined as:

$$P_{MRT} = \beta H \quad (1)$$

$$y_{MRT} = \sqrt{\rho}\, \beta H^H H s + n \quad (2)$$

Where β is the scaling factor that is employed to limit the transmission power of the signal. The fundamental concept in the MRT technique is to optimize the signal gain for the intended user [19], [21], However, it does not take into account the interference between different users, therefore thus is only suitable to scenarios that have low channel correlation. In highly correlated channels, a scheme's performance will decrease significantly. Additionally, as the number of base station antennas increases, the channel vectors in H tend to be mutually orthogonal, making H^H H similar to a diagonal matrix. The MRT scheme's performance starts to progressively become apparent [22], [23]. Thus, the MRT method is more appropriate for situations involving a large number of the base station antennas.

The MRT system ignores the interference among several users and concentrates just on the valuable signal for the target user. ZF represents the reverse. It is dedicated to remove the interference between several users and ignores the effect of noise. One may represent the precoding matrix as well as the signal vector for the ZF technique as[24]:

$$P_{ZF} = \beta H (H^H H)^{-1} \quad (3)$$

$$y_{ZF} = \sqrt{\rho}\ \beta H^H H (H^H H)^{-1} s + n \quad (4)$$

The ZF solution can achieve a good system sum rate in the area with high SNR; in the area with low SNR, because it does not take into account the impact of noise, the overall rate that the system is capable of achieving is not as high as the rate that the MRT solution is able to achieve. [24]. The ZF solution needs to perform inverse operations on the (K × K) dimensional matrix, and the number of operations will increase with the increase of the number of users. Therefore, the ZF approach is appropriate for situations in which there are a limited number of users.

However, ZF can significantly amplify noise, especially when a channel matrix exhibits ill-conditioning or when the signal-to-noise ratio is low. This noise enhancement can degrade overall system performance. Regularized Zero Forcing (RZF) is considered one of the most practical and reliable precoding schemes in large-scale MIMO platforms [25]. It aims to address the limitations of ZF by incorporating a regularization term that balances interference cancellation and noise enhancement. The fundamental concept is to reduce the mean square error of the received and transmitted signals referred as minimum mean square error (MMSE) precoding method. The signal received and the precoding matrix are computed as follows.:

$$P_{RZF} = \beta H (H^H H + \alpha I_K)^{-1} \quad (5)$$

$$y_{RZF} = \sqrt{\rho}\ \beta H^H H (H^H H + \alpha I_K)^{-1} s + n \quad (6)$$

Where α is the regularization coefficient, which is related to the total transmission power P of the base station and the noise power σ^2. RZF precoding combines the advantages of ZF and MRT schemes. When α → 0, Equation (5) becomes the ZF scheme, and when α → ∞, Equation (5) evolves into the MRT scheme [26]. RZF needs matrix inversion, with a computational complexity of 3〖MK〗^2. [27]. Thus, this technique is appropriate for situations involving a limited number of users. Furthermore, numerous studies have shown that a simpler iterative method may serve as a substitute for the inversion operation of RZF [7], [25].

With developing RZF, the TPE evolved from the RZF scheme [13]. The fundamental concept is to employ matrix polynomials for approximating the inverse value of the matrix within the RZF framework. According to Lemma 1 in reference [14], equation (5) can be transformed into the TPE precoding matrix through a series of transformations:

$$P_{TPE} = \sum_{l=1}^{j-1} \omega_l\, (H^H H)^l H^H \quad (7)$$

$$y_{TPE} = \sqrt{\rho}\ \sum_{l=1}^{j-1} \omega_l\, (H^H H)^l H^H s + n \quad (8)$$

Where ω_l is a scalar coefficient and j represents the polynomial order. In fact, when j = 1, the polynomial becomes $P_{TPE} = \omega_l = \omega_l H^H$, that is, the MRT precoding matrix, and when j = K, the RZF precoding matrix can be obtained. The TPE precoding algorithm can avoid complex inversion operations, and the polynomials can be solved simultaneously to improve the computational efficiency. Furthermore, due to the divisibility of parameter j, the technique can be readily implemented via hardware. Nevertheless, in terms of performance, its performance can only approach that of the RZF algorithm when j is very large, and the larger the j, the greater the hardware overhead. In addition, the TPE algorithm can only approximate the performance of the RZF when the number of base station antennas is much larger than the number of users. When the number of base station antennas decreases or the number of users increases, its performance will be affected and deteriorate. Table 1 summarizes the pros and cons of different digital precoding schemes.

TABLE I. PROS AND CONS OF DIFFERENT DIGITAL PRECODING SCHEMES

Precoding Scheme	Pros	Cons
MRT/MF	• Maximize the signal gain of the target user • Low computational complexity • Better performance in low SNR areas • Near-optimal performance can be achieved when there are enough base station antennas	• Interference between users is not considered • When the number of base station antennas is small, the system can reach, and the rate is low
ZF	• Low computational complexity • Better performance in high SNR areas • Eliminates interference between multi-user channels • Achieves performance similar to dirty paper coding	• If the channel is highly correlated, the noise will be amplified • Channel inversion is required • Cannot support a large number of users
RZF/MMSE	• Combines the advantages of MF and ZF, while considering the effects of interference and noise	• Channel inversion is required • Cannot support a large number of users
TPE	• Avoids inversion and improves computational efficiency • A compromise between precoding complexity and system throughput • •When there are much more base station antennas than users, better performance can be obtained.	• Performance is limited because of the polynomial series • High performance needs high hardware consumption • When the amount of the base station antennas is limited, the system's reach is constrained, and the rate is diminished

4.2 Analog Precoding Scheme

Analog precoding refers to the manipulation of the input symbol stream subsequent to digital-to-analog conversion. This method may simultaneously link several antennas to a radio frequency chain. It is highly appropriate for scenarios involving a substantial number of antennas for massive MIMO platforms. It can substantially decrease hardware expenses and exhibits minimal computational complexity. Analog precoding could be classified into two groups based on the distinct devices employed: The initial category involves a phase shift solution utilizing an economical phase shifter to regulate the signal phase emitted by every antenna; the subsequent category pertains to an antenna selection solution. Utilize cost-effective RF switches that activate the necessary portions of the antenna.[28].

Phase-shift-based scheme Finding a suitable phase-shift matrix is the key to the phase-shift-based scheme. The simplest strategy is to use the channel matrix's phase shift matrix to derive the components' phases[29], however, the phase shifter's restriction in practical applications requires quantization of the ($M \times K$) phases., and the quantization error will greatly reduce the performance of the precoding scheme. In [30], the author uses the power iteration approach to solve the set of phase sets. This algorithm can converge after 3 to 4 iterations, but it requires the sender to continuously send training sequences to the receiver, which results in a large training overhead. In other hand, the antenna selection-based on-off (OF) analog precoding scheme [32] uses cheap RF switches to replace analog phase shifters. When transmitting a signal, antenna subarrays with similar phases and better channel conditions are selected to be activated to generate transmit beams. Hence, the selection of antenna is dependent on the criterion of maximizing SNR. The results show that their scheme can obtain full antenna gain and full diversity gain, however, its performance can't exceed that of the scheme based on phase shift. The upper limit of the difference between the two achievable total rates is ($2 \log \pi$). Simulation results in the literature show that this type of scheme performs better when the number of base station antennas is large. When selecting working antennas, the maximum power standard [33], [34] can also be used to select the transmit antenna set corresponding to the channel vector with the maximum power. This solution does not require SNR calculation and has low complexity, but the antenna gain is low, and the overall performance is poor. Compared with the solution based on phase shift, the solution based on antenna selection can further reduce the hardware cost and power consumption, but its performance is worse than the precoding solution based on phase shift, and it requires the support of a certain complexity of antenna selection algorithm. The complexity of the algorithm increases exponentially with the number of antennas [35]. Generally speaking, the analog precoding scheme does not need to configure an RF chain for each transmitting antenna, which greatly reduces the hardware cost. However, it lacks the adjustment of signal amplitude, so the performance is generally not as good as the digital precoding scheme. Table 2 summarizes the pros and cons of different analog precoding schemes.

TABLE II. PROS AND CONS OF DIFFERENT ANALOG PRECODING SCHEMES

Precoding Scheme	Pros	Cons
Phase-shift based approach	• Signal phase can be adjusted • All antennas are activated, antenna gain is high • Low cost	• Signal amplitude cannot be adjusted
Antenna selection-based solution	• Low cost	• Only part of the antenna is activated, and the antenna gain is low • Signal phase and amplitude cannot be adjusted • Only one user can be served at a time

4.3 Hybrid Precoding Scheme

In massive MIMO platforms, digital precoding can achieve good system performance, However, it necessitates an RF chain for every transmit antenna, resulting in high costs. Analog precoding is more economically favored than digital precoding; however, every coefficient of an analog precoding matrix maintains a constant modulus as well as lacks amplitude control, leading to inferior performance compared to digital precoding. The hybrid digital/analog precoding technologies amalgamates the benefits of both methodologies, facilitating amplitude and phase adjustments while minimizing the number of radio frequency chains. The hybrid precoding transmission structure is illustrated in Figure 2 [36].

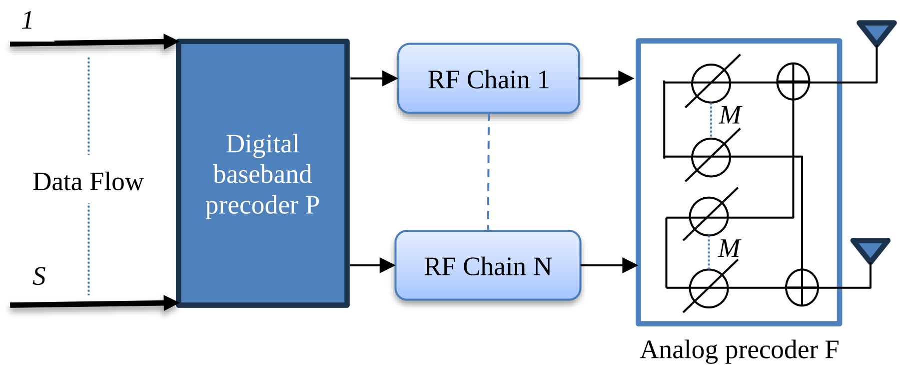

Fig. 2. Hybrid precoding system structure[35]

The RF chain in Figure 2 consists of a digital-to-analog converter (DAC)/analog-to-digital converter (ADC), a mixer, and a power amplifier. Each RF chain is connected to all antennas through a phase shifter, and each antenna array element outputs a linear combination of all RF signals. The phase of the channel matrix is extracted to form an analog precoding matrix. The channel after the analog precoding matrix is used as the baseband equivalent channel. At the baseband, the ZF scheme is used to solve the digital precoding matrix. Its precoding matrix consists of two parts. At the RF, the analog precoding matrix can be expressed as[35]:

$$F_{i,j} = \frac{1}{\sqrt{M}} e^{j\varphi_{i,j}} \tag{9}$$

Where $F_{i,j}$ represents the (i,j)th element of the matrix F, and $\varphi_{i,j}$ represents the phase of the (i,j)th element of the channel matrix H.

5. METHODOLOGY AND SIMULATED SYSTEM

Based on hybrid precoding transmission structures are shown in Figure 2, we intend to reduce complicity by combined the ZF and MRT schemes based on the structure in Figure 2 to divide the antenna array into several groups. The antenna array can be divided into N subarrays, and every RF chain has been connected to a subarray that can reduces the system complexity. The baseband data stream transmission is passes through the digital precoder to form N output streams, and is up transformed to RF chain, and next it mapped to M antennas through the analog precoder and sent out. Hence, the MRT scheme is utlized within the group, while the ZF scheme is utilized between the groups. In this paper, we simulate the performance of the proposed scheme based on the measured small cell scenario. Figure 3 show the proposed model scheme.

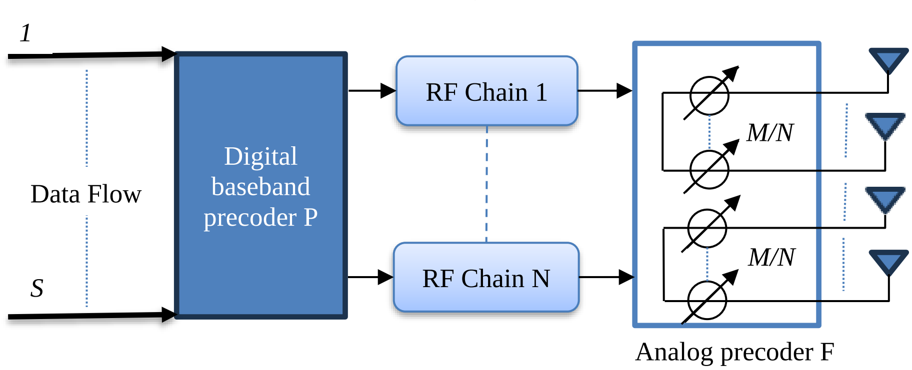

Fig. 3. Hybrid precoding system structure

At the baseband, the digital precoding matrix can be expressed as:

$$P_{ZF} = H_{eq}^{H}(H_{eq}H_{eq}^{H})^{-1}\Lambda \tag{10}$$

where, H_{eq} is the equivalent channel after F, $H_{eq} = H^{H}F$, and Λ is a diagonal matrix used to limit the power of the transmitted signal. It can be seen that the equivalent channel H_{eq} is a (K × K) dimensional matrix. Compared with the original channel matrix, the number of rows is reduced from M rows to K rows, which greatly reduces the complexity of the inverse operation. In addition, the PZF scheme can support the simultaneous transmission of K data streams and only requires K RF chains; but its performance will be constrained by the ZF scheme to varying degrees and can never exceed the ZF scheme. However, the hybrid precoding transmission structures is a complex structure, thus in this study we presented a hybrid precoding transmission with low-complexity structure. Multiplying a preprocessed matrix with the P IoT data stores the result in a submitted data transformation, which represents prepackaged data ready to be transmitted. Transmitted data can now be transmitted over 5G networks, leveraging the benefits of preencryption to improve the efficiency and reliability of wireless connectivity in IoT applications. Interference is added to broadcast data because the interference in the received data reflects the actual conditions of wireless communication and enables analysis of system robustness and performance in the presence of noise precoded data transmitted over the 5G network, which includes the transmitted variant. Interference throughout the transmission-receiving process is simulated via this random vector. The received data contain random noise or interference due to interference added to the transmitted data. To improve the accuracy of the decoded data so that it closely matches the transmitted data, we can use either TPE or RZF instead of simple ZF. TPE, as explained in section 4.1 (table 1) requires a lot of hardware consumption in order to achieve high performance so it is not useful to IoT networks. Thus, RZF is the preferred choice that can add a regularization parameter to balance interference cancellation and noise amplification. Hence, the equation 10 can be rewritten based on equation:

$$P_{PRZ} = \beta H_{eq}^{H}(H_{eq}H_{eq}^{H} + \alpha I_{K})^{-1} \tag{11}$$

The alpha parameter (α) helps to balance between noise amplification and interference cancellation. Where it can adjust this value based on system requirements.

The post-coding matrix Q_{PRZ} is calculated similarly to balance the system via the following equation:

$$Q_{PRZ} = \beta H_{eq}^{H}(H_{eq}H_{eq}^{H} + \alpha I_{K})^{-1} \tag{12}$$

H_{eq}^{H} represents the pregenerated channel matrix with numIoT dimensions according to the number of antennas. The denominator $H_{eq}^{H}H_{eq}^{H}$ represents the substitution product of H_{eq}^{H}.

This matrix function is often used in communication systems to improve the acquired signals by applying postprocessing techniques. The post coding matrix is crucial for enhancing reception quality and mitigating congestion for wireless communication systems. This facilitates the extraction of significant data out of the received signal to subsequent processing and analysis. The acquired data are extracted using a post-encoding matrix, denoted as Q, representig the previously calculated post-coding matrix. The returned data include the recovered information, incorporating additive overlap. The decoded data variable is obtained by multiplying the post-encoding matrix Q by the received data, thereby representing the encoded form of the received data. This decoding process aims to mitigate interference and recover the original data transmitted by IoT devices. The processed data can subsequently yield significant insights, enhancing decision-making in IoT implementations and strategies. MATLAB R2023b software was employed to develop code simulating IoT and 5G networks. The code was designed to configure the network and simulate data transmission and reception. The simulation framework of the proposed system is illustrated in Figure 4.

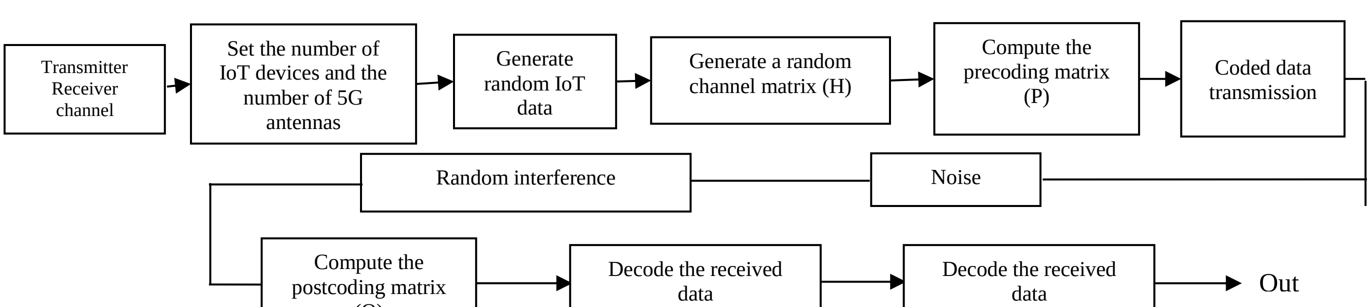

Fig. 4. The scheme of the proposed system

Figure 4 show the application of precoding and post-coding techniques within a 5G network framework comprising multiple IoT devices and antennas. These strategies aim to enhance the reliability and quality of data transmission. In a Multiple Input Multiple Output (MIMO) system, the channel matrix Hrepresents the interaction between the transmitting antennas and the receiving apparatus. Here, H=rand (number of IoT Devices, number of Antennas) generates a random channel matrix $H$with dimensions 50 (IoT devices) x 10 (antennas). Each element in this matrix denotes a channel coefficient that signifies the interaction strength between an IoT device and an antenna.

6. RESULTS AND DISCUSSION

The simulation demonstrates the application of precoding and post-coding techniques within a 5G network context, comprising multiple IoT devices and antennas. These strategies aim to enhance the reliability and quality of data transmission..

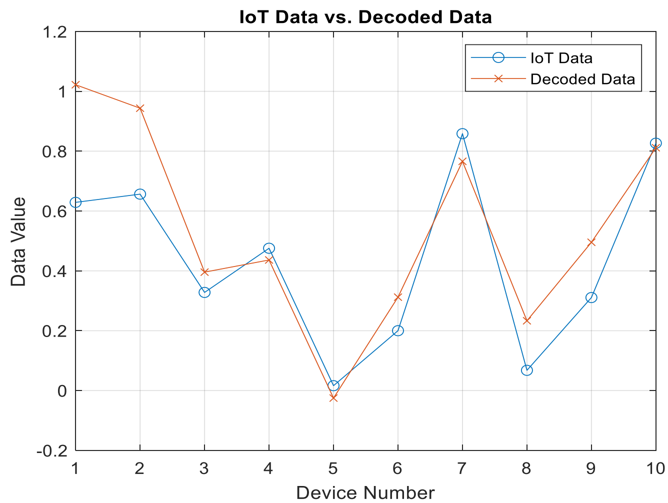

Fig. 5. IoT data versus decoded data

Figure 5 shows the comparison between the transmitted IoT data and the decoded data. The transmitted data points are marked with circles (o-), while the decoded data points are marked with crosses (x-). The results show that the decoded data are closely matches the original IoT data, indicating the effectiveness of the proposed approach. The precoding strategy enhances transmission by utilizing alterations to the data depending entirely on the channel matrix H. These changes mitigate the effects of noise and interference in wireless communication networks. The computed precoding matrix P ensures that the given transmitted records match the particular type of the channel.

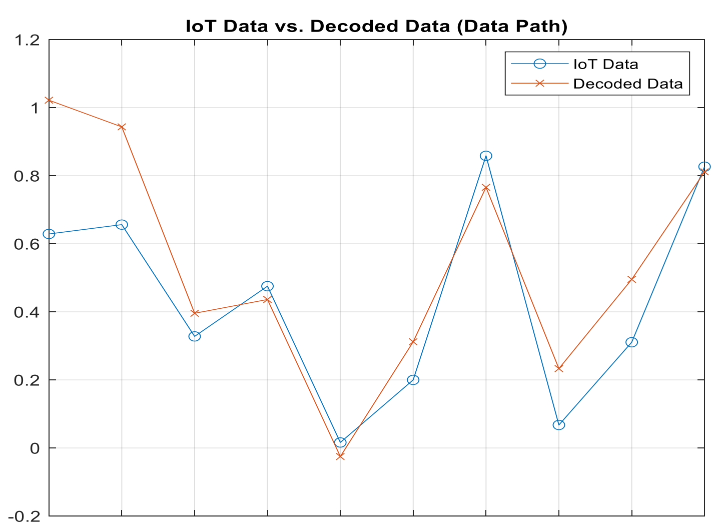

Fig. 6. IoT data versus decoded data with a data path

Figure 6 provides a comparison of the transmitted IoT data and the decoded data with specific data path. The X-axis represents the antenna index, and the Y-axis represents the data values. Figure 6 helps visualize how each antenna's data was transmitted and decoded to replicate real-world circumstances during transmission, random interference was included to the obtained data. Other wireless transmissions, environmental restrictions, and signal attenuation are among the several causes of this interference. This noise addition to the obtained data helps the simulation to consider the challenges in real-world wireless communication situations.

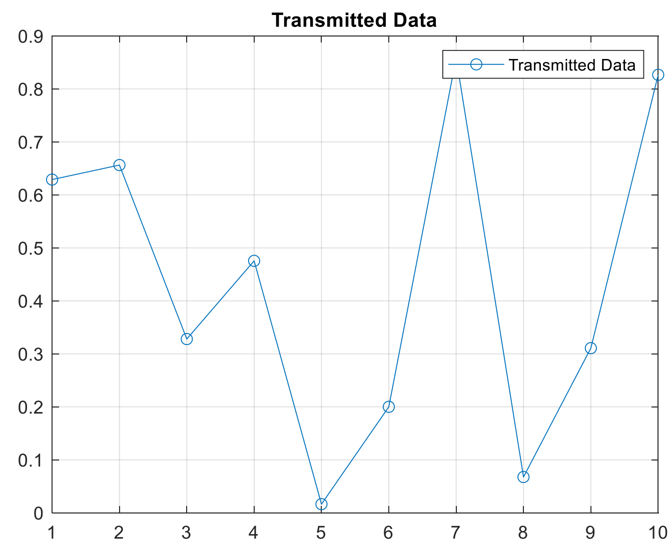

Fig. 7. Transmitted data over 5G

Figure 7 displays the transmitted data over a 5G network, marked with circles (o-). The results show the values of the data being transmitted from the IoT devices through the 5G network, showing the initial data set before any interference or noise is added. By use of the projected post coding matrix Q, the post coding process seeks to reverse the influence of precoding and eradicate the generated interference. By means of a post coding matrix, multiplying the acquired data generates decoding data, which ought to fit the original IoT data rather effectively.

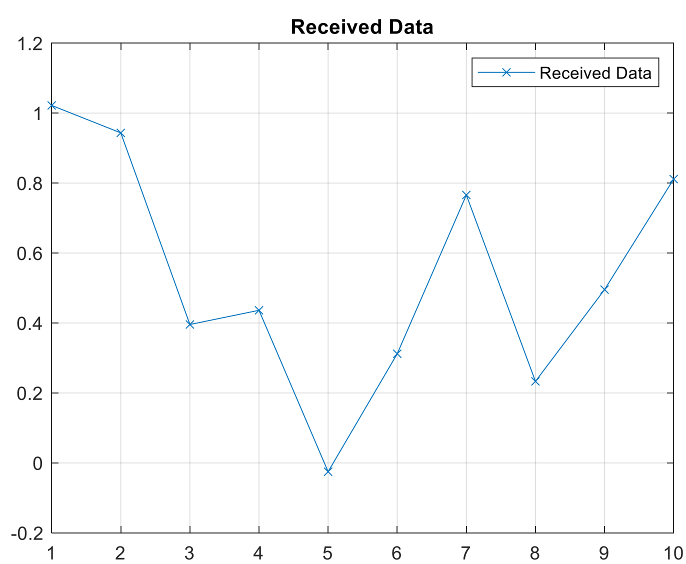

Fig. 8. Received data over 5G

Figure 8 presents the received data after the decoding process, also marked with crosses (x-). It illustrates the efficacy of the decoding method by alleviating the impacts of interference along with noise, presenting the rectified values for the received data. The findings indicate that employing precoding and post-coding techniques can improve the accuracy and reliability of data transmission in 5G networks; however, it is crucial to recognize that this artificial environment has been simplistic and does not capture the more complex real-world applications and algorithmic principles.

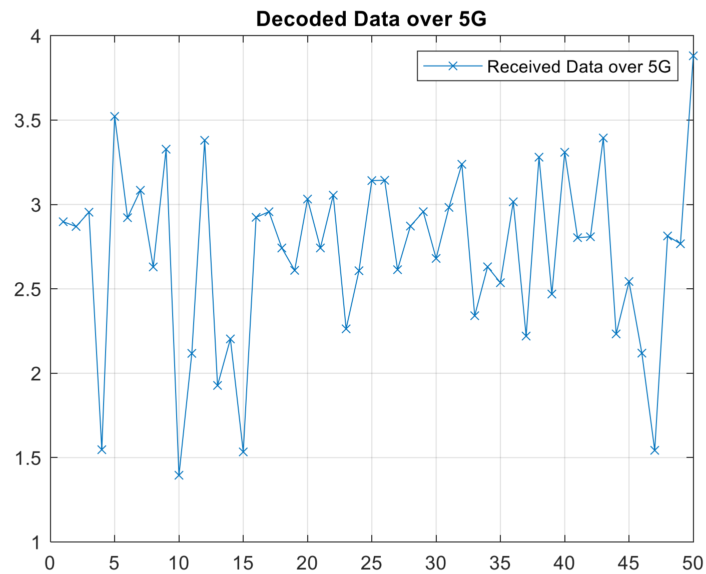

Fig. 9. Decoded data received via 5G

Figure 9 illustrates the received data including interference represented by crosses (x-). The data displayed has been sent via the 5G network and subjected to noise or as interference, potentially compromising the integrity for the received signal.

7. CONCLUSION

This study illustrates the application of precoding and post coding techniques in a 5G network environment equipped with numerous IoT devices and antennas. The objective of these techniques is to enhance the precision and accuracy of data transmission. The precoding process improves transmission by applying transformations to the data on the premise of the channel matrix H. This modification mitigates the interference and potential noise effects in wireless communication systems. The transmitted data are sufficient to accommodate the channel's distinctive characteristics, as guaranteed by the computed precoding matrix P. The randomized intervention was expanded to replicate a real-world scenario and was incorporated into the existing data. This interference can be the result of a variety of factors, including signal weakness, environmental interference, and other line propagation. By incorporating this cacophony into the acquired data, the simulation replicates the obstacles that arise in real-world wireless communication scenarios. Using the calculated post coding matrix P, the post coding process endeavours to eradicate the effect of precoding and the added interference. Post coding the image of the acquired data is necessary to decode the due data in order to achieve a satisfactory match with the original IoT data. However, in large-scale MIMO systems, digital baseband precoding can achieve good performance, but the hardware overhead is large. Among them, when there are many antennas in the system or the noise elimination requirements are high, RZF precoding should be used first; when the number of system antennas is small or the channels are highly correlated, ZF precoding should be used; when the system has high requirements for algorithm complexity and performance, TPE algorithm should be considered. Analog precoding schemes can be used in cases where the cost is not considerable, among which the scheme based on antenna selection has the lowest system hardware cost requirements. In cases where there are high requirements for system performance and hardware overhead, hybrid precoding schemes can be used. Among them, the PZF scheme is suitable for the situation where multiple data streams are transmitted simultaneously, and the ZF-MRT scheme can flexibly adjust the number of RFs and can compromise between system performance and hardware overhead according to actual needs. Based on the hybrid precoding transmission structures, we propose a method to reduce system complexity by combining Zero-Forcing (ZF) and Maximum Ratio Transmission (MRT) schemes. The antenna array is divided into N sub-arrays, each connected to a dedicated RF chain, thereby simplifying the overall architecture. The baseband data stream is processed through a digital precoder to produce N output streams, which are subsequently upconverted to RF and mapped to M antennas using an analog precoder. The MRT method is implemented within each group, while the ZF method has been implemented between groups. In summary, the combination of hybrid precoding methods in IoT and 5G networks presents a promising opportunity to enhance performance and reduce system complexity, thereby facilitating more reliable and effective wireless communication.

Conflicts of interest

The authors declare no conflicts of interest.

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