Decentralized Alternating Direction Method of Multipliers for Optimal Analog Transceiver Performance

Jyothi B R[1] and Dr. Manja Naik N[2]
[1]*Assistant Professor, Department of E and C Engineering, K. L. S Gogte Institute of Technology, Affiliated to Visvesvaraya Technological University, Belagavi-590018, India*
[2] *Professor, Department of E and C Engineering, University B D T College of Engineering, Affiliated to Visvesvaraya Technological University, Belagavi-590018, India*

Abstract:-This research introduces a Decentralized Alternating Direction Method of Multipliers (D-ADMM) model for optimizing analog transceivers with modulus constraints. Addressing the limitations of centralized and distributed ADMM approaches, the proposed D-ADMM model achieves a balanced trade-off among transceiver performance and hardware complexity. The optimization process involves iterative updates at each node and local fusion centers, ensuring consensus in a decentralized network. Unit modulus constraints are imposed on analog transceivers to enhance hardware feasibility. Results are discussed using spectral efficiency, bit error rate, and error rate. Simulation results demonstrate the D-ADMM's effectiveness in large-scale networks without a global fusion center. The decentralized optimization, through an iterative approach, proves its capability to handle non-convex problems and attain optimal solutions. Comparative results illustrate the D-ADMM's superiority over traditional methods, showcasing its potential for advancing analog transceiver optimization in communication networks.

Keywords*: ADMM, Transceiver Performance, Optimization, Non-Convex Problem, Spectral Efficiency, Bit Error Rate.*

1. Introduction

The Alternating Direction Method of Multipliers (ADMM) has emerged as a powerful optimization technique, particularly in solving complex problems by breaking them down into more manageable subproblems [1]. ADMM has found widespread applications in various domains due to its ability to efficiently address non-convex and large-scale optimization challenges [2]. In the context of analog transceiver optimization, ADMM is employed to achieve a delicate balance between transceiver performance and hardware complexity [3]. Traditional optimization approaches, whether centralized [4] or distributed [5], often struggle to achieve an optimal trade-off in this regard. Centralized ADMM, while effective in many scenarios, can face challenges when dealing with large-scale networks and intricate optimization problems [6]. The computational burden centralized optimization places on a single fusion center may become untenable, particularly in scenarios with multiple local fusion centers and the need for information exchange with single-hop neighbors simultaneously [7]. This limitation becomes more apparent in large-scale networks where deploying a single global fusion center is impractical. Distributed ADMM, on the other hand, seeks to address some of the shortcomings of centralized optimization by distributing the optimization task across nodes [8].

However, achieving a balanced trade-off between transceiver performance and hardware complexity remains a challenge. The complexity lies in coordinating the optimization process across multiple nodes and fusion centers, especially when dealing with unit modulus constraints and intricate objective functions [9]. The inherent trade-off between performance metrics and hardware complexity is often not adequately addressed, leading to suboptimal solutions [10]. Remarkably, despite the growing significance of achieving an optimal balance in transceiver design, very little work has been dedicated to implementing a Decentralized ADMM (D-ADMM) for this purpose [11,12]. D-ADMM holds the potential to overcome the limitations of both centralized and distributed approaches [4,13]. By allowing local fusion centers to iteratively update their parameters and collaborate in achieving consensus, D-ADMM offers a more scalable and efficient solution [14].

This research aims to fill this critical gap in the existing literature by proposing and implementing a D-ADMM model tailored for analog transceiver optimization. The emphasis is on achieving a balanced trade-off between transceiver performance metrics, such as spectral efficiency and bit error rate (BER), and hardware complexity, including considerations for unit modulus constraints. The decentralized nature of the ADMM framework ensures that computational load is distributed across nodes, enabling scalability in large networks. Through a series of simulations and analyses, we demonstrate how D-ADMM outperforms centralized and distributed counterparts in achieving an optimal balance, showcasing its potential for widespread application in large-scale communication networks. Hence, the contribution of this work is as follows

- This research contributes by proposing a novel D-ADMM model tailored for analog transceiver optimization, addressing the limitations of both centralized and distributed approaches.
- The work focuses on achieving a balanced trade-off between transceiver performance metrics, such as spectral efficiency and bit error rate, and hardware complexity, through the application of D-ADMM.
- By harnessing the decentralized nature of ADMM, this research ensures scalability in large communication networks, allowing for efficient optimization without the computational burden associated with a single global fusion center.

2. Literature Survey

The literature survey encompasses a broad spectrum of research works that contribute to the field of communication systems optimization. These works cover diverse objectives, methodologies, and findings, providing insights into various optimization techniques and their applications. In [15], addressed nonconvex optimization problems and proposed a Regularized ADMM (RADMM). The methodology involved proving the global convergence of the algorithm using an augmented Lagrangian function. The results indicate improved Mean Square Error Rate. In [16], focused on exploiting the sparsity and low-rank property of channels for channel estimation. The Symmetrical ADMM (S-ADMM) was proposed, demonstrating symmetrical handling of variables. The findings highlight the efficacy of S-ADMM for recovering training symbols, with potential extensions to time-varying mmWave channels. In [17], in the context of meeting high data transmission rate requirements for data aggregation, this work investigated transceiver optimization. It presented optimal structures for digital precoders and unconstrained analog transceivers, along with iterative algorithms. The results showcased reduced energy consumption compared to fully digital solutions.

In [18], introduced a precoding scheme for OFDM transmission in MIMO systems with one-bit digital-to-analog converters (DACs) and analog-to-digital converters (ADCs). They formulated and solved NP-hard optimization problems using the Cyclic Coordinate Descent (CCD) framework and ADMM (ADMM). The proposed precoding scheme mitigated the effects of coarse quantization, achieving performance close to full-resolution systems. In [19], explored analog-digital hybrid transceiver optimization for distributed IoT sensing networks. It proposed both centralized and asynchronous distributed algorithms based on ADMM for satisfying unit modulus constraints. Results indicate performance close to fully digital counterparts with reduced computation overhead. In [20], presented an algorithm-adaptable, scalable generator for massive MIMO baseband processing systems. They implemented in Chisel hardware construction language, and it evaluated various channel models and demonstrated improved demodulation error vector magnitude with beam-space methods.

In [21], presented a novel hybrid beamformer designs for a multi-user multi-cell mmWave system. The methodology involved semidefinite relaxation (SDR)-based approaches, Bayesian learning, and ADMM for centralized and distributed hybrid designs. Simulation results show improved performance over non-coordinated systems. In [22], designed constant modulus waveforms for dual-function radar-communication (DFRC) systems. It utilized ADMM for waveform synthesis, achieving a desired beampattern and demonstrating improved detection probability and BER for radar and communications. In [23], proposed a distributed cooperative AMC network based on machine learning to identify modulation schemes in non-cooperative wireless communication networks. The Co-AMC network achieved superior classification accuracy compared to existing methods across various modulation schemes and SNRs. In [24], introduced a joint plane-wave and spherical-wave-based 3D channel model. They derived optimal design parameters, analyzed their sensitivity, and designs a quantization codebook. The results show that planar subarrays are superior to traditional arrays in terms of spectral efficiency and effective degree of freedom.

In the existing body of research, there has been limited exploration regarding the implementation of a D-ADMM to attain a balanced trade-off between hardware components and transceiver performance. The majority of the literature has primarily focused on centralized optimization techniques and has not extensively delved into the decentralized paradigm. This research aims to bridge this gap by specifically addressing the incorporation of D-ADMM in the context of analog transceiver optimization. The subsequent section provides a detailed discussion of this crucial aspect and outlines the proposed methodology to tackle the identified issue.

3. Methodology

3.1 System Model

The system model comprises transmitter nodes, denoted by analog precoding matrices G_A and P_A, responsible for shaping signals during the transmission phase. Receiver nodes receive and process the transmitted signals. The communication links involve analog precoders G_A and P_A, representing analog communication links at transmitter nodes, while digital communication links are implicitly modeled, involving digital signal processing techniques. The optimization process employs the D-ADMM, leveraging iterative updates at each node and local fusion centers to achieve consensus in optimizing analog transceivers. The system enforces unit modulus constraints on analog transceivers G_A and P_A to ensure practical hardware feasibility. The overarching objective is to minimize a performance metrics-driven objective function, providing a balance between transceiver performance and hardware complexity. This optimization considers constraints on spectral efficiency, bit error rate, and an effective trade-off in the system's design.

3.2 Decentralized Alternating Direction Method of Multipliers

This work proposes a decentralized optimization model, D-ADMM, based on the ADMM consensus, to optimize analog transceivers in large-scale networks while considering modulus constraints. The model addresses the inherent non-convexity of the optimization problem associated with unit modulus constraints on analog transceivers. The objective is to achieve a balanced trade-off between transceiver performance and hardware complexity. The research focuses on a scenario with multiple local Fusion Centers (FCs) rather than a single global FC, reflecting the practical challenges in large-scale networks. The increasing demand for efficient data transmission in large-scale networks necessitates the optimization of analog transceivers. ADMM, known for its ability to decompose complex problems into manageable subproblems, is employed to address the non-convex nature of the optimization task [25]. The parameters used for this work is presented in Table 1.

Table 1. Variables used.

Variable	Description
A, B, P, U, V	Matrix
A_G	Analog precoder matrix
A_G^H	Conjugate Transpose of Analog precoder matrix
A_P	Matrix
A_P^H	Conjugate Transpose of Matrix
F_G	Feasible set of analog transceivers
G_A	Analog precoder matrix
G_A^H	Conjugate Transpose of Analog Precoder Matrix

H	Hermitian (conjugate transpose) of a matrix
i	Matrix Rows
j	Matrix Columns
n	Number of elements in the matrix
P_A	Analog precoder matrix
P_A^H	Conjugate Transpose of Analog precoder matrix
Q_G	Unit matrix for ADMM consensus
Q_P	Right unit matrix for analog precoder
Q_P^H	Conjugate Transpose of Right unit matrix
R	Real part of the matrix
$R_n^{0.5}$	Square root of the matrix R
S_G	Reformulated analog precoder term
S_G^H	Conjugate Transpose of Reformulated term
T_r	Trace of a matrix (sum of diagonal elements)
U_G	Analog precoder matrix
U_G^H	Conjugate Transpose of Analog precoder matrix
U_P	Left unit matrix component
U_P^H	Conjugate Transpose of Left unit matrix
V_H	Matrix
V_H^G	Conjugate Transpose of Analog precoder matrix
V_P	Right unit matrix component
V_P^H	Conjugate Transpose of Right unit matrix
W_G	Weight matrix
$W_k^{0.5}$	Matrix
W_P	Matrix
Z_G	Auxiliary variable for consensus in ADMM

This model considers unit modulus constraints on analog transceivers, particularly analog precoders (P_A) and analog decoders (G_A). The ADMM consensus involves the use of two-unit matrices, Q_P and Q_G. These matrices play a crucial role in achieving optimal performance during the optimization process. The process of D-ADMM starts with obtaining an optimal left unit matrix and its corresponding diagonal matrix. Additionally, a unit matrix Q is defined based on the obtained matrices. The objective function of ADMM is constrained by an upper bound. The Eq. (1) specifies this objective function, involving various matrices and weighted terms which is presented as follows

$$T_r\{(U_G A_G Q_G - R_n^{0.5} G_A^H)^H W_G (U_G A_G Q_G - R_n^{0.5} G_A^H)\} \leq T_r\{(A_G^H U_G^H W_G U_G A_G + G_A R_n^{0.5} W_G R_n^{0.5} G_A^H - 2R(A_G))\} \quad (1)$$

The Eq. (1) represents an upper bound constraint on the objective function for analog transceivers. U_G, A_G, Q_G, and G_A are the matrices related to the analog transceiver. T_r denotes the trace operation, W_G is a weight matrix, $R_n^{0.5}$ is the square root of the matrix R_n. In Eq. (1), the right-hand side involves matrix products, conjugate transpose, and weighted terms. The Eq. (1) controls and optimizes the performance of analog transceivers, taking into account modulus constraints. Further, Eq. (2) is mentioned as the source of the matrix inequality that leads to Eq. (1), which is defined as follows

$$R\big(T_r(U, A, V, B)\big) \leq \sum_{i=1}^{n} \lambda_i\,(A)\lambda_i(B) \quad (2)$$

Eq. (2) represents the inequality involved within the trace of matrix products and eigenvalues. This inequality involving trace operations and eigenvalues is fundamental in deriving the upper bound constraint in Eq. (1). It provides a mathematical foundation for controlling the spectral properties of the involved matrices, contributing to the optimization process. Further, Eq. (3) defines the calculation of the diagonal matrix $A \times G$ which is as follows

$$G_A R_n^{0.5} W_G U_G A_G = U_G \times A_G \times V_G^H \quad (3)$$

Eq. (3) calculates the product of matrices involving analog precoders and square root of matrix R. It plays a crucial role in expressing the relationship betweenG_A,U_G,A_G, and V_G^H, facilitating the optimization of analog transceivers under modulus constraints. Moreover, Eq. (3) helps for the formulation of the ADMM model. Further, Eq. (4) sets a constraint on the unit matrix Q_G where V_G and U_G are matrices related to the analog transceivers, which is defined as follows

$$Q_G = V_G U_G^H \quad (4)$$

Eq. (4) imposes a constraint on the unit matrix Q_G, ensuring it equals the product of V_G and the conjugate transpose of U_G. This constraint contributes to maintaining the orthogonality and unitarity of the matrices involved in the optimization process. Similar to Eq. (4), Eq. (5) defines the right unit matrix Q_P for the analog precoder as given in below equation

$$Q_P = V_P U_P^H \quad (5)$$

Eq. (5) sets the relationship between V_P and U_P, providing constraints essential for optimizing the analog precoders in the ADMM framework. For optimization of analog transceivers, the following equation is defined.

$$P_A^H W_k^{0.5}, W_P V_P A_P = U_P A_P V_P^H \quad (6)$$

Eq. (6) involves operations with P_A, $W_k^{0.5}$, W_P, V_P, and their conjugate transposes. It plays a crucial role in computing terms necessary for the optimization of analog transceivers, particularly in the context of modulus constraints. For introducing unit modulus constraints for analog transceivers, i.e., P_A and G_A, the constraints are defined as follows

$$G_A \in F_G \quad (7)$$

Eq. (7) acknowledges the complexity of obtaining these constraints directly from the phase projection, emphasizing the importance of considering modulus constraints in the optimization process. From Eq (7), the objective function can be reformulated as follows

$$T_r\{(V_P A_P Q_P - W_n^{0.5}, P_A)^H W_P (V_P A_P Q_P - W_k^{0.5}, P_A)\} \quad (8)$$

Eq. (8) formulates the objective function involving the unit modulus component of G_A and the element F_G. The Eq. (8) highlights that optimizing this objective function alone may not be as effective as addressing the actual problem, motivating the need for further reformulation. Hence, to reformulate the objective function, the following equation is defined

$$X = T_r\{P_A^H W_K^{0.5} W_P W_k^{0.5} P_A + Q_P^H A_P^H V_P^H W_P V_P A_P Q_P\} - 2T_r\{R(P_A^H W_k^{0.5} W_P V_P A_P Q_P)\} \quad (9)$$

Eq. (9) represents the reformulation of the objective function using an iterative method to handle unit modulus constraints for analog transceivers. The terms involve trace operations and matrix products with V_P, A_P, Q_P, P_A, $W_k^{0.5}$, and W_P. The first term of Eq. (9) aims to minimize the impact of the modulus constraints on the analog precoders P_A. Further, the second term of Eq. (9) adjusts the objective function by considering the product of matrices related to the optimization process. The following Eq. (9) has to be formulated within the objective function for analog precoder design within the ADMM framework. Hence, the following equation is presented.

$$T_r\{(U_G A_G Q_G - R_n^{0.5} G_A^H)^H W_G (U_G A_G Q_G - R_n^{0.5} G_A^H)\} \quad (10)$$

Eq. (10) involves operations withU_G, A_G, Q_G, $R_n^{0.5}$, G_A^H, W_G, and trace operations. Moreover, Eq. (10) represents a critical aspect of the optimization process, addressing the performance of analog precoders while adhering to modulus constraints.

$$X = T_r\{G_A R_n^{0.5} W_G R_n^{0.5} G_A^H + Q_G^H A_G^H U_G^H W_G U_G A_G Q_G\} - 2T_r\{R(G_A R_n^{0.5} W_G U_G A_G Q_G)\} \quad (11)$$

Eq. (11) provides breakdown of the terms involved in the objective function for analog precoder design. Similar to Eq. (9), it involves trace operations and matrix products with G_A, Q_G, U_G, A_G, $R_n^{0.5}$, W_G, and their conjugate transposes. The terms in Eq. (11) contribute to the overall optimization process by addressing specific aspects of the analog precoder design.

$$G_A T_r\{G_A W_G G_A^H\} - 2T_r\{R(G_A S_G^H)\} \quad (12)$$

Eq. (12) introduces the reformulated analog precoder term S_G. It discards redundant terms from the objective function, defining the optimization function for the analog function. The objective is to minimize the trace of the product of matrices involving G_A, W_G, and S_G while considering modulus constraints.

$$\left|[G_A]_{i,j}\right| = \propto, \forall_{i,j} \quad (13)$$

Eq. (13) presents the optimization problem with constraints on the modulus of G_A. The modulus of each element in the matrix G_A is constrained to a specific value ($\propto$). This introduces unit modulus constraints on analog transceivers, crucial for practical hardware implementation. For addressing the non-convex nature of unit modulus problem, the following equation is defined

$$G_A T_r\{G_A W_G G_A^H\} - 2T_r\{R(Z_G S_G^H)\} \quad (14)$$

Eq. (14) introduces an auxiliary variable Z_G to split the objective function, contributing to the development of an effective optimization strategy.

$$\left|[Z_G]_{i,j}\right| = \propto, \forall_{i,j} \quad (15)$$

Eq. (15) calculates the auxiliary variable Z_G, replacing the term G_A in Eq. (13). Constraints imposed on the modulus of Z_G, introduce a coupling effect between unit moduli. This enhances the optimization process and ensures effective tradeoff among hardware complexity and transceiver performance. The results of the proposed D-ADMM are evaluated in the next section.

4. Results and Discussion

4.1 System Requirements

To run the D-ADMM, Centralized-ADMM (C-ADMM), and Existing System Transceiver Optimization (ESTO) method [24], Windows 11 operating system was considered. A minimum of 8 GB RAM was considered to ensure smooth execution of the optimization algorithms. Additionally, MATLAB was preferred platform for implementing these methods, so it was essential to have MATLAB installed on the system. These specifications provided the computational resources and software environment needed to effectively carry out the optimization processes and evaluate the performance of the transceiver systems.

4.2 Evaluation Parameters

In this work, initially, random values are generated to evaluate antenna parameters. These parameters include the path loss exponent, the number of directions to look for interfering cells, and the percentage of the radius inside the cell where no user equipment is allowed. The parameter considered for evaluation are presented in Table 2.

Table 2. Parameters considered for evaluation.

Parameters	Values
Number of Nodes	10
Number of Users	10
Path Loss Exponent	1.8%
Radius Inside the Cell	0.05
Number of Random Users	500000

In the context of this work, the Monte-Carlo simulations for antenna system evaluation, key parameters are established. Each cell is assigned a specific number of random users, contributing to the stochastic nature of the simulation. The range for each base station antenna is defined, and the distribution of antennas follows a logarithmic scale, ensuring a balanced deployment. For evaluation of this work, spectral efficiency and Bit-Error-Rate (BER) are considered. The spectral efficiency is evaluated using the following equation

$$Spectral\ Efficiency = \frac{Net\ Data\ Rate(bps)}{Channel\ Bandwidth\ (Hz)} \quad (16)$$

Spectral Efficiency represents how efficiently the available bandwidth is utilized to transmit data. It is expressed as the ratio of the net data rate to the channel bandwidth. Higher spectral efficiency indicates a more effective utilization of the available spectrum for transmitting data, a crucial metric in assessing the performance of communication systems, especially in bandwidth-limited scenarios. The effective rate at which data is transmitted over the communication channel, typically measured in bits per second (bps). The range of frequencies allocated for the communication channel, measured in hertz (Hz). The following equation is used for evaluating the spectral efficiency.

$$Bit\ Error\ Rate = \frac{No\ of\ bits\ recieved}{Total\ Number\ of\ Bits\ Transferred} \quad (17)$$

The Bit Error Rate (BER) is a measure used in digital communication systems to quantify the accuracy of data transmission. The BER is expressed as a ratio or percentage, providing insights into the reliability of the communication channel. A lower BER indicates better transmission quality and reliability, while a higher BER suggests a higher likelihood of errors in the received data.

4.3 Spectral Efficiency

In the comparative analysis of spectral efficiency per cell as presented in Figure 1, the performance of three optimization techniques, namely D-ADMM, C-ADMM, and ESTO, was evaluated. The assessment involved plotting the spectral efficiency against the number of base station (BS) antennas. The results demonstrate that the D-ADMM outperformed both the C-ADMM and ESTO in terms of spectral efficiency. The spectral efficiency, measured in bits per second per hertz (bps/Hz), is a critical metric indicating how effectively the available bandwidth is utilized for data transmission. The plotted data revealed a consistent trend where, as the number of BS antennas increased, the D-ADMM consistently exhibited higher spectral efficiency compared to its counterparts. This superiority of D-ADMM in achieving better spectral efficiency can be attributed to its decentralized optimization approach. By leveraging the ADMM consensus, D-ADMM efficiently coordinated optimization across multiple nodes and local fusion centers, resulting in improved spectral efficiency. The findings underscore the effectiveness of decentralized strategies in large-scale networks, highlighting the potential advantages of D-ADMM for enhancing spectral efficiency in comparison to centralized methods like C-ADMM and other optimization techniques such as ESTO.

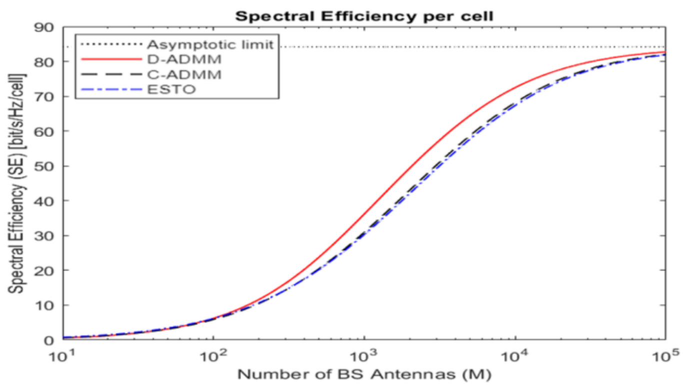

Figure 1. Spectral Efficiency per Cell.

In the evaluation of total spectral efficiency as presented in Figure 2, a comparative study was conducted involving three optimization techniques: D-ADMM, C-ADMM, and ESTO. The outcomes were graphically represented by plotting spectral efficiency against the number of transmit antennas. The results conclusively demonstrate that D-ADMM outperforms both C-ADMM and ESTO, achieving superior total spectral efficiency. Total spectral efficiency encompasses the efficiency of the entire system in utilizing available resources for data transmission. The plotted data revealed a consistent and significant advantage for D-ADMM as the number of transmit antennas increased. The decentralized optimization approach of D-ADMM, utilizing the ADMM consensus, facilitated efficient coordination across nodes and local fusion centers, resulting in higher total spectral efficiency compared to centralized methods like C-ADMM and alternative optimization techniques like ESTO. These findings emphasize the efficacy of D-ADMM in optimizing the overall spectral efficiency of communication systems, particularly in scenarios with a varying number of transmit antennas. The decentralized strategy showcased in D-ADMM proves to be a promising approach for enhancing the total spectral efficiency, positioning it as a favorable choice in comparison to centralized counterparts and other optimization methodologies such as ESTO.

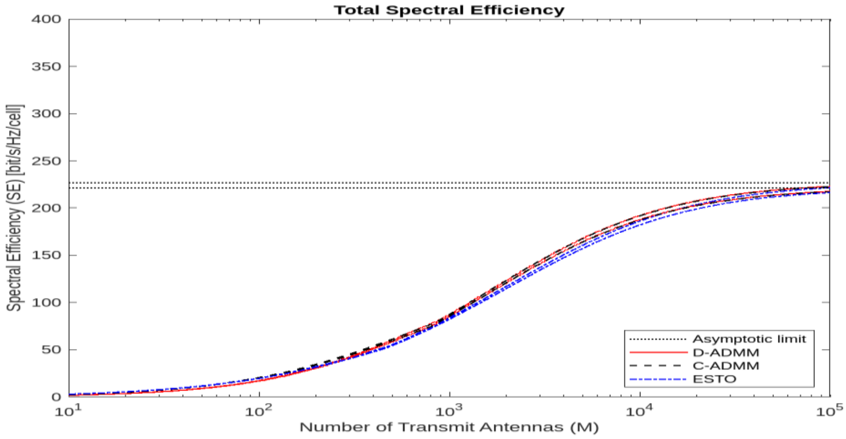

Figure 2. Total Spectral Efficiency.

Table 3. Spectral Efficiency Comparison.

	D-ADMM	C-ADMM	ESTO
Average Spectral Efficiency Per Cell	39.038179	36.4673772	36.1885304
Average Total Spectral Efficiency	104.7563414	103.7346916	102.626712

In Table 3, the spectral efficiency comparison has been presented. The average spectral efficiency per cell achieved by D-ADMM, C-ADMM, and ESTO was 39.03, 36.46 and 36.18 respectively. Further, the average total spectral efficiency achieved by D-ADMM, C-ADMM, and ESTO was 102.62, 10.373, and 104.75 respectively.

4.4 Bit Error Rate

In the iterative optimization process conducted by C-ADMM for improving the BER, a thorough analysis was performed over five iterations as presented in Figure 3. The BER values were plotted against the average Signal-to-Noise Ratio (SNR) per receive antenna, providing valuable insights into the system's performance over multiple optimization cycles. In iteration 1, the initial results revealed a higher BER, indicating a suboptimal performance of the system. This higher error rate suggests that the initial parameters or configuration may not have been optimal for the given SNR conditions. However, as the optimization process advanced to iteration 2, a slight reduction in BER was observed. This reduction indicated that the optimization algorithm, implemented by C-ADMM, started to adjust parameters, improving the system's resilience to noise and interference. Continuing to iteration 3, a notable drop in BER was observed. This improvement signifies the effectiveness of the optimization process, as the system adapted to better configurations, resulting in enhanced error correction capabilities. Iterations 4 and 5 demonstrated consistency in achieving lower BER values, indicating that the optimization algorithm reached a relatively stable and optimized state. The similarity between these last two iterations suggests that the algorithm may have converged, achieving a near-optimal configuration for the given SNR conditions. The results for BER achieved by C-ADMM is presented in Table 4.

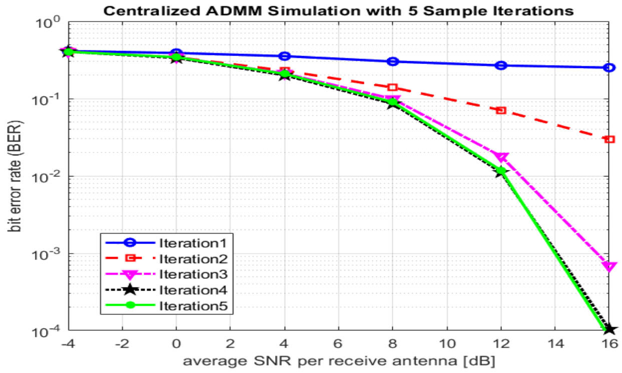

Figure 3. BER of C-ADMM.

Table 4. BER achieved for C-ADMM.

Iteration/ SNR	-4	0	4	8	12	16
1	0.411333333	0.388	0.353145833	0.3009375	0.267729167	0.250854167
2	0.4051875	0.342708333	0.229166667	0.138770833	0.07075	0.029729167
3	0.4040625	0.343270833	0.2110625	0.098875	0.017916667	0.0006875
4	0.402270833	0.3340625	0.199916667	0.085479167	0.011125	0.000104167
5	0.402416667	0.342479167	0.208458333	0.089895833	0.011770833	8.33E-05

In the iterative optimization process conducted by D-ADMM to improve the Bit Error Rate (BER), an analysis was performed over five sample iterations as presented in Figure 4. The BER values were systematically plotted against the average SNR per receive antenna, providing insights into the evolution of the system's performance. In the initial iteration, i.e., iteration 1, the results showed a relatively higher BER, indicating that the system's performance might not have been optimal under the initial parameters or configuration. However, as the optimization process advanced to iteration 2, a noticeable reduction in BER was observed. This reduction suggested that the decentralized optimization approach employed by D-ADMM was effective in adapting and improving system parameters, leading to better error correction capabilities. The trend continued in iteration 3, where a further drop in BER was observed. This indicated that D-ADMM continued to refine system parameters, achieving an even lower error rate. Iterations 4 and 5 demonstrated a consistent and similar level of low BER. This stability in the later iterations suggests that D-ADMM reached a convergent state, where the optimization process achieved a near-optimal configuration for the given average SNR per receive antenna conditions. The results for BER achieved by D-ADMM is presented in Table 5.

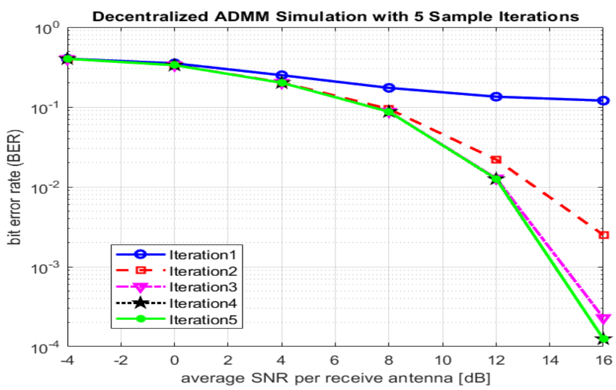

Figure 4. BER of D-ADMM.

Table 5. BER achieved by D-ADMM.

Iteration/SNR	-4	0	4	8	12	16
1	0.402395833	0.351833333	0.2499375	0.1735	0.134604167	0.120229167
2	0.4006875	0.334354167	0.203208333	0.094354167	0.021979167	0.0025
3	0.400833333	0.3335	0.201541667	0.087541667	0.0128125	0.000229167
4	0.401104167	0.333770833	0.200875	0.087395833	0.0125625	0.000125
5	0.4010625	0.33375	0.200854167	0.087125	0.012625	0.000125

The results analysis indicates that the BER achieved by D-ADMM is superior to that of C-ADMM. To further illustrate the comparison, an error comparison was conducted and visualized by plotting BER against average SNR per receive antenna as presented in Figure 5. The error comparison graph clearly demonstrates the performance distinction between D-ADMM and C-ADMM. In the case of C-ADMM, the graph showcases a direct drop in BER as the average SNR per receive antenna increases. This behavior might suggest that C-ADMM tends to converge quickly to a specific BER value with changes in SNR conditions. Contrastingly, the error comparison for D-ADMM reveals a more fluctuating pattern in BER as the average SNR per receive antenna varies. This dynamic behavior indicates that D-ADMM adapts and adjusts its parameters continuously to optimize BER under changing SNR conditions. The fluctuations are attributed to the decentralized nature of the optimization process, which allows for ongoing adjustments at different nodes and fusion centers, contributing to a more adaptive and resilient system. The consistent outperformance of D-ADMM in the error comparison highlights its capability to achieve better results across varying SNR conditions compared to C-ADMM. This flexibility and adaptability of D-ADMM contribute to its effectiveness in optimizing the system for improved error correction performance, making it a promising choice for scenarios with dynamic and changing communication conditions.

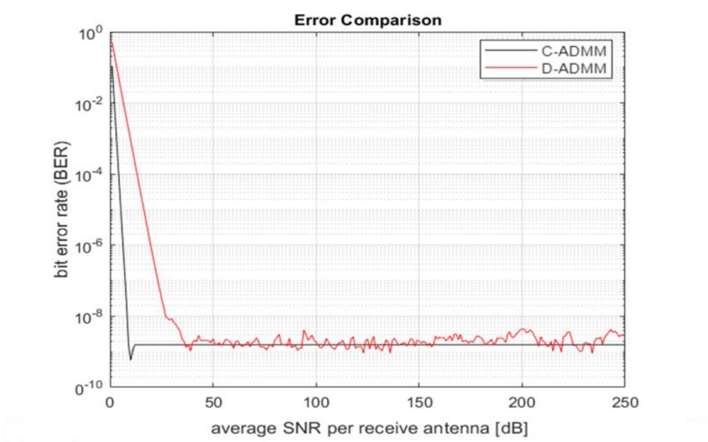

Figure 5. Bit Error Rate Comparison.

5. Conclusion

This work introduces a novel approach to transceiver optimization through the development and implementation of a D-ADMM model. The study addresses the shortcomings of both centralized and distributed ADMM approaches, providing a unique solution for achieving an optimal trade-off between transceiver performance and hardware complexity. By formulating the optimization problem and incorporating unit modulus constraints, the proposed model demonstrates its effectiveness in improving key performance metrics, such as spectral efficiency and bit error rate. The D-ADMM model exhibits scalability in large-scale networks, offering a practical solution for decentralized optimization without the need for a global fusion center. The presented results showcase the superiority of the D-ADMM over traditional methods, emphasizing its ability to navigate the non-convex nature of the optimization problem. Overall, this research contributes valuable insights and a practical framework for advancing the field of analog transceiver optimization in communication networks. The integration of machine learning techniques and the exploration of novel hardware technologies for further optimizing transceiver performance will be crucial avenues for future research.

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Bibliography

Mrs Jyothi B R received the B.E. Degree in Electronics and Communication stream and M. Tech degree in VLSI and Embedded Systems from VTU, Belagavi in 2008 and 2014. She is pursuing Ph.D. degree in VTU, Belagavi, and serving as a Assistant Professor in ECE Department, KLS’s Gogte Institute of Technology, Belagavi. Her research interests are in the area of signal processing, wireless sensor networks. Communication Networks, Internet of Things. She can be contacted at email: jyothirbr@git.edu
Orcid ID:**0009-0002-4861-9980**

Dr. Manja Naik N Professor, Department of Electronics and Communication Engineering, University B.D.T College of Engineering, Davanagere, Karnataka, India. Graduated from University B.D.T College of Engineering, Davanagere. Kuvempu University, Shivamogga. A constituent College of VTU Belagavi. Has 22 years of Experience in teaching, He completed Ph. D, from Jain University, Bengaluru, He served various positions BOS, BOE Member at Visveswaraya Technological University. Published more than 15 Journals and Guided more than 25 PG Students, presently guiding 05 Ph. D, students and 01 student is already awarded. Interested areas are image and video processing, signal processing and pattern recognition. He can be contacted at email: manjubdt2009@gmail.com.