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Energy-Efficient Joint User Selection and Power Allocation Optimization for MU-MIMO Systems with Limited Feedback

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Abstract

Multi-user multiple-input multiple-output (MU-MIMO) technology is widely regarded as a key enabler for next-generation wireless communication systems (WCS), since it exploits spatial degrees of freedom to increase system throughput without requiring additional bandwidth. However, realizing these gains in practice depends on effective base station (BS)-to-user association and transmit power allocation policies, and on accurate channel state information (CSI) for interference-suppressing precoding. Because uplink feedback bandwidth is limited, base stations in practical MU-MIMO deployments typically operate with only partial CSI, which weakens interference suppression, lowers the signal-to-interference-plus-noise ratio (SINR), and ultimately reduces both the achievable data rate and the energy efficiency (EE) of the system. At the same time, the growing energy demand of wireless networks makes energy-efficient design, rather than throughput alone, an increasingly urgent objective. Motivated by this gap, this paper investigates the joint optimization of user selection and power allocation for maximizing system EE in MU-MIMO systems operating under limited feedback, subject to constraints on maximum transmit power and quality of service (QoS). The resulting optimization problem is formulated as a mixed-integer nonlinear programming (MINLP) model, which is both non-convex and NP-hard, making it intractable to solve directly. To overcome this difficulty, fractional programming is used to recast the problem into an equivalent subtractive form, after which an iterative algorithm is developed that combines a modified Kuhn-Munkres algorithm for optimal user selection with a Lagrangian dual decomposition technique for optimal power allocation. Extensive simulation results show that the proposed algorithm consistently achieves higher system EE and throughput than existing energy-efficient joint user selection and power allocation (JUSPA) schemes under limited feedback, while converging within a small number of iterations and incurring only modest computational overhead. These findings confirm that explicitly accounting for the impact of limited feedback on SINR, rather than assuming perfect CSI, is essential for realizing energy-efficient resource allocation in practical MU-MIMO networks.

Keywords

Energy Efficiency, User Selection, Power Allocation, Limited Feedback, MU-MIMO

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1. Introduction

Multi-User Multiple-Input Multiple-Output (MU-MIMO) systems are systems capable of utilizing spatial resources effectively to boost throughput in broadband wireless communication systems (WCS) without requiring additional bandwidth. To fully harness the advantages of MU-MIMO, it is vital to implement effective strategies for base station (BS) to user associations and transmit power allocation [1, 2].Given the dynamic and location-sensitive nature of wireless channels in MU-MIMO environments, user scheduling is employed to exploit favorable channel conditions while avoiding poor ones. This strategy enhances spectral efficiency by prioritizing users experiencing better channel states [3] .

The growing demand for environmentally sustainable communications has brought energy consumption to the forefront [4]. The proliferation of mobile devices and the surge in data traffic have significantly increased energy usage. Therefore, energy-efficient design strategies are essential, aiming to maximize the number of bits transmitted per unit of energy consumed. Among these strategies, optimal power allocation is key to achieving energy-efficient communication. According to Shannon's theory, the achievable data rate depends on spectrum bandwidth, transmission power, and channel conditions simultaneously. Therefore, to maximize energy efficiency (EE), user selection and power allocation must be jointly optimized. Another significant challenge lies in precoding, which is used in MU-MIMO systems to mitigate co-channel interference among users. This process depends on accurate channel state information (CSI). However, acquiring full CSI is challenging in practice due to the limited availability of uplink bandwidth, which restricts the amount of feedback that can be transmitted. Consequently, systems rely on limited feedback, which impairs the ability to fully suppress interference. As a result, the base station's signal-to-interference-plus-noise ratio (SINR) is reduced, which lowers the system's overall energy efficiency and the possible data rate.

Existing studies on joint user selection and power allocation largely focus on scenarios assuming full channel state information (CSI) feedback [5–9], which limits their effectiveness in optimizing energy efficiency (EE). To the best of our knowledge, little research has been done on the joint optimization of power allocation and energy-efficient user selection in MU-MIMO systems under limited CSI feedback. Driven by this research gap, the current study suggests an energy-efficient architecture that simultaneously optimizes power allocation and user selection, accounting for limited input, while meeting maximum transmit power restrictions and quality of service (QoS) standards.

The novelty of the present work lies in jointly solving user selection and power allocation for energy-efficiency maximization under an explicit limited-feedback constraint, using a closed-form feasible-rate expression combined with a modified Kuhn-Munkres assignment algorithm and a Lagrangian dual decomposition technique, rather than assuming full CSI or treating user selection and power allocation as separate design stages. Recent studies continue to explore adjacent aspects of this problem: dynamic user-selection strategies for MU-MIMO downlink precoding under limited feedback have been proposed in [10], energy-efficient joint antenna selection and user scheduling for massive MIMO has been examined in [11], and the present authors have separately investigated energy-efficient power allocation for cell-free massive MIMO architectures in [12]. None of these works, however, jointly optimizes user selection and power allocation with Block-Diagonalization precoding for MU-MIMO systems operating under an explicit limited-feedback constraint, which is precisely the gap addressed here. For transparency, we note that a subset of the present authors previously investigated a related but distinct energy-efficiency optimization problem for MU-MIMO systems in [13], which addressed joint remote-radio-head (RRH)-user selection, transmit-antenna-number adjustment, and power allocation via a Lagrange dual decomposition and successive convex approximation approach. The present manuscript differs in problem formulation, precoding design, and solution method: it considers a fixed BS-antenna configuration with Block-Diagonalization precoding for multi-antenna users, formulates user selection via a modified Kuhn-Munkres assignment algorithm rather than antenna-number adjustment, and reports new simulation results under limited-feedback conditions not considered in [13].

The optimization issue is classified as a mixed-integer nonlinear programming (MINLP) problem, which presents major computer hurdles because it is non-convex and NP-hard. In order to get around this, fractional programming is used to reformulate the problem into a more manageable subtractive form. Next, a modified Kuhn-Munkres algorithm for optimal user selection and a Lagrangian dual decomposition method for optimal power allocation are incorporated into an iterative process to improve energy efficiency.

The following is a summary of this work's main contributions:

1) The feasible data rate of a user under restricted feedback settings is obtained using a simple closed-form formula. This expression serves as the foundation for an energy efficiency optimization framework that is organized in an

intermediate form that reduces computational complexity by directly capturing the user's data rate.

2) We suggest an energy-efficient approach that simultaneously maximizes power allocation and user selection. For optimal user assignment, the algorithm uses a modified Kuhn-Munkres method; for optimal power allocation, it uses the Lagrangian dual decomposition technique. This method is particularly suited for real-world implementation in MU-MIMO systems since it guarantees globally optimal solutions while retaining minimal computational cost.
3) Comprehensive simulation studies are performed to evaluate the performance and robustness of the proposed algorithm. The results confirm notable improvements in energy efficiency over existing methods.

The rest of this document is structured as follows: Section 2 reviews the existing literature. Section 3 presents the system model for MU-MIMO systems with limited feedback. Section 4 presents the proposed optimization approach for energy-efficient joint user selection and power allocation. Section 5 presents performance evaluations and a detailed discussion of the results. Finally, Section 6 summarizes the key findings and suggests possible avenues for future research.

2. Related Works

Previous research has mostly focused on either power allocation [1, 12, 14] or user selection [5] and [15]. However, by tackling both factors simultaneously, current research trends have shifted toward improving overall system energy efficiency. In order to reduce intercell interference, for example, the study in [3] suggested a Joint User Selection and Power Allocation (JUSPA) strategy.Similarly, research in [16] and [7] used JUSPA-based algorithms to increase MIMO systems' spectral efficiency. Considering user delay requirements, the authors in [6] investigated downlink JUSPA in a single-cell distributed antenna system. Furthermore, [16] presented a novel algorithm that concurrently improved precoding, power allocation, and user selection, resulting in significant increases in system throughput. Additionally, the authors of [15], [5], and [17] created JUSPA algorithms with the goal of maximizing energy efficiency.

The goal of the JUSPA algorithms created in [18] and [19] was to maximize spectrum efficiency while maintaining proportional fairness. The authors of [7] suggested an algorithm that integrated beamforming, transmit power, and optimum user selection while taking interference and fair resource distribution among users into account. In [20], resource allocation algorithms that optimized subchannel and power distribution in downlink multi-user MIMO-OFDM networks were investigated. Additionally, [21] presented a technique to take advantage of multiuser diversity in MIMO-OFDM systems by concurrently allocating subcarriers, bits, and power. The authors of [8] suggested an integrated approach for beamforming, power regulation, and user selection in multi-user MIMO-OFDM systems. Lagrange dual decomposition is used to maximize system throughput. In order to reduce overall power consumption, the study in [22] examined a JUSPA technique for MIMO systems with delay limitations. A low-complexity JUSPA technique for MIMO systems with faulty CSI was presented by the authors in [23]. Additionally, JUSPA approaches for huge MIMO systems were the focus of the research in [9] and [14], with an emphasis on lowering overall power consumption.The lack of an efficient design framework that improves energy economy through power allocation and user choices, particularly in MU-MIMO systems operating under limited feedback settings, is the main driving force for our work.

3. System Model and Problem Formulation

We consider MU-MIMO systems operating under a constrained (limited) feedback CSI regime, where the base station (BS) is equipped with multiple antennas, as illustrated in Figure 1. Up to M users may be scheduled simultaneously, with user m equipped with $k_m (1 \leq m \leq M)$ receive antennas. Rayleigh fading can be used to represent the channel between the BS and the users. Nevertheless, 80% of the network's energy is used by the base station (BS), mostly during the downlink transmission phase. Thus, we shall examine the network's downlink transmission in this research [24].

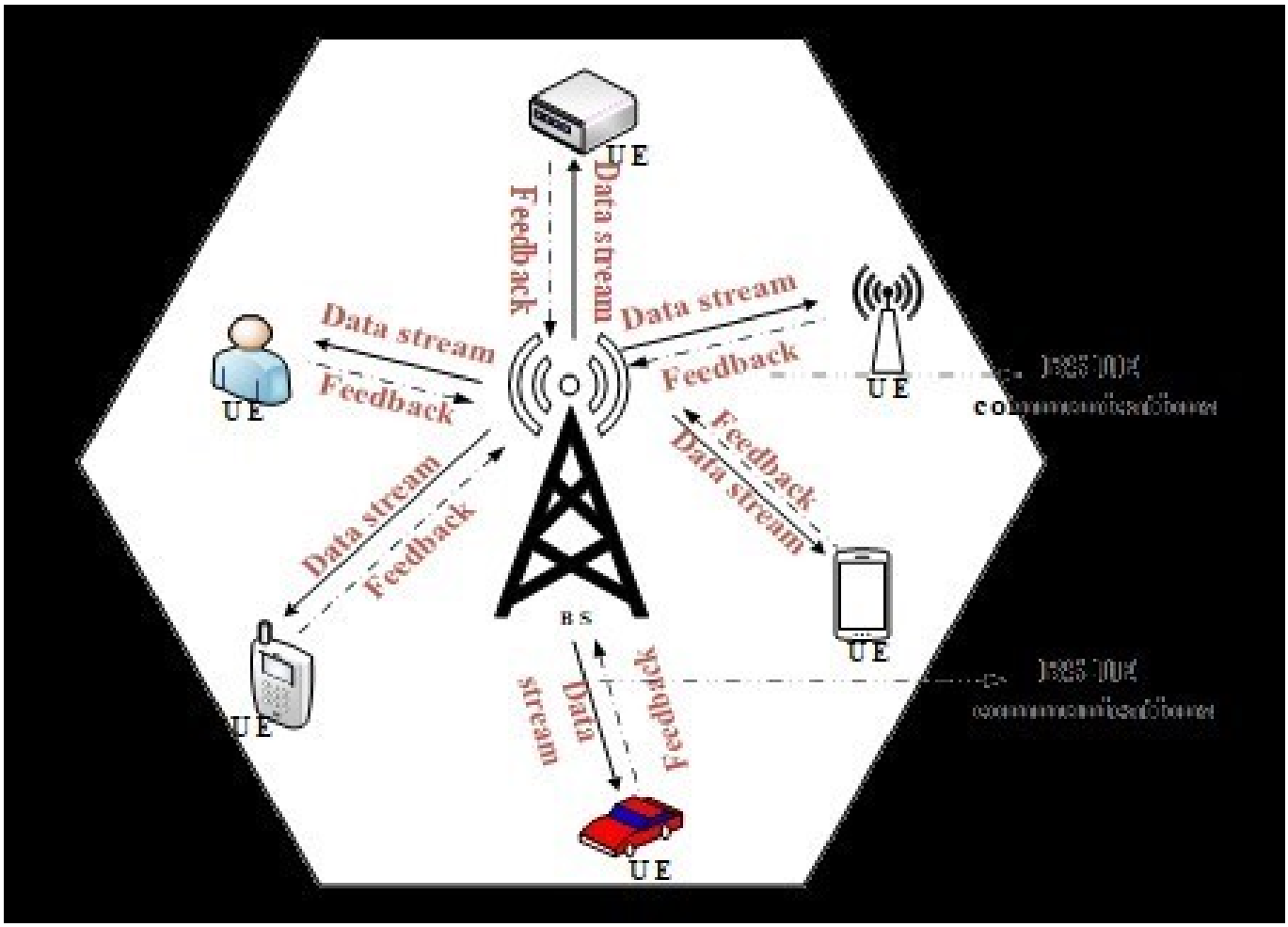


Figure 1. *System Model.*

Figure 1: System model. The base station (BS), located at the centre of the hexagonal cell, communicates with M distributed user equipment (UE) – shown here as a router, an access point, a smartphone, a handheld terminal, and a vehicle-mounted terminal – each over a dedicated downlink data-stream link and an uplink feedback link. The dash-dotted BS-to-BS links at the cell edge represent inter-cell communication boundaries, illustrating that each UE's channel state information and feedback are local to its serving BS under the limited-feedback constraint studied in this paper. In MU-MIMO systems, precoding techniques are employed to eliminate co-channel interference among users sharing the same time-frequency resource, which influences the maximum number of users that can be scheduled. Dirty Paper Coding (DPC) is a commonly used precoding technique; however, its high computational complexity makes it impractical.. However, zero forcing (ZF) and Block diagonalization (BD) are widely used practical precoding transmission techniques. In this paper BD is applied because the users have multiple antennas. In BD technique, a well-made precoding matrix can be used to remove the interference.

3.1. Modeling Assumptions

To keep the optimization problem tractable while preserving its essential practical features, the following modeling assumptions are adopted throughout this paper:

1) The wireless channel between the BS and each UE follows block Rayleigh fading, i.e., channel coefficients remain constant over one scheduling interval and vary independently between intervals.
2) The BS has access only to limited (quantized/partial) channel state information (CSI) fed back by each UE, rather than full or perfect CSI.
3) Each UE is equipped with $k_m \geq 1$ receive antennas, and the number of spatial streams assigned to a scheduled UE does not exceed k_m.

4) User scheduling decisions and power allocation are performed jointly and centrally at the BS once per scheduling interval.
5) Perfect time and frequency synchronization is assumed between the BS and all UEs.
6) A single-cell scenario is considered; inter-cell interference is not explicitly modeled .

3.2. Rationale for Block Diagonalization Precoding

Precoding is required in MU-MIMO systems to suppress co-channel interference (CCI) among simultaneously scheduled users sharing the same time-frequency resource. Dirty Paper Coding (DPC) achieves the information-theoretic capacity region of the MIMO broadcast channel, but its successive, non-linear encoding procedure incurs computational complexity that grows rapidly with the number of users and antennas, making it impractical for real-time implementation. Zero-Forcing (ZF) precoding is a much lower-complexity linear alternative, but it is designed primarily for single-antenna receivers; when applied to users with multiple receive antennas it either wastes spatial degrees of freedom or requires ad hoc antenna selection at the receiver, and it is also known to suffer from noise enhancement when the effective channel is poorly conditioned. Block Diagonalization (BD) generalizes ZF to the multi-antenna-receiver case: by nesting a receive-side singular value decomposition (SVD) within the precoder design for each user, BD completely eliminates inter-user interference while allowing every scheduled UE to retain the full spatial multiplexing gain of its k_m antennas, at a computational cost that remains polynomial in the number of users and antennas. Because every UE in the system model of this paper is equipped with multiple antennas, BD is therefore selected as the precoding technique that best balances interference suppression, spatial efficiency, and implementation complexity for the problem considered here.

3.3. Rationale for the Modified Kuhn-Munkres User-Selection Algorithm

Conventional user-selection strategies for MU-MIMO scheduling are typically either greedy (ranking users by instantaneous channel gain or SINR and selecting sequentially, which is fast but offers no global optimality guarantee and can converge to a locally optimal assignment) or exhaustive-search-based (which guarantees the globally optimal assignment but has factorial complexity O(M!) and is computationally intractable for realistic values of M). The classical Kuhn-Munkres (Hungarian) algorithm instead solves the bipartite assignment problem to global optimality in polynomial time by iteratively augmenting a feasible labeling until a perfect matching is found. In this paper, the Kuhn-Munkres algorithm is modified to operate directly on the energy-efficiency utility metric derived in Section 4, rather than a fixed cost matrix, and it is embedded within the outer Lagrangian dual decomposition loop so that user selection and power allocation are jointly refined at every iteration. This modification reduces the per-iteration complexity of the user-selection stage to $O(M^2)$ (Section 5) while retaining the algorithm's key advantage over greedy heuristics: at each iteration it returns the assignment that maximizes the aggregate utility metric among all feasible one-to-one matchings, rather than a locally optimal or arbitrary ordering. This combination of global optimality (within each iteration) and polynomial complexity is why the modified Kuhn-Munkres algorithm is more suitable for the problem considered here than either greedy selection (lower complexity but no optimality guarantee) or exhaustive search (globally optimal but computationally intractable). In the BD method, the precoder is constructed using singular value decomposition (SVD) [25] Let the precoding matrix, the transmitted signal vector, and the received signal for user m be denoted as follows:

$$T_m \in H^{K_T \times k_m} \quad x_m \in H^{k_m \times 1}, \quad y_m \in H^{k_m \times 1}, \quad m = 1, 2 \ldots, M$$

it follows :

$$y_m = H_m \sum_{j=1}^{M} T_j x_j + z_m = H_m T_m x_m + H_m \sum_{j=1}^{M} T_j x_j + z_m \tag{1}$$

where $H_m \in H^{K_T \times k_m}$ represent Gaussian random channel matrix of user m, generally, $K_T \geq k_m$ and $rank(H_m) = k_m$. $z_m \in H^{k_m \times}$ represents the additive white Gaussian noise with the zero mean value and covariance matrix. $\sigma^2 I_{k_m}$ where I_{k_m} denotes an identity matrix.

Let $\hat{H} = [H_1^T, H_2^T, \ldots, H_{m-1}^T, H_{m+1}, \ldots, H_M^T]^T$ and assume $\hat{H}_m$ is a full rank matrix, i.e., $\text{rank}(\hat{H}) = \sum_{j=1}^{M} k_j$, the precoding matrix $T_m(T_j)$ above satisfies $T_m = V_m^{(0)} \cdot V_m^{(0)}$ can be achieved

by employing singular value decomposition (SVD) on $\hat{H}_m$ and can be written as:

$$\hat{H}_m = U_m[\sum_m, 0][V_m^1, V_m^0]^H \tag{2}$$

The number of columns of $\hat{H}_m$ must not be more than the number of rows of $\hat{H}_m$. It implies that the upper bound of k_m is given by

$$\sum_{j=1, j\neq m} k_j \leq K_T, \quad \forall m = 1, 2, \ldots M \tag{3}$$

Moreover, V_m^1 can be achieved by utilizing SVD on $\hat{H}_m V_m^{(0)}$:

$$H_m V_m^{(0)} = U_m^{'}[\Lambda_m, 0][V_m^1, V_m^0]^H \tag{4}$$

where $U_m^{'}$ denotes a left unitary matrix.Λ_m denotes a diagonal matrix which consists of the singular values of $H_m V_m^0$. $[V_m^1, V_m^0]$ represents a unitary matrix, where the columns of V_m^1 and V_m^0 correspond to the non-zero and zero singular values right unitary matrixes of $H_m V_m^0$ respectively. We choose $T_m = V_m^0$, which is the precoding matrix of user m . Substituting T_m into (1), we obtain

$$y_m = H_m V_m^0 x_m + H_m \sum_{j=1, j\neq m} V_j^0 x_j + z_m \tag{5}$$

$V_m^{0'} = V_m^0$ if $V_j^{'} = V_j$ in (4), then CCI in (5) is zero, but quantization error of codeword leads to residual CCI , $H_m \sum_{j=1, j\neq m} V_j^{0'} x_j$. When the CCI is present, SINR is needed to derive an expression for the achievable bit rate of the user. In this paper, we introduce the concept of multi-channel integrated Signal-to-Interference-plus-Noise Ratio (SINR) and demonstrate how it relates to consumers' achievable bit rates. We define the multi-channel integrated SINR as a number directly proportional to the user's feasible bit rate, since codewords are assigned to users on each subcarrier. When the User Equipment (UE) applies the Minimum Mean Square Error (MMSE) receiver [26], the estimated signal for user m can be expressed as follows:

$$x_m^{'} = g_m y_m = g_m H_m V_m^{0'} x_m + g_m H_m \sum_{j=1, j\neq m}^{M} V_j^{0'} x_j + g_m z_m \tag{6}$$

This expression consists of three terms representing the useful signal, interference signal, and noise signal, respectively, the equilibrium matrix is denoted g_m.Various techniques, including zero forcing and MMSE algorithms, can be applied to construct the matrix g_m. In this work, the MMSE receiver is selected due to its superior performance compared to the zero forcing approach. The MMSE receiver operates by minimizing the square root of the error between the estimated signal and the original signal:

$$min\mathbf{E}\left[||x_m^{'} - x_m||^2\right] = \mathbf{E}\left[(x_m^{'} - x_m)^{''}(x_m^{'} - x_m)\right] \tag{7}$$

where $x_m^{'}$ estimated signal and x_m is the original signal. Substitute $x_m^{'} = g_m y_m$ into (7), it follows;

$$Min\mathbf{E}\left[||x_m^{'} - x_m||^2\right] = \mathbf{E}\left[tr\left(y_m^H g_m^H g_m y_m - y_m^H g_m^H x_m - x_m^H g_m y_m + x_m^H x_m\right)\right] \tag{8}$$

Where tr is the trace of user channel matrix. Take the partial derivative with respect to g_m and let it be zero, we obtain

$$y_m^H g_m^H y_m = x_m^H y_m \tag{9}$$

and

$$g_m = (H_m V_m)^H \left((H_m V_m)(H_m V_m)^H + \frac{1}{\beta} I_{k_m}\right)^{-1} \tag{10}$$

where $(\cdot)^H$ represents the conjugate transformation matrix, $(\cdot)^{-1}$ represent converse matrix, $I_{k_m} = k_m \times k_m$ unit matrix $\beta = \dfrac{P}{M\sigma^2}$. Substitute $H_m = U_m \sum_m V_m^H$ into (10), it follows

$$g_m = \sum_m^H U_m^H \left(U_m \sum_m \sum_m^H U_m^H + \frac{1}{\beta} I_{k_m}\right)^{-1} = \sum_m^H diag\left(\frac{1}{\lambda_{m_1}^2 + \frac{1}{\beta}}, \ldots, \frac{1}{\lambda_{m_k}^2 + \frac{1}{\beta}}, \ldots, \frac{1}{\lambda_{m_{r_m}}^2 + \frac{1}{\beta}}, 0 \ldots\right) U_m^H \tag{11}$$

where λ_{m_k} is the *k-th* singular value of user m's channel matrix. Substitute (11) and $H_m = U_m \sum_m V_m^H$ into (6) yields:

$$\begin{cases} x_m^{'} = \begin{bmatrix} \frac{\lambda_{m_1}^2}{\lambda_{m_1}^2 + \frac{1}{\beta}} & 0 & 0 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\lambda_{m_i}^2}{\lambda_{m_i}^2 + \frac{1}{\beta}} & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\lambda_{m_r}^2}{\lambda_{m_r}^2 + \frac{1}{\beta}} & 0 \\ 0 & 0 & 0 & 0 & 0 & \ddots \end{bmatrix} V_m^H V_m^0 x_m \\ + \begin{bmatrix} \frac{\lambda_{m_1}^2}{\lambda_{m_1}^2 + \frac{1}{\varphi}} & 0 & 0 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\lambda_{m_k}^2}{\lambda_{m_k}^2 + \frac{1}{\varphi}} & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\lambda_{m_r}^2}{\lambda_{m_r}^2 + \frac{1}{\varphi}} & 0 \\ 0 & 0 & 0 & 0 & 0 & \ddots \end{bmatrix} V_m^H \sum_{\substack{j=1 \\ j \neq m}}^{M} V_j^0 x_j \\ + g_m z_m \end{cases} \tag{12}$$

(12) shows that the MIMO channel can be divided into r_m comparable channels.

The useful signal power in the kth analogous channel can be written as:

$$\frac{\lambda_{m_k}^2}{\lambda_{m_k}^2 + \frac{1}{\beta}} \left| [V_m^H]_k [V_m^0]_k \right|^2 = \frac{\lambda_{m_k}^2}{\lambda_{m_k}^2 + \frac{1}{\varphi}} \left| [U_m H_m^H]^2 [V_m^0]_k \right|$$

where $[V_m]_k$ = k-th column of the user's right unitary matrix, $[V_j^0]_k = [V_m^0]_k$ = k-th column of the precoding matrix. The interference signal's associated power can be written as:

$$\frac{\lambda_{m_k}^2}{\lambda_{m_k}^2 + \frac{1}{\beta}} \left| [V_m]_k^H [V_j^{0'}]_k \right|^2 \frac{\lambda_{m_k}^2}{\lambda_{m_k}^2 + \frac{1}{\varphi}} \left| [V_m]_k^H \right|^2 [\hat{V}_j^{0'}]_k$$

Therefore, in the k-th equivalent channel of user m, the ratio of useful signal power to interference plus noise power $SINR_{m_k}$ can be expressed as:

$$SINR_{m_k} = \frac{\lambda_{m_k}^2 \left| [V_m]_k^H [V_m^{0'}]_k \right|^2}{\lambda_{m_k}^2 \sum_{j=1, j \neq m} \left| [V_m]_k^H [V_j^{0'}]_k \right|^2 + \frac{1}{\beta}} \tag{13}$$

because $SINR_{m_k} \gg \frac{1}{\beta}$, it follows

$$SINR_{m_k} = \frac{\left| [V_m]_k^H [V_m^{0'}]_k \right|^2}{\sum_{j=1, j \neq m} \left| [V_m]_k^H [V_j^{0'}]_k \right|^2} \tag{14}$$

Hence, the achievable bit rate of user m can be written as:

$$R_m = B \sum_{k=1}^{r_m} \log_2 (1 + SINR_{m_k}) \tag{15}$$

An alternate theorem is used to obtain an intermediate expression that appropriately represents the user's achievable bit rate because the expression represented by equation (15) has a large processing load. This intermediate expression, rather than the original expression given in equation (15), will be the basis for the design of user selection and subcarrier allocation in the following section.

Theorem 1

$$R_m = \log_2\left(1 + \frac{1}{r_m}\frac{\left\|V_m^H V_m^{0'}\right\|^2}{\sum_{j=1,j\neq m}\left\|V_{m,n}^H V_j^{0'}\right\|_D^2}\right) \tag{16}$$

Proof

$\log_2(1 + SINR_{m_k})$ is a convex function. We derive the following using the Jensen's inequality characteristic of convex function in [25]:

$$\sum_{k=1}^{r_m}\frac{1}{r_m}\log_2\left(1 + SINR_{m_k}\right) \geq \log_2\left(1 + \sum_{k=1}^{r_m}\frac{1}{r_m}SINR_{m_k}\right) = \log_2\left(1 + \frac{1}{r_m}SINR_{m_k}\right) \tag{17}$$

Where

$$\sum_{k=1}^{r_m}\frac{1}{r_m}\log_2\left(1 + SINR_{m_k}\right) = \frac{1}{r_m}\log_2\left(1 + SINR_{m_k}\right) = \frac{R_m}{r_m} \tag{18}$$

Substituting (17) into (18), we can get:

$$R_m \geq r_m \log_2\left(1 + \sum_{k=1}^{r_m}\frac{1}{r_m}SINR_{m_k}\right) \geq \log_2\left(1 + \sum_{k=1}^{r_m}\frac{1}{r_m}SINR_{m_k}\right) \tag{19}$$

According to (14), $\sum_{k=1}^{r_m} SINR_{m_k}$ can be expressed as

$$\begin{aligned}\sum_{k=1}^{r_m} SINR_{m_k} &= \frac{\left|[V_m]_1^H [V_m^{0'}]_1\right|^2}{\sum_{j=1,j\neq m}^{M}\left|[V_m]_1^H [V_j^{0'}]_1\right|^2} + \cdots + \frac{\left|[V_m]_k^H [V_m^{0'}]_k\right|^2}{\sum_{j=1,j\neq m}^{M}\left|[V_m]_k^H [V_j^{0'}]_k\right|^2} + \cdots \\ &\geq \frac{\left|[V_m]_1^H [V_m^{0'}]_1\right|^2}{\sum_{j=1,j\neq m}^{M}\left|[V_m]_1^H [V_j^{0'}]_1\right|^2} + \cdots + \frac{\left|[V_m]_k^H [V_m^{0'}]_k\right|^2}{\sum_{j=1,j\neq m}^{M}\left|[V_m]_k^H [V_j^{0'}]_k\right|^2} + \cdots \\ &= \frac{\left\|V_m^H V_m^{0'}\right\|_D^2}{\sum_{j=1,j\neq m}^{M}\left\|V_m^H V_j^{0'}\right\|_D^2}\end{aligned} \tag{20}$$

Where $\|\cdot\|_D^2$ denotes the sum of squares of the diagonal element $k \in r_m$. $\log_2\left(1 + \sum_{m_k}\frac{1}{r_m}\mathrm{SINR}_{m_k}\right)$ is the monotonic function of $\sum_{m_k}\frac{1}{r_m}\mathrm{SINR}_{m_k}$, so

$$\log_2\left(1 + \frac{1}{r_m}\sum_{m_k}\mathrm{SINR}_{m_k}\right) \geq \log_2\left(1 + \frac{1}{r_m}\frac{|[\bar{V}_m^1]^H[\tilde{V}_m^1]|^2}{\sum_{j=1,j\neq m}^{M}|[\bar{V}_m^1]^H[\tilde{V}_j^1]|^2} + \cdots + \frac{|[\bar{V}_m^c]^H[\tilde{V}_m^c]|^2}{\sum_{j=1,j\neq m}^{M}|[\bar{V}_m^c]^H[\tilde{V}_j^c]|^2} + \ldots\right) \tag{17}$$

Substitute (20), (21) into (19), we can get:

$$R_m \geq \log_2\left(1 + \frac{1}{r_m}\frac{|\bar{V}_m^{1H}\tilde{V}_m^1|^2}{\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2}\right), \text{ Hence theorem is proved!}$$

From the theorem the expression $\frac{|\bar{V}_m^{1H}\tilde{V}_m^1|_D^2}{\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2}$ represents the lower bound of the achievable bit rate. $\frac{|\bar{V}_m^{1H}\tilde{V}_m^1|^2}{\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2}$ can be viewed as the user terminal's signal to noise ratio brought on by the codeword's quantization error. Suppose quantization error = 0, $\tilde{V}_m^1 = \bar{V}_m^1$ and $\bar{V}_j^1 = V_j^0$ since $\bar{V}_j^1$ is in the null space of H_m^H, the interference $\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2$ becomes zero, which aligns with the notion of BD precoding. However, the base station cannot compute $\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2$ directly, because in addition to using codeword $\tilde{V}_m^1$ to execute the precoding, it still uses the actual channel parameter $\bar{V}_m^1$. When choosing users in the base station, it is required to substitute the codeword $\tilde{V}_m^1$ instead of $\bar{V}_m^1$ as the base station can only obtain the codeword from the codebook, it is necessary to replace $\bar{V}_m^1$ with $\tilde{V}_m^1$ in $\sum_{j=1,j\neq m}^{M}|\bar{V}_m^{1H}\tilde{V}_j^1|^2$, it follows:

$$\mathrm{SINR}_m = \frac{|\tilde{V}_m^{1H}\tilde{V}_m^1|^2}{\sum_{j=1,j\neq m}^{M}|\tilde{V}_m^{1H}\tilde{V}_j^1|^2} \tag{22}$$

$SINR_m$ in (22) can be expressed as the multi-channel integrated SINR of user m on subcarrier n. Instruction cycle of add = 1, instruction cycle of log = 8 [27]. The number of instruction cycles of using the multi-channel integrated SINR is $\frac{1}{8r_m}$ less than that of computing user achievable bit rate directly.

$\rho = (\rho_m)$ is the user selection and $\rho = (\rho_m)$ is the transmit power of the user m

$\rho =$

$$\begin{cases} 1, & user\quad m\quad selected\quad at\quad the\quad BS, \\ 0, & otherwise \end{cases}$$

For the user selection, the intermediate expression that accurately represent the user's attainable bit rate is provided by ;

$$R_m = B\rho_m \sum_{k=1}^{r_m}\log_2\left(1+\frac{p_m\left\|\mathbf{V}_m^H\mathbf{V}_m^{0'}\right\|_D^2}{\sum_{j=1,j\neq m}^{M}\left\|\mathbf{V}_m^H\mathbf{V}_j^{0'}\right\|_D^2}\right) \tag{23}$$

Therefore, the total system throughput is given by

$$R_s = B\rho_m \sum_{j=1,j\neq m}^{M}\sum_{k=1}^{r_m}\log_2\left(1+\frac{p_m\left\|\mathbf{V}_m^H\mathbf{V}_m^{0'}\right\|_D^2}{\sum_{j=1,j\neq m}^{M}\left\|\mathbf{V}_m^H\mathbf{V}_j^{0'}\right\|_D^2}\right) \tag{24}$$

4. Energy Efficiency Optimization

Concerns over power consumption and environmental sustainability have made energy efficiency (EE) in wireless communication systems more important. The ratio of the total system throughput to the total power used is known as EE [28]. Per our research, no work has investigated Energy Efficient optimization under restricted feedback settings using joint power allocation and user selection. Inspired by this gap, we suggest an energy-efficient optimization method that uses limited feedback CSI in Multi-user MIMO systems to jointly perform power allocation and user selection. EE can be optimized in the following ways based on the overall system throughput and power consumption:

The user m's overall system throughput is represented below;

$$R_s = B\rho_m \sum_{j=1,j\neq m}^{M}\sum_{k=1}^{r_m}\log_2\left(1+\frac{p_m\left\|\mathbf{V}_m^H\mathbf{V}_m^{0'}\right\|_D^2}{\sum_{j=1,j\neq m}^{M}\left\|\mathbf{V}_m^H\mathbf{V}_j^{0'}\right\|_D^2}\right) \tag{25}$$

4.1. Problem Formulation

During the downlink communication step, power consumption is considered. We concentrate on a realistic power consumption model because the base station (BS) uses a large amount of power. The total power transmitted is provided by ;

$$P_s = P_T + P_c \tag{18}$$

and $P_T = MP_m$ where P_c is the fixed circuit power consumption and is the transmit power. The system energy efficiency can be defined as the total achievable data rate to the total power consumption which can be expressed as ;

$$\eta = \frac{\sum_m^M R_m(\rho,p)}{P_s(\rho,p)} \tag{19}$$

we represent ρ and P as ρ_m and P_m correspondingly. The optimization problem can be written as

$$P1: \max_{\{\boldsymbol{\rho},\mathbf{p}\}}\eta(\boldsymbol{\rho},p) = \max_{\rho,p}\frac{\sum_{m=1}^{M}R_m(\boldsymbol{\rho},P)}{P_s(\boldsymbol{\rho},P)} \tag{28}$$

$$\text{s.t.}\quad C1:\rho_m\in\{0,1\}\quad\forall m$$

$$C2:\sum_{m=1}^{M}\rho_m = 1$$

$$C3:\rho_m R_m \geq R_{\min},\quad\forall m$$

$$C4:\sum_{m=1}^{M}\rho_m p_m \leq P_{\max}\quad\forall m$$

$$C5: p_m \geq 0\quad\forall m$$

Where and ensures user selection in a BS. guarantees QoS requirements for the users, represents the maximum transmit power constraint for the BS, indicates that the transmit power is always positive.

4.2. Problem Transformation

Most of the time, there is no workable solution to the non-convex, MINLP issue P1. The fractional form is transformed into integral form in order to address this issue.

$$F(\eta) = \max_{\rho,p} \sum_{m=1}^{M} R_m(\rho, P) - \eta P_s(\rho, P) \tag{29}$$

Suppose ρ^*, P^* indicate the best options for power allocation, subcarrier allocation, and user selection, respectively, and η^* represents the optimal EE,

$$\eta^* = \frac{\sum_{m=1}^{M} R_m(\rho*, P^*)}{P_s(\rho^*, P^*)} = \max \frac{\sum_{m=1}^{M} R_m(\rho, P)}{P_s(\rho, P)} \tag{30}$$

on condition that

$$F(\eta*) = \max \sum_{m=1}^{M} R_m(\rho, P) - \eta P_s(\rho, P) = 0 \qquad ((31))$$

Finding the optimal answer for the initial problem is equivalent to finding the optimal answer for (31). Therefore, we can emphasize the solution to (31)by rephrasing the issue as;

$$\begin{cases} P2 : \max_{\rho,p} \sum_{m=1}^{M} R_m(\rho, P) - \eta P_s(\rho, P) \\ S.t. C1, C2, C3, C4, C5 \end{cases} \tag{32}$$

We investigate the properties of the problem's objective function and constraints in order to find a solution. Furthermore, if and only if the condition is met, the problem in (31) has a workable solution.

4.3. Relaxation

$$\begin{cases} C1 : \rho_m \in \{0, 1\} \quad \forall m \\ C2 : \sum_{m=1}^{M} \rho_m = 1 \quad \forall m \end{cases} \tag{33}$$

The MINLP problem in (33) is solved using relaxations and decompositions. Constraints C1 and C2 are loosened using continuous variables.To tackle (28), the problem is decomposed into two subproblems: the user selection subproblem and the power allocation subproblem.

4.4. User Selection Subproblem

Presuming that the same power is assigned to each subcarrier, i.e. $P_m = \frac{P_{\max}}{N}, \quad \forall m$, the problem in (28) can be transformed into

$$\begin{cases} P3 : \max_{\rho} \sum_{m=1}^{M} \rho_m \frac{\sum_{m=1}^{M} R_m(\rho^*)}{P_s(\rho^*)} \\ S.t. \quad C1 : \rho_m \in \{0, 1\} \quad \forall m \\ \qquad C2 : \sum_{m=1}^{M} \rho_m = 1, \forall m \end{cases} \tag{34}$$

The optimization problem with mixed integer constraints presented in equation (34) requires a notably high computing cost. In terms of the optima matching problem, the optimization problem is similar to a complete bipartite graph given the constraints in user selection. Additionally, the greatest perfect weight matching in a complete bipartite graph is found by solving the optimal matching problem using the modified Kuhn-Munkres (KM) algorithm [29]. Using the fastest path search in the enhanced route algorithm, a modified KM algorithm resolves the user selection issue. Therefore, as in equation (34), we may utilize the KM search algorithm to achive the best user selection. We show the entire bipartite graph as ;

$G = (\phi_1, \rho_2, E)$, where ρ_1 and ϕ_2 is the set of vertices in the graph, representing the BS and UEs, and signifies the set of edges connecting ρ_1 and ϕ_2 vertices respectively. Vertex ρ_1 connects to every vertex of ϕ_2

4.5. The optimal User Selection

Suppose $G = (Y \cap Z, Y \times Z)$ is a weighted complete bipartite graph with linked edges and assigned weight $\omega(y, z)$, where matching from to determines the maximum weight.

Definition 1: A real-valued function l on $Y \cup Z$ is a viable vertex labeling in G if, for each $y \in Y$ and $z \in Z$, $\quad l(y) + l(z) \geq \omega(y, z)$ holds. Therefore, we can determine the vertex labeling that is reasonable to get the maximum under the condition that

$$\begin{cases} l(y) = \max \quad \omega(y, z) \quad \forall \quad y \in Y, z \in Z \\ l(z) = 0, \forall z \in Z \end{cases} \tag{35}$$

Definition 2: If G_l represents the subgraph of G made up of connected edges. If the linked edges of UE, where the line segment ends, satisfy the constraint $l(y) + l(z) = \omega(y, z)$, the graph G_l becomes an equality subgraph.

Theorem 2: Let Φ_1 represents the vertex of the BS and Φ_2 denotes the set of vertex UEs on the subcarrier as $\Phi_2 = \{UE_1, UE_2, UE_3, \ldots, UE_M\}$. In addition, we can determine the weight in connecting edges of Φ_1 and Φ_2 from the BS to the m^{th} UE as follows.

$$\omega(BS, UE) = \frac{\sum_{m=1}^{M} R_m(p^*)}{P_s(p^*)} \tag{36}$$

The process for addressing the best user selection can be summed up as follows:

Step 1: Set the feasible vertex labeling $l(u)$ to its initial value.

Step 2: to find the maximum matching D in G, choose $l(u)$ and determine G_l from G.

Step 3: To solve the optimization problem in (34) and arrive at an ideal user selection solution, let D be considered an optimal matching of G.

Step 4: Or else, there exist unmatched $y \in \Phi_1$, on the condition that y has not been allocated. Establish $S = \{y\}$, and $T = \Phi$.

Step 5: Let $F_{G_l}(S)$ represents the set of Φ_1 and Φ_2 to associate S in G_l. Find $F_{G_l}(S) \neq T$ as

$$\lambda = \min_{y,z}\{l(y) + l(z) - \omega(y,z)\} \tag{37}$$

Where the new labeling $l'(u)$ is defined as

$$l'(u) = \begin{cases} l(u) - \lambda, & u \in S \\ l(u) + \lambda, & u \in T \\ l(u), & \text{otherwise} \end{cases} \tag{38}$$

$\lambda > 0$, and $F_{G_l}(S) \neq T$, put $l(u)$ for $l'(u)$, go to step 2.

Step 6: If $F_{G_l}(S) = T$, go to step 4.

We obtain a new optimal matching solution that is identical to the best user selection policy by carrying out the KM algorithm's iterative procedure.

4.6. Power Allocation

After the user selection policy, the optimal power allocation can be determined. The power allocation optimization problem can be formulated as

$$P4: \max_{\{\mathbf{p}\}} \frac{\sum_{m=1}^{M} R_m(P)}{P_s(P)} \quad \text{s.t.} \quad C3, C4, C5 \tag{39}$$

In (39), the objective function is non-convex. To evade the extraordinary complexity of the solution to $P4$, We introduce parameter conversion. Without loss of generality, the network maximum energy efficiency is given by

$$\eta^* = \max_{p} \frac{\sum_{m=1}^{M} R_m(P)}{P_s(P)} = \frac{\sum_{m=1}^{M} R_m(p^*)}{P_s(p^*)} \tag{40}$$

The problem in (40) can be converted to integral form as follows [30].

$$\max_{p} \sum_{m=1}^{M} R_m(P) - \eta P_s(P) \quad \text{s.t.} \quad C3, C4, C5 \tag{41}$$

where η is a variable presented to scale the weight P_s. When η The solution to the problem (41) is represented by P and the optimal solution to (41) is denoted by p^*. We define the function as

$$F(\eta) \Delta \max \left\{ \sum_{m=1}^{M} R_m(P) - \eta P_s(P) \right\} \tag{42}$$

Clearly, $F(\eta)$ is convex with respect to η. Hence, tackling (42) is equal to determining the maximum EE, which can be attained on condition that

$$F(\eta^*) = \max \left\{ \sum_{m=1}^{M} R_m(P) - \eta^* P_s(P) \right\} = \sum_{m=1}^{M} R_m(p^*) - \eta^* P_s(p^*) = 0 \tag{43}$$

The optimal power allocation is represented by p^*. The EE is enhanced for each iteration until it converges, when the maximum tolerance and maximum iteration number are known.

In each iteration, the Lagrange dual method is utilized to tackle the problem in (43). The Lagrangian function is given by.

$$\mathcal{L}(P, \alpha, \mu) = \sum_{m=1}^{M} R_m(P) - \eta P_s(P) + \alpha \left(\rho_m R_m(P) - R_{\min}\right) - \mu \left(\sum_{m=1}^{M} \rho_m P_m(P) - P_{\max} \right) \tag{44}$$

where α and μ are the Lagrange multipliers for and in (41) respectively. The constraints are Karush-Kuhn-Tucker (KKT) conditions for optimizing power allocation, Hence, the dual problem of (44) is given by

$$\min_{\mu,\alpha} \max_{P} \quad \mathcal{L}(P, \alpha, \mu) \quad \text{s.t.} \quad \alpha \geq 0, \mu \geq 0 \tag{45}$$

The optimal power allocation for the m^{th} user can be solved as.

$$P_m^* = \left[\frac{(M+\alpha)B}{(\eta+\alpha)M \ln 2} - \frac{\sum_{j=1, j\neq m} ||V_m'^H V_j^{0'}||_D^2}{||V_m'^H V_m^{0'}||_D^2} \right]^+ \quad (46)$$

$$[X]^+ = \max\{0, X\}$$

Therefore, the Lagrange multipliers α and μ can be updated according to

$$\alpha(t+1) = \left[\alpha(t) - \gamma(t) \left(\rho_m R_m(P) - R_{\min} \right) \right]^+ \quad (47)$$

$$\mu(t+1) = \left[\mu(t) - \Omega(t) \left(P_{\max} - \sum_{m=1}^{M} \rho_m P_m(P) \right) \right]^+ \quad (48)$$

where t is the iteration index, γ and Ω are the step sizes.

Algorithm 1 illustrates the suggested method to maximize energy efficiency. The K-M algorithm is used to find the best solution for user selection, and the Lagrangian dual decomposition approach is used to find the best power allocation. Algorithm 1 summarizes the execution of the iterative algorithm.

Algorithm 1: Proposed Energy-Efficient JUSPA Optimization with Limited Feedback Algorithm

Input: Maximum iteration number $I_{\max} = 1000$ and maximum tolerance $\varepsilon = 10^{-4}$, $R_{\min}$, $P_{\max}$

Output: η and ρ, P

```
Initialize the user selection;
Set the power allocation P_m = P_max / N;
Initialize Lagrange multipliers (α, μ) ≥ 0;
Set the iteration index t = 0;
while Σ_{m=1}^{M} R_m(ρ, P) − ηP_s(ρ, P) ≥ ε or t ≤ I_max do
    Compute the optimal user selection by utilizing the procedure steps from Kuhn-Munkres algorithm;
    Update Lagrange multipliers using (47) and (48);
    t = t + 1;
Compute the optimal power allocation using (46);
Compute the η using (27);
```

4.7. Computational Complexity Analysis

There are always a lot of different user selection methods in Multi-user MIMO systems with both users and BS. This section looks at the suggested approach's computational complexity. The technique assigns subcarriers to each user equipment (UE) by calculating M at the start of each loop.

To assign just one base station (BS) to each M of the UE, iteration N is carried out. As a result, M^2 determines the overall complexity in the first stage.

The subgradient approach is applied in the second stage, yielding a complexity of $O(M)$ each iteration. This approach rapidly converges in $O\left((M+1)^2\right)$ iterations. Furthermore, the subgradient approach results in a complexity of $O\left(M(M+1)^2\right)$. By introducing the accuracy parameter φ for bisection search, the computational complexity becomes $O\left(M(M+1)^2 \cdot \log_2(1/\varphi)\right)$.

The computational complexity per iteration is expected to be $O(M)$ solely in the third stage, when data transmission is consistent from the BS to the m^{th} UE. Consequently, the complexity for this stage is $O\left(M(M+1)^2 \cdot \log_2(1/\varphi)\right)$. Since each user equipment (UE) only chooses one base station (BS), the first stage iteration is limited by M. This suggests that the second and third iterations determine the computational complexity of the approach. As a result, the total computational complexity can be roughly expressed as $O\left(M(M+1)^2 \cdot \log_2(1/\varphi)\right)$. This demonstrates that the suggested approach is appropriate for real-world applications in MU-MIMO systems and has polynomial complexity.

4.8. Complexity Comparison with Baseline Schemes

Table 1. Complexity Comparison with Baseline Schemes.

Scheme	Per-iteration complexity	Notes
Proposed (modified Kuhn-Munkres + Lagrangian dual decomposition)	$O(M(M+1)^2.\log_2(1/\psi))$	Polynomial; jointly optimizes user selection and power allocation
Equal Power Allocation (EPA)	$O(1)$ per user	No user-selection optimization; power split equally
Distance-based selection	$O(M \log M)$	Simple sort by BS-UE distance; no power optimization
All-active-antennas	$O(1)$	No selection performed; higher circuit power consumption

Table compares the per-iteration computational complexity of the proposed algorithm with the three baseline schemes used in the simulation study (Section 4). As expected, the low-complexity heuristics (EPA, distance-based selection, and all-active-antennas) incur substantially lower computational cost than the proposed approach, since none of them jointly optimizes user selection and power allocation. This additional complexity is the price paid for the higher energy efficiency and system throughput achieved by the proposed algorithm, as reported in Section 4. Because the overall complexity $O(M(M+1)^2.\log_2(1/\psi))$ grows polynomially rather than exponentially with the number of users M, the proposed algorithm remains tractable as the network scales; Section 4.6 discusses this scalability behaviour with reference to the simulation results in Figure 3.

5. Simulation Results and Discussions

We analyze Multi-user MIMO systems with minimal feedback in this part, as shown in Figure 1. Through simulations, we evaluate the efficacy of the suggested combined power allocation and user selection optimization approach. We also compare the suggested algorithm with current schemes and talk about how quickly it converges. For shadowing, the standard deviation is 8dB. With a radius of 1000 meters, the 20 users in the cell are dispersed randomly throughout it.

Rayleigh fading and Hata-COST231 are the small scale and large scale fading models that are taken into consideration [31]. Table 3 also includes the path loss model. The system parameters used in the simulations are displayed in Table 3 below.

Table 2. System parameters.

Parameter	Value
Channel Model	Rayleigh fading
Transmission bandwidth	10MHz
BS radius	1000m
power consumption at BS	10W
Maximum transmit power	10W
Maximum error tolerance	10^{-4}
Noise power	10^{-15}W
BS Antennas	20
UE Antennas	2
Path Loss Model	$PL = 128.1 + 37.6\log_{10}(d)$
Minimum achievable data rate	12Kbps
Circuit power consumption	10W

Authors used MATLAB R2024a, together with the number of independent channel realizations averaged per data point.

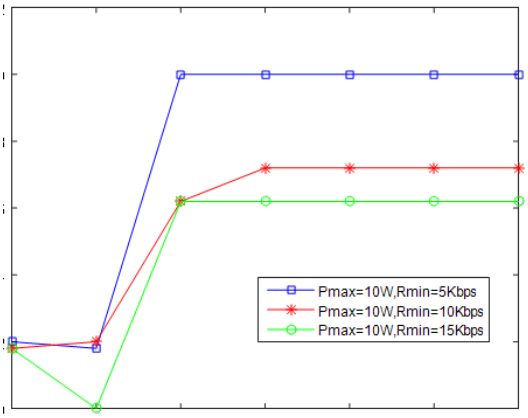


Figure 2. *Energy efficiency versus the number of iterations for QoS criteria.*

Figures 2 and 3 plots the proposed algorithm's energy efficiency versus the number of iterations for various QoS criteria. The suggested approach's Kuhn-Munkres algorithm and Lagrangian dual decomposition method's respective rates of convergence are shown in Figures 2 and 3, respectively.The maximum transmit power is set to be $P_{\max} = 10W$ and the various bit rate requirements are Set to be 15Kbps, 10Kbps, and 5Kbps and in order to achieve the convergence speed. The Kuhn-Munkres algorithm and the Lagrangian dual decomposition technique both converge after a limited number of iterations, as can be observed. Additionally, maximizing is with lower QoS demands has a greater energy efficiency but needs more convergence iterations. This implies that the proposed algorithm has a satisfactory rate of convergence. The first iteration in Figure 2 shows a decline in performance. The initial iteration cannot be a viable zone, which is the cause. However, after all the optimized parameters are provided in the viable range after the first iteration, the performance rises significantly.

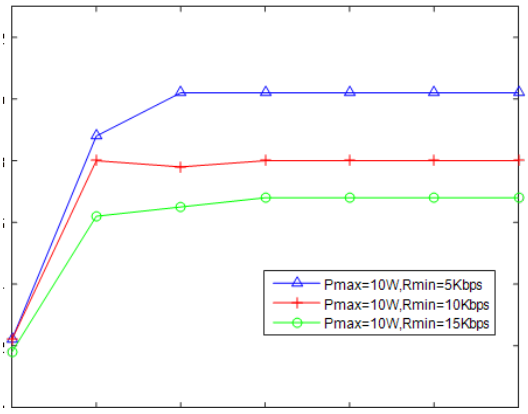


Figure 3. *Energy efficiency versus the number of iterations for QoS criteria.*

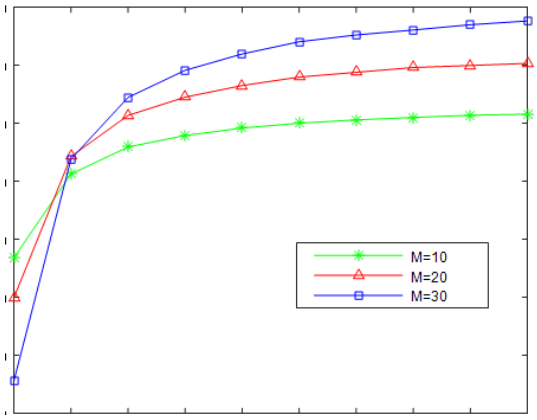


Figure 4. *System throughput versus the number of BS antennas.*

Figure 4 plots the proposed algorithm's system throughput versus the number of BS antennas. The system throughput is shown against the number of BS antennas in Figure 4. Figure 4 shows that for a fixed total number of network users, system throughput increases as the number of BS antennas increases. This is because when there are more antennas, more users may be allowed, increasing the system throughput.

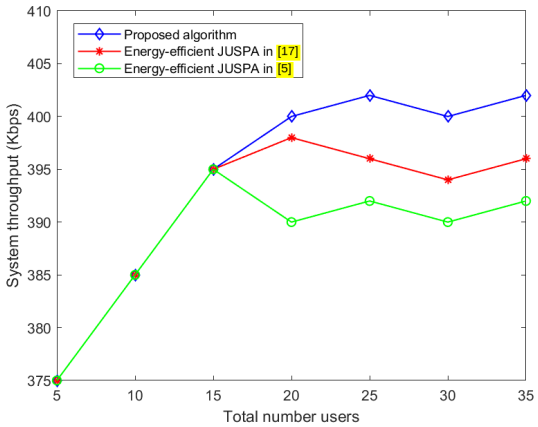


Figure 5. *System throughput for various algorithms shown against the overall number of users.*

In Figure 5, which plots system throughput against the total number of users, it is clear that as the total number of users rises, so does system throughput. In the restricted feedback situation, compared to the energy-efficient JUSPA algorithms already in use in [5] and [17], the suggested approach has a higher system throughput. The rationale is that, in contrast to other studies, which provide disappointing results, we took into account the impact of reduced SINR brought on by limited input on the system throughput while optimizing the resource allocation. Consequently, the proposed technology provides

a higher syetem thtoughput than the existing energy-efficeint JUSPA systems.

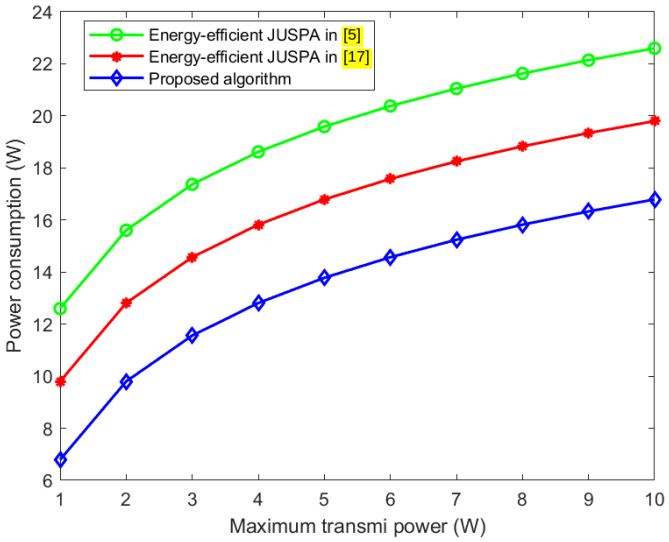


Figure 6. *This figure displays the power usage in relation to the maximum transmit power for different algorithms.*

Figure 6 shows the rise in power consumption when the system's maximum transmit power is used and the number of users remains constant.

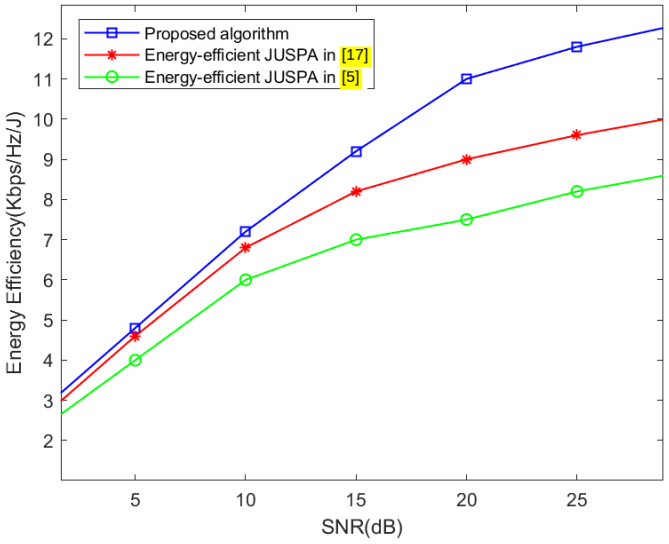


Figure 7. *Compares energy efficiency and SNR for various algorithms.*

According to Figure 7, for a fixed number of users, the system EE grows as the SNR does. This is due to the fact that an increase in SNR suggests a decrease in noise power. Consequently, the higher attainable bit rate may be reached while a little power is used. Additionally, Figure 6 shows that the proposed algorithm's system energy efficiency is higher than that of the current energy-efficient JUSPA systems in [5] and [17]. This is because the suggested algorithm has lower power consumption and performs better in terms of system throughput than the currently known energy-efficient JUSPA algorithms, increasing the method's system energy efficiency.

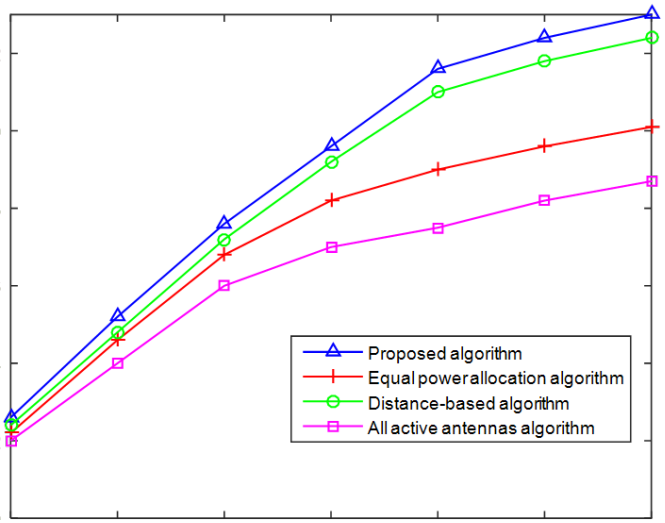


Figure 8. *Energy efficiency versus maximum transmit power for the suggested method and other current schemes.*

Figure 8 shows the relationship between energy efficiency and maximum transmit power for various methods when $R_{\min} = 10Kbps$ .The suggested technique is contrasted with various energy-efficient algorithms, including the distance-based algorithm, the equal power allocation (EPA) algorithm, and the algorithm that makes use of all active antennas. The distance-based system delivers power to the closest users, the all-active antennas approach serves all users, and the base station (BS) distributes the same amount of power to all of its users under the EPA algorithm. Figure 8 clearly shows that the proposed scheme surpasses the baseline methods in system energy efficiency (EE). Compared to the all active antennas algorithm, there is a notable increase in EE. When the transmit power is increased, the EPA approach does not stop users' co-channel interference from growing, but the suggested scheme can handle this problem. Since the suggested approach successfully balances user loads, both it and the distance-based scheme display a consistent interval. However, the distance-based approach allows the BS to serve a large number of users, increasing user co-channel interference and requiring more power to achieve QoS requirements. Due to the high energy required to run the antenna's circuit parts, the all-active antenna system has the lowest EE. As the

maximum transmit power increases, the suggested algorithm's EE increases until it reaches its maximum.

5.1. Quantitative Performance Summary

Table 3 summarizes the approximate quantitative gains of the proposed algorithm relative to the baseline schemes shown in Figures 5 to 8.

Table 3. Approximate quantitative gains of the proposed algorithm relative to the baseline schemes.

Source	Metric	Proposed	Baseline	Approx.gain
Figure 8 ($P_{max} = 7W$)	Energy efficiency (Kbps/Hz/J)	13.0	EPA: 10.1	+28.7%
Figure 8 (($P_{max} = 7W$))	Energy efficiency (Kbps/Hz/J)	13.0	All-active antennas: 8.7	+49.4%
Figure 8 (($P_{max} = 7W$))	Energy efficiency (Kbps/Hz/J)	13.0	Distance-based: 12.4	+4.8%
Figure 7 (SNR = 30dB)	Energy efficiency (Kbps/Hz/J)	12.4	JUSPA [17]: 10.1	+22.8%
Figure 7 (SNR = 30dB)	Energy efficiency (Kbps/Hz/J)	12.4	JUSPA [5]: 8.7	+42.5%
Figure 6 (($P_{max} = 10W$))	Power consumption (W)	16.7	JUSPA [17]: 19.7	−15.2%
Figure 6 (($P_{max} = 10W$))	Power consumption (W)	16.7	JUSPA [5]: 22.6	−26.1%
Figure 5 (35 users)	System throughput (Kbps)	400	JUSPA [17]: 397	+0.8%
Figure 5 (35 users)	System throughput (Kbps)	400	JUSPA [5]: 392	+2.0%

5.2. Computational Running Time

The computational-complexity analysis in Section 4 is theoretical (Big-O). It is observe that, the proposed Algorithm has less execution time compared to the benchmark algorithms as shown in below;

Table 4. Comparison of Algorithms with users, Runtimes, and Absolute Differences in runtime.

Algorithm	Proposed Algorithm (A)	JUSPA in [17] (B)	JUSPA in [5] (C)	$\|B - A\|$	$\|C - A\|$
N0.of users	4	4	4	4	4
Runtime (S)	83.65	167.3	334.6	83.65	250.95
N0.of users	8	8	8	8	8
Runtime (S)	155.3	310.6	621.2	155.3	465.9
N0.of users	10	10	10	10	10
Runtime(S)	195.2	390.4	780.8	195.2	585.6

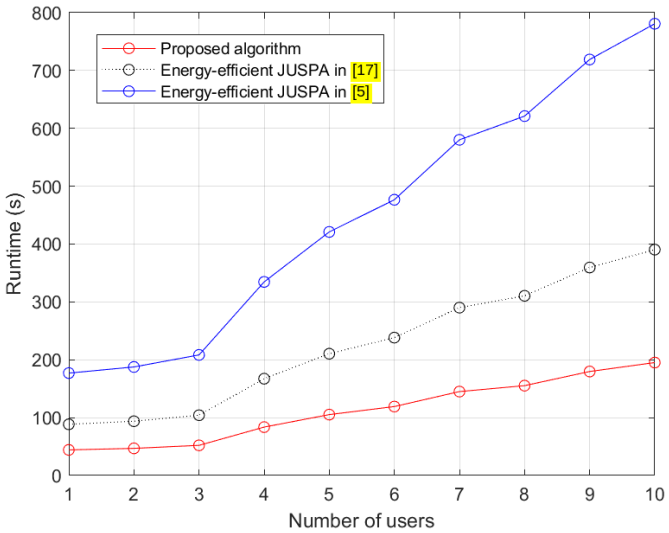


Figure 9. Execution time in relation to the Users M.

The results clearly show that the runtime of all algorithms increases with the number of users due to the higher optimization dimensionality and increased computational burden associated with larger MU-MIMO networks. However, the proposed algorithm consistently achieves the lowest runtime across all simulation scenarios.

5.3. Sensitivity Analysis and Comparison with Additional Benchmarks

The simulation study already provides a sensitivity analysis with respect to several key parameters: transmit power (Figures 6 and 7), number of BS antennas (Figure 4), number

of users (Figures 4 and 5), SNR (Figure 7), and QoS rate requirement (Figure 2), each varied over a representative range while holding the remaining parameters fixed. The current simulation study compares the proposed method against the energy-efficient JUSPA algorithms of [5] and [17], together with three simpler heuristics (EPA, distance-based selection, all-active-antennas).

5.4. Practical Implementation Challenges

Deploying the proposed algorithm in a practical MU-MIMO system involves several implementation considerations beyond the idealized simulation setting studied here. First, the limited-feedback channel between each UE and the BS introduces quantization error and feedback delay, both of which can degrade the accuracy of the CSI used for user selection and power allocation; the present analysis captures the resulting SINR degradation but does not explicitly model feedback delay or specific quantization codebooks. Second, the algorithm's iterative structure (Algorithm 1) requires centralized computation at the BS within each scheduling interval, which places real-time processing demands on the BS as the number of users M grows; Section 4.1 shows that this computational cost remains polynomial in M, but a hardware/software implementation would still need to complete the required iterations within the coherence time of the channel. Third, the analysis assumes perfect time and frequency synchronization between the BS and all UEs (Section 3.1), which in practice requires an accurate synchronization mechanism, particularly as the number of scheduled users increases.

5.5. Scalability Discussion

Because the overall computational complexity of the proposed algorithm,$O(M(M+1)^2\log_2(1/\phi))$, grows polynomially rather than exponentially with the number of users M (Section 4), the algorithm is expected to remain tractable as the network scales to a larger number of users. This is supported by Figure 3, where the algorithm is evaluated for up to 30 users and 100 BS antennas without a breakdown in the observed throughput trend. Nevertheless, for very large-scale MU-MIMO deployments (e.g., hundreds of users), the polynomial growth in complexity, combined with the centralized computation discussed in Section 5.5, may still translate into non-trivial per-scheduling-interval computation time; extending the proposed approach with a distributed or clustered implementation would be a natural direction for improving scalability to such large-scale deployments.

5.6. Limitations

This study has several limitations. First, the system model considers a single isolated cell and does not explicitly model inter-cell interference, which would be present in a multi-cell deployment. Second, although the BS operates under a limited-feedback constraint, the channel estimate itself is assumed to be otherwise accurate; imperfect channel estimation at the UE side is not separately modeled. Third, the reported results are obtained entirely from simulation; the algorithm has not yet been validated on a hardware testbed or with real channel measurements. Finally, as noted in Sections 5.2-5.4, the current results do not include measured execution time, statistical confidence intervals, or a direct comparison with the most recently published (2023-2026) benchmark algorithms; addressing these points would further strengthen the empirical evaluation in a future revision.

5.7. Practical Applications in Future Wireless Communication Systems

The joint user-selection and power-allocation framework proposed in this paper is directly relevant to two major directions in next-generation wireless communication systems. In 5G-Advanced networks, multi-antenna base stations already schedule large numbers of multi-antenna users under practical CSI-feedback constraints, and the proposed algorithm's polynomial complexity (Section 5) and demonstrated energy-efficiency gains (Section 5.1) make it a suitable candidate for energy-aware scheduling in such networks, particularly as network densification increases the number of candidate users per cell. Looking further ahead, 6G systems are expected to rely heavily on massive and cell-free MIMO architectures, often combined with reconfigurable intelligent surfaces (RIS), where feedback overhead becomes an even more critical bottleneck due to the larger number of antennas and distributed access points; the limited-feedback formulation adopted in this paper (Section 3) provides a natural starting point for extending energy-efficient joint scheduling to such architectures, as outlined in the future-work directions in Section 6.

6. Conclusion

MU-MIMO systems offer a viable way to reduce energy usage and increase system throughput. The problem of energy-efficient transmission in MU-MIMO networks with limited feedback CSI is discussed in this paper. In particular, it seeks to satisfy limits on maximum transmission power and QoS while improving system EE through cooperative user selection

and power allocation. The underlying optimization issue is expressed as a MINLP model, which makes direct solutions more difficult due to its non-convexity and NP-hardness. To make the problem more tractable, fractional programming techniques are employed to transform it into a subtractive form. The paper proposes an energy-efficient iterative algorithm that combines a modified Kuhn-Munkres algorithm for effective user selection with a Lagrangian dual decomposition method for optimal power allocation. In MU-MIMO systems with little input, this integrated strategy significantly improves EE. Simulation results confirm that the suggested approach outperforms current algorithms in terms of energy efficiency. The study also looks at the computational complexity and convergence rate of the algorithm.

In particular, the simulation results indicate energy-efficiency improvements of up to approximately 42% and power-consumption reductions of up to approximately 26% relative to existing energy-efficient JUSPA schemes, alongside modest system-throughput gains.

In order to further lower feedback overhead in MU-MIMO systems, future research will look into integrating cutting-edge machine learning techniques such as deep learning and reinforcement learning, extending the proposed framework to multi-cell and reconfigurable-intelligent-surface-assisted MU-MIMO deployments, developing a distributed or clustered version of the algorithm for large-scale scalability, and validating the approach experimentally on a hardware testbed.

Abbreviations

BD	Block Diagonalization
BS	Base Station
CCI	Co-Channel Interference
CSI	Channel State Information
DPC	Dirty Paper Coding
EE	Energy Efficiency
EPA	Equal Power Allocation
JUSPA	Joint User Selection and Power Allocation
MINLP	Mixed-Integer Nonlinear Programming
MMSE	Minimum Mean Square Error
MU-MIMO	Multi-User Multiple-Input Multiple-Output
QoS	Quality of Service
SINR	Signal-to-Interference-plus-Noise Ratio
SNR	Signal-to-Noise Ratio
SVD	Singular Value Decomposition
UE	User Equipment
WCS	Wireless Communication Systems
ZF	Zero Forcing
PL	Path Loss

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Conflicts of Interest

The authors declare no conflict of interest.

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