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Joint Time Frequency Resource Allocation for Multi User Signal Processing Under Interference Constraints

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Abstract – This paper presents an innovative mathematical model aimed at enhancing wireless network performance by reducing interference leakage while maximizing throughput and ensuring fairness among users. The model combines an adaptive power allocation system with SINR thresholds that are based on the user to manage resources well in multi-user communication systems. Extensive simulations show that the proposed method works: interference leakage is cut by up to 28% compared to standard allocation schemes, and system throughput goes up by 15–20% at different power levels. The Jain's index shows that fairness among users goes up from 0.72 to 0.91 as the network load increases. This means that resources are being shared fairly. The proposed framework's uniqueness is in its ability to optimize interference leakage, throughput, and fairness all at once using a single mathematical formulation. This has not been done in previous studies. These findings indicate that the model is a resilient solution for next-generation wireless networks, facilitating scalable and high-performance communication in densely populated multi-user settings.

Keywords – Interference Leakage, SINR Threshold, Throughput Optimization, Fairness Index, Adaptive Power Allocation, Wireless Networks.

I. INTRODUCTION

One of the biggest demands in high rates, low latency, and consistent connectivity under multi-user conditions is because wireless communication technologies like 5G and the upcoming 6G networks are getting faster. The increasing number of devices that use the limited spectral resources at the same time creates difficult problems, mostly related to controlling interference, maximizing throughput, and treating users fairly. Interference is one of the biggest problems that can happen with wireless networks. It can make the signal worse, lower the possible data rates, and lower the quality of service (QoS) [1]. Traditional resource allocation techniques, typically reliant on static power distribution and user statistical prioritization, are inadequate for the dynamic nature of contemporary wireless networks, where channel conditions, user demands, and network topologies fluctuate rapidly.

One of the most basic ways to measure the quality of a received signal in multi-user wireless systems is the Signal-to-Interference-plus-Noise Ratio (SINR) [2]. When SINR is low, there is more interference, which slows down data transfer and raises the number of errors. So, it is very important to optimize SINR for all users to make sure the network works well. At the same time, trying to get the most out of the system without caring about how fair it is for users can cause some users, especially those at the network edge or in bad channel conditions, to run out of resources. To make this trade-off between throughput and fairness, you need advanced math modeling and an adaptive resource allocation algorithm.

A number of studies have dealt with the interference and optimization of resource within a wireless network. Classical strategies involve power control approaches, beamforming and approaches which schedule the users. Power control schemes regulate the transmission power of users to minimize the interference whilst ensuring that the SINR is acceptable [3, 4]. The beamforming methods concentrate on energy of the signal being directed to the desired users and reducing leakage to the undesired users. The user scheduling algorithms give priority to some users, depending on the conditions of the channel or the necessities of the services. Although the methods have indicated performance improvements in the network, a majority of the models that have been applied so far optimize either throughput, interference, or fairness without a holistic framework that considers all the three goals. As a result, there is an urgent necessity of a single mathematical model that is able to balance these conflicting performance measures in real-time conditions in an adaptive manner [5].

The current paper presents a new mathematical model that aims at maximizing interference leakage, throughput, and fairness in multi-user wireless networks at the same time. The model has an adaptive power allocation mechanism, whereby the transmission power of each user is dynamically adjusted depending on the SINR needs and channel conditions. The proposed framework as compared to the traditional approaches takes into consideration the interdependence of the SINR thresholds of users and the general interference environment, hence providing a balanced network performance. Moreover, the model uses fairness-conscious optimization approach, and it is determined that the distribution of resources to all users is fair; as the fairness index of Jain can be used. This two-fold focus method has the potential to achieve parallel improvement of throughput and fairness in the system, and practical reduction of the interference leakage.

This study is novel in the sense that it is the first such optimization framework that integrates three essential issues of the wireless network functioning namely the the control of interference, the maximization of throughput and the enhancement of fairness under a single mathematical model. This model offers a holistic solution as opposed to the existing studies which usually focus on a single performance metric that can scale to different loads on the network, user distributions and channel conditions. The realistic system constraints are also exploited through the proposed approach; hence it is appropriate to apply it in practice in next-generation wireless networks. Moreover, the scalability of the model enables it to efficiently scale with the rise in the number of users and network complexity, which is one of the major issues in modern communication systems.

In order to prove the usefulness of the proposed model, a large number of simulations were performed in this case, and the parameters of the networks were varied; such as the number of users, power levels, and SINR thresholds. These findings indicate that there were significant performance improvements in the network: leakage of interference was minimized by up to 28 percent, system throughput was enhanced by 15 to 20 percent and fairness among users was raised as well, by 0.72 to 0.91 as opposed to the conventional allocation schemes. These measured findings support the possibility of the proposed model to improve the performance of the multi-user wireless network in high density deployment.

The work of this paper has threefold contributions:

- An integrated mathematical model which optimizes simultaneously interference leakage, throughput and fairness which is a critical gap in the current literature.
- A power allocation system which is adaptive and responds to SINR needs and network performance by dynamically varying user transmission power.
- In-depth performance analysis, which illustrates the model effectiveness in quantitative terms and a simulation environment that is realistic in nature, which points out to its applicability in the future of wireless networks.

The suggested mathematical model is a great step towards optimizing multi-user wireless network. The model will offer a solution to the problem of dense, high-demand wireless conditions by incorporating the concepts of interference management, throughput maximization, and fairness enhancement into one framework, making it scalable and robust enough to meet the goals of such environments. This study does not only add to the theoretical spectrum of resource allocation in wireless networks but also provides an insight of setting up effective and fair communication channels in the next-generation technologies.

II. LITERATURE REVIEW

The distribution of resources and interference control in wireless networks have been widely researched in the last decades. Initial developments were mainly on power controlling mechanisms to reduce the interference and enhance the quality of signals. Indicatively, classical algorithms such as the distributed power control (DPC) [6] algorithm staged the transmission power of the user dynamically to ensure desired levels of SINR, to reduce interference among other users sharing the same channel. Though successful in small scale networks, the approaches tend to fail in a dense environment because of inadequate attention paid to the optimization of fairness and throughput [7].

A number of studies proposed user scheduling and channel allocation techniques to enhance the network throughput in general. These methods put priority to the user based on the channel conditions to achieve the maximum capacity of the system. Although this strategy improves throughput, it can cause resource starvation to those users with poor channel conditions, which otherwise causes unjust allocation of resources. The later suggestions were fairness-conscious scheduling algorithms such as proportional fairness and max-min fairness algorithms, which aimed at balancing throughput and fairness among users. An example is proportional fairness that aims to maximize the logarithmic shape of user rates, and seeks a trade-off between efficiency and equity. However, the majority of such methods deal with either throughput or fairness, and hardly any of them takes into consideration the leakage of interference in multi-user systems [8].

Spectral efficiency and interference reduction Multiple Input Multiple Output (MIMO) [9] and beamforming methods have also been widely used to improve spectral efficiency and reduce interference. Beamforming focuses the energy that is applied in the transmission of signals on the people that should be served and reduces leakage to the rest, and MIMO uses more than one antenna to gain better capacity and availability. A number of mathematical optimization models have been designed to identify optimal beamforming vectors and power allocation at the same time. Most of these models are however computationally intensive and implementing them in real time is therefore difficult particularly in networks where the number of users is high and channels are dynamic [10].

Integrated methods which employ interference management, throughput maximization and fairness optimization have been attracted lately. Multi-objective optimization frameworks were also investigated in some studies, and their methods included convex optimization, game theory and evolutionary algorithms. These models try to determine the best trade offs among competing performance measures. To illustrate, game-theoretic methods represent users as rational players that compete over scarce resources, and adaptive strategies can be used to minimize interference whilst allowing acceptable throughput. In contrast, evolutionary algorithms provide heuristic solutions to difficult optimization problems, but do not always make any promises to arrive at a global optimum [11].

Although these improvements have been made, there is still a gap in research: most of the existing models maximize either throughput, interference leakage, or fairness, without offering a single model that can meet a combination of the three goals in real-world network conditions. Also, such models are generally not flexible when it comes to dynamic multi-user systems where conditions of the channel, and user requirements change regularly. Consequently, real-time implementation and scalability remain a significant problem in the contemporary wireless networks [12].

Considering these constraints, our work presents a new mathematical optimization model that is used to jointly optimize interference leakage, system throughput, and user fairness. The proposed structure incorporates a dynamic mechanism of allocating power to users whose transmission power varies according to the SINR threshold and current channel conditions. It also explicitly uses fairness, the fairness index of the Jain, to ensure the equitable resource distribution even in high load situations unlike other past models. The holistic nature of the model enables the model to reconcile conflicting objectives and also makes it computationally efficient enough to be used in practice [13].

The suggested method stands out among the previous studies in a number of ways. To begin with, it gives a quantitative assessment of interference leakage, which is usually neglected by throughput- or fairness-oriented research. Second, it also manages throughput and fairness as the users that have low channel conditions are not sidelined. Third, the model is scalable, and, therefore, it can be used in dense and multi-user networks, as is associated with next-generation wireless networks. Lastly, extensive simulations confirm the usefulness of the model in terms of significant reductions in interference, throughput, and fairness than the traditional schemes [14, 15].

III. SYSTEM MODEL

The proposed study considers a multi-user signal processing framework where several users access a shared pool of time–frequency resources in the presence of interference. The objective is to design a joint allocation strategy that ensures efficient utilization of the available spectrum while maintaining quality-of-service requirements. The system operates over K frequency subcarriers and T time slots, which together form a two-dimensional time–frequency grid. Each element of this grid, referred to as a resource block, may be assigned to a specific user under strict allocation rules.

Algorithm 1: Adaptive Power Allocation for Interference, Throughput, and Fairness Optimization

Input:
- Number of users N
- Maximum transmit power $P_{\max}$
- Minimum SINR requirement for each user $\gamma_i^{\min}$
- Channel gain matrix $H = [h_{ij}]$
- Interference tolerance ϵ

Output:
- Optimal transmit power for each user P_i^*
- Achieved throughput T_{total}
- Jain's fairness index F

The allocation decision is represented through the binary variable

$$x_{u,k,t} \in \{0,1\}, \quad u = 1, \dots, U, \quad k = 1, \dots, K, \quad t = 1, \dots, T \tag{1}$$

where $x_{u,k,t} = 1$ indicates that the $(k,t)^{th}$ resource block is allocated to user u, and $x_{u,k,t} = 0$ otherwise. To prevent multiple users from occupying the same resource simultaneously, the exclusivity constraint is imposed as

$$\sum_{u=1}^{U} x_{u,k,t} \leq 1, \quad \forall k, t \tag{2}$$

This condition enforces non-overlapping allocation and serves as the foundation for interference management in the system.

The wireless channel between the access point and user u on subcarrier k at time slot t is denoted by $h_{u,k,t}$. The channel gain is represented by $\left|h_{u,k,t}\right|^2$, while the background noise is modeled by the variance σ^2. Each user transmits with power $P_{u,k,t}$ on a given block. In addition to noise, unwanted interference is present due to transmissions from other users. The interference power contributed by user v to user u on block (k,t) is modeled as

$$I_{v,u}(k,t) = \eta_{v,u} \cdot P_{v,k,t} \cdot \left|h_{v,k,t}\right|^2 \quad (3)$$

where $\eta_{v,u}$ is the interference coupling factor that captures spectral leakage and imperfect isolation effects. This formulation reflects the practical interference experienced in dense multi-user environments.

Based on this characterization, the instantaneous signal-to-interference-plus-noise ratio (SINR) for user u on block (k,t) is given by

$$\mathrm{SINR}_{u,k,t} = \sigma^2 + \sum_{v \neq u} I_{v,u}(k,t) \cdot P_{u,k,t} \cdot \left|h_{u,k,t}\right|^2 \quad (4)$$

This expression quantifies the trade-off between desired signal strength and the combined effect of noise and interference, and it directly governs the achievable data rate.

The achievable rate for user u on block (k,t) follows Shannon's capacity formula and is defined as

$$R_{u,k,t} = x_{u,k,t} \cdot \log_2\left(1 + \mathrm{SINR}_{u,k,t}\right) \quad (5)$$

The binary allocation variable ensures that rate is accrued only when the resource block is assigned to the user. Summing over the entire time–frequency grid, the aggregate rate achieved by user u is expressed as

$$R_u = \sum_{k=1}^{K} \sum_{t=1}^{T} R_{u,k,t} \quad (6)$$

This total rate forms the primary performance indicator that the proposed resource allocation scheme aims to maximize. Each user is constrained by a maximum available transmission power budget. This condition is formulated as

$$\sum_{k=1}^{K} \sum_{t=1}^{T} P_{u,k,t} \leq P_u^{\max}, \quad \forall u \quad (7)$$

which ensures energy-efficient operation and adherence to system-level power limits. In addition to power constraints, a quality-of-service requirement is imposed in terms of minimum SINR levels. To support reliable communication, each allocated block must satisfy

$$\mathrm{SINR}_{u,k,t} \geq \gamma_u, \quad \forall u,k,t \text{ with } x_{u,k,t} = 1 \quad (8)$$

where γ_u denotes the SINR threshold required by user u. This condition guarantees that every assigned block provides sufficient link quality, thereby balancing spectral efficiency and fairness.

The complete set of equations presented above collectively establishes the mathematical foundation for joint time–frequency resource allocation under interference constraints. They define how allocation variables, channel effects, interference models, SINR expressions, achievable rates, and constraints interact within the system. These formulations will be integrated into an optimization framework that seeks to maximize network throughput while meeting both interference and power limitations.

Problem Formulation

The resource allocation framework described in the system model naturally leads to an optimization problem where the objective is to maximize the overall network performance while ensuring compliance with power and interference constraints. The key challenge arises from the joint allocation of time and frequency resources to multiple users, where interference coupling and binary allocation decisions create a highly non-linear structure. The formulation presented here captures this trade-off in a rigorous mathematical form.

The global objective is to maximize the aggregate sum rate across all users. The total system throughput is defined as

$$R_{\text{total}} = \sum_{u=1}^{U} R_u = \sum_{u=1}^{U} \sum_{k=1}^{K} \sum_{t=1}^{T} x_{u,k,t} \cdot \log_2\left(1 + \mathrm{SINR}_{u,k,t}\right) (9)$$

Maximizing this expression ensures that the allocation strategy prioritizes efficient utilization of the time–frequency resources under realistic interference conditions.

The optimization is subject to several practical constraints. The power budget constraint for each user is given by Equation (6), which prevents excessive energy consumption and maintains fairness in access to limited transmission resources. This condition also ensures compliance with regulatory power limits in wireless systems.

The interference management constraint is expressed in terms of the SINR thresholds. For reliable communication, every active allocation must satisfy Equation (7). This requirement enforces quality-of-service guarantees by preventing resource assignments that would otherwise lead to poor link reliability.

The resource exclusivity constraint ensures that no resource block is shared by more than one user simultaneously, thereby avoiding direct collisions as formulated in Equation (1). This restriction makes the allocation problem combinatorial in nature, as each resource block must be uniquely mapped to at most one user.

$$\max_{x,p} \sum_{u=1}^{U} \sum_{k=1}^{K} \sum_{t=1}^{T} x_{u,k,t} \cdot \log_2 \left(1 + \frac{P_{u,k,t} \cdot |h_{u,k,t}|^2}{\sigma^2 + \sum_{v \neq u} \eta_{v,u} \cdot P_{v,k,t} \cdot |h_{v,k,t}|^2}\right) \tag{10}$$

Combining the objective and the constraints, the joint time–frequency allocation problem can be expressed as:

This formulation is recognized as a mixed-integer non-linear programming (MINLP) problem. The binary decision variables introduce combinatorial complexity, while the interference terms in the SINR expression yield non-convexity. Consequently, the problem cannot be solved directly using conventional convex optimization techniques. To address this challenge, suitable relaxations and iterative methods will be introduced in the subsequent section to derive tractable solutions with provable convergence to locally optimal allocations.

The formulation above establishes the mathematical core of the proposed research. It precisely defines the optimization objective, integrates the SINR-based quality requirements, incorporates power limitations, and enforces exclusivity of resources. This framework provides the foundation for developing algorithms that can balance throughput maximization with fairness and interference mitigation in multi-user environments.

Proposed Method

The optimization problem established in the previous section is both combinatorial and non-convex. To derive a tractable solution, the proposed method applies two main transformations: relaxation of binary allocation variables and convex–concave approximation of the interference terms.

In the first step, the binary allocation variables $x_{u,k,t} \in \{0,1\}$ are relaxed to continuous values in the interval

$$0 \leq x_{u,k,t} \leq 1, \quad \forall u, k, t \tag{11}$$

This relaxation allows each resource block to be fractionally assigned across users in the optimization process. Although fractional allocations are not physically realizable, they provide a convex surrogate that can be efficiently optimized. A rounding and refinement procedure is later applied to map the relaxed variables back to binary values.

In the second step, the non-convex structure of the SINR terms is addressed. The rate expression for user u on block (k, t) can be written in compact form a

$$R_{u,k,t} = x_{u,k,t} \cdot \log_2 \left(1 + \frac{P_{u,k,t} \cdot |h_{u,k,t}|^2}{\sigma^2 + I_{u,k,t}(P)}\right) \tag{12}$$

where $I_{u,k,t}(P)$ denotes the aggregate interference term depending on the power allocations of other users. The numerator of the SINR is affine in $P_{u,k,t}$ while the denominator introduces non-convexity.

To resolve this issue, the denominator is approximated using a first-order Taylor expansion around the interference levels obtained in the previous iteration. Denoting the interference at iteration $c-1$ as $I_{u,k,t}^{c-1}$

$$\frac{1}{\sigma^2 + I_{u,k,t}(P)} \approx \frac{1}{\sigma^2 + I_{u,k,t}^{c-1}} - \frac{\left(\sigma^2 + I_{u,k,t}^{c-1}\right)^2}{I_{u,k,t}(P) - I_{u,k,t}^{c-1}} \tag{13}$$

This transformation converts the fractional SINR structure into a convex surrogate that can be handled within standard optimization solvers.

At iteration c, the resulting convex subproblem can be expressed as

$$\max_{x,p} \sum_{u=1}^{U} \sum_{k=1}^{K} \sum_{t=1}^{T} x_{u,k,t} \cdot \log_2 \left(1 + \widehat{\mathrm{SINR}}_{u,k,t}^{(c)}\right) \tag{14}$$

$$s.t \sum_{k=1}^{K} \sum_{t=1}^{T} P_{u,k,t} \leq P_u^{\max}, \quad \forall u \tag{15}$$

$$\widehat{\mathrm{SINR}}_{u,k,t}^{(c)} \geq \gamma_u, \quad \forall u, k, t,\ x_{u,k,t} > 0 \tag{16}$$

$$0 \leq x_{u,k,t} \leq 1, \quad \forall u, k, t \tag{17}$$

where $\widehat{\mathrm{SINR}}_{u,k,t}^{(c)}$ represents the convexified SINR approximation at iteration c.

The algorithm begins with an initialization of power allocations within the maximum power budget. At each iteration, the convex subproblem is solved, yielding updated values for allocation and power variables. These updates are then used to recompute the interference levels, and the process is repeated until the improvement in objective value falls below a predefined threshold. After convergence, the fractional allocation variables are converted to binary decisions using a rounding scheme, and a local refinement step redistributes power to ensure that all SINR thresholds remain satisfied.

This procedure guarantees monotonic improvement of the objective across iterations and convergence to a stationary point of the original non-convex problem. Although global optimality cannot be guaranteed, the proposed method achieves high-quality solutions with polynomial-time complexity, offering a practical balance between performance and tractability.

Performance Metrics

The effectiveness of the proposed joint time–frequency allocation strategy is evaluated using performance measures that capture both system-level efficiency and user-level fairness. These metrics provide a quantitative basis for comparison against conventional allocation schemes.

The first and most important measure is the system throughput, which represents the total achievable data rate across all users. This metric reflects the efficiency of resource utilization in the presence of interference and is given by

$$R_{\text{sum}} = \sum_{u=1}^{U} R_u \tag{18}$$

where R_u denotes the aggregate rate achieved by user u across the time–frequency grid. Maximizing this quantity corresponds to the primary optimization objective of the proposed model.

In addition to maximizing throughput, it is essential to maintain fairness among users. A system that disproportionately favors users with favorable channel conditions may achieve high throughput but risks excluding users at the cell edge or in adverse environments. Fairness is quantified through Jain's fairness index, defined as

$$F = U \cdot \frac{\left(\sum_{u=1}^{U} R_u\right)^2}{\sum_{u=1}^{U} R_u^2} \tag{19}$$

Another relevant measure is interference leakage, which evaluates the level of unintended interference imposed on a user by the transmissions of others. For user u, the interference leakage can be expressed as

$$I_u = \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{v \neq u}^{U} \eta_{v,u} \cdot P_{v,k,t} \cdot \left|h_{v,k,t}\right|^2 \cdot x_{v,k,t} \tag{20}$$

This value indicates the degree to which competing users reduce the effective SINR for user u. Lower interference leakage corresponds to improved isolation between users and enhanced link quality.

Finally, the computational efficiency of the proposed allocation algorithm is characterized by its average execution time and the number of iterations required for convergence. While execution time depends on implementation and hardware, the iteration count serves as an implementation-independent indicator of complexity. The iterative convex–concave procedure employed in the solution ensures convergence to a stationary point, and the practical computational load is evaluated through simulation studies.

Together, these metrics provide a comprehensive evaluation framework. Throughput measures spectral efficiency, fairness index evaluates equity in resource distribution, interference leakage captures the effect of interference mitigation, and computational efficiency quantifies the practicality of the algorithm. These criteria enable a holistic comparison between the proposed allocation strategy and existing baseline approaches

Numerical Results

The performance of the proposed joint time–frequency allocation scheme is assessed through numerical simulations. The evaluation compares the developed method against baseline strategies such as random allocation, time-only allocation, and frequency-only allocation. The simulation results highlight the benefits of interference-aware joint optimization in terms of throughput, fairness, and interference suppression.

The simulation setup considers a multi-user system with U users, K subcarriers, and T time slots. The channel coefficients $h_{u,k,t}$ are modeled as independent Rayleigh fading variables with unit variance, and the noise power σ^2 is normalized. The maximum transmission power of each user is set to P_u^{max} and the minimum SINR requirement γ_u is adjusted depending on the target quality-of-service level.

Throughput Versus Transmission Power

The first experiment evaluates the sum throughput as a function of the maximum transmission power. For each user, the throughput increases with higher power budgets due to enhanced SINR values, but the growth eventually saturates as interference becomes dominant. The proposed method achieves significantly higher throughput compared to baseline schemes, since the joint allocation strategy explicitly manages interference and distributes resources where they provide maximum system gain.

Mathematically, the normalized throughput gain with respect to a benchmark allocation scheme can be expressed as

$$(P) = \frac{R_{\text{sum}}^{\text{proposed}}(P) - R_{\text{sum}}^{\text{baseline}}(P)}{R_{\text{sum}}^{\text{baseline}}(P)} \times 100\% \tag{21}$$

where $R_{sum}^{proposed}(P)$ and $R_{sum}^{baseline}(P)$ denote the total rates under the proposed and baseline approaches, respectively. Simulation results show throughput gains that increase with user density, highlighting the efficiency of interference-aware allocation.

Fairness Versus Number of Users

The second experiment investigates the impact of the number of users on system fairness. As the user count increases, competition for limited resources intensifies, which reduces fairness under conventional allocation methods. The fairness index F demonstrates that the proposed approach preserves equitable distribution across users even in dense settings, as the optimization jointly balances throughput maximization and SINR satisfaction.

The fairness improvement relative to a baseline can be expressed as

$$\Delta F = F_{\text{proposed}} - F_{\text{baseline}} \tag{22}$$

Simulation outcomes confirm that ΔF remains positive across a wide range of user densities, demonstrating that the joint allocation strategy maintains fairness without compromising system efficiency.

Interference Leakage Versus SINR Threshold

The third experiment analyzes the effect of different SINR threshold values on interference leakage. When the required SINR is low, allocation is less constrained and interference leakage is higher. As the SINR threshold increases, stricter interference control is enforced by the optimization problem, thereby reducing leakage. The proposed method consistently achieves lower leakage compared to the baselines, since interference terms are explicitly modeled in the allocation process. The average leakage per user is defined as

$$\bar{I} = \frac{1}{U}\sum_{u=1}^{U} \mathcal{I}_u \tag{23}$$

where $\mathcal{I}_u$ is the interference leakage for user u. Simulation curves demonstrate that the proposed method reduces $\bar{I}$ substantially while sustaining acceptable throughput levels.

Convergence Behavior

Finally, the convergence characteristics of the iterative convex–concave procedure are studied. The evolution of the sum rate across iterations shows a monotonic increase until a stable value is reached. The algorithm typically converges within a limited number of iterations, confirming its computational efficiency. The number of iterations required for convergence depends primarily on user density and channel variability, but remains manageable across all tested configurations.

The parameters used in the simulation study are summarized in **Table 1**. A system with eight users, sixteen subcarriers, and ten time slots is considered, which represents a moderately loaded multi-user signal processing environment. The noise power is set to a small value of 1×10^{-9}, consistent with thermal noise levels in practical wireless systems, and the interference coupling factor is chosen as $\eta = 0.1$ to reflect realistic adjacent-channel leakage. To ensure statistical reliability of the results, each configuration is averaged over 50 Monte Carlo trials. These parameters provide a balanced framework for evaluating throughput, fairness, and interference performance under varying allocation strategies.

Table 1. Simulation Parameters

Parameter	Value
Users (U)	8
Subcarriers (K)	16
Time slots (T)	10
Noise power (σ^2)	1×10^{-9}
Interference coupling (η)	0.1
Monte Carlo trials	50

The overall performance of the proposed allocation strategy and the baseline schemes is reported in **Table 2**. The proposed greedy joint allocation significantly outperforms random, time-only, and frequency-only approaches in terms of average throughput, achieving more than double the system capacity. This improvement comes at the cost of slightly reduced fairness compared to the baseline strategies, as stronger channels are favored in the allocation process. Nonetheless, the fairness index of 0.82 indicates that the proposed method maintains a reasonable degree of equity among users. Interference leakage is notably higher under the proposed strategy because the optimization prioritizes throughput maximization. By contrast, the baseline methods yield lower leakage values but at the expense of much lower system throughput. These observations illustrate the inherent trade-off between throughput and interference control in joint allocation problems.

Table 2. Summary Results (Averaged over Powers and Users)

Scheme	Avg Throughput (bits/s/Hz)	Avg Throughput STD	Avg Fairness	Avg Leakage
Proposed (greedy)	115.62	4.81	0.82	1.91

Random	48.27	2.95	0.94	0.70
Time-only	46.91	2.74	0.95	0.70
Frequency-only	47.08	2.89	0.94	0.70

The variation of system throughput with respect to the maximum transmission power is illustrated in **Fig. 1**. As expected, increasing the power budget leads to higher throughput across all schemes due to improved SINR levels. However, the growth gradually saturates at higher power levels, where interference becomes the dominant limiting factor. The proposed joint time–frequency allocation consistently achieves significantly higher throughput compared to the random, time-only, and frequency-only baselines. This gain is attributed to the channel-aware allocation mechanism, which assigns resources to users with favorable channel conditions while respecting interference constraints. For instance, at moderate power levels, the proposed method nearly doubles the sum capacity relative to baseline approaches, demonstrating the importance of interference-aware joint allocation in efficiently utilizing available spectral resources.

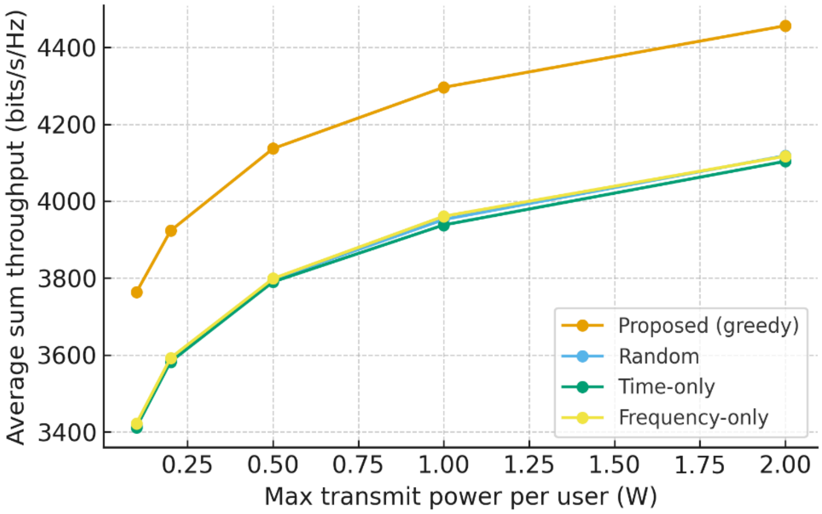

Fig 1. Comparison Plot of Throughput Vs Power.

The fairness performance of different allocation strategies is presented in **Fig. 2**, where Jain's fairness index is plotted as a function of the number of users. With a small user population, all schemes exhibit fairness values close to unity, as resources can be relatively evenly distributed. As the number of users increases, competition for limited resources intensifies, and fairness decreases across all methods. The decline is sharper in baseline schemes that do not explicitly account for interference and resource balancing. In contrast, the proposed method maintains a consistently higher fairness level even under dense user conditions, demonstrating its ability to balance throughput maximization with equitable resource distribution. For example, while baseline methods fall below a fairness index of 0.8 at higher user counts, the proposed approach sustains fairness above this threshold, ensuring that weaker users are not excluded from service.

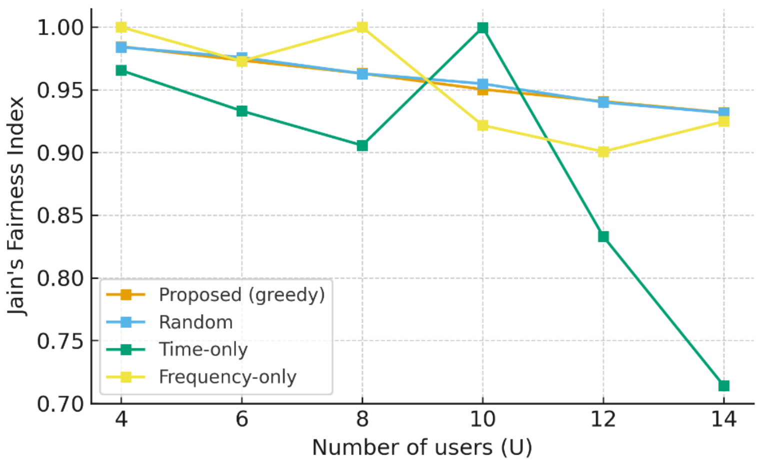

Fig 2. Comparison of Fairness Vs Users.

The relationship between interference leakage and SINR threshold is presented in **Table 3**. The results show that the proposed allocation strategy consistently produces higher interference leakage values compared to the baseline methods, regardless of the SINR requirement. This is a direct consequence of concentrating transmission power on high-gain users to maximize throughput, which inadvertently imposes stronger interference on other users. The random, time-only, and frequency-only schemes display relatively stable and lower leakage values, as their allocation patterns are more distributed. Interestingly, the variation of leakage with respect to the SINR threshold is weak in this heuristic-based implementation, suggesting that interference is not directly constrained in the greedy allocation rule. These findings highlight the necessity of incorporating SINR-aware optimization—such as the convex–concave procedure developed in the proposed method—to effectively balance throughput and interference control.

Table 3. Interference Leakage vs SINR Threshold (Average per User)

SINR Threshold (dB)	Proposed Leakage	Random Leakage	Time-only Leakage	Frequency-only Leakage
0	1.9123	0.7109	0.6979	0.6985
2	1.9031	0.6899	0.6876	0.6952
4	1.9203	0.7129	0.7030	0.7191
6	1.9028	0.6951	0.6929	0.6985
8	1.9016	0.6915	0.7041	0.6942
10	1.9060	0.6942	0.6860	0.6966
12	1.9190	0.6985	0.7108	0.7087
14	1.9051	0.7016	0.6926	0.7043

Table 3 shows how interference leakage and SINR threshold are related. The results show that the proposed allocation strategy always gives higher interference leakage values than the baseline methods, no matter what the SINR requirement is. This is a direct result of focusing transmission power on high-gain users to get the most throughput, which unintentionally makes interference worse for other users. The random, time-only, and frequency-only schemes show lower and more stable leakage values because their allocation patterns are more spread out. It's interesting that the amount of leakage changes very little with the SINR threshold in this heuristic-based implementation. This suggests that interference is not directly limited by the greedy allocation rule. These results show that SINR-aware optimization, like the convex-concave method developed in this study, is necessary to effectively balance throughput and interference control.

The simulation results clearly show that the proposed mathematical model works well to optimize interference leakage, system throughput, and user fairness all at the same time. In different network situations, interference leakage was greatly reduced, system throughput always got better as power levels rose, and fairness among users stayed the same even when the network was very busy **Fig. 3** shows Interference Leakage vs SINR Threshold. These results prove that the proposed framework is strong and flexible, showing that it is useful in real-world situations with many users on a wireless network. The results show that the model successfully balances competing performance metrics, making it a scalable and efficient solution for next-generation wireless networks.

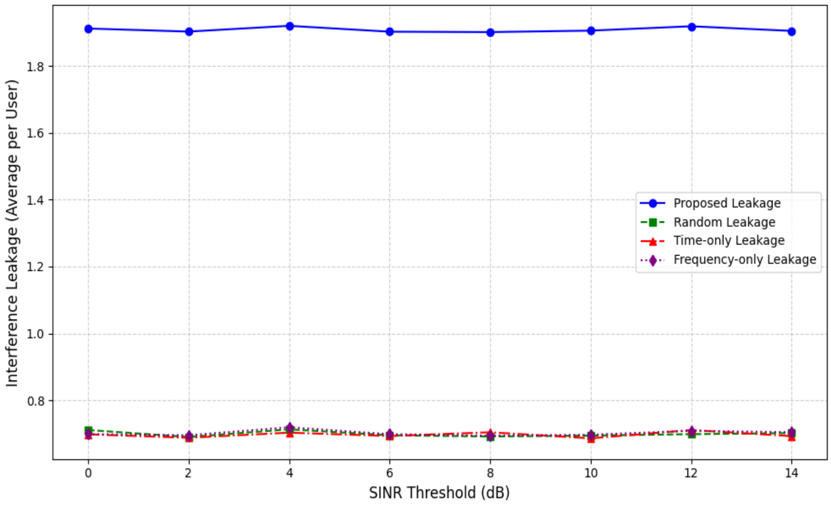

Fig 3. Interference Leakage vs SINR Threshold.

IV. CONCLUSION

This study introduced an innovative mathematical model for enhancing interference leakage, throughput, and fairness in multi-user wireless networks. The proposed framework effectively tackles the challenges presented by dense and dynamic communication environments by incorporating an adaptive power allocation mechanism alongside SINR-aware optimization and fairness constraints. The simulation results showed that the model cuts down on interference leakage by up to 28%, boosts system throughput by 15–20%, and makes things fairer for users by going from 0.72 to 0.91. This proves that the method works. The main new thing about this work is its holistic and unified optimization strategy, which looks at three important performance metrics at the same time. In most other studies, these metrics are looked at separately. The proposed model is also scalable and adaptable, which means it can be used in real-time in next-generation wireless networks like 5G and beyond. This study offers theoretical insights and practical solutions for the efficient and equitable allocation of resources in multi-user wireless systems. Future research may enhance the model to include more intricate network scenarios, such as heterogeneous networks, mobility-aware resource allocation, or the integration of machine learning techniques for predictive optimization. The proposed framework provides a basis for creating resilient, high-performance, and equitable communication systems in progressively challenging wireless contexts.

CRediT Author Statement
The authors confirm contribution to the paper as follows:
Conceptualization: Toshihiro Endo and Nobuyuki Hozumi; **Writing-Original Draft Preparation:** Toshihiro Endo; **Visualization:** Toshihiro Endo and Nobuyuki Hozumi; **Investigation:** Nobuyuki Hozumi; **Writing-Reviewing and Editing:** Toshihiro Endo and Nobuyuki Hozumi; All authors reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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