Game Theory Algorithms for Resource Allocation in 5G MIMO

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Abstract— Efficient resource allocation is essential in 5G MIMO networks due to increasing demands for high-quality communications. This paper compares four game theory algorithms: Stackelberg, Nash Bargaining, Mean Field Game, and Potential Game, evaluating their effectiveness in allocating resources dynamically. A simulation environment is developed to represent realistic user mobility by continuously updating User Equipment (UE) positions. Each algorithm is assessed based on UE distribution, fairness, bandwidth consumption, and energy efficiency. The simulation results show clear differences among the algorithms, highlighting specific advantages and limitations that help inform resource allocation strategies in practical 5G network scenarios.

Keywords—Game Theory, 5G Networks, Multiple Input Multiple Output (MIMO), Stackelberg, Nash Bargaining, Mean Field Game, Potential, Resource Allocation.

1 Introduction

5G Multiple Input Multiple Output (MIMO) networks represent a significant advancement in wireless communication technologies, offering solutions designed to address rapidly growing demands for high data rates, extensive coverage, and improved reliability. These networks leverage advanced Base Station (BS) systems, multiple simultaneous data streams, an enhanced spectral efficiency to provide better User Equipment (UE) experiences and support diverse, data-intensive applications. As emerging applications such as virtual reality, augmented reality, high-definition streaming, smart cities, and the Internet of Things (IoT) increase their demands on network resources, efficient and adaptive resource management becomes increasingly critical.

Efficient distribution of resources within 5G MIMO networks, particularly in dynamic scenarios characterized by mobile UEs, directly influences network performance, UE fairness and energy consumption. Current research recognizes that traditional static allocation methods may not adequately address the challenges posed by UE mobility and dynamic channel conditions. Consequently, interest in adaptive resource allocation methods that can respond effectively to these dynamics has increased significantly.

In response to these challenges, this paper introduces a unified platform for examining multiple resource allocation Game Theory strategies within a single 5G MIMO environment. In particular, it implements four game-theoretic algorithms Stackelberg [1], Nash Bargaining [2], Mean Field [3], and Potential Game [4]. Within each algorithm UEs act as players competing to maximize their individual profit, while considering factors such as distance, velocity, path loss, and Signal-to-Noise Ratio (SNR). After every time interval, the algorithm assigns random movement directions base on initially velocities to each UE, recalculating distances to each BS. This allows for a more accurate observation of how mobility affects key performance metrics such as fairness, energy use, and user allocation. By evaluating all four algorithms under the same mobility conditions, the study highlights their individual advantages and weaknesses for each game theory algorithm in a practical setting. As a result, the findings offer useful guidance for researchers and network designers aiming to build better or combined strategies that are suited for dynamic and realistic 5G environments. Also, these four game theory algorithms cover the main approaches used for resource allocation in 5G MIMO networks. The Stackelberg game captures the leader–follower link between a BS and its UE, the Nash bargaining game frames cooperative negotiation to maintain fairness; the mean-field game scales to many UEs by reacting to their average behavior and the potential game guides distributed choices toward a network-wide optimum. [5], [6], [7], [8].

The rest of this paper is organized as follows: Section 2 presents a review of recent research concerning resource allocation methods based on Game Theory approaches in 5G MIMO systems. Section 3 introduces the mathematical algorithm employed in the simulation environment. Section 4 provides a detailed analysis of the algorithms used as the foundation for developing experimental scenarios. In Section 5, the simulation environment and methodology used to evaluate algorithm performance are described. Section 6 presents the simulation results along with a comprehensive analysis of the findings. Finally, Section 7 concludes the paper and identifies potential directions for future research.

2 Related Work

Recent studies have explored multiple approaches, ranging from optimization algorithms and heuristic methods to advanced strategies using game-theoretic principles. This section briefly examines representative works that address different dimensions of resource allocation, providing a clear context for identifying how this current paper contributes uniquely, particularly by considering realistic UE mobility and dynamic channel conditions.

In the work presented by the authors in [9], a pilot allocation strategy based on coalitional game theory is developed to address pilot contamination challenges in distributed MIMO systems, a common problem exacerbated by increasing numbers of UE terminals in 5G networks. Their proposed algorithm transforms pilot allocation into an optimization problem aimed at minimizing the Normalized Mean Squared Error (NMSE) in channel estimation. By adopting a coalitional game framework and designing a symmetric, additive separable preference function related to Mean Squared Error (MSE), the researchers achieve results comparable to exhaustive methods but with significantly reduced complexity. Simulation findings demonstrate substantial improvements over random pilot reuse, highlighting the efficiency of game theory techniques in managing resource constraints in distributed MIMO scenarios.

The research in [10] introduces a dynamic resource allocation approach specifically designed for downlink scenarios in 5G Radio-over-Fiber (RoF) networks utilizing Wavelength Division Multiplexing Passive Optical Networks (WDM-PON) combined with Multiple-UE MIMO (MU-MIMO). The proposed method focuses on efficiently reallocating wireless Resource Blocks (RB) within Component Carriers (CC), aiming to optimize wavelength usage, reduce system cost, and enhance throughput. To achieve this, a heuristic algorithm is developed to dynamically adjust RB assignments based on varying network demands. Simulation results presented by the author indicate that this method effectively reduces wavelength consumption and improves throughput performance under diverse UE conditions and block error rates. The work highlights the potential benefits of dynamic resource reallocation strategies, particularly emphasizing their significance in managing resource utilization efficiently in complex 5G scenarios involving MIMO technology and varying UE demands.

Authors in [11] proposes a generalized resource allocation framework tailored for MU-MIMO systems utilizing Orthogonal Frequency Division Multiple Access (OFDMA). The presented strategy addresses key challenges associated with spatial multiplexing, particularly focusing on efficient co-scheduling of multiple UEs to increase system capacity while preserving fairness among UEs. Central to this approach is a scheduling algorithm that dynamically allocates resources by considering both transmitting power distribution and inter UE interference, crucial factors that impact overall performance. Simulation results based on the SCM-5G channel model demonstrate that the proposed framework successfully achieves a beneficial trade-off between increased network capacity and sustained UE fairness. Moreover, the findings emphasize the necessity of precise resource allocation strategies in MU-MIMO systems, reinforcing that capacity improvements gained through advanced BS systems must be managed carefully to ensure balanced throughput among UEs.

The manuscript in [12] investigates resource allocation strategies for downlink transmission in cell-free massive MIMO networks. The work specifically aims to maximize the minimum achievable data rate across UE, focusing on optimal transmit precoding and power allocation strategies. The author tackles the inherent non-convexity of this optimization problem by employing the uplink-downlink duality principle, proposing an iterative algorithm to achieve efficient and practical solutions. The analysis further incorporates the impact of channel estimation errors, deriving a lower bound for network capacity. Through comprehensive system-level evaluations, the author demonstrates that the proposed algorithm significantly surpasses traditional allocation methods, validating its practicality and effectiveness in realistic wireless communication environments.

Unlike previous studies, which often keep UEs fixed or consider limited random movements, this paper explicitly incorporates realistic mobility in two dimensions. Thus, intervals how UE mobility impacts performance aspects such as fairness, energy efficiency, and UE distribution. By directly comparing these four algorithms' side by side, this work provides clear insights into each algorithm's practical strengths and limitations when mobility is realistically considered. Researchers and engineers can therefore easily understand the effectiveness of each method, supporting the development of improved or hybrid strategies tailored specifically for dynamic and realistic 5G deployment scenarios.

3 Mathematical Model

This section defines mathematically the problem of dynamic UE allocation using principles from game theory. In this scenario, each UE, denoted by index i, selects a fraction of its allocation to each available BS, indicated by index j, aiming to optimize its individual or global profit. Several parameters, such as distance, pathloss, data rate, SNR, and UE velocity, are factored into the profit calculation. Four game-theoretic algorithms Stackelberg, Nash Bargaining, Mean Field, and Potential Game are applied to distribute a total of 1810 UEs among 7 BSs throughout 50 distinct time intervals.

Formally, let the set of UEs be represented by U={1,2,…,N} with ∣U∣=1810, and let the set of BSs be denoted by B={1,2,…,M} with ∣B∣=7. The allocation fraction a_{ij} represents the portion of UE i's total allocation assigned specifically to BS j. To ensure consistency and resource utilization constraints, we enforce the following normalization constraint across all BSs for each UE:

$$\sum_{j=1}^{M} \alpha_{ij} = 1 \tag{1}$$

The variables utilized in calculating the profit are clearly defined. The distance from UE i to BS j is d_{ij}, based on their two-dimensional positions. Pathloss between UE i and BS j is represented as PL_{ij}, and the corresponding SNR (uplink, downlink, or a combination of both) is denoted SNR_{ij}. Additionally, DR_{ij} indicates the data rate for UE i from BS j, while vi describes UE i's velocity. A constant factor, referred to as the penalty factor, modifies the utility calculation based on distance and velocity. Meanwhile, the resource parameter resources[j], associated with BS j, is scaled iteratively by the game-theoretic algorithms. The profit function is formulated as follows, using a small constant ε>0 to prevent division by zero:

$$\text{Profit}_{ij} = \frac{\alpha_{ij} \times \left(DR_{ij} \times SNR_{ij}\right)}{\left(1 + PL_{ij}\right) \times \left(\left(d_{ij} + 1\right)\left(v_i + 1\right) \times \text{penalty\_factor} + \varepsilon\right)} \tag{2}$$

The total profit for UE i across all BSs is simply the sum of the profits associated with each BS j. In numerical computations, introducing a small positive constant, commonly referred to as epsilon (ε), is a standard technique to maintain numerical stability. This approach prevents issues like division by zero when variables such as a user's distance (d_{ij}) or velocity (v_i) are extremely small or zero. By adding ε (typically around 10^{-8} or smaller) to the denominator, computations avoid instability and infinite values without significantly affecting the model's accuracy. This practice is widely adopted in numerical simulations to ensure robust and reliable calculations.

Each of the four game-theoretic algorithms employs the above profit function and the allocation constraint, but they differ in the method by which they iteratively update allocations. In the Stackelberg Game, a leader BS iteratively adjusts its resource scaling strategy, and follower UEs subsequently adapt their allocations, typically using a lower penalty factor. Nash Bargaining Game introduces a logarithmic transformation to balance utility across UEs and BSs, commonly using moderate penalty factors. The Mean Field Game presumes each UE responds independently to the average allocations of other UEs, updating its choice using an exponential or softmax function. Lastly, the Potential Game maximizes a global potential, measured as the sum of squared UE profits, thus guiding allocations toward resources with collectively greater utilities.

Also, other performance metrics are calculated to evaluate allocation effectiveness. The fairness index is a dimensionless measure, defined as follows:

$$f = \frac{\left(\sum_{i=1}^{N} \mathrm{thr}_i\right)^2}{N \times \sum_{i=1}^{N} \mathrm{thr}_i^2 + \varepsilon} \tag{3}$$

Energy efficiency is defined as follows:

$$\eta = \frac{\sum_{i=1}^{N} \mathrm{thr}_i}{\sum_{i=1}^{N} \left(\left(d_{i,*}\right)^2 \times v_i\right) \times \mathrm{power\_factor} + \varepsilon} \tag{4}$$

where d_i, is the average distance of UE i to the BSs, and power_factor can differ per algorithms [13], [14].

Thus, for bandwidth allocation we calculate the maximum needs in Mbps of each UE in each BS, using the Shannon-Hartley theorem [15]. The Shannon-Hartley theorem is a principle used to determine the maximum theoretical rate at which information can be transmitted over a communication channel with a given bandwidth, accounting for the presence of noise. It is an application of the noisy-channel coding theorem and is commonly applied to continuous analog communication channels affected by Gaussian noise. This theorem establishes the channel capacity, which refers to the maximum amount of error-free information that can be transmitted per unit time, given a specific bandwidth and assuming limited signal power and knowledge of the noise properties. Named after Claude Shannon and Ralph Hartley, the theorem is an important concept in information theory and is widely utilized in the design and analysis of communication systems. In practical terms, the Shannon-Hartley theorem allows communication system designers to optimize their systems by finding the optimal balance between information transfer rate and error minimization. By mathematically relating to the channel capacity (denoted as C), the signal power (S), the noise power (N), and the bandwidth, the theorem provides a framework for maximizing information transfer while considering the limitations imposed by noise and available bandwidth. This is particularly relevant in scenarios where the channel is subject to Additive White Gaussian Noise (AWGN). In essence, the Shannon-Hartley theorem provides a valuable tool for understanding and designing communication systems, enabling engineers to determine the maximum amount of reliable information that can be transmitted through an analog communication channel in the presence of noise. By optimizing the factors involved, such as signal power and bandwidth, communication systems can be designed to achieve efficient and effective data transmission while minimizing errors.

$$\mathrm{C} = \mathrm{B}\log_2(1 + \mathrm{S}/\mathrm{N}) \tag{5}$$

The channel capacity, denoted as C in bits per second, represents the maximum achievable net bit rate without using error-correction codes. The channel's bandwidth, denoted as B and measured in hertz, refers to the passband bandwidth for a bandpass signal. The average received signal power, denoted as S and measured in watts (or volts squared), is the average power of the signal over the bandwidth. In carrier-modulated passband transmission, it is often referred to as C. The average power of noise and interference over the bandwidth is represented as N and measured in watts (or volts squared). The SNR or Carrier-to-Noise Ratio (CNR) is expressed as a linear power ratio of the communication signal to the noise and interference at the receiver, rather than in decibels.

To efficiently allocate a specific frequency range from the antenna for each user without interference, variable B needs to be determined. This is achieved using a modified formula that considers the SNR value and a predefined threshold value for variable C. The term "pre-set" indicates that a randomly assigned bandwidth value is given to users of a particular service (during our simulations we define specific service, more information is section VI Simulation Environment and Table II).

Finally, equations directly represent how the algorithm dynamically allocates UEs. Each game algorithms iteratively updates $\alpha_{i,j}$ by maximizing or adjusting profit, whether individually Potential Game and Mean Field Game, through pairwise negotiations Nash Bargaining, or leader–follower strategies Stackelberg. Penalty factors and SNR combinations differ by algorithms, but all share the same underlying profit function and constraints that account for distance, pathloss, and velocity.

4 Algorithm Analysis

This section provides a detailed analysis of the theoretical algorithm I used for modeling UE mobility and dynamically allocating resources within a multi BS 5G MIMO environment. The analysis follows the algorithm's logical steps closely, outlining essential computations, processes, and interactions involved in its implementation.

Algorithm I: A Dynamic Game-Theoretic Algorithm for Multi BSs n UE Allocation

1. **Step 1: Initialization & Parameter Configuration:**

2. In this step, the code reads the configuration constants that specify the number of UEs (N) and BSs (M), the total simulation time intervals, and the dataset paths for UE velocity, pathloss, SNR, and data rates. It also defines the resource array resources[j]. The dataset is then loaded into arrays for velocity, pathloss, uplink_SNR, downlink_SNR, data_rate, and BS locations. Finally, each UE's initial position is randomized in a 2D plane.
3. **Step 2: Network Representation & Topology:**
4. The algorithm computes the distance matrix $d_{i,j}$ in 2D from each UE i to each BS j. It associates each UE with velocity v_i and prepares data structures to store each algorithm's time-varying results (fairness, latency, energy efficiency). These values are updated at each iteration of the selected game algorithms.
5. **Step 3 Implementing Each Game Theory Algorithms:**
6. Stackelberg Game: Iteratively updates a leader strategy (resource scaling) and a follower response (UE allocation). A smaller penalty_factor is often applied, reflecting a more optimistic assessment of distance–velocity costs.
7. Nash Bargaining Game: Uses a log-based utility function and medium iteration count. It incorporates both uplink and downlink SNR in a combined form and reassigns allocations based on bargaining power.
8. Mean Field Game (MFG): Treats each UE as responding to the average (mean field) of all allocations. Each UE updates its allocation by applying an exponential (softmax-like) function to its utility.
9. Potential Game: Aims to maximize global potential, defined as the sum of squares of UE utilities. Each UE tries different resource allocations that yield the highest increase in this potential.
10. **Step 4: Performance Evaluation & Metric Computation:**
11. For each algorithm, the algorithm computes UE distribution, Fairness, Bandwidth Consumption and Energy Efficiency. These metrics are stored and plotted over time. Allocation decisions follow mathematical equations, with UE movement affecting utility and assignment. While all algorithms share the core utility, differences in penalties, iterations, and updating rules impact UE distribution, fairness, Bandwidth Consumption, and energy efficiency.

Initially, the algorithm starts by defining the simulation parameters, including the total number of UEs, the number of BSs, the simulation's duration, and the file paths for datasets containing UE velocities, pathloss measurements, downlink SNR, and data rates. These datasets are structured into arrays to facilitate efficient computational handling. Additionally, each UE is assigned an initial random position within a two-dimensional plane, forming the basis for initial connectivity and influencing subsequent resource allocation decisions. The available resources at each BS are also defined at this stage, establishing foundational constraints for allocation.

Following initialization, the algorithm builds the network representation by accurately calculating distances between each UE and every BS. These distances are continuously updated and play a critical role in determining signal strength, potential interference, and overall connectivity quality. Additionally, UE velocities assigned randomly and updated at each simulation interval introduce realistic UE movement scenarios. Such movements significantly impact the quality of the network's channel conditions, making resource allocation decisions dynamic and responsive to changes in UE distribution and connectivity. Data structures are simultaneously prepared to track key performance indicators throughout the simulation, including fairness and energy efficiency.

The algorithm then individually applies four distinct game-theoretic algorithms to address the resource allocation problem. First, the Stackelberg game algorithm is implemented, adopting a leader-follower structure. Here, BSs act as leaders adjusting the allocation of available resources strategically, while UEs function as followers, responding to these allocation strategies. A penalty factor reflecting distance-velocity relationships guides UE decision-making, typically set low to encourage more optimistic resource allocation even under challenging connectivity scenarios.

Next, the Nash Bargaining game algorithm is implemented, relying on a bargaining-based utility approach. This algorithm integrates both uplink and downlink signal qualities into a unified, logarithmic-based utility function, facilitating cooperative interactions among UEs. Resource allocation occurs through negotiation, ensuring balanced benefits and equitable distribution among the UE, especially under changing connectivity conditions.

Subsequently, the Mean Field Game approach is employed, wherein each UE independently optimizes its resource allocation decisions based on the collective behavior of other UE. In this scenario, every UE considers the overall average (mean field) allocation within the network to adapt its individual resource demands accordingly. The allocation updates are made through exponential decision rules, allowing smooth adaptation to dynamic network states.

Finally, the Potential Game algorithm focuses explicitly on optimizing a global system objective, specifically defined as the cumulative squared utilities of all UEs. Under this algorithm, each UE explores alternative allocation possibilities, selecting those that offer the most significant increase in the global potential value. This collective optimization approach helps achieve desirable system-wide outcomes, enhancing overall network performance.

The final stage of the algorithm involves rigorous performance evaluation. The algorithm computes and tracks fairness, latency, energy efficiency, and load balancing throughout the entire simulation. Continuously updating these performance metrics, the algorithm enables an extensive comparative analysis of the four implemented game-theoretic approaches. This structured approach highlights the adaptability and effectiveness of each algorithm in realistic mobility scenarios, facilitating deeper understanding of their respective strengths, limitations, and practical implications in dynamic 5G MIMO network environments.

5 Simulation Environment

In this section, the simulation environment used in the presented experiments is described. The network structure, including BS positioning and UE distribution, is adapted from a simplified scenario based on the DeepMIMO dataset [16]. The specific topology implemented is illustrated in Fig. 1. The UEs appear in a straight horizontal line because this layout comes directly from the DeepMIMO dataset rather than any custom placement. The DeepMIMO O1 scenario defines user locations on a uniform grid along the main street, with 1810 rows (R1–R1810) of UEs, each row consisting of 181 UEs positioned at the same y-coordinate, aligned horizontally. Using the default dataset parameters, selected the primary street grid 1 thus, the UE positions in our experiment naturally form a horizontal line segment in the topology. This linear arrangement is an inherent property of the DeepMIMO scenario's predefined geometry, as each "row" represents a group of UEs uniformly spaced along a line. The experimental setup represents an urban scenario simplified into a smaller scale 5G MIMO system.

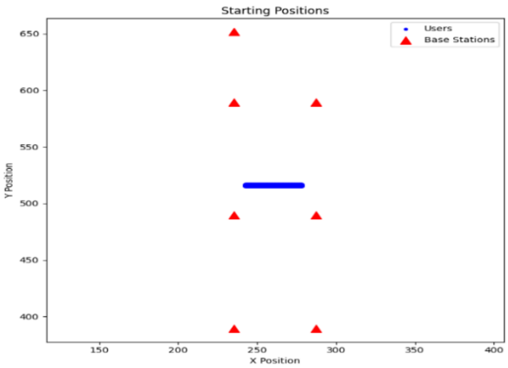

Fig.1. Topology of Simulation.

In addition, the topology consists of 7 BSs, strategically positioned to ensure optimal coverage within the defined area. Each BS is positioned at a height of 6 meters, establishing uniform vertical alignment across the network. According to the chosen scenario, seven BSs are arranged in a defined symmetrical pattern. Specifically, the BSs form a structured distribution consisting of two vertical groups, each containing three BSs, aligned symmetrically along both sides of the topology. Additionally, one BS is positioned individually, located centrally at the top, ensuring coverage from the upper central side. This symmetrical yet non-centralized arrangement provides balanced coverage of the experimental area, allowing for accurate evaluation of resource allocation strategies under realistic yet simplified network conditions.

For the experimental simulations, three distinct datasets, each containing different UE densities specifically, 362, 543, and 905 UEs are used separately within the same topology. These datasets are subsequently merged into one larger, comprehensive dataset. Combining these datasets allows the conducted experiments to reflect realistic scenarios involving varying UEs densities, facilitating deeper and more comprehensive analyses of resource allocation strategies. Note also, that the operating frequency of the network in which simulations were implemented is at 140 GHz, the Number of 5G NR resource blocks is 60 and 5G Subcarrier spacing in kHz is 120.

After completing the simulation intervals and updating UEs' velocities and directions randomly, the distribution of UEs transforms significantly. As illustrated in Fig. 2, the final positions of the UEs spread radially outward from the central area, evenly dispersing around the BSs. The resultant UE distribution closely resembles realistic urban scenarios, capturing UE mobility and spatial diversity effectively. UEs occupy positions around all seven BSs, reflecting a balanced distribution pattern across the entire defined topology area. This dynamic change in UE positions results in varied and realistic distances and connectivity conditions, allowing the experimental algorithms to be evaluated comprehensively in terms of adaptability, performance, and robustness under changing UE distributions.

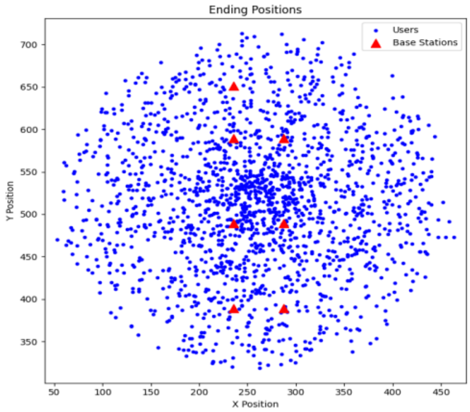

Fig.2. Topology of Final UEs Positions.

In addition to the spatial arrangements described, critical technical parameters are predefined to achieve accurate and consistent simulations. Specifically, the BS transmit power is fixed at 45 dBm, with each BS equipped with BS gain of 21 dBi. The bandwidth capacity allocated for each BS is 400 MHz. Moreover, as previously stated, the simulations involve combined scenarios from the three datasets containing 362, 543, and 905 UEs, respectively. The transmit power for all UEs is consistently set at 20 dBm. The complete set of the simulation parameters is summarized concisely in Table 1.

Table 1. SIMULATION PARAMETERS

Parameter	**Value**
Transmit power(dbm)	45 dbm
BS height (m)	6 m
BS/UE gain (dbi)	21 dbi, 0 dbi
Bandwidth (MHz)	400 Mhz
Number Of UEs	362,543, 905
Power Noise	Pnoise= -74+10log(Bandwidth(hz))
Number of Resource Blocks	60
Subcarrier Spacing	120 kHz
Frequency	140 GHz

This defined simulation environment, along with dynamically evolving UE distributions, enables effective and thorough analysis of each game-theoretic algorithm's adaptability and robustness under realistic conditions. Finally, each UE is randomly generated and assigned to one of the services defined in Table 2, which outlines the downstream and upstream demand requirements for each service.

Table 2. TYPE OF SERVICES

Services	Downstream	Upsteam
Browsing/Email	5 Mbps	2 Mbps
HDTV	16 Mbps	0.5 Mbps
Video Streaming	25 Mbps	1 Mbps
Podcasts	2 Mbps	0.5 Mbps
VoIP	1 Mbps	1 Mbps

6 Performance Evaluation

This section analyzes the performance evaluation results obtained by applying four distinct game-theoretic algorithms Potential Game, Mean Field Game, Nash Bargaining, and Stackelberg Game in the described 5G MIMO scenario. The primary aim is to examine how effectively each algorithm allocates UEs to BS over time. UE distributions generated by these methods are compared based on their average allocations across the entire simulation period. Understanding these distributions clarifies how each approach manages resources under realistic mobility and network dynamics. Furthermore, examining these distributions highlights the inherent trade-offs among fairness, throughput optimization, present in each algorithm.

Beginning with the Nash Bargaining algorithm, as shown in Fig. 3, the UE distribution remains uneven, with some BSs becoming significantly more loaded than others. At the end of the simulation, BS2 has the highest number of connected users, reaching around 580 users. In contrast, BS3 only serves about 30 users, which is a very small portion of the total. The other BSs vary between 210 and 360 users. This pattern suggests that the leader-follower mechanism in Stackelberg allows certain BSs those offering better performance conditions to attract and retain more users. However, this behavior does not always result in balanced use of all available resources. The imbalance can lead to congestion in the most popular cells and underuse of others. While the algorithm does adapt during the simulation, it still leaves certain stations, like BS3, almost empty.

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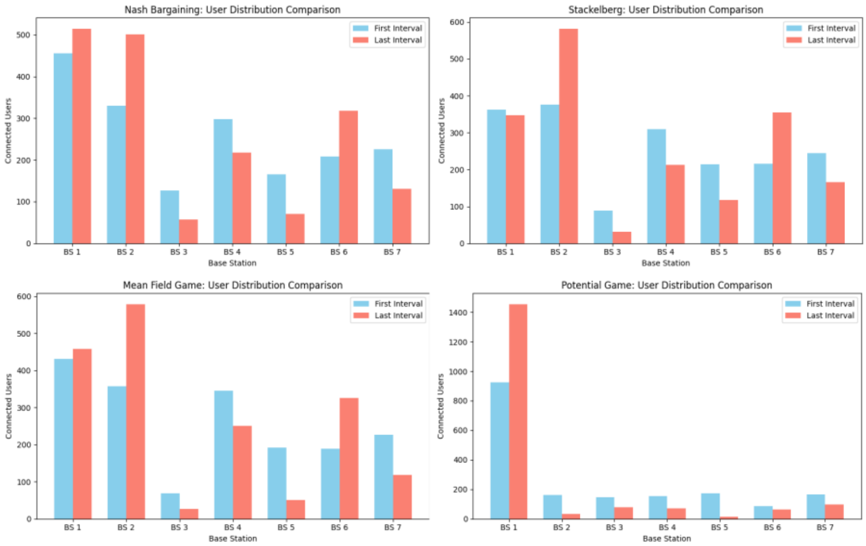

Fig.3. UE distribution over time for Game Theory Algorithms.

The Mean Field Game algorithm (Fig. 3) produces a slightly more balanced outcome but still shows noticeable skew. BS2 stands out with the highest load, reaching close to 580 users, while BS1 and BS6 have around 460 and 330 users respectively. In contrast, BS3 and BS5 serve very few users, with BS3 having around 30 and BS5 only about 50. The remaining BSs BS4 and BS7 handle around 250 and 120 users each. The fact that a few BSs attract the majority of the users, while others remain mostly underused, suggests that although each user acts independently in this algorithm, many of them are still drawn to a small number of stations that consistently offer better conditions. This self-organizing behavior helps avoid the extreme overconcentration seen in Potential, but it still does not ensure even resource usage.

Contrasting sharply with these balanced approaches is the Potential Game algorithm (Fig. 3), which shows a skewed distribution. Initially, BS 1 already holds around 930 UEs, dramatically overshadowing all other stations. Instead of correcting this imbalance, the algorithm further concentrates UEs over time, culminating in approximately 1450 UEs (around 80% of all UEs) allocated to BS 1 by the end. Other BSs are severely underutilized, each connecting fewer than 100 UEs. This drastic unevenness aligns with Potential Game's observed tendency toward heavy resource concentration, resulting in the lowest fairness values and highlighting potential congestion risks.

By comparing all these outcomes, the Mean Field Game algorithm stands out as the most effective algorithm for distribution of UE. It maintains balanced resource utilization throughout the simulation, thereby preventing significant congestion and ensuring equitable UE experiences. Stackelberg and Nash Bargaining approaches also perform well, demonstrating flexibility and adaptability but with slightly less consistency than the Mean Field approach. In contrast, the Potential Game's extreme concentration strategy, while potentially optimizing specific criteria, reveals significant practical drawbacks concerning fairness and operational stability. Thus, the comprehensive evaluation of these distribution patterns underscores the importance of selecting an appropriate game-theoretic approach depending on network performance goals, emphasizing balanced resource allocation as key to sustainable and efficient network operations.

Another essential aspect of resource allocation analysis is fairness, a metric indicating how evenly UEs are allocated across BSs during the simulation, as shown in Fig. 4. Fairness is quantified through an index ranging from 0 to 1, with values closer to 1 representing a more uniform distribution and as a consequence such values indicate indicates a perfect Fairness. Observing the fairness index allows for an understanding of whether BSs are equally utilized or if certain BSs disproportionately serve most of the UEs. This assessment reveals fundamental characteristics of each allocation algorithm.

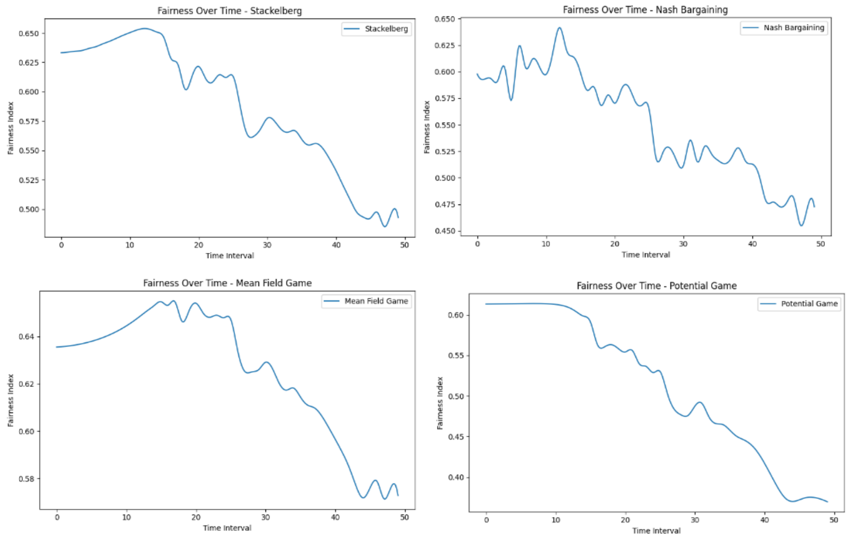

Fig.4. Fairness Index over time for Game Theory Algorithms.

The fairness index for the Stackelberg Game algorithm (Fig. 4) begins high, slightly above 0.625, and quickly rises slightly higher within the first intervals, reaching approximately 0.65. After this early peak, a gradual downward trend occurs due to the algorithm's leader–follower dynamics, which progressively concentrate UE assignments toward a select few BSs deemed optimal. By the midpoint of the simulation, the fairness index has declined to about 0.55 and continues decreasing toward the end, eventually reaching below 0.50. This moderate decline illustrates that the Stackelberg algorithm achieves a reasonable balance, centralizing resource utilization without creating the extreme imbalances seen in the Potential Game.

Analyzing the Nash Bargaining Game algorithm (Fig. 4), the fairness index shows a moderate starting point around 0.60, occasionally spiking up to about 0.65 during early intervals. As the simulation proceeds, however, fairness gradually declines, reaching approximately 0.45 near the end of the simulation. The Nash Bargaining algorithm attempts to balance UE utilities and BS loads. However, dynamic movements of UEs inevitably lead to certain BSs becoming preferable, thus increasing UE concentrations on these resources. While the distribution never becomes extremely skewed, fairness does decrease over time, settling into a moderate range reflective of a balanced yet uneven UE allocation.

In contrast, the Mean Field Game algorithm (Fig. 4) maintains higher fairness throughout most of the simulation. Initially starting at slightly below 0.64, fairness rises slightly, reaching a peak around 0.65 within the first few intervals. However, over time, minor fluctuations, and the continuous mobility of UEs lead to a gradual decrease, settling below 0.58 toward the final intervals. Despite this mild decline, the fairness index remains high, demonstrating the Mean Field Game's objective to maintain an even distribution across BSs and avoid significant UE clustering on specific resources. Thus, the Mean Field Game algorithm, known for promoting balanced UE distributions, maintains consistently higher fairness values.

For the Potential Game algorithm (Fig. 4), the fairness index begins around 0.62, indicating initially moderate balance. As the simulation progresses, fairness declines noticeably, dropping gradually below 0.50 after approximately 20 time intervals, and eventually reaching near 0.40 by the end of the simulation. This drop occurs because the Potential Game algorithm progressively directs UEs towards the single BS offering the highest potential benefit (e.g., lowest path loss or highest SNR). Such heavy concentration results in lower fairness, reflecting the strong preference for throughput optimization over balanced UE distribution. Also, the Potential Game typically produces significant UE concentration on very few BSs, naturally resulting in a lower fairness index over time.

The fairness analysis provides essential clarity for understanding each algorithm’s inherent behavior and effectiveness. Networks prioritizing throughput maximization might find the Potential Game suitable despite fairness loss, whereas scenarios demanding fair and balanced UE allocations would benefit most from Mean Field. For balanced scenarios requiring moderate fairness alongside performance optimization, Nash Bargaining and Stackelberg emerge as practical choices, aligning their distribution patterns with intermediate fairness outcomes. It is important to note that, Nash Bargaining and Stackelberg Games fall between these extremes, achieving moderate fairness scores due to their partial UE concentration on specific BSs. Such behaviors underline the inherent differences among these algorithms in balancing throughput optimization against equitable resource distribution.

Proceeding with the analysis of bandwidth consumption, we observe distinct and algorithm-specific patterns throughout the simulation, which directly reflect the internal logic of each game-theoretic approach, as shown in Fig. 5. To accurately determine the Mbps demand of each UE and calculate the required bandwidth per base station, we apply the Shannon-Hartley theorem, which is also analytically presented in the mathematical algorithm section.

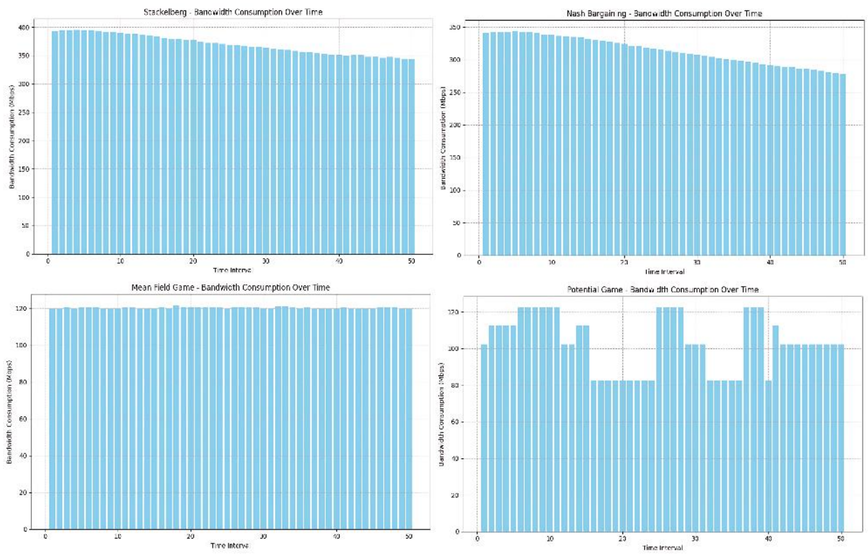

Fig.5. Bandwidth Consumption for Game Theory Algorithms.

In the Stackelberg algorithm (Fig. 5), bandwidth consumption begins just under 395 Mbps and steadily declines across the simulation period. By the final interval, the usage drops to about 342 Mbps. This pattern reflects the algorithm's leader–follower strategy. Early in the simulation, resource allocation is aggressively optimized as users quickly attach to the most beneficial base stations. However, as users begin to move, this controlled advantage diminishes. Towers that initially attracted higher loads may no longer be optimal due to increased distance or mobility-induced degradation, leading to a gradual reduction in bandwidth efficiency.

The Nash Bargaining algorithm (Fig. 5) starts slightly lower, near 348 Mbps, and also exhibits a downward trend, reaching approximately 277 Mbps by the end. This consistent decline mirrors the fairness-oriented mechanism of Nash Bargaining. Although the algorithm initially provides a balanced allocation that supports efficient use of resources, it is not highly responsive to continued user mobility. As users move away from their ideal locations, the equal-load distribution becomes less effective in maintaining high throughput, and consequently, bandwidth consumption reduces steadily.

For the Mean Field Game algorithm (Fig. 5), the bandwidth consumption remains extremely stable throughout the simulation. Starting around 120 Mbps, it fluctuates slightly but shows no clear upward or downward trend. This behavior corresponds with the decentralized logic of the algorithm. Since each user acts independently while considering the overall network state, the outcome is a stable and near-uniform distribution. This uniformity, although fair, results in relatively low but consistent bandwidth usage reflecting a cautious allocation that favors system robustness over instantaneous performance peaks.

The Potential Game algorithm (Fig. 5) displays a highly variable bandwidth pattern. Usage oscillates between approximately 82 Mbps and 123 Mbps over the intervals.

These fluctuations stem from the algorithm's global optimization objective. Unlike the other algorithms, Potential Game allows users to concentrate heavily on one or two highly efficient base stations, maximizing localized utility. However, this approach is very sensitive to mobility. As users shift positions, the ideal assignment changes, causing abrupt swings in demand and utilization. These bursts of high efficiency are interspersed with periods of underutilization, resulting in the observed irregular pattern. Collectively, these bandwidth consumption results align closely with the previously observed distribution patterns and fairness. Highly concentrated algorithms, such as the Potential Game, show minimal bandwidth usage due to focusing UE allocations primarily on one or two BSs, resulting in sharply reduced fairness. Conversely, uniformly distributed algorithms like the Mean Field Game consistently maximize bandwidth usage by even utilizing all available BSs, maintaining stable and high fairness levels. Intermediate approaches like Nash Bargaining and Stackelberg balance resource distribution and concentration, which explains their fluctuating but rising bandwidth consumption over time. Each algorithm's bandwidth utilization highlights its underlying resource allocation strategy, reflecting essential trade-offs between achieving equitable UE distribution and maximizing BS utilization efficiency under dynamic UE mobility conditions.

The evaluation continues by examining the energy efficiency of each game theory algorithm over the simulation's time intervals, as shown in Fig. 6. Energy efficiency reflects the ability of each algorithm to effectively manage available resources, balancing data throughput and power consumption in the presence of user mobility and varying antenna assignments. A detailed exploration of the energy efficiency trends reveals how each game algorithm behaves when facing dynamic user distributions and distance variations, further enhancing the understanding of their operational characteristics.

Starting with the Stackelberg Game algorithm scenario (Fig. 6) a different pattern, starting from 2.3×10^{-6} and consistently climbing to a peak of about 3.0×10^{-6} near intervals 15–20. This peak highlights the algorithm's initial capability of efficiently managing user allocations in a leader–follower dynamic, where users are optimally matched to antennas. Following this plateau, however, the efficiency declines, eventually reaching around 2.2×10^{-6} by the simulation's end. This trajectory aligns with Stackelberg's moderate skew toward a select few antennas, optimizing performance initially but suffering as users drift away, thus increasing overall power usage disproportionately.

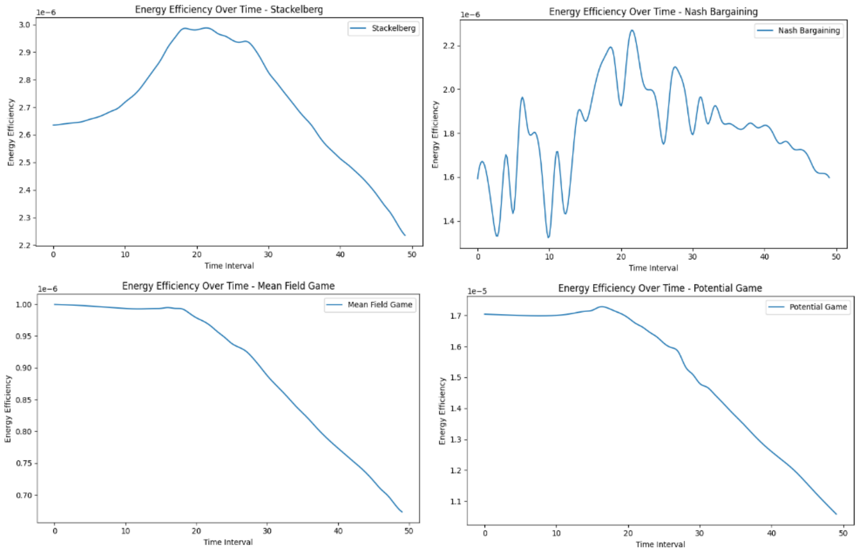

Fig.6. Energy Efficiency Over Time for Game Theory Algorithms.

The Nash Bargaining Game algorithm (Fig. 6) presents an interesting fluctuation. Initially beginning at about 1.4×10^{-6}, efficiency fluctuates briefly before rising sharply to a peak of roughly $2.3–2.4\times10^{-6}$ between intervals 15 and 20. This peak suggests a transient optimization wherein users align efficiently with antennas yielding favorable throughput-to-power ratios. Beyond this peak, however, a gradual decline sets in as user mobility leads to increased distances from chosen antennas. Eventually, efficiency settles back down to around 1.6×10^{-6}. This dynamic corresponds well to Nash Bargaining's intermediate distribution and fairness results, reflecting a balance between concentration and uniformity that initially boosts efficiency before mobility introduces inefficiencies.

Moving to the Mean Field Game algorithm (Fig. 6), energy efficiency begins steadily around 1.0×10^{-6} and exhibits a mild increase early on, reaching around 1.01×10^{-6} at about interval 10. This modest rise represents the equilibrium distribution of users evenly across all antennas. Nevertheless, as users continue to move randomly throughout the simulation, the uniform distribution cannot maintain optimal user-antenna proximities. Consequently, energy efficiency gradually diminishes, falling to approximately 0.85×10^{-6} by interval 30 and further down to around 0.70×10^{-6} by the simulation's conclusion. This decline mirrors Mean Field's characteristic high fairness, which, while distributing resources uniformly, is less responsive to individual user movements that could enhance efficiency.

Finally, the Potential Game algorithm (Fig. 6) the initial energy efficiency starts around 1.7×10^{-5}. In the early intervals, the efficiency remains relatively stable. However, as the simulation progresses and users move away from their initially favorable antennas, the energy efficiency begins a notable decline. By mid-simulation (around interval 20–30), efficiency dips noticeably to 1.4×10^{-5}, ultimately concluding below 1.1×10^{-5} towards the end. This significant drop aligns directly with the previously observed distribution pattern where a vast majority of users were concentrated on just one or two antennas. Such heavy centralization initially offers acceptable efficiency but deteriorates quickly when user mobility causes significant distances to their chosen antennas, thus increasing power consumption disproportionately relative to data throughput.

These results collectively emphasize the consistent connection between user distributions, fairness, and energy efficiency. The more skewed an algorithm's user distribution such as the Potential Game the steeper its decline in efficiency becomes due to increased distances and resulting power demands. Meanwhile, Mean Field's uniform distribution, despite offering high fairness, cannot entirely prevent efficiency decline due to continuous user mobility. Nash Bargaining and Stackelberg represent intermediate strategies, providing moderate fairness and distribution skew, resulting in efficiency trends that start strong but weaken over time. Therefore, each game-theoretic algorithm's approach directly influences its energy efficiency trajectory, revealing how effectively each balances resource utilization, mobility, and fairness under dynamic conditions.

7 Conclusion and Future Work

In this research, we examined four distinct game-theory approaches Potential Game, Mean Field Game, Nash Bargaining Game, and Stackelberg Game to address the challenge of dynamically allocating a large number of UEs 1810 to seven BSs over 50 discrete time intervals. The main goal was to observe how each theoretical algorithm handles the dynamic distribution of UEs and resource allocation, influenced by key parameters such as UE positions, signal quality, and mobility.

Furthermore, before presenting the final conclusions, some limitations of the simulation setup must be acknowledged. The simulation rely on a synthetic dataset, which provides controlled channel data but omits many real-world effects such as irregular fading patterns, user hotspots, and hardware impairments. User mobility is represented as two dimensional motion at a fixed speed; actual users pause, change direction, and vary speed, which can shift allocation performance. The model also excludes inter-cell interference coordination, MAC-layer scheduling, and device-level power costs, so the reported fairness, bandwidth, and energy metrics are comparative rather than absolute.

The Potential Game tends to concentrate UEs heavily on a limited number of BSs, typically achieving high throughput initially. However, this approach results in significant drawbacks: as UEs move overtime, the distance to their originally optimal BS increases, causing a notable drop in fairness and quality of service. Bandwidth utilization remains minimal, primarily due to reliance on a few BSs, leaving most network resources underutilized.

In contrast, the Mean Field Game takes a completely different route by uniformly distributing UEs across all available BSs from the start. While this ensures stable and high fairness, it provides modest performance regarding throughput and quality of service. Bandwidth is maximally utilized since every BS serves UEs continuously, yet energy efficiency and the fraction of UEs surpassing quality thresholds remain low, as the uniform spread does not specifically cater to UEs' individual needs or movements.

The Nash Bargaining Game offers a balanced middle ground. UEs negotiate to find allocations beneficial for all parties, initially producing a promising increase in both throughput and the number of satisfied UEs. Over time, UE mobility introduces fluctuations in bandwidth consumption and throughput, resulting in moderate fairness and performance metrics. This strategy effectively balances the need for network fairness against the desire for high individual throughput.

Finally, the Stackelberg Game introduces a hierarchical approach, with a leading BS influencing UE decisions. This results in gradually improving performance, notably high throughput, and increased UE satisfaction early in the simulation. Despite initial successes, as UEs inevitably drift further from the chosen BSs, efficiency and satisfaction slightly decline, demonstrating the trade-off between initial optimal allocation and the limitations imposed by UE mobility.

Overall, these simulations highlight the fundamental trade-offs involved in dynamic UE allocation for wireless networks. Each game-theoretic algorithm uniquely balances the competing priorities of fairness, resource utilization, throughput, and service quality, illustrating the complexities of achieving sustained performance in real-world mobile environments. The results emphasize the importance of selecting an allocation strategy aligned with specific network objectives, mobility patterns, and service quality requirements.

In future research, the study presented can be significantly enhanced by incorporating Machine Learning (ML) techniques [17]. Specifically, ML methods can be employed to predict the optimal movement directions and connectivity choices of UEs in dynamic wireless network environments. Through the integration of predictive algorithms, such as neural networks or reinforcement learning approaches, it would be possible to proactively determine UE trajectories and anticipate changes in signal quality, distance, and network load. This evolution would allow network resources to be allocated not merely based on the current state of the system, but on accurately predicted future conditions. As a result, resource allocation algorithms could become more adaptive, improving the quality of service by dynamically reassigning UEs to BSs before significant performance degradation occurs due to UE mobility. Additionally, future studies might explore hybrid solutions that combine predictive ML methods with game-theoretic approaches. Such hybrid systems could leverage the strengths of each method utilizing game theory's strategic resource distribution capabilities alongside machine learning's predictive accuracy to achieve robust and efficient network performance under a wider range of mobility scenarios and UE behaviors.

Finally, expanding the experimental scenarios to include varying numbers of UEs, different mobility patterns, and diverse environmental conditions would further validate the flexibility and reliability of the proposed ML-enhanced allocation strategies. This comprehensive future direction promises substantial improvements in practical applicability, network responsiveness, and UE experience in dynamically changing wireless communication networks.

8 Acknowledgment

The research project was supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the "2nd Call for H.F.R.I. Research Projects to support Faculty Members & Researchers" (Project Number: 02440).

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