

A Study on User Association Based on Game Theory to Mobile Communications

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Abstract—This work discusses user association methods in the 6G era such as maximum-signal-to-interference-plus-noise ratio (SINR) method and the minimum-distance method, and proposes a decentralized, non-cooperative game-theoretic approach to balance the access point (AP) load and penalize congestion by introducing a utility function that weighs individual link quality against network crowding.

Index Terms—Game Theory, Load Balancing, 6G, User Association.

I. INTRODUCTION

As mobile networks evolve towards the 6G era, they face severe infrastructural requirements to successfully maintain low latency, with massive connectivity, high reliability, and energy-aware operation being jointly supported [1] [6]. In this context, radio resource management becomes increasingly challenging because many user equipments (UEs) may compete for a limited number of APs, spectrum resources, and favorable interference conditions. User association is one of the fundamental decisions in this process: the AP selected by each UE directly affects its received signal quality, the interference level, the capacity distribution, the outage probability, and the energy efficiency of the network [2].

Classical association rules are attractive because of their low complexity and ease of implementation. A minimum-distance strategy tends to reduce path loss by connecting each UE to the geographically closest AP, whereas a maximum-SINR strategy selects the AP that provides the best instantaneous link quality. However, both approaches are essentially local decisions and may ignore the global load distribution of the network. As a result, dense regions can lead to overloaded APs, underutilized infrastructure, higher outage for edge users, and reduced fairness.

Among various widely studied solution tools, game theory emerges as a tool that models interactions between users in a non-cooperative game, in which each UE acts as a rational agent seeking to maximize their own utility function. This approach considers situations where link quality improvements are sought while avoiding AP overload, allowing the network to converge to an equilibrium among them [3], [4]. This perspective is particularly useful when the utility function combines a link-quality reward, such as a spectral efficiency (SE), with a congestion penalty related to the number of UEs

associated with the same AP. Such a design encourages users to seek strong radio links while also avoiding excessively crowded APs, creating a balance between individual performance and network-level load distribution [5].

The key contribution of this paper is the evaluation of three user-association models under the same simulated wireless environment: minimum-distance association, maximum SINR association, and a non-cooperative game-theoretic association based on a specific utility function. The comparison is performed through Monte Carlo simulations with random UE locations and channel effects including distance-dependent path loss, log-normal shadowing, and multipath fading. The performance evaluation considers user capacity, outage probability, allowing the trade-off between simple link-based rules and a load-aware game-theoretic strategy to be quantified.

II. SYSTEM MODEL

This work considers a coverage area of $L \times L$ square meters with M single-antenna APs equally distributed among this area in a grid mode. There are also single-antenna K UEs randomly distributed. The spatial distribution of UEs is modeled using a two-decimal-place precision for location coordinates. This provides a 1-centimeter resolution, better reflecting real-world conditions by ensuring a minimum physical separation between devices. The bandwidth used is B_T MHz distributed across a single channel.

The channel effects considered were path gain, shadowing, and multipath propagation. Let $g_{i,j} \in \mathbb{R}_{\geq 0}$ be the channel gain between the i -th UE and the j -th AP :

$$g_{i,j} = x_{i,j}(\sigma_X) \cdot \frac{k}{d_{i,j}^\alpha} \cdot h_{i,j}^2. \quad (1)$$

In this equation, $x_{i,j}(\sigma_X)$ is the shadowing effect, $\frac{k}{d_{i,j}^\alpha}$ the path loss and $h_{i,j}^2$ the fast fading. The shadowing effect models the signal degradation caused by macroscopic terrain features, such as buildings, and is characterized by:

$$x_{i,j}(\sigma_X) = 10^{\frac{X_{i,j}}{10}}, \quad (2)$$

where $X_{i,j}$ is a normal random variable, expressed in decibels (dB), that represents the localized terrain and structural variations between transmitter i and receiver j , and σ_X represents the shadowing standard deviation (in dB) from a normal distribution, i.e., $X_{i,j} \sim \mathcal{N}(0, \sigma_X^2)$, which quantifies the severity and density of the physical obstacles in the simulated deployment area. In this work, shadowing values are assumed to be independent for each spatial link (i, j) . This

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independence is maintained despite limiting the UEs spatial distribution to two decimal places, which could theoretically yield perfectly correlated shadowing values for users sharing the same location. The path loss is represented by:

$$\frac{\kappa}{d_{i,j}^n}, \quad (3)$$

where κ is the attenuation constant, $d_{i,j}$ is the distance between user i and AP j , and n is the path loss exponent characterizing the propagation environment.

In Equation (1), the term $h_{i,j}$ denotes the small-scale fading amplitude, which is modeled as a Rayleigh fading process typical of dense urban environments with parameter σ_h . The SINR of user i at AP j is defined as:

$$\text{SINR}_{i,j} = \frac{p_i g_{i,j}}{\sum_{k=1, k \neq i}^K p_k g_{k,j} + N_0}, \quad (4)$$

where p_i denotes the transmit power of user i , $g_{i,j}$ is the channel gain between user i and AP j , Finally, N_0 denotes the noise power at each AP receiver.

The capacity of user i at AP j is calculated using the Shannon-Hartley Theorem [7]:

$$C_{i,j} = B_T \log_2(1 + \text{SINR}_{i,j}), \quad (5)$$

in which B_T denotes the system bandwidth. The outage probability is a critical performance metric used to evaluate the reliability and Quality of Service (QoS) of a wireless communication network. It is defined as the statistical probability that the instantaneous channel capacity $C_{i,j}$ falls below a minimum acceptable threshold C_{th} . Mathematically, it is expressed as [7]:

$$P_{out} = \mathbb{P}(C_{i,j} < C_{th}). \quad (6)$$

III. GAME FORMULATION

In this section, we detail the modeling of the user association problem as a non-cooperative game. The game-theoretic approach allows each UE to act as a rational player, making independent decisions to maximize its own utility function while considering the actions of the other players.

A. Game Components

Let Γ be the proposed association game defined by the triplet $\Gamma = (\mathcal{K}, \mathcal{S}, \{U_i\}_{i \in \mathcal{K}})$, where:

- **Players:** The set of UEs, denoted by $\mathcal{K} = \{1, 2, \dots, K\}$, represents the finite set of K rational players in the network.
- **Strategies:** For each player $i \in \mathcal{K}$, the strategy space is defined as $\mathcal{S} = \{1, 2, \dots, M\}$, representing the set of M available APs for association.
- **Utility Function:** Characterized by the set $\{U_i\}_{i \in \mathcal{K}}$, where $U_i : \mathcal{S}^K \rightarrow \mathbb{R}$ corresponds to the utility function of player i mapping a strategy profile to a real-valued payoff.

B. Utility Function Design

The utility function is designed to guide each UE toward an AP that offers a good radio link while avoiding excessive concentration of users at the same AP. For UE i , the selected strategy is denoted by $s_i = j$, meaning that UE i is associated with AP j . The vector s_{-i} represents the association choices of all other UEs. Therefore, the utility of UE i depends not only on its own AP choice, but also on the current network association state created by the remaining users. The utility function of UE i is represented by:

$$U_i(s_i, s_{-i}) = \lambda \log_2(1 + \text{SINR}_{i,s_i}) - \sum_{j=1, j \neq i}^K \delta(s_j - s_i), \quad (7)$$

where s_i is the AP selected by UE i , s_{-i} represents the strategies of the remaining UEs, λ is a scaling factor, and SINR_{i,s_i} is the SINR obtained by UE i when associated with AP s_i . The function $\delta(\cdot)$ is given by:

$$\delta(s_j - s_i) = \begin{cases} 1, & s_j = s_i, \\ 0, & s_j \neq s_i. \end{cases} \quad (8)$$

where $\lambda \in \mathbb{R}_{>0}$ is a scaling factor used to balance the trade-off between the achievable capacity and the network congestion. The scaling factor λ is represented by:

$$\lambda = \frac{1}{\log_2(1 + \gamma_{\max})}, \quad (9)$$

where $\gamma_{\max}$ is an upper-bound approximation of the maximum SINR. It is given by:

$$\gamma_{\max} = \frac{P_{\max} \left(\frac{k}{d_0^n} \right) X_{0.99} h_{0.99}}{P_N}, \quad (10)$$

where $P_{\max}$ is the UE transmit power, P_N is the noise power, k , n , and d_0 are path-loss parameters, and $X_{0.99}$ and $h_{0.99}$ represent the shadowing and fading high-percentile gains.

C. Initial State

The initial state is created by the allocation of the UEs using the minimum distance to the APs. This choice creates a suitable initial equality scenario for comparing the allocation methods. Other initial states could reach the Nash equilibrium with less iterations, however, that would be unfair for comparison purposes when it comes to the energy efficiency. The first uses the utility function itself, the second randomly allocates users to APs, the third uses the minimum distance as a condition, and the fourth uses the maximum SINR. The Maximum-SINR strategy is a method where each UE independently selects the AP that provides the highest received signal quality. Since the final network topology is unknown during the decision phase, each UE evaluates the available APs using an estimated SINRs based on long-term channel gains. As we can see in the Figure 1, using conditions like the utility function generates fewer iterations until convergence.

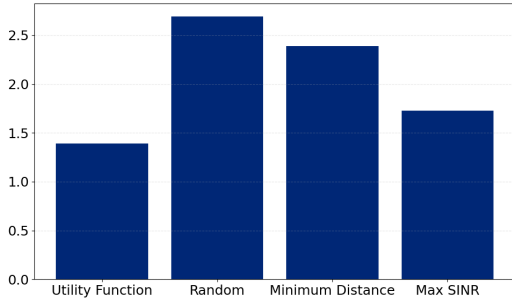


Fig. 1. Average number of iterations for different initial conditions.

TABLE I
SIMULATION PARAMETERS

Symbol	Description	Value
$L \times L$	Geographical simulation area	$1000 \times 1000 \text{ m}^2$
M	Total number of Access Points (APs)	64
K	Total number of User Equipments (UEs)	32
B_T	Total system bandwidth	100 MHz
p_i	UE transmit power	1.0 W
κ	Path loss attenuation constant	10^{-4}
n	Path loss constant exponent	4
σ_X	Shadowing deviation	8.0 dB
N_0	Noise power	$10^{-17} \text{ W/Hz} \times B_c$
σ_h	Rayleigh constant	1.0
$X_{0.99}$	Shadowing high-percentile gains	2.3263
$h_{0.99}$	Fading high-percentile gains	3.0348

IV. RESULTS AND DISCUSSIONS

A. User Capacity

By observing the results of Figure 2, it is evident that the game-theoretic algorithm has benefited the worst users. By shifting the load away from congested APs, the proposed method effectively doubles the capacity for the worst-case users compared to the Maximum-SINR approach. Furthermore, this gain in network fairness does not impose a severe loss for the UEs of the 70th percentile onward the capacity is very similar to the SINRs allocation.

B. Outage Probability

As shown in Figure 3, the outage probability for the game-theoretic approach dropped to 7.92%. This nearly 36% relative improvement over the SINR baseline. As we can observe in

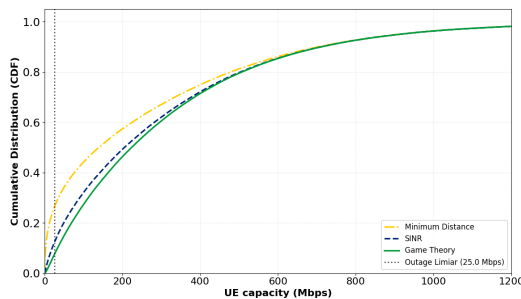


Fig. 2. CDF of user capacity.

Figure 3 the outage probability has decreased considerably to almost twice the value of the SINRs probability. This occurs due to the Equation (7) that displaces UEs that would impact edge UEs.

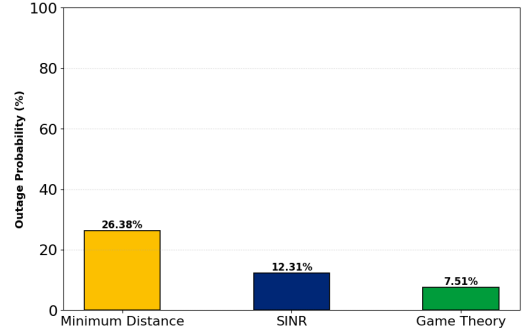


Fig. 3. Comparison of outage probability by method.

C. Nash Equilibrium

The proposed algorithm reaches a Nash Equilibrium when no UE changes its AP association between two consecutive iterations. At this point, the trade-off between signal strength and load penalty is balanced. To prevent the ping-pong effect, a secondary criterion was established: the maximum number of iterations is 10. If this limit is reached, the allocation changes stop.

V. CONCLUSIONS

A capacity and outage analysis was made comparing different allocation methods for different scenarios of UEs distribution. The results validate that incorporating a mathematically calibrated congestion penalty effectively mitigates network congestion. The proposed game-theoretic algorithm proves to be a highly effective, self-organizing solution that guarantees both fairness and reliability, making it a candidate for the dynamic demands of future 6G networks.

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