

Original article

Comparative Analysis of User Association and Load Balancing Strategies in Cellular Networks: A MATLAB-Based Simulation Study

Mabroka Bobreeg^{*1} , Fathia Adwep² 

¹Electrical and Electronic Engineering, Faculty of Engineering, Omar Al-Mukhtar University, Al Bayda, Libya

²Electrical and Computer Engineering, Faculty of Engineering, Elmergib University, Al Khums, Libya

Corresponding Email. mabroka.bobreeg@omu.edu.ly

Abstract

Load imbalance is an important challenge in cellular networks because conventional user association mechanisms may produce uneven traffic distribution among neighboring base stations. This study compares three user association and load-balancing strategies using a MATLAB-based cellular network simulation. The investigated network consists of three base stations (BSs) and 300 users distributed over a $1000 \times 1000 \text{ m}^2$ geographical area, with a maximum capacity of 100 Mbps assigned to each base station. Three scenarios are considered in the proposed comparative framework. The first scenario employs conventional nearest-base-station association and serves as the baseline. The second scenario applies a Decision Tree-based user association mechanism that incorporates network-related information into the association process. The third scenario employs a machine learning-based load balancing strategy designed to distribute users and traffic more evenly among the available base stations. The three strategies are evaluated under the same network configuration using base-station load, utilization level, user distribution, and load imbalance as comparative performance indicators. The simulation results illustrate the differences between distance-based association, load-aware Decision Tree association, and machine learning-based load balancing. Rather than assuming a predefined superior strategy, the study evaluates the behavior of each approach under identical simulation conditions and provides a MATLAB-based framework for comparative analysis of user association and load management strategies in cellular networks.

Keywords. Cellular Networks, User Association, Load Balancing, Decision Tree, Machine Learning.

Introduction

The exponential increase in mobile data demand and the growing complexity of cellular architectures have made efficient resource allocation a critical requirement. In scenarios where users are unevenly distributed, traditional association schemes that rely solely on proximity often create substantial load variations across adjacent base stations. This uneven loading leads to suboptimal usage of network resources, where some cells become congested while others remain underutilized, ultimately degrading overall performance. Consequently, user association plays a pivotal role in managing radio resources. The widely adopted nearest-base-station approach offers a straightforward rule based on geometric distance. Although nearest-base-station association is computationally simple, relying exclusively on geographical distance does not account for differences in traffic demand or the current utilization of candidate base stations. Consequently, a user may be assigned to a heavily loaded station even when another station has sufficient capacity to accommodate additional traffic. This study therefore compares three association and load-management strategies under the same simulation conditions to examine their effects on user distribution and base-station utilization.

To address the limitations of conventional methods, recent attention has shifted toward load-aware and data-driven solutions, particularly in dense and heterogeneous deployments. Machine learning models are capable of integrating diverse network parameters into the decision-making process, providing a more adaptive alternative to purely distance-based association. A number of studies have explored ML for resource management and optimization in wireless systems, including load balancing solutions for 5G and beyond [1-3]. Nevertheless, the adoption of a learning-based technique does not automatically guarantee superior performance in all conditions. Its outcome is contingent upon factors such as network setup, the quality of input features, training methodology, and the defined objective function. Therefore, a systematic and fair comparison between different association paradigms under identical conditions is essential to understand their respective impacts on load distribution.

In this context, this paper presents a controlled, MATLAB-based comparative evaluation of three distinct approaches: (i) the conventional nearest-BS association as a baseline, (ii) a load-aware Decision Tree-based association, and (iii) a machine learning-driven load balancing strategy. By keeping the network topology, user population, cell capacities, and simulation area constant, the experimental framework ensures that any observed differences in load and user distribution are attributable solely to the association strategy itself.

The main contributions of this study are as follows:

1. A common cellular network simulation environment containing three base stations and 300 users is established in MATLAB.
2. Three user association and load management strategies are implemented and evaluated under identical network conditions.
3. The conventional nearest-base-station strategy is used as a baseline for comparison.
4. A Decision Tree-based association mechanism is evaluated as a load-aware user association strategy.

5. A machine learning-based load balancing mechanism is evaluated according to its ability to reduce disparities in base-station load.
6. The three approaches are compared using user distribution, base-station load, utilization, and load imbalance indicators.

The remainder of this paper is organized as follows. Section II describes the relevant background and motivation. Section III presents the system model and simulation configuration. Section IV describes the three investigated strategies and their mathematical formulation. Section V presents the simulation results and comparative analysis. Section VI discusses the comparative findings, while Section VII concludes the study and outlines possible directions for future work.

Background and related context

User Association and Load Balancing in Cellular Networks

In cellular networks, the user association function is responsible for assigning each user to a serving base station. Legacy systems commonly adopt criteria related to radio measurements or user location. Despite its low complexity and suitability as a reference approach, a purely distance-based association does not reflect the heterogeneous traffic demands or the instantaneous utilization levels across base stations. When users are clustered unevenly across the coverage area, associating users based solely on distance tends to create hotspots, where a large number of users are assigned to a few base stations. As a result, certain base stations can become overloaded or operate near their capacity limits, whereas nearby stations may still have abundant unused resources.

To mitigate this uneven resource usage, load balancing techniques take the current network state into account during the association phase. This challenge has been extensively studied in the context of heterogeneous networks and emerging next-generation systems. Furthermore, machine learning approaches have been explored as a promising tool to embed real-time network awareness into dynamic association and resource management decisions [1,2]. Accordingly, this work concentrates specifically on the user association dimension of load balancing and provides a comparative assessment of three association mechanisms within a unified simulation environment.

Machine Learning for Wireless Network Management

Machine learning enables the modeling of the relationship between network conditions and association choices. Under a supervised classification framework, an algorithm can be trained to map a set of input features to a set of predefined association categories. Decision Trees represent a commonly used class of such classifiers. In MATLAB, this functionality is available via the `fitctree` function, where the trained model can subsequently predict the serving base station for unseen user observations through the `predict` method [4,5].

For the specific task of cellular user association, relevant input features typically comprise the distances from a user to each candidate base station, the user's traffic requirement, and the current loading status of those base stations. In this formulation, the output of the classifier, i.e., the predicted class label, corresponds to the chosen serving base station. The performance of such an approach is highly dependent on the definition of the training dataset, the selection of input features, the labeling strategy, and the handling of capacity constraints. For this reason, the present study does not presume that a machine learning-based solution is inherently better. Rather, its performance is objectively examined in comparison with two other distinct association schemes under identical network conditions.

Relevance to Future Cellular Networks

Next-generation cellular systems are anticipated to accommodate diverse service types, ultra-dense infrastructure, highly dynamic traffic patterns, and a greater degree of network intelligence. These evolving characteristics further emphasize the need for adaptive mechanisms for resource allocation and user-to-base-station association.

Advancements related to 5G, 6G, edge computing, intelligent network orchestration, and heterogeneous architectures have driven extensive research toward data-driven optimization paradigms. In this landscape, user association and load balancing continue to be critical challenges, as limited radio and network resources must be efficiently shared among users with varying and often unpredictable traffic requirements [6,9]. Instead of attempting to capture the full complexity of a 5G/6G deployment, this study investigates the problem through a controlled and simplified simulation setup that isolates the core dynamics of user association.

System model and simulation setup

The simulated network consists of 300 users distributed randomly within a $1000 \times 1000 \text{ m}^2$ area and served by three base stations located at [200, 500], [500, 500], and [800, 500]. Each base station is assigned a capacity of 100 Mbps. In the baseline scenario, users are associated with the nearest base station based on Euclidean distance. Accordingly, the number of users served by each station is determined by the generated user locations and the association procedure rather than by a predefined fixed allocation.

The three base stations are positioned at:

- BS1 = [200, 500]
- BS2 = [500, 500]
- BS3 = [800, 500]

Therefore,

$$N_{\text{total}} = N_1 + N_2 + N_3 = 300. N_{\text{total}} = N_1 + N_2 + N_3 = 300.$$

The identical network layout and system parameters are preserved across all three evaluated strategies. This consistency is essential to ensure that any observed differences in performance can be attributed solely to the association and load-balancing logic itself, rather than to variations in topology or available capacity.

Table 1. Simulation Parameters

Parameter	Value
Number of users	300
Number of base stations	3
Simulation area	1000 × 1000 m ²
BS1 position	[200, 500]
BS2 position	[500, 500]
BS3 position	[800, 500]
Capacity of each BS	100 Mbps
Initial users in Region 1	107
Initial users in Region2	100
Initial users in Region3	93

Investigated User Association and Load Balancing Strategies

Strategy 1: Conventional Nearest-Base-Station Association

The first scenario implements the traditional distance-based association and serves as the baseline for comparison. In this approach, the Euclidean distance from each user to every base station is computed, and the user is associated with the base station that offers the shortest distance.

This method is computationally simple and requires minimal network information. However, it does not incorporate the instantaneous traffic load of the candidate base stations into the decision. Consequently, under non-uniform spatial user distributions, this scheme may lead to a highly uneven allocation of users and traffic across base stations. It is important to note that such load imbalance is not interpreted as proof of the inadequacy of the conventional approach in all cases; rather, it characterizes its baseline performance against which the two alternative strategies are assessed.

Strategy 2: Decision Tree-Based User Association

The second scenario examines a Decision Tree-based association scheme. In contrast to the baseline method, this mechanism incorporates multiple network-aware attributes into the association process. Specifically, the classifier can utilize features such as the user-to-base-station distances, the user's traffic demand, and the current load levels of the candidate base stations. The purpose of this scenario is to assess how a load-aware classification approach modifies the user distribution relative to the conventional baseline.

Conceptually, a classification tree assigns a categorical output by traversing decision rules from the root node to a leaf node. In MATLAB, this is supported by the Classification Tree model, where the predict function provides the estimated class labels for new input samples. For the problem considered here, the predicted class label corresponds to the selected serving base station [4][5].

The Decision Tree scenario is therefore evaluated according to:

1. the number of users assigned to each base station;
2. the resulting load of each base station;
3. the utilization level;
4. the reduction in excessive concentration of users.

The aim is not to achieve perfect load equalization, but rather to quantify the shift in the network's load distribution induced by the Decision Tree-based strategy.

Strategy 3: Machine Learning-Based Load Balancing

The third scenario investigates a machine learning-driven mechanism that explicitly targets load distribution across the three base stations. This model leverages prevailing network conditions to guide user-to-base-station association decisions, with the goal of alleviating excessive user concentration at any single station and promoting more efficient utilization of the available capacity. Consistent with the previous cases, the evaluation is performed using the same underlying network configuration. Therefore, any differences observed in user distribution and base-station load can be directly attributed to the association mechanism itself. In general terms, the objective function can be formulated as minimizing the load disparity among base stations:

$$\min_{\{x_{u,b}\}} \mathcal{D} = \min_{\{x_{u,b}\}} \left[\max_{b \in \{1,2,3\}} L_b - \min_{b \in \{1,2,3\}} L_b \right]$$

(1) subject to

$$L_b \leq C_b, \quad b = 1, 2, 3$$

(2)

$$L_b = \sum_{u=1}^N x_{u,b} T_u$$

$$x_{u,b} \in \{0, 1\}, \quad \sum_{b=1}^B x_{u,b} = 1$$

(3)

where L_b denotes the traffic load of base station b , C_b represents its capacity, $\mathcal{D}$ represents a load-disparity measure, N represents the total number of users, and $x_{u,b}$ is a binary association variable indicating whether user u is associated with BS b . The exact implementation of the optimization and training procedure follows the MATLAB simulation used in this study.

Mathematical formulation

The distance used in the model is the Euclidean distance [10]:

$$d_{u,b} = \sqrt{(x_u - x_b)^2 + (y_u - y_b)^2} \quad (4)$$

where $d_{u,b}$: Euclidean distance between user u and base b station; u is

User index, b is Base station index.

The user is associated with the base station with the minimum distance in the first stage [11]:

(5)

$$BS_u = \arg \min_b (d_{u,b})$$

where: BS_u is the selected base station for user u ; Base Station Load

$$L_b = \sum_{u \in b} T_u \quad (6)$$

where: L_b is the total load of base station b ; b is base station; u is the user, T_u is Traffic/load generated by user u [12].

Utilization Rate [12]:

(7)

$$U_b = \frac{L_b}{C_b} \times 100$$

where: U_b is Base station utilization, and C_b is Capacity of the base station. Handover Condition [12]:

$$L_b + T_u \leq C_b \quad (8)$$

Training Parameters [4]:

(9)

$$X = [d_{u,b}, T_u, b, \frac{d_{u,b}}{\max(d_u)}]$$

From the following equations, the selection score can be calculated and the capacity constraint can be imposed, then the station with the highest possible score is selected without exceeding the capacity.

$$S_{u,b} = P_{u,b} - 0.15 D_{u,b}^{norm} \quad (10)$$

where: $S_{u,b}$ is Score for user u and base station b , $P_{u,b}$ is Base preference or score of user u for base station b .

Experimental framework

The experimental procedure consists of three scenarios under the same network configuration.

Scenario 1: Conventional Association

300 Users + 3 Base Stations

↓

Nearest-Base-Station Association

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Baseline User Distribution

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Base-Station Load Measurement

Scenario 2: Decision Tree-Based Association

300 Users + 3 Base Stations

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Decision Tree-Based User Association

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Load-Aware User Redistribution

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Load Distribution Measurement

Scenario 3: Machine Learning-Based Load Balancing

300 Users + 3 Base Stations

↓

Load-Aware Machine Learning

↓

User Association

↓

Load Distribution Measurement

The final stage of the experiment compares the three resulting network states using common performance indicators.

Simulation results

The MATLAB simulation was performed for 300 users and three base stations, each with a capacity of 100 Mbps. Before optimization, the user distribution was 107, 100, and 93 users for BS1, BS2, and BS3, respectively, with a maximum load utilization of 108.16%. The traffic demand of each user is modeled as a value between 0.5 and 1.5 Mbps. Specifically, 300 traffic-demand values are generated using a linearly spaced sequence over this interval and then randomly permuted. The aggregate load of each base station is calculated by summing the traffic demands of its associated users. Base-station utilization is defined as the ratio of the aggregate traffic load to the configured capacity of 100 Mbps, expressed as a percentage. Consequently, utilization depends on both the number of associated users and their individual traffic demands. After applying the proposed load-balancing approach, the distribution changed to 101, 102, and 97 users, reducing the maximum utilization to 100.01%. The final AI-based association further redistributed the users to 91, 106, and 103 users, maintaining the maximum utilization at approximately 100.01% and providing a more load-aware network configuration.

Conventional Association

The baseline scenario is used as a reference for assessing the performance of the two learning-based methods. The network setup consists of three base stations serving 300 users. Results from the initial MATLAB implementation reveal an uneven allocation of users across the stations, resulting in notable variations in their respective load levels, with 107, 100, and 93 users associated with BS1, BS2, and BS3, respectively.

Decision Tree-Based Association

The second simulation examines how the inclusion of network-related information influences user association. Compared to the conventional nearest-BS rule, the Decision Tree approach alters the association pattern. This redistribution of users is assessed based on the resulting base-station loads and utilization. As described in the original simulation, this approach alleviates the load on highly utilized base stations, although it does not fully eliminate load disparities among the three stations. This finding is presented as an observed outcome of the implemented Decision Tree strategy, and not as a claim of universal optimality or suboptimality.

Machine Learning-Based Load Balancing

The third simulation evaluates the machine learning-based load balancing strategy. The purpose of this stage is to examine whether incorporating network load conditions into the association mechanism produces a more balanced distribution of users and traffic. The resulting user distribution is compared with both the conventional and Decision Tree-based scenarios.

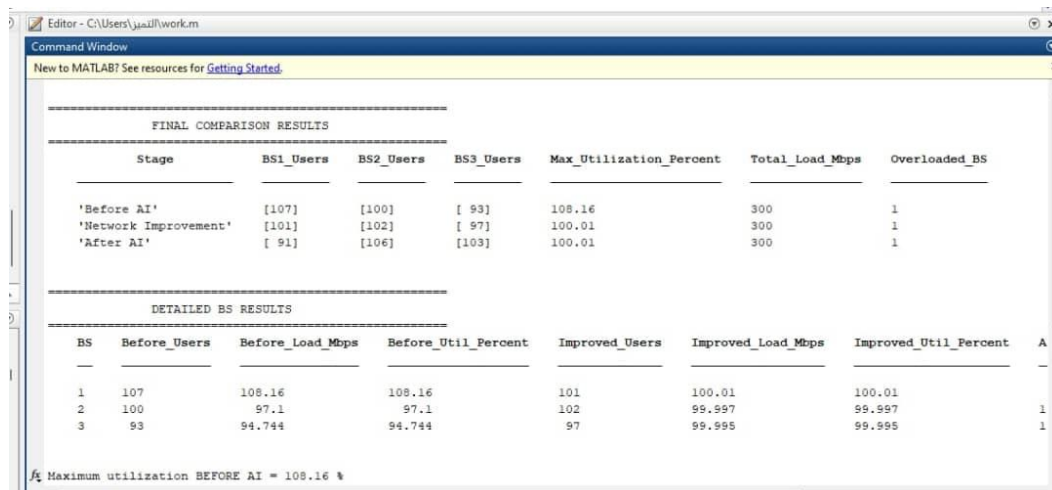


Figure 1. (a) Comparative network performance obtained from the MATLAB simulation.

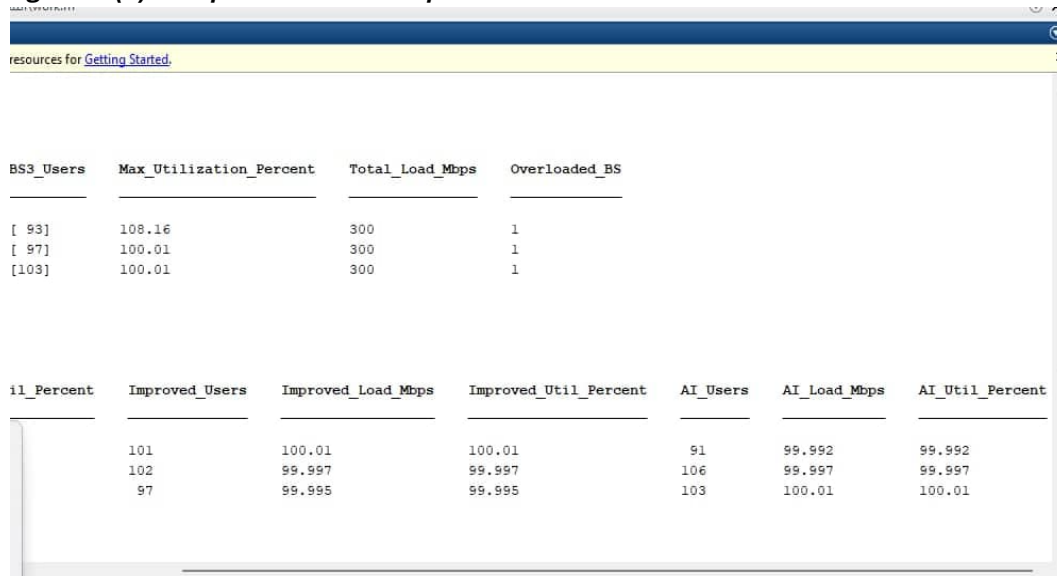


Figure 1. (b) Comparative network performance obtained from the MATLAB simulation.

From (Figure 1 a,b), conventional association produces an uneven load distribution among the three base stations, indicating the presence of load imbalance. The number of overloaded base stations is defined as the number of stations whose utilization exceeds 100%. Therefore, a value of Overloaded_BS = 1 indicates that exactly one base station exceeds its configured capacity. Stations operating below 100% utilization are not classified as overloaded. This metric is calculated independently for the baseline, network-improvement, and AI-based scenarios.

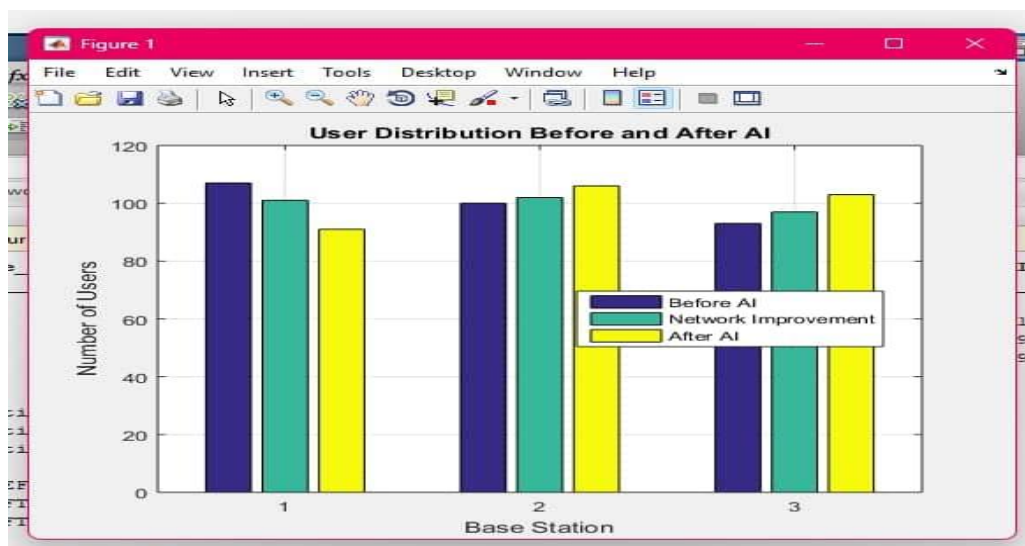


Figure 2. User distribution across the three base stations for the investigated strategies.

Decision Tree-based association reduces load concentration by incorporating network-related information into the user association process, as shown in (Figure 2).

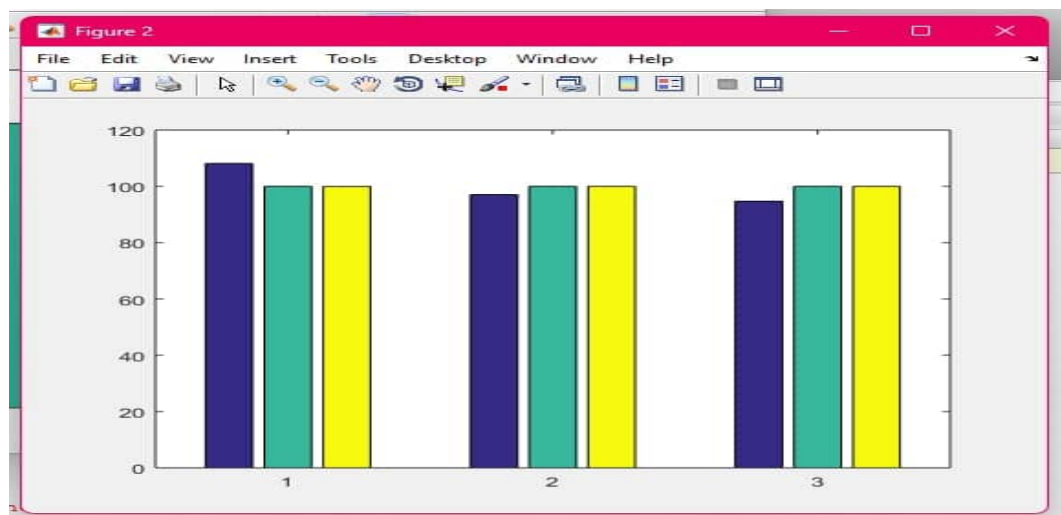


Figure 3. Comparative impact of the load-aware machine learning strategy on user distribution.

In (Figure 3) the Machine learning-based load balancing further redistributes users and achieves a more balanced utilization of the available base-station capacity.

Discussion

The conducted comparative analysis confirms that the user association mechanism has a direct impact on the resulting network load distribution. The conventional nearest-base-station approach is adopted as a distance-based benchmark, wherein association is established solely on geographical proximity without explicit consideration of the candidate base stations' current load. The Decision Tree approach augments the association process with additional network knowledge, leading to decisions that diverge from a purely proximity-driven rule.

Simulation results show that this method redistributes users and mitigates load accumulation at heavily loaded stations, albeit inter-station imbalance remains. The ML-based load balancing approach introduces a more comprehensive load-aware mechanism whose goal is not limited to offloading a single station but rather to achieve a balanced load distribution across the three base stations. Thus, the three schemes correspond to three progressive levels of information utilization for association: distance-based, load-aware classification, and load-aware balancing. The validity of this comparison is ensured by evaluating all strategies under identical network topology, user population, geographical area, and base-station capacities.

Conclusion

This work has presented a comparative MATLAB-based evaluation of three user association and load balancing strategies for a cellular network comprising three base stations and 300 users. The strategies under investigation include conventional nearest-base-station association, Decision Tree-based association, and a machine learning-driven load balancing approach. The conventional distance-based scheme establishes the baseline association pattern determined solely by geographical proximity. The Decision Tree-based approach enriches the decision process with network-related features, leading to a notably different user distribution compared to the baseline. The third, machine learning-based strategy explicitly incorporates network load conditions, aiming to mitigate load disparity among base stations. The results confirm that the choice of user association mechanism directly affects the spatial distribution of users and the resulting traffic load across the network. Furthermore, the study demonstrates that load-aware, learning-based techniques can be systematically assessed against conventional methods within a unified MATLAB simulation framework. Future research will expand this analysis to larger-scale heterogeneous deployments with more base stations, user mobility, time-varying traffic profiles, interference considerations, and more advanced learning paradigms, such as reinforcement learning. These extensions will enable a more comprehensive evaluation of adaptive association and load balancing for next-generation wireless networks.

Conflict of interest. Nil

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