Cascade Fuzzy Logic for Handover Optimization in Mobile Networks

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***Abstract*—Handover management plays a vital role in load balancing by strategically transferring users from overloaded base stations to less congested stations, ultimately optimizing network performance. This paper proposes a novel handover management solution that leverages a two-layer cascaded fuzzy logic controller (FLC) for enhanced load balancing efficiency. The first layer focuses on signal quality evaluation for both the serving and target base stations. It employs separate fuzzy inference systems that consider reference signal received power (RSRP) and signal-to-interference-plus-noise ratio (SINR) to assess overall signal quality. This information is then fed into the second layer. Here, the FLC analyzes four key inputs: load levels of both the serving and target base stations, alongside the signal quality for each (obtained from the first layer's output). By employing a hierarchical architecture, the cascaded FLC significantly reduces *the number of fuzzy rules* required for decision-making, leading to faster processing and improved system performance. Simulations indicate the proposed FLC solution efficiently associates 80% of users with less congested stations (below 50% load level), ultimately increasing network capacity by up to 51.39% compared to competitive algorithms.**

***Index Terms*—handover, handover optimization, load balancing, fuzzy logic, heterogeneous networks, TOPSIS.**

I. Introduction

The explosion of smart devices and data-intensive applications fuels the demand for ultra-high data rates and exceptional user experience in mobile broadband services [1]. To meet this demand, 6G networks are envisioned as highly dynamic, densely deployed, and heterogeneous networks (HetNets). While millimeter wave (mmWave) frequencies offer the vast bandwidth needed for these ultra-high data rates, mmWave links are susceptible to rapid signal variations and blockages due to their high frequency [2]. To address these limitations and ensure satisfactory service quality, ultra-dense deployment of mmWave base stations is proposed [3].

Small base stations in HetNets play a crucial role in enhancing network capacity, filling coverage gaps, and alleviating congestion in overloaded areas. This benefit can be undermined, however, by traditional user association schemes based solely on received signal strength, which can lead to significant load imbalance. This is because macro base stations typically have higher transmit power compared to small base stations, leading users to connect to the strong macro base station signal even when a nearby small base station might offer better overall network performance [4]. This results in underutilized resources in small base stations, hindering their potential to alleviate network congestion. Conversely, users associated with overloaded macro base stations experience lower data rates due to resource scarcity. To address this inefficiency, some users in overloaded cells may need to be transferred to a different base station that offers more resources despite a slightly weaker signal strength and some interference from the previously connected base station. Load balancing acts as a network equalizer, dynamically managing user associations in real-time based on a comprehensive set of criteria, including network congestion and factors impacting signal strength. This ensures optimal resource utilization and a more balanced network load.

Handover, or user association management, ensures seamless user experience in dynamic networks. It triggers connection transfers to suitable target stations based on factors like fluctuating signal strength, network congestion, or stronger nearby signals. The key challenge lies in determining the optimal handover moment and target base station selection. This requires balancing sufficient base station capacity (handling user demands) with strong signal strength for a seamless connection. Selection based on broader criteria like load level and signal quality is demonstrably more efficient than relying solely on received signal strength (RSRP) [5], [6].

Handover decision determines the precise moment for transition, ensuring a seamless and efficient handover while minimizing unnecessary handovers that can degrade user experience. Traditional handover decision methods often rely on fixed thresholds for various network metrics. These methods can struggle to account for the inherent uncertainty of network conditions. Fuzzy logic stands out as a powerful tool for handover decision-making due to its ability to effectively address this challenge.

In fact, number of research studies have explored the use of fuzzy logic for handover decision control in wireless networks. For example, the authors in [8] investigate load balancing in satellite-terrestrial integrated networks using a fuzzy logic controller (FLC). This FLC employs a 125-rule adaptive neuro-fuzzy system to pre-evaluate user impact on overload, considering signal reception, user equipment (UE) speed, and data requirements. This system further integrates reinforcement learning for access control to proactively prevent network overload. The paper [9] addresses the conflict between mobility robustness and load balancing in handover decision-making by proposing a fuzzy-coordinated self-optimizing scheme utilizing a FLC with three input parameters: SINR, load level,

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and UE speed. A study in [10] also exploits the FLC based on RSRP, reference signal received quality (RSRQ), and UE speed to set appropriate handover margins. The fuzzy logic system employed 36 rules for decision-making. Simulation results demonstrate that the proposed algorithm suppresses handover ping-pong effects, maintaining them below 1% in all investigated scenarios. In [11], the authors leverage fuzzy logic for dynamic handover margin determination based on both the UE's signal-to-interference plus noise ratio (SINR) and the rate of its change. This fuzzy logic system employs 9 rules. The paper [12] propose a fuzzy logic algorithm for dynamically adjusting handover margin and time-to-trigger based on RSRP, RSRQ, and UE speed. Another study in [13] proposes a FLC with 36 rules for handover decision-making. This FLC leverages three key parameters: RSRP, SINR, and the load level difference between the serving and target base stations. In addition to the FLC-based solutions explored in [8]–[13], the study in [14] proposes a conditional handover decision algorithm. This algorithm utilizes RSRP as a handover trigger and assigns a bias based on the target base station type and resource availability. A heuristic approach for user association decisions based on RSRP, SINR, and available resource blocks is proposed in [15].

Unfortunately, the current single-layer FLC approaches [8]–[13] face several challenges in highly complex 6G network environments due to the inherent trade-off between accuracy and interpretability in FLC systems. These challenges can be summarized as:

- FLC systems with a limited *number of rules* prioritize interpretability, making them easier to understand and manage. However, this simplicity can limit their ability to capture the nuances of handover decisions in 6G scenarios.
- Single-layer FLCs with limited rules may struggle to adapt to the dynamic nature of 6G networks, i.e., networks that are expected to experience rapid changes in traffic patterns, user mobility, and network conditions. Limited rule sets might not be able to capture these dynamic changes effectively.
- While single-layer FLCs with a large *number of rules* can achieve higher accuracy, this increased complexity presents challenges. The "explosion of rules" makes the system difficult to interpret and maintain. This complexity can also limit its scalability for real-world deployments, especially in resource-constrained environments. Besides, large rule sets require more processing power and memory, which can be scarce on network devices with limited computational resources.

To address the limitations of single-layer FLC approaches, we propose a *novel cascaded FLC* framework. By dividing the decision process into manageable stages, this cascaded FLC significantly reduces *the number of rules*, overcoming a key challenge faced by single-layer systems. This strategic design achieves a balance between accuracy and efficiency, making the FLC more interpretable and suitable for real-world 6G networks. The proposed hierarchical model leverages two distinct fuzzy inference systems – Mamdani [16] in the first layer and Takagi-Sugeno [17] in the second layer – to cater to the specific requirements of each stage in the handover decision process. The first layer evaluates overall signal quality for both serving and target base stations using RSRP and SINR as fuzzy inputs. The second layer, then, determines handover necessity based on load and signal qualities of serving and target base stations. By strategically combining these systems, the cascaded approach achieves a significant reduction in complexity and accelerates the inference process compared to traditional single-layer systems. This improvement in efficiency is crucial for ensuring seamless and timely handover decisions. Building upon this cascaded FLC framework, we further enhance the handover decision process by integrating a target base station selection approach that leverages the technique for order preference by similarity to ideal solution (TOPSIS) algorithm. The TOPSIS algorithm enables the selection of the optimal target base station based on three key criteria: RSRP, SINR, and load level. TOPSIS offers faster decision-making due to its deterministic nature, ideal for real-time applications in dynamic 6G environments. This advantage stems from its efficiency compared to traditional methods reliant on exhaustive search or complex calculations [7]. The proposed solution efficiently associates 80% of users with stations experiencing load levels below 50%, ultimately leading to increased network capacity by up to 51.39% compared to the competitive algorithms.

The present paper is organized as follows: Section II lays the groundwork for this study by establishing the simulation model and formulating the key problem that is being addressed. Section III outlines the proposed cascaded FLC framework. Section IV entails an analysis and discussion of the simulation results, while Section V provides an overview of the study's conclusions.

II. System Model and Problem Formulation

This section describes the network model, channel model, traffic load model, target base station selection based on TOPSIS decision engine, and lastly also formulate a problem.

A. Network model

We consider a two-tier network consisting of the macro base stations (MBSs) and the small base stations (SBSs), as shown in Fig. 1. In this network, we denote $\boldsymbol{M}$ and $\boldsymbol{N}$ as the set of MBSs and SBSs, respectively. Let $\boldsymbol{J}$ represent the combined set of all base stations, defined as $\boldsymbol{J} = M \cup N$. The MBSs and SBSs operate in separate frequency bands (sub-6 GHz for MBS and mmWave for SBS) to avoid interference between them. Let $\boldsymbol{I}$ denote the set of UEs in the network. During the movement of the UEs, handovers are performed to keep the UE connect to a suitable base station. The base stations use the *Xn* interface to communicate with one another to share control information during the handover process. Each UE can only be associated with one base station (MBS or SBS) at a time, while each base station can serve several UEs simultaneously.

B. Channel model

We define $x_{ij} = 1$ as a binary association indicator, where $x_{ij} = 1$ if user i is associated with base station j, and 0

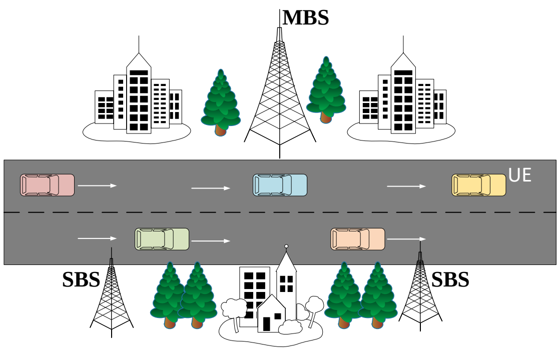


Fig. 1: Illustrative example of the network model.

otherwise. Then, the SINR received by user i from base station j is denoted by γ_{ij}

$$\gamma_{ij} = \begin{cases} \frac{P_j g_{ij} x_{ij}}{\sigma^2 + \sum_{k \in N, k \neq j} P_k g_{ik}}, & \text{if } j \in N \\ \frac{P_j g_{ij} x_{ij}}{\sigma^2 + \sum_{k \in M, k \neq j} P_k g_{ik}}, & \text{if } j \in M \end{cases} \tag{1}$$

where P_j is the transmit power of base station j and g_{ij} is the channel gain from base station j to user i, the term $\sum_{k \in (M or N), k \neq j} P_k g_{ik}$ represents the co-channel interference from other base stations, P_k is the transmit power of the base station k representing the interference to the user i, g_{ik} corresponds to the channel gain between the user i and the interfering base station k, and σ^2 represents the noise power.

The achievable channel capacity between base station j and user i is calculated as follows:

$$C_{ij} = B_{ij} \log(1 + \gamma_{ij}) \tag{2}$$

where B_{ij} represents the bandwidth allocated by base station j to user i.

C. Traffic load model

To capture resource utilization, we define ρ_j (traffic load level for base station j) as:

$$\rho_j = \frac{R_j^{utilized}}{R_j^{total}} \tag{3}$$

where $R_j^{utilized}$ and R_j^{total} represent the utilized and available radio resources in base station j, respectively. This normalization allows for a comparative assessment of traffic load across base stations with different capabilities.

D. Target base station selection with TOPSIS decision engine

TOPSIS, a multi-criteria decision-making method, is well-suited for target base station selection due to its ability to consider multiple performance metrics [18]–[20]. This is achieved through a decision matrix, denoted as $D = [\ d_{j,p}]$, where each row (j) represents a potential base station and each column (p) represents a network performance metric (e.g., RSRP, SINR, and load level of potential base stations). This matrix allows for a side-by-side comparison of potential targets. Since these criteria might be measured on different scales (e.g., RSRP in dBm, load level as a percentage, SINR in dB), the decision matrix is normalized to ensure all criteria contribute equally to the evaluation. Next, TOPSIS defines two theoretical points within this multi-dimensional space: the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). PIS represents a hypothetical potential target base station with ideal values for all criteria (highest possible RSRP, lowest possible load level, highest possible SINR). Conversely, NIS embodies the opposite extreme, with the lowest possible RSRP, highest possible load level, and lowest possible SINR.

TOPSIS employs a mathematical concept of distance to measure how close a target station's performance metrics (like RSRP, SINR, and load level) align with the ideal (PIS) and how much they deviate from the worst-case (NIS) scenario. Finally, TOPSIS combines these distances into a single score called the Similarity to Ideal Solution (SIS). Higher SIS scores indicate target stations closer to the ideal scenario. By ranking stations based on their SIS scores, TOPSIS facilitates the selection of the optimal target base station for handover, the one with the best combination of these performance metrics.

E. Problem formulation

This paper aims to maximize the sum capacity of the network through an efficient handover process. We formulate the problem of the sum capacity maximization as follows:

$$\max_{x} \quad \sum_{i \in I} \sum_{j \in J} C_{ij} \tag{4a}$$

$$\text{subject to:} \quad \sum_{j \in J} x_{ij} = 1, \quad \forall i \in I \tag{4b}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in I, \ \forall j \in J \tag{4c}$$

$$c_{ij} \geq c_{thr}, \quad \forall j \in J \forall i \in I \tag{4d}$$

$$\rho_j \leq 1, \quad \forall j \tag{4e}$$

The formulated problem considers four constraints: 4b ensures that each user is associated with only one base station at a time, 4c defines the association indicator, x_{ij}, is a binary variable that takes a value of 1 when the association between base station j and user i is active and 0 otherwise, 4d guarantees that the channel capacity between base station j and user i is not lower than the threshold capacity, and 4e imposes the load level of each base station j to be not larger than 1.

III. Proposed Cascaded FLC Framework

A crucial step in fuzzy logic systems involves determining the optimal number of fuzzy linguistic sets for each input variable. These sets, representing various parameters like signal strength, influence the system's decision-making granularity. More sets allow for nuanced control over the handover process but can lead to an explosion of fuzzy rules, increasing complexity and potentially hindering real-time applications. Conversely, too few sets can limit the system's ability to handle the dynamic and uncertain nature of wireless networks, potentially compromising accuracy.

Our fuzzy model leverages three key metrics to optimize handover decisions: RSRP, SINR, and base station load level. The RSRP variations are monitored as users move across the network to determine the optimal timing for initiating handovers, ensuring a seamless connection with satisfactory signal quality. The SINR complements RSRP by providing a more nuanced perspective. It considers the strength of the desired signal relative to the combined interference and background noise, offering a more accurate picture of signal quality. Finally, load level analysis helps identify base stations experiencing heavy traffic and prioritize handovers to those with lower congestion levels. We monitor these metrics for both the serving and target base stations, resulting in six distinct input variables for the fuzzy model.

For fuzzification, all collected attribute values are mapped to the corresponding fuzzy sets through the membership functions. These membership functions define the degree of an input value's belonging to a particular fuzzy set. The membership functions of all three attributes are defined using triangular membership functions. Triangular membership functions are a popular choice in fuzzy logic systems due to their simplicity and ease of computation [21]. For all these attributes, we define the intervals and granularity of these parameters based on experience and the ranges of values commonly expected in mobile networks, e.g., as assumed in 3GPP [22]. The following fuzzy states are defined for each attribute:

- RSRP – denoted as $\mu RSRP$

$$\mu RSRP = \begin{cases} \text{Low} & \text{for -160 to -95 dBm} \\ \text{Moderate} & \text{for -100 to -73 dBm} \\ \text{High} & \text{for -80 to -20 dBm} \end{cases} \tag{5}$$

- SINR – denoted as $\mu SINR$

$$\mu SINR = \begin{cases} \text{Low} & \text{for -60 to 1.5 dB} \\ \text{Moderate} & \text{for 0 to 14.5 dB} \\ \text{High} & \text{for 13 to 20 dB} \\ \text{Very High} & \text{for 18.5 to 30 dB} \end{cases} \tag{6}$$

- Load level – denoted as μLL

$$\mu LL = \begin{cases} \text{Low} & \text{for 0 to 0.35} \\ \text{Moderate} & \text{for 0.3 to 0.65} \\ \text{High} & \text{for 0.6 to 1} \end{cases} \tag{7}$$

After fuzzifying each input attribute, the resulting fuzzified values are forwarded to the inference engine to derive the fuzzy output. Within the inference engine module, a set of IF-THEN rules is constructed to encapsulate the decision-making logic for handover. Despite its effectiveness in capturing the multifaceted nature of handover decisions, employing a single fuzzy inference system to process all six input variables (RSRP, SINR, load level for both serving and target base stations) presents a practical challenge. The model's strength lies in its ability to consider the complex interplay between these parameters using fuzzy logic. However, this very strength translates to a significant computational burden. To represent the various relationships within the knowledge base, a substantial number of fuzzy rules would be required. Specifically, considering RSRP, SINR, and load level attributes, each with their respective fuzzy linguistic sets for both serving and target base stations, the total number of possible rule combinations is calculated as $3^2 \times 4^2 \times 3^2 = 1296$. Here, 3 represents the number of fuzzy linguistic sets for RSRP and load, while SINR utilizes 4 sets, and exponents represent the number of fuzzy sets per attribute (serving and target base stations have the same attributes, so we square the number of fuzzy sets). This significant number arises from the combination of input features and the fuzzy sets used to represent these features. Manually adjusting these numerous rules to maintain optimal performance becomes increasingly difficult and error-prone for human experts. To address the limitations of complex fuzzy rule sets, we propose a hierarchical fuzzy inference system (depicted in Fig. 2). This system utilizes three cascaded FLCs to make a final handover decision.

TABLE I: Fuzzy rules of the first layer.

Rule	RSRP	SINR	Signal Quality
1	Low	Low	Low
2	Low	Moderate	Low
3	Low	High	Moderate
4	Low	Very High	Moderate
5	Moderate	Low	Low
6	Moderate	Moderate	Moderate
7	Moderate	High	High
8	Moderate	Very High	High
9	High	Low	Low
10	High	Moderate	Moderate
11	High	High	High
12	High	Very High	High

Signal Quality FLC (First layer): This layer employs two separate Mamdani-type fuzzy inference systems to evaluate the overall signal quality for both the serving and target base stations. Each system focuses on a qualitative concept, making Mamdani-type fuzzy inference systems a suitable choice due to their ability to effectively represent qualitative information like signal strength. Their fuzzy outputs, in the form of membership degrees, provide a natural and interpretable way to assess this concept. We opted for three linguistic sets (Low, Moderate, High) to represent signal quality. This choice strikes a good balance between capturing essential variations in signal strength and maintaining interpretability within the cascaded model. While a higher number of levels might offer finer granularity, it could potentially complicate the rule base and introduce redundancy in this specific two-layer architecture.

A Mamdani-type fuzzy inference engine, based on 12 fuzzy rules listed in Table I, processes the two signal quality-related inputs. Signal Quality FLC generates a fuzzy output that

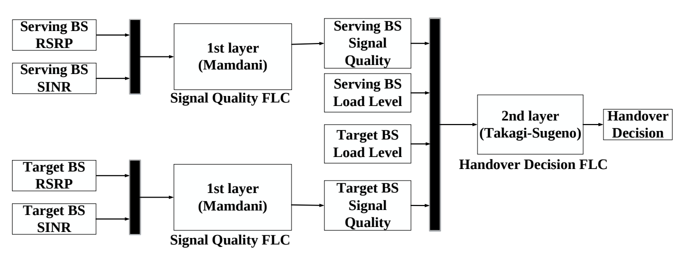


Fig. 2: Block diagram illustrating the proposed cascaded FLC system.

represents the overall signal quality for the respective base station (either the serving base station or the target base station). These three sets correspond to the attribute signal quality. Finally, the fuzzy output is used in a process called defuzzification to generate a real-valued score in the range of $\{0, 1\}$ for evaluating the signal quality of the respective base station. This defuzzification process leverages the membership functions (same membership function as load level) that define the fuzzy sets used for signal quality assessment.

Handover Decision FLC (Second layer): This layer takes into account four attributes: load level of the serving base station, load level of the target base station, signal quality of the serving base station, and signal quality of the target base station (obtained from the output of the first layer, Signal Quality FLC). To ensure seamless user experience and maximize system capacity in 6G networks, this layer prioritizes two critical aspects for handover decisions: signal quality and network load. The handover decision FLC continuously monitors signal, triggering handovers for significant degradation to maintain high-quality connections. Additionally, this layer considers network congestion. By strategically initiating handovers to less congested base stations, the handover decision FLC achieves a more balanced distribution of network resources. The critical function of this layer is determining the necessity of a handover. Here, the need for clear and actionable outputs takes precedence. Takagi-Sugeno fuzzy inference systems provide crisp output values, making them ideal for triggering actions like handover initiation. Their linear output functions also contribute to improved computational efficiency in this layer, which is crucial when dealing with multiple input variables (load levels and signal qualities). Since "no handover" is the default decision, we focus primarily on handover-triggering rules within the Takagi-Sugeno framework. Through simplification and consolidation, a knowledge base for this layer is established with 11 fuzzy rules. These rules are presented in Table II.

Employing a hierarchical architecture demonstrably enhances the efficiency of the fuzzy inference system. This approach significantly reduces both the complexity and processing time required for decision-making. By leveraging this hierarchical structure, the final rule set is streamlined to 35 rules, a substantial decrease compared to the 1296 rules needed in a non-hierarchical architecture. This reduction in complexity translates to faster processing and improved system performance.

TABLE II: Fuzzy rules of the second layer. These abbreviations are used in the table: $Serv_{SQ}$ - serving base station signal quality, $Serv_{LL}$ - serving base station load level, Tar_{SQ} - target base station signal quality, Tar_{LL} - target base station load level, HO - handover.

Rule	$Serv_{SQ}$	$Serv_{LL}$	Tar_{SQ}	Tar_{LL}	HO Decision
1	Low		Moderate	Low	HO
2	Low		Moderate	Moderate	HO
3	Low		High	Low	HO
4	Low		High	Moderate	HO
5		High	Moderate	Low	HO
6		High	Moderate	Moderate	HO
7		High	High	Low	HO
8		High	High	Moderate	HO
9	High	Low			No HO
10			Low	High	No HO
11	Moderate		High	Low	HO

IV. Simulation Model

We performed simulations in MATLAB to assess the performance of the proposed model. The MBSs and SBSs are deployed in a uniform grid pattern along the highway. This simulation model incorporates two types of UEs: stationary and mobile. The number of stationary UEs at each base station is dynamically adjusted to emulate random traffic patterns. The mobile UEs move along a straight line to mimic the movement of vehicles on highways. To evaluate the handover decision system under dynamic traffic conditions, 15 mobile UEs are chosen. For the first simulation cycle, 15 mobile UEs are randomly distributed along the highway segment. During each simulation cycle, all mobile UEs move along the highway segment at a constant speed in a predetermined direction. Note that simulations are done for 2000 simulation cycles. Each simulation cycle independently evaluates user performance. The reported results represent the average performance metrics measured across all mobile UEs throughout the entire simulation. A summary of the key simulation parameters is provided in Table III.

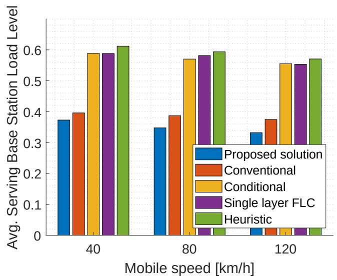
The performance of the proposed solution is compared with four existing schemes: [13] (labeled as "Conventional"), [14] (labeled as "Conditional"), and [12] (labeled as "Single layer FLC"), and [15] (labeled as "Heuristic").

V. Performance Evaluation and Discussion

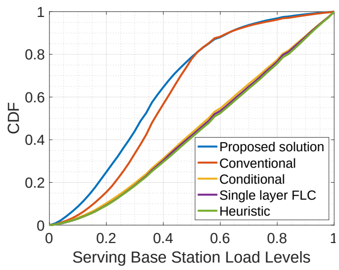
Fig. 3a illustrates the average serving base station load levels across various UE speeds. The proposed solution achieves reductions in average serving base station load level of 5.83%, 10.21%, and 11.37% for UE speeds of 40 km/h, 80 km/h, and 120 km/h, respectively, compared to the conventional algorithm (provide second-lowest average load level). However, Fig. 3a provides limited insight into the actual distribution of load levels throughout the network. To address this limitation, Fig. 3b presents the cumulative distribution function (CDF) of load levels achieved by the proposed solution and competitive handover algorithms. The CDF plot allows us to determine the probability of encountering various serving base station load levels. Fig. 3b indicates that 80% of users associated with base stations are served by stations with load levels below 50% by

TABLE III: Parameters used in the simulation model [23]–[25].

Parameter	Value	
	MBS	SBS
No. of base station	39	117
Carrier frequency (GHz)	2.1	28
System bandwidth (MHz)	20	500
TX power (dBm)	46	30
Shadowing standard deviation (dB)	6	7.8
UE's speed (km/h)	40, 80, 120	
HO preparation time (ms)	50	
HO execution time (ms)	40	



(a)



(b)

Fig. 3: Average serving base station load levels for different UE speeds (a) and CDF of serving base station load levels (b).

the proposed solution. These results highlight the effectiveness of the proposed solution in achieving fair resource allocation and enhancing overall network performance.

Fig. 4 presents the average capacity for each mobile speed scenario, considering all mobile UEs and simulation cycles. The proposed solution achieved the highest average capacity in all mobile speed scenarios. The proposed solution outperforms the conventional algorithm (achieved second-highest average capacity) across various mobile speed scenarios (40 km/h, 80 km/h, and 120 km/h). These improvements are 15.30%, 51.39%, and 40.57%, respectively.

The proposed cascaded FLC, in conjunction with the TOPSIS algorithm for selecting optimal target base stations, ensures robust connections and efficient resource allocation by triggering handovers for deteriorating signal quality and balancing network load. This ultimately maximizes network capacity.

VI. Conclusion

This paper introduces a novel multi-criteria cascaded FLC for efficient handover management in dynamic 6G networks, incorporating load balancing considerations. The proposed cascaded FLC tackles complex decision-making by dividing the process into two layers. The first layer evaluates signal quality for both the serving and target base stations. The second layer, leveraging the results from the first, prioritizes signal quality and load balancing to determine the necessity and suitability of a handover. This cascaded approach significantly reduces the *number of rules* required, leading to faster processing and improved efficiency in decision-making. Our simulations demonstrate that the cascaded FLC effectively balances network load by strategically initiating handovers to less congested base stations, resulting in improved overall network capacity.

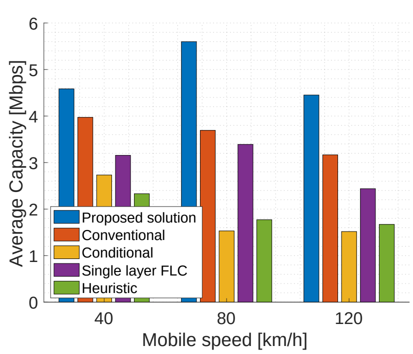


Fig. 4: Average capacity vs UE speeds.

References

[1] E. Gures, *et al.*, "A comprehensive survey on mobility management in 5G heterogeneous networks: Architectures, challenges and solutions," *IEEE Access*, vol. 8, pp. 195883-195913, 2020.

[2] T. Rappaport, *et al.*, "Overview of millimeter wave communications for fifth-generation (5G) wireless networks—With a focus on propagation models," *AP IEEE Trans.*, vol. 65, no. 12, pp. 6213-6230, 2017.

[3] R. Baldemair, *et al.*, "Ultra-dense networks in millimeter-wave frequencies," *IEEE Commun. Mag.*, vol. 53, no. 1, pp. 202-208, 2015.

[4] J. Andrews, *et al.*, "An overview of load balancing in HetNets: Old myths and open problems," *IEEE Wirel. Commun.*, vol. 21, no. 2, pp. 18-25, 2014.

[5] P. Dastranj, *et al.*, "Energy-efficient deep-predictive airborne base station selection and power allocation for UAV-assisted wireless networks," *Comput. Commun.*, vol. 191, pp. 274-284, 2022.

[6] R. Thakur, *et al.*, "A load-conscious cell selection scheme for femto-assisted cellular networks," *IEEE PIMRC*, pp. 2378–2382, 2013.

[7] A. Yadav, *et al.*, "ECCANS: Enhanced CRITIC-based Context-Aware Network Selection algorithm for 5G HetNet," *Sustain. Energy Technol. Assessments*, vol. 60, pp. 103477, 2023.

[8] Y. Gao, *et al.*, "A Fuzzy-Logic-Based Load Balancing Scheme for a Satellite-Terrestrial Integrated Network," *Electronics*, vol. 11, no. 17, pp. 2752, 2022.

[9] A. Alhammadi, *et al.*, "Intelligent coordinated self-optimizing handover scheme for 4G/5G heterogeneous networks," *ICT Express*, vol. 9, no. 2, pp. 276-281, 2023.

[10] K. Silva, *et al.*, "Adaptive hysteresis margin based on fuzzy logic for handover in mobile networks with dense small cells," *IEEE Access*, vol. 6, pp. 17178-17189, 2018.

[11] Y. Chen, *et al.*, "Fuzzy-Logic-Based Handover Algorithm for 5G Networks," *IEEE WCNC*, pp. 1-7, 2021.

[12] W. Hwang *et al.*, "Adaptive handover decision using fuzzy logic for 5G ultra-dense networks," *Electronics*, vol. 11, no. 30, pp. 3278, 2022.

[13] E. Gures, *et al.*, "Fuzzy logic-based load balancing algorithm in heterogeneous networks," *IEEE MTTW*, pp. 210-215, 2022.

[14] G. Ghatak *et al.*, "Coverage analysis and load balancing in HetNets with millimeter wave multi-RAT small cells," *IEEE Trans. Wirel. Commun.*, vol. 17, no. 5, pp. 3154-3169, 2018.

[15] P. Han *et al.*, "User association for load balance in heterogeneous networks with limited CSI feedback," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1095-1099, 2020.

[16] E. Mamdani *et al.*, "An experiment in linguistic synthesis with a fuzzy logic controller," *Int. J. Man-Mach. Stud.*, vol. 7, no. 1, pp. 1-13, 1975.

[17] W. Ho *et al.*, "Design of optimal controllers for Takagi–Sugeno fuzzy-model-based systems," *IEEE Trans. Syst. Man. Cybern.*, vol. 37, no. 3, pp. 329-339, 2007.

[18] M. Alhabo, *et al.*, "Multi-criteria handover using modified weighted TOPSIS methods for heterogeneous networks," *IEEE Access*, vol. 6, pp. 40547-40558, 2018.

[19] Q. Liu, *et al.*, "Fuzzy-TOPSIS Based Optimal Handover Decision-making Algorithm for Fifth-generation of Mobile Communications System," *J. Commun.*, vol. 14, no. 10, pp. 945-950, 2019.

[20] Y. S. Hussein *et al.*, "A novel cell-selection optimization handover for long-term evolution (LTE) macrocellusing fuzzy TOPSIS," *Computer Communications*, vol. 73, pp. 22-33, 2016.

[21] W. Pedrycz *et al.*, "Why triangular membership functions?," *Fuzzy sets and Systems*, vol. 64, no. 1, pp. 21-30, 1994.

[22] Evolved Universal Terrestrial Radio Access, "Requirements for support of radio resource management (3gpp ts 36.133 version 12.6. 0 release 12)," *ETSI TS*, vol. 136, no. 133, pp. V11, 2015.

[23] "125 942 (V3. 3.0): Universal Mobile Telecommunications System (UMTS)," RF system scenarios (3GPP TR 25.942 version 3.3.0).

[24] A. Goldsmith, "Wireless communications," 2005.

[25] E. Gures, *et al.*, "Load balancing in 5G heterogeneous networks based on automatic weight function," *ICT Express*, 2023.