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Performance Analysis of Weighting Methods for Handover Decision in HetNets

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Highlights

- This paper focuses on comparing multiple weighting methods for handover decision-making in HetNets.
- It evaluates the impact of different weighting methods by considering multiple KPIs.
- The study considers the most relevant real-life scenarios in the network.

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Abstract

The increasing demand for data, driven by advancements in technology, requires expanding coverage and enhancing network capacity. This expansion presents certain challenges, such as unnecessary Handover (HO) and interference, which can lead to a degradation in Quality of Service (QoS). To provide better QoS, it is vital to precisely model the HO decision-making process with optimal cell selection ensuring service continuity with minimal disruption. This paper investigates the performance of Analytic Hierarchy Process (AHP), Entropy, Standard Deviation (STD), and Weighted Sum Model (WSM) comparatively, while considering attributes such as Reference Signal Received Power (RSRP), Signal-to-Interference-Plus-Noise Ratio (SINR), channel capacity, and cell capacity. Additionally, the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is utilized to rank candidate cells for HO decisions. The performance of the considered weighting methods has been analyzed in a dense Small Cell (SC) Long-Term Evolution-Advanced (LTE-A) Heterogeneous Network (HetNet) environment based on system Key Performance Indicators (KPIs) such as HO Rate (HOR), HO Failure (HOF), Radio Link Failure (RLF), and HO Ping-Pong (HOPP). The evaluations have shown a trade-off between the methods in different KPIs. The findings highlight the importance of the weighting methods on HO decision, considering the significance of the specific KPIs.

1. INTRODUCTION

The rapid growth in mobile communications and the diversity in cellular networks have created an unprecedented demand for mobile data. As such, numerous Small Cells (SCs) are located inside the coverage area of traditional Macro Cells (MCs) resulting in Heterogeneous Networks (HetNets). Specifications for SCs are defined in the 3rd Generation Partnership Project (3GPP), with the aim of achieving multiple objectives, including expanding coverage, enhancing spectrum efficiency, offloading MC traffic, and reducing total transmission power [1]. The integration of SCs and MCs caters to more extensive coverage and increased capacity, which transforms into improved connectivity opportunities for mobile users (MUs). When an MU traverses cell boundaries, it becomes necessary to switch the serving Base Station (BS) to ensure optimal link quality. This transition, known as a Handover (HO), involves transferring the MU's connection to a new BS that can provide the most favorable signal quality. Despite the advantages, the integration of a dense number of SCs with MCs will create some challenges like interference and unnecessary Frequent Handover (FHO) which leads to a degradation in Quality of Service (QoS) of the MUs [2].

The Long-Term Evolution-Advanced (LTE-A) HetNets comprise several layers of BSs with different capacities, coverage areas, and sizes. Interference issue arises when different BS types, such as MCs and

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SCs (i.e. microcells, picocells, and femtocells) coexist in the same network [3]. Inter-layer interference and intra-layer interference are two different ways that interference can arise [4]. The network's performance can be severely harmed by interference between nearby cells, which will lower throughput, increase latency, and diminish coverage. In the worst case, the interference will cause a connection failure in the network. In order to maintain effective spectrum use, increased network capacity, and improved QoS for MUs, interference control is an essential component of LTE-A HetNets. The issue of interference is crucial in dense deployed SCs HetNets. Thus, researchers are trying to propose various interference cancellation methods to be able to reduce the overall effects of interference on QoS in the next generation networks. Various techniques have been proposed in the literature to address the interference issue and mitigate its effects. The simplest and common technique is the usage of dedicate channel which solves the issue, but the chance of resource dissipation is high. Starting from 3GPP Release 10 and subsequent versions, the introduction of Enhanced InterCell Interference Coordination (E-ICIC) and Carrier Aggregation (CA) techniques aim to alleviate the interference [5]. Furthermore, the Fractional Frequency Reuse (FFR) is another favoured technique for frequency resource management in LTE-A HetNets to mitigate both inter-layer and intra-layer interferences. There are various versions of FFR proposed in the literature. The most popular ones are Optimal Static FFR (OSFFR) [6], FFR with three Regions (FFR-3R) [7], FFR with three sectors (FFR-3) [8], and FFR with three Sectors and three Layers (FFR-3SL) [9, 10]. However, FFR is an effective technique for mitigating the interference; it can cause FHO to the mobile users due to the reuse of the frequency resource in multiple sectors and layers.

In order to address the FHO issue, it is necessary to choose the optimal cell to ensure connection continuity and prevent unstable connections with BSs. For this purpose, the attributes (metrics) of the network and the MU preferences are considered and evaluated. It is an important factor to choose the attributes in dense deployed SCs HetNets, where each attribute has its effect for the selection of the BS. There are numerous methods proposed in the literature which consider various attributes and select the optimum alternative (cell/BS) for HO decision. One of the popular methods is Multi Attribute Decision Method (MADM), which is considered as an effective method for optimal cell selection; as the HO decision is normally affected by multiple attributes. There are a number of methods in MADM set. The popular ones are namely, Weighted Sum Model (WSM) which is also known as Simple Additive Weighting (SAW) [11], Viˇsekriterijumsko Kompro- Misno Rangiranje (VIKOR) meaning (multi-criteria optimization and compromise solution), Weighted Product Method (WPM), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), Grey Relational Analysis (GRA), Analytic Hierarchy Process (AHP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Elimination Et Choix Traduisant la Realit`e (ELECTRE) meaning (elimination and choice expressing reality), and Criteria Importance Through Inter-Criteria Correlation (CRITIC) [12, 13].

TOPSIS is a well-known technique in MADM. Its fundamental concept is based on the idea that the ideal alternative should have the shortest proximity to the positive ideal solution while maintaining the maximum distance from the negative ideal solution. When applied to wireless networks, TOPSIS plays an effective role in selecting targets that are closest to the desired outcome while being farthest away from undesired ones. This selection is based on the best attribute values for the positive ideal solution and the worst attribute values for the negative ideal solution [14]. Furthermore, attribute weighting holds significant importance in MADM as it enables decision-makers to efficiently evaluate and select the most suitable alternative from a provided set of options. There are various approaches available for assigning weights to attributes, such as Entropy and Standard Deviation (STD), instead of the MADM methods discussed earlier. Each of the weighting methods brings its unique approach to assign weights to attributes and prioritize the decision-making process.

In general, MADM techniques have been used for solving complicated decision making problems in different fields. There has been a considerable attention on using MADM techniques in cell selection problem for HO decision. Many researchers in the literature have applied the TOPSIS method to deal with the HO decision problem in mobile networks. The authors in [15], proposed a TOPSIS method as compensatory MADM algorithm to rank the candidate alternatives (networks: Universal Mobile Telecommunications System (UMTS), Wireless Local Area Network (WLAN), and LTE) for service delivery to the MUs considering cost, bandwidth (B), network utilization, packet delay, packet jitter, and packet loss. The weighting of the attributes is done based on requested service requirements by the MU or by the network operator based on the subscription profile of the MU. In [16], the authors chose the Entropy method for weighting the attributes and they proposed TOPSIS to select the optimal network in a wireless heterogeneous environment where they have considered data transfer cost, available bandwidth, quality of service level, and security level. The authors in [17] proposed AHP method to determine the weights of the attributes and TOPSIS to rank the alternatives, where they have considered different networks as UMTS, Worldwide Interoperability for Microwave Access (WiMAX), and two standards of WLAN. The attributes observed in this work are cost, delay, jitter, packet loss, security, and throughput. Also, in [18], the authors applied AHP and TOPSIS for weighting the attributes and ranking the alternatives, respectively. They considered energy consumption, packet loss, propagation delay, and Received Signal Strength (RSS) as attributes of the alternatives. In [19], the authors introduced the TOPSIS method as a solution to mitigate Radio Link Failure (RLF), minimize packet loss, and reduce unnecessary HO while enhancing MU throughput within a HetNet environment. The HetNet consists of SCs deployed within a single MC coverage area. The attributes of movement angle, Time-of-Stay (ToS), Signal-to-Interference-Plus-Noise Ratio (SINR), and Reference Signal Received Power (RSRP) were integrated into the TOPSIS method. These attributes were assigned predetermined weights in the evaluation process. However, fixed weighting of the attributes may have inadequacy in cell selection due to variation in signal power. In [20], the authors introduced the TOPSIS method as a means of ranking alternatives. Additionally, they utilized two weighting methods, namely Entropy and STD, to calculate the weights assigned to the attributes. The attributes considered in their work are SINR, ToS inside the target cell, and MU movement angle. The authors argue that combining STD with the TOPSIS method results in better performance than using Entropy with TOPSIS in various speed scenarios for the outdoor users. However, it was mentioned that implementing STD with TOPSIS is more complex compared to Entropy applied with TOPSIS.

To the best of our knowledge, our study addresses a notable gap in the literature concerning the consideration of multiple weighting methods in dense SCs HetNet environment. While prior studies have primarily focused on one or two weighting methods, we evaluate the impact of multiple techniques including AHP, Entropy, STD, and WSM on HO decision within dense SCs LTE-A environment. Our analysis includes metrics such as Handover Rate (HOR), Handover Failure (HOF), RLF, and Handover Ping-Pong (HOPP), along with critical attributes like RSRP, SINR, channel capacity, and cell capacity. Additionally, we employ the TOPSIS method to rank alternatives and consider practical scenarios such as varying MU speeds (ranging from pedestrian walking speeds to 50 meters/sec) and the ratio of MC to SCs coverage areas to ensure real-life applicability and energy efficiency. Through our research, we provide valuable insights into network optimization strategies and address key aspects of performance enhancement and sustainability in dense LTE-A environments.

The rest of the paper is organized as follows. Section 2 defines the system model and discusses the attributes considered in our work. In section 3, the methods which are considered for weighting the attributes and ranking the alternatives are explained along with their deployment steps. Section 4 lists the simulation parameters, discusses the Key Performance Indicators (KPIs), and depicts the simulation results. Finally, section 5 concludes the paper.

2. SYSTEM MODEL

In our study, we analyze a two-tier HetNet setup consisting of a dense number of SCs deployed within the coverage area of an MC divided into three sectors, as illustrated in Figure 1. The MUs are uniformly distributed within the MC coverage area and exhibit mobility characterized by two parameters: the velocity of the MUs and their movement direction. The propagation model employed in this work includes the path loss, small-scale fading, and log-normal shadowing between the BS and each MU. We have employed FFR technique, as in [10], to efficiently allocate frequency resources across the network.

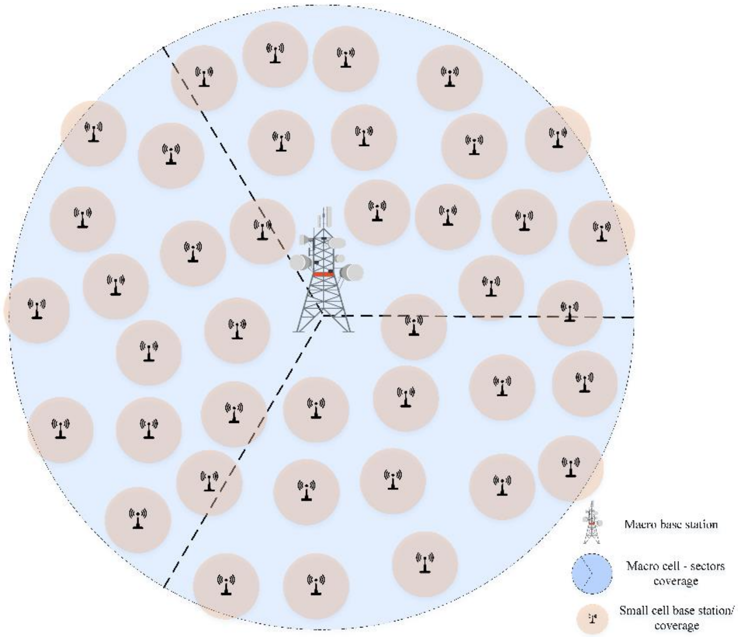

***Figure 1**. Proposed HetNet system model*

2.1. Downlink RSRP

The downlink RSRP, represented as (P^r), of the ith BS in dBm received in jth MU can be expressed by the following equation:

$$P^r_{BS_i \to MU_j} = P^t_{BS_i} - PL_{BS_i \to MU_j} + G_{BS_i} + G_{MU_j} + \mathcal{F}_{MU_j} \quad (1)$$

where $P^t_{BS_i}$ represents the transmission power of the ith BS, $PL_{BS_i \to MU_j}$ denotes the path loss between ith BS and jth MU, G_{BS_i} is the antenna gain of the ith BS, G_{MU_j} represents the antenna gain of the jth MU, and $\mathcal{F}_{MU_j}$ is the fading received in the jth MU.

2.2. Path Loss

To estimate the path loss (PL) experienced by an MU connected to the network, the urban propagation model specified in [21] is applied. This model is utilized for calculating the attenuation and loss of signal strength in urban environments. The model is expressed as follows:

$$PL_{BS \to MU} = 40(1 - 4 \cdot 10^{-3} h_{BS})\, log_{10}(d_{BS \to MU}) - 18 \times log_{10}(h_{BS}) + 21\, log_{10}(f) + 80. \quad (2)$$

In Equation (2), h_{BS} represents the BS antenna height measured from the average rooftop level in meters (m), $d_{BS \to MU}$ denotes the distance between the BS and MU in kilometers (km), and f is the carrier frequency in megahertz (MHz). It is assumed that all MUs are located outside the building, and no wall penetration loss is considered.

2.3. Downlink SINR

In a wireless mobile network, the MU may receive unwanted signals from unauthorized transmitters in the downlink channel, causing interference. In an LTE-A HetNet, the downlink SINR is significantly degraded due to interference between Macro Base Stations (Ms) and Small Base Stations (Ss). When MU_j operates in subcarrier c, the SINR received from the M and the kth S at the jth MU can be defined as follows [22]:

$$\Gamma^{r}_{M\rightarrow MU_j} = \frac{P^{t}_{M}\mathcal{g}^{c}_{M\rightarrow MU_j}}{\sum_{S} P^{t}_{S}\, \mathcal{g}^{c}_{S_k\rightarrow MU_j} + N_0\Delta_B}, \tag{3}$$

$$\Gamma^{r}_{S_k\rightarrow MU_j} = \frac{P^{t}_{M}\mathcal{g}^{c}_{M\rightarrow MU_j}}{\sum_{M,S\neq S_k} P^{t}_{M,S}\, \mathcal{g}^{c}_{M,S\rightarrow MU_j} + N_0\Delta_B}. \tag{4}$$

In Equations (3) and (4), $\mathcal{g}^{c}_{BS_i\rightarrow MU_j}$ indicates the channel gain between i$^{\text{th}}$ BS and j$^{\text{th}}$ MU in the specific subcarrier, N_0 represents the noise power density, Δ_B denotes the subcarrier spacing, and the expression $\sum_{M,S\neq S_k} P^{t}_{M,S}\, \mathcal{g}^{c}_{M,S\rightarrow MU_j}$ shows the summation of the downlink power related to M and Ss, except the desired S, which are transmitting on the interfering subcarrier.

2.4. Channel Gain

The channel gain ($\mathcal{g}$) between i$^{\text{th}}$ BS and j$^{\text{th}}$ MU is obtained by assuming a Rayleigh fading channel, as expressed below [23]:

$$\mathcal{g}_{BS_i\rightarrow MU_j} = 10^{(-PL_{BS_i\rightarrow MU_j}+\varepsilon)/10} \times |h|^2 . \tag{5}$$

In Equation (5), $PL_{BS_i\rightarrow MU_j}$ represents the path loss between the i$^{\text{th}}$ BS and j$^{\text{th}}$ MU in decibels (dB), ε denotes the log-normal shadowing expressed in dB, and $|h|$ represents the envelope of Rayleigh channel coefficient.

2.5. Channel Capacity

The channel capacity (R) of i$^{\text{th}}$ BS for j$^{\text{th}}$ MU utilizing c$^{\text{th}}$ subcarrier can be calculated as Equation (6) [23], which is extracted from the Shannon's theorem

$$R^{c}_{BS_i\rightarrow MU_j} = \Delta_B\, log_2\left(1 + \beta\Gamma^{r}_{BS_i\rightarrow MU_j}\right) \tag{6}$$

where Δ_B represents the spacing among subcarriers, the constant β shows the SINR gap for a predefined Bit Error Rate (BER) in the system, where $\Gamma^{r}_{BS_i\rightarrow MU_j}$ denotes the downlink SINR in j$^{\text{th}}$ MU from the i$^{\text{th}}$ BS, and $\beta = -1.5/\, ln(5BER)$ [24].

2.6. Cell Capacity

The role of cell capacity (C) in the cell selection or HO procedure is crucial as it influences HOF rates and ensures user satisfaction while guaranteeing QoS for the MUs in terms of throughput. The capacity allocated to j$^{\text{th}}$ MU from i$^{\text{th}}$ BS can be described as follows [25]:

$$C_{BS_i\rightarrow MU_j} = \left(1 - W^{i}_{u}\right)B\, log_2\left(1 + \Gamma^{r}_{BS_i\rightarrow MU_j}\right). \tag{7}$$

In Equation (7), B represents the system bandwidth, while W_u^i denotes the ratio of total resources assigned to active MUs by the ith BS to the overall resources of that particular BS (W_Σ^i)

$$W_u^i = \frac{\sum_{\forall j} W_{MU_j}^i}{W_\Sigma^i} \tag{8}$$

where $W_{MU_j}^i$ represents the resources allocated to jth MU, thereby the expression $\sum_{\forall j} W_{MU_j}^i$ denotes the total resources assigned to all active MUs in ith BS.

3. RELATED METHODS

In an MADM problem, a collection of m alternatives, denoted as A_i (where $i = 1, 2, \ldots, m$), is typically evaluated based on n attributes, represented as Q_j (where $j = 1, 2, \ldots, n$). The evaluations are conducted to determine the weighting vector $V_j = (v_1, v_2, \cdots, v_j, \cdots, v_n)$ and the decision matrix $D_x = x_{ij}$. The weighting vector V_j indicates the relative significance of the attributes, while the decision matrix D_x captures the performance ratings, denoted as x_{ij}, of the alternatives A_i concerning the attributes Q_j. The objective, given the vector V_j and matrix D_x, is to rank the alternatives by assigning an overall preference rate to each alternative, concerning all attributes [26].

D_x is given as below:

$$D_x = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{9}$$

where each row shows a specific alternative, while the columns correspond to the attributes. The value x_{ij} represents the jth attribute of the ith alternative.

3.1. AHP Method

AHP is a widely used measurement theory introduced by T. L. Saaty in 1971 [27]. It serves as an efficient subjective weighting method and is commonly employed in MADM problems that involve a finite number of alternatives. AHP's popularity stems from its robust mathematical computational capabilities and its relative simplicity. The method can be executed by sequentially following the outlined steps.

Step 1. Describe the pairwise comparison matrix (D_p).

During this step, the attributes are systematically compared to one another, and the number of comparisons performed is directly related to the number of attributes being considered. The number of comparisons increases proportionally with the increase in the number of attributes. Consequently, the pairwise comparison matrix will have dimensions of $n \times n$, where n represents the number of attributes. The matrix size expands to accommodate the varying number of attributes being compared. The pairwise comparison is performed using the scale table provided in Table 1, which is derived from [28].

Table 1. *Scale table*

Saaty's scale	Fair scale	Linguistic values
1	1	Equal importance
2	1.22	---
3	1.5	Moderate importance
4	1.86	---
5	2.33	Strong importance
6	3	---
7	4	Very strong importance
8	5.67	---
9	9	Extreme importance

D_p is expressed as follows:

$$D_p = \begin{bmatrix} 1 & \cdots & p_{1j} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{j1} & \cdots & 1 & \cdots & p_{jn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nj} & \cdots & 1 \end{bmatrix}. \tag{10}$$

Given that $p_{jj} = 1$ and $p_{jk} = {}^{1}/_{p_{kj}}$, where p_{kj} represents the elements in matrix D_p, the attributes are compared to each other and are assigned weights. The diagonal values in the matrix are set to one, indicating that the importance of an attribute in relation to itself is given a value of 1.

Step 2. Establish the weights assigned to the attributes, known as normalized eigenvectors, within the matrix D_p.

To obtain v_j^a, firstly, create the normalized matrix (D_n) from the matrix D_p. This can be done by dividing each element of the matrix D_p by the sum of the values within the respective column. This ensures that the resulting values in each column add up to 1.

D_n is illustrated as below:

$$D_n = \begin{bmatrix} \frac{p_{11}}{\sum_{j=1}^{n} p_{n1}} & \cdots & \frac{p_{1j}}{\sum_{j=1}^{n} p_{nj}} & \cdots & \frac{p_{1n}}{\sum_{j=1}^{n} p_{nn}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{p_{j1}}{\sum_{j=1}^{n} p_{n1}} & \cdots & \frac{p_{jj}}{\sum_{j=1}^{n} p_{nj}} & \cdots & \frac{p_{jn}}{\sum_{j=1}^{n} p_{nn}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{p_{n1}}{\sum_{j=1}^{n} p_{n1}} & \cdots & \frac{p_{nj}}{\sum_{j=1}^{n} p_{nj}} & \cdots & \frac{p_{nn}}{\sum_{j=1}^{n} p_{nn}} \end{bmatrix}. \tag{11}$$

Then, v_j^a is obtained by averaging over the rows in Equation (11)

$$v_j^a = \frac{\sum_{j=1}^{n} p_{jj}}{n}. \tag{12}$$

Step 3. Calculate the Consistency Ratio (CR).

It is essential to initially establish the Consistency Index (CI) before calculating the CR [29].

$$CI = \frac{\lambda_{max} - n}{n-1}. \tag{13}$$

In Equation (13), λ_{max} can be obtained as:

Obtain the eigenvalue (v_j') by multiplying the matrix D_p with the eigenvector v_j^a.

$$v_j' = D_p\, v_j^a. \tag{14}$$

Get λ_{max} by summing the ratios of v_j' to v_j^a and then dividing the overall summation by the total number of attributes, as expressed below:

$$\lambda_{max} = \frac{1}{n}\left(\frac{v_1'}{v_1^a} + \cdots + \frac{v_j'}{v_j^a} \cdots + \frac{v_n'}{v_n^a}\right). \tag{15}$$

Next, find the Random Index (RI) corresponding to the number of attributes used in matrix D_x from Table 2.

Table 2. *Random Index (RI)* [27]

n	**RI**
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45

Finally, compute the CR using the following formula:

$$CR = \frac{CI}{RI}. \tag{16}$$

In AHP method, it is generally considered acceptable for the inconsistency to be within a maximum limit of 10%.

3.2. Entropy Method

The Entropy method utilizes probability theory to measure the uncertainty in data. The breadth of the data distribution is taken into account, where a wider distribution suggests greater uncertainty, while a narrower distribution suggests lower uncertainty. The method effectively quantifies the informational contribution or relevance associated with each attribute in the decision matrix. Belonging to the category of objective weighting techniques, the Entropy weighting technique assesses attribute weights based on their relative differences. The entropy weight is derived by normalizing the obtained weight for each attribute [13, 30]. To apply the Entropy method and obtain objective weights for the attributes, several steps need to be followed.

Step 1. Normalize the performance ratings in matrix D_x given in (9) by the equation below:

$$x_{ij}^{norm} = \frac{x_{ij} - \min\,(x_j)}{\max(x_j) - \min\,(x_j)}, \tag{17}$$

$$x_{ij}^{norm} = \frac{x_{ij} - \max\,(x_j)}{\min(x_j) - \max\,(x_j)}. \tag{18}$$

Equation (17) is applied for beneficial attributes, while Equation (18) is applied for non-beneficial ones.

Step 2. The divergence degree of the jth entropy coefficient, denoted as d_j, can be derived considering the normalized decision matrix

$$d_j = 1 - q_j \tag{19}$$

where q_j is obtained from the below equation:

$$q_j = \left[\frac{1}{ln(n)} \sum_{i=1}^{n} x_{ij}^{norm}\, ln(x_{ij}^{norm})\right]. \tag{20}$$

In Equation (20), the constant term $\frac{1}{ln(n)}$ ensures the coefficient q_j remains confined within the range [0,1].

Step 3. Obtain the weights of the attributes.

Finally, the entropy weight for the jth attribute can be expressed as follows:

$$v_j^e = \frac{d_j}{\sum_{j=1}^{n} q_j}. \tag{21}$$

3.3. STD Method

The STD method is employed to evaluate the weight of each attribute based on its standard deviation. This approach quantifies the importance of attributes within each alternative and provides a measure of their significance. The weighting technique based on STD assigns a lower weight to an attribute when its value remains constant across all existing alternatives. When an attribute exhibits identical values across all alternatives, it is considered to have a minimal influence on the HO decision-making process. As a result, its weight is considered negligible. Put simply, attributes that exhibit minimal variation (low STD) are assigned lower weights, while attributes with larger variation (higher STD) receive higher weights [31].

The weights of the attributes using STD method can be calculated as below

$$v_j^s = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j}. \tag{22}$$

In Equation (22), σ_j is described as:

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(x_{ij}^{norm} - \bar{X}_j\right)^2} \tag{23}$$

where $\bar{X}_j$ is expressed as:

$$\bar{X}_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}^{norm}. \tag{24}$$

3.4. WSM Method

WSM is a widely used and versatile framework that finds applications in various domains. It is a straightforward and commonly employed technique in MADM methods. In WSM, weights are assigned to each attribute independently. The alternative that attains the greatest cumulative score, determined by summing the weighted values, is chosen as the most desirable option. Decision-makers determine these weights based on their subjective judgment or expert opinions. WSM allows decision-makers to explicitly prioritize attributes by assigning weights according to their perceived importance, providing a flexible and intuitive approach for HO decision-making [32, 33].

The overall score of an alternative in WSM is obtained by calculating the weighted sum of all attribute values, as depicted below

$$r_i^w = \sum_{j=1}^{n} v_j^w \, x_{ij}^{norm} \tag{25}$$

where v_j^w represents the fixed weight assigned for each attribute, and i $= 1,2,3,\cdots,$ m.

3.5. TOPSIS Method

The TOPSIS method has gained significant popularity for addressing diverse MADM problems since its development by Hwang and Yoon in 1981. Its primary purpose is to rank alternative candidates based on different attributes [12]. The method operates on the fundamental assumption that the selected alternative should exhibit the minimum distance to the positive-ideal solution and the maximum distance from the negative-ideal solution. It establishes an index that identifies a solution that is both the closest to the best solution and the farthest from the worst solution. The index is used to rank the existing alternatives [34].

The TOPSIS method consists of the following subsequent calculation steps:

Step 1. Calculate the normalized performance ratings (x_{ij}^{norm}) as below:

$$x_{ij}^{norm} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2}. \tag{26}$$

The normalized decision matrix (D_x^{norm}) will be illustrated as below:

$$D_x^{norm} = \begin{bmatrix} x_{11}^{norm} & \cdots & x_{12}^{norm} & \cdots & x_{1n}^{norm} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{21}^{norm} & \cdots & x_{22}^{norm} & \cdots & x_{21}^{norm} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1}^{norm} & \cdots & x_{m2}^{norm} & \cdots & x_{mn}^{norm} \end{bmatrix}. \tag{27}$$

Step 2. Integrate the weights with the normalized performance ratings to get the weighted-normalized performance ratings (x_{ij}^{w}) as following:

$$x_{ij}^{w} = v_j x_{ij}^{norm}. \tag{28}$$

The weighted-normalized decision matrix (D_{ij}^{w}) is given as follows:

$$D_{ij}^{w} = \begin{bmatrix} x_{11}^{w} & \cdots & x_{12}^{w} & \cdots & x_{1n}^{w} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{21}^{w} & \cdots & x_{22}^{w} & \cdots & x_{21}^{w} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1}^{w} & \cdots & x_{m2}^{w} & \cdots & x_{mn}^{w} \end{bmatrix}. \tag{29}$$

Step 3. Obtain the positive and negative-ideal solutions.

The positive-ideal solution (I^{+}) and is obtained as below:

$$I^{+} = \left\{ \left(\max_{i \in m} D_{x_{ij}}^{w} | j \in j^{+} \right), \left(\min_{i \in m} D_{x_{ij}}^{w} | j \in j^{-} \right) \right\} = \left\{ x_1^{w^{+}}, x_2^{w^{+}}, \cdots, x_m^{w^{+}} \right\}, \tag{30}$$

and the negative-ideal solution (I^{-}) is explained as:

$$I^{-} = \left\{ \left(\min_{i \in m} D_{x_{ij}}^{w} | j \in j^{+} \right), \left(\max_{i \in m} D_{x_{ij}}^{w} | j \in j^{-} \right) \right\} = \left\{ x_1^{w^{-}}, x_2^{w^{-}}, \cdots, x_m^{w^{-}} \right\}. \tag{31}$$

In Equations (30) and (31), j^{+} and j^{-} correspond to benefit and cost attributes, respectively.

Step 4. Calculate the separation measures.

The separation measure relates to the distance between each alternative rating and both the positive-ideal and negative-ideal solutions. The Euclidean theory is utilized to calculate the separation measure for both solutions, as demonstrated below:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(D_{x_{ij}}^{w} - I_j^{+} \right)^2}, \tag{32}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(D_{x_{ij}}^{w} - I_j^{-} \right)^2}. \tag{33}$$

Step 5. Calculate the relative closeness to the ideal solution.

The relative closeness (r) of each alternative to the ideal solution is calculated as below:

$$r_i = \frac{S_i^-}{\left(S_i^+ + S_i^-\right)}. \tag{34}$$

Step 6. The result from Step 5 is ranked in descending order. The highest ranked alternative is selected as the optimum alternative (A_{Opt}).

$$A_{Opt} = arg\,max(r_i). \tag{35}$$

4. PERFORMANCE ANALYSIS

To investigate the performance of the considered methods, different attributes are considered, namely RSRP, SINR, channel capacity, and cell capacity. We analyze the impact of these attributes on the HO decision in dense deployed SCs HetNets. The methods to calculate the weights of the attributes are AHP, Entropy, STD and WSM. TOPSIS is considered to rank the alternatives. It is worth mentioning that we did not apply the TOPSIS with WSM method in order to compare the results with other methods that applied TOPSIS for ranking the alternatives. The weighting methods are evaluated based on several performance metrics, including the HOR, HOF, RLF, and HOPP. These metrics are used to compare the performance of mentioned weighting methods against each other. Table 3 lists the simulation parameters.

Table 3. *Simulation parameters*

Parameters	**Values**
Carrier Frequency (f)	2.6 GHz
System Bandwidth (B)	20 MHz
Carrier Spacing (Δ)	15 kHz
Macro Cell Radius	1000 m
Small Cell Radius	100 m
MBS Transmission Power (P_{T_M})	43 dBm
SBS Transmission Power (P_{T_S})	30 dBm
Number of MBSs	1
Number of MCs	3
Number of SCs	40
Number of MUs	100
MU Speeds	{5,40,80,120,180} km/h
RSRP Threshold	-80 dBm
Noise Power Density	-174 dBm/Hz
Simulation Period	1500 × 40 ms

4.1. Handover Rate (HOR)

HOR is the term used to describe number of HOs that may occur during the mobility of a user in the network. This metric is sometimes known as HO probability. The average HO probability versus speed scenarios and versus time for all the considered weighting methods are shown in Figure 2 and Figure 3, respectively.

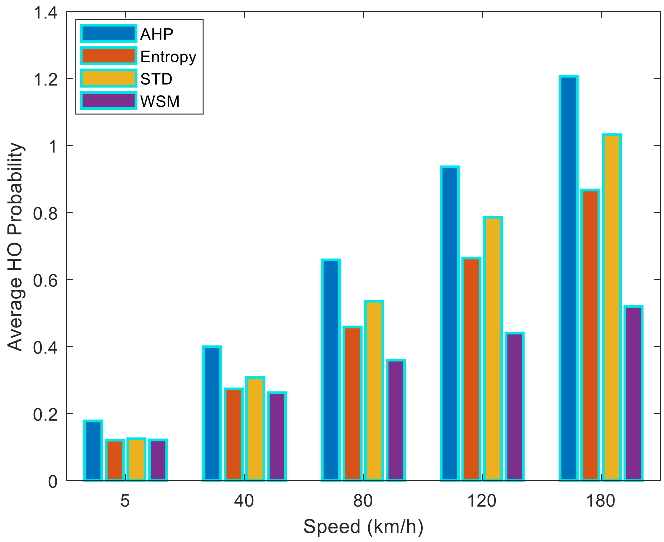

Figure 2. *Average HO probability overall MUs versus MU speed scenarios*

Figure 2 provides clear evidence that as mobility speed increases, the serving BS undergoes faster changes, resulting in a higher HOR for the MU.

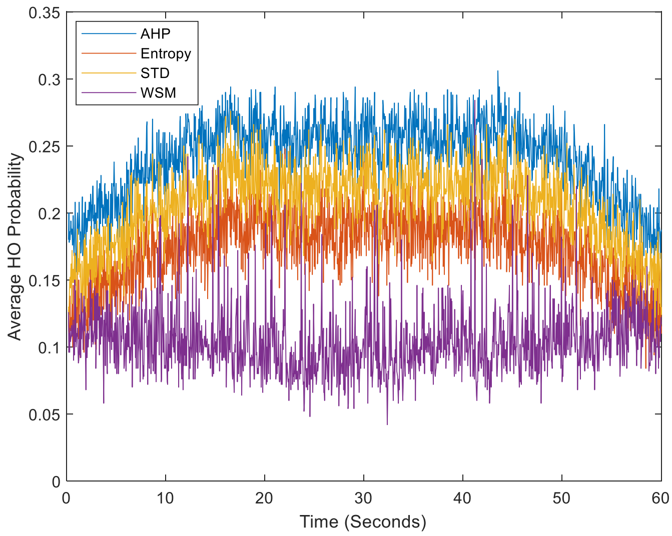

Figure 3. *Average HO probability overall MU speed scenarios versus time*

Both Figures 2 and 3 show that the AHP method indicates a higher probability of HO occurrence, while the WSM method demonstrates the lowest probability of HO compared to other methods. This is due to the preference of the system designer in weighting the metrics within the system. In the pair-wise comparison matrix of the AHP method, the RSRP has been assigned greater importance than other attributes. RSRP is a crucial metric in the handover decision, and fluctuations in this metric can result in a higher HOR. In addition, the performance of Entropy method is better than STD and AHP for this KPI. This superiority can be attributed to the implementation of the max-min normalization method within the Entropy approach depicted in Equations (17) and (18). Furthermore, the STD method displays a higher number of HOs, potentially due to the allocation of greater weights to attributes. Notably, within the STD method, attributes with larger variations (higher STD) are assigned higher weights. As previously mentioned, it is important to note that all attributes considered in this study exhibit fluctuations over time.

4.2. Handover Failure (HOF)

HOF in LTE-A HetNets can be attributed to several factors. Among them, interference, load imbalance between BSs, coverage issues leading to sudden degradation in received power level, and inadequate mobility management techniques are crucial factors in contributing to HOFs. Figures 4 and 5 demonstrate the average HOF probability versus MU speed scenarios, and the average HOF probability overall time period versus all considered methods, respectively. The figures show that HOF is zero for all the methods and all speed scenarios. This is due to some reasons including the implementation of FFR in our proposed system, which aims to achieve load balancing and mitigate interference. We have utilized FFR to efficiently allocate frequency resources to both MC and SCs, while also assigning these resources to MUs. Also, in all the weighting methods, it is evident that the best alternative is chosen as the target BS. When the BS with the strongest signal level is selected, it is clear that the probability of HOF becomes zero. However, another potential reason for HOF could be the cell capacity limitations. In our study, we have attempted to address this by optimizing the distribution of frequency resources among the BSs and the MUs, as illustrated in Equations (7) and (8), through the implementation of the FFR technique. Furthermore, other factors affecting HOF, such as interference and coverage holes, may have been optimally managed.

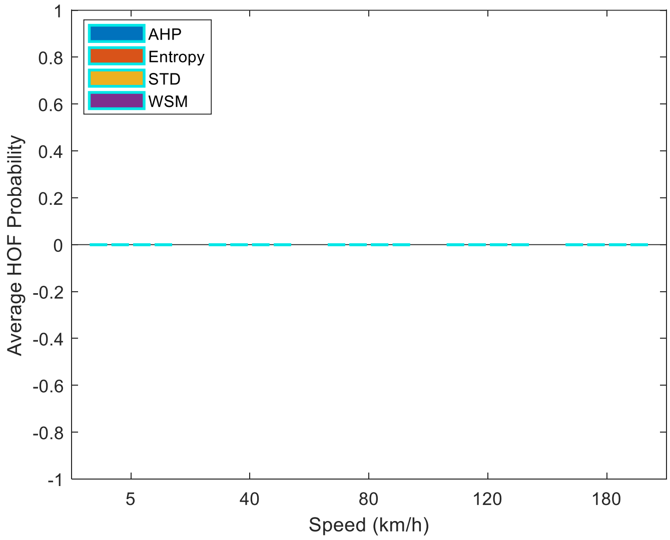

Figure 4. *Average HOF probability versus MU speed scenarios*

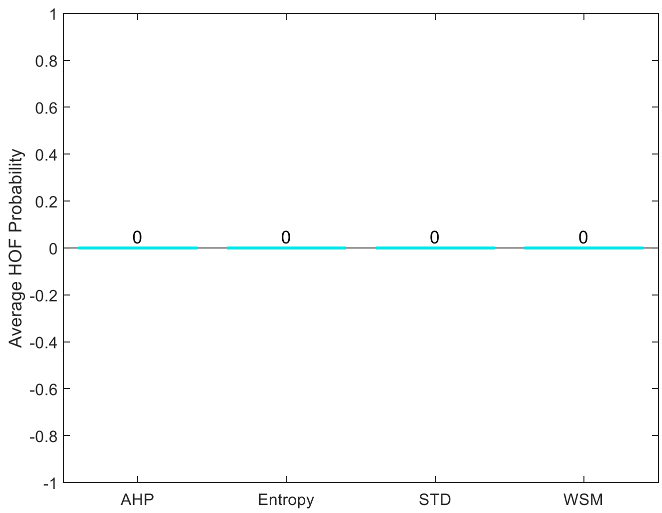

Figure 5. *Average HOF probability overall system*

4.3. Radio Link Failure (RLF)

RLF serves as a crucial metric to assess network performance. An RLF is determined when a HO is triggered to the target BS, but the downlink SINR of that BS falls below a predefined threshold value within a certain duration. Figure 6 illustrates the average RLF probability versus MU speed scenarios. Mostly, RLF is proportional to the speed; with higher mobility speeds the RLF probability increases and vice versa. Figure 7 represents the average RLF probability versus all considered weighting methods in overall system. In both Figures 6 and 7, it is shown that the AHP method has the least RLF probability, while WSM has the highest RLF. Giving greater importance to RSRP in the AHP method results in an improvement in the SINR, leading to a decrease in the number of RLFs. Conversely, the WSM method's utilization of fixed weights for attributes increases the likelihood of RLFs. On the other hand, STD outperforms the Entropy method in terms of this performance metric. The rationale behind this is that in the STD method, attributes with greater variance are assigned higher weights, as demonstrated in Equation (22), implying that the alternative with the highest rank is selected as the target. While this helps in reducing RLF occurrences, it may lead to a higher number of HOs.

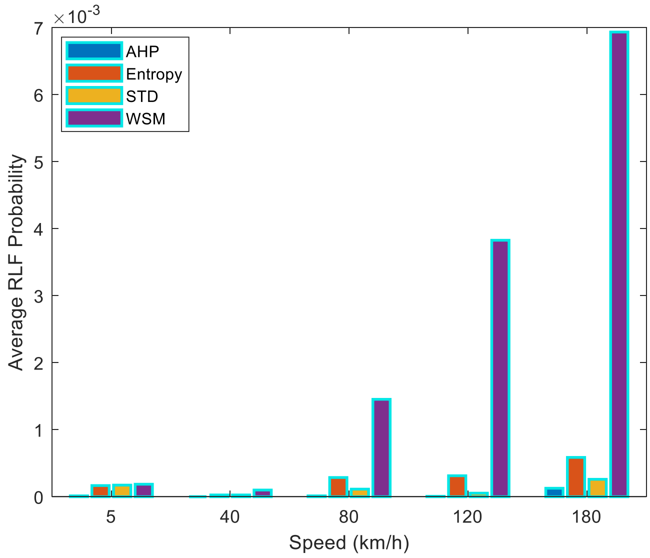

Figure 6. *Average RLF probability versus MU speed scenarios*

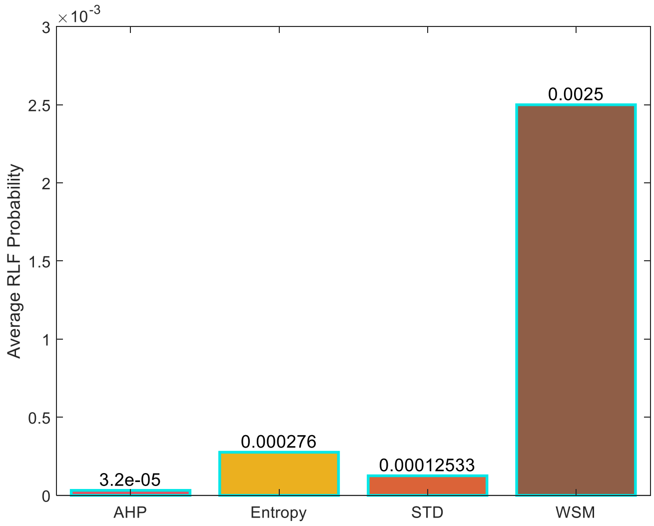

Figure 7. *Average RLF probability overall system*

4.4. Handover Ping-Pong (HOPP)

HOPP is the situation in a wireless network where the MU experiences frequent and repetitive HOs between two BSs. In LTE-A HetNet, a HO is classified as a ping-pong HO when a connection is transferred to a new BS and then returned to the original BS within duration shorter than 1 second [2]. Figures 8 and 9 illustrate the average HOPP probability versus MU speed scenarios and considered weighting methods, respectively. In both figures, it is demonstrated that the AHP method has higher HOPP probability, while WSM has the least among other methods. Similar to HOR, the large fluctuations in RSRP level and the higher importance assigned to RSRP in the AHP method increase the HOPP probability. The Entropy method shows better performance than STD method in this metric. As mentioned in Subsection 4.1, the use of the max-min normalization method in the Entropy weighting technique may help reduce HORs. This is also applicable for HOPP. In contrast, as explained in Subsection 3.3, the STD method assigns higher weights to attributes with greater variation. Consequently, this leads to the selection of alternatives as the target BS more frequently, resulting in increased HORs and HOPP probabilities. It is worth noting that there exists a trade-off between RLF and HOPP/HORs.

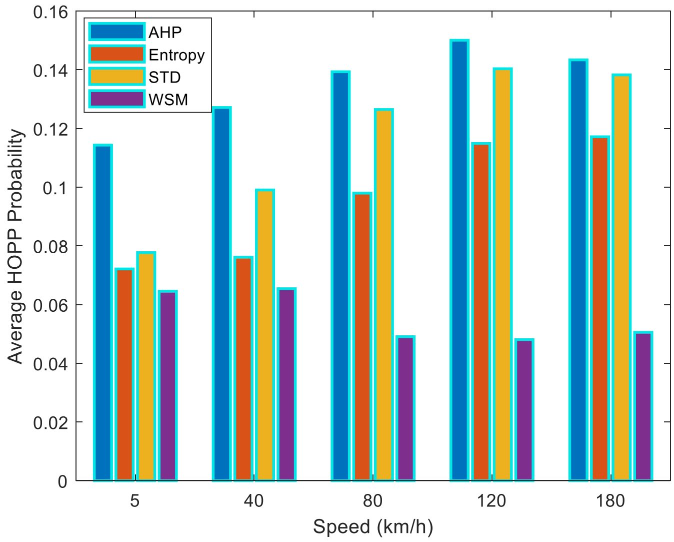

Figure 8. *Average HOPP probability versus MU speed scenarios*

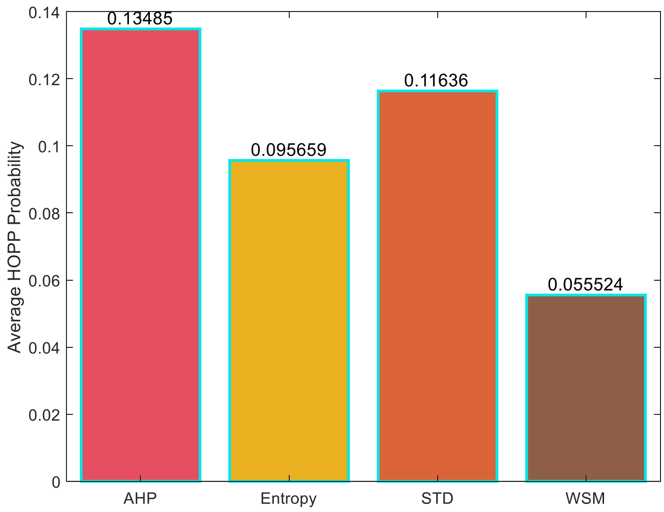

Figure 9. *Average HOPP probability overall system*

5. CONCLUSION

In conclusion, our study thoroughly investigated the impact of various weighting methods, including AHP, Entropy, STD, and WSM on the assignment of weights to network metrics such as RSRP, SINR, channel capacity, and cell capacity. Additionally, we utilized the TOPSIS method to rank alternatives in HO decision-making, with a comprehensive analysis of their performance across key metrics like HOR, HOF, RLF, and HOPP.

Our findings highlight the significance of selecting a weighting method that aligns with specific performance objectives, taking into account the associated trade-offs. For example, while AHP tends to increase HO occurrences due to its emphasis on RSRP, WSM effectively reduces the HORs by maintaining fixed weights. In addition, all evaluated methods exhibit negligible HOF probabilities. This outcome is attributed to the effective implementation of FFR technique, optimizing frequency resource allocation and mitigating interference. Also, the selection of the best alternative as the target BS and optimization of resource distribution among BSs and MUs contribute to minimizing HOF. Furthermore, effective management of factors such as interference and coverage gaps contributes to the overall mitigation of HOF occurrences.

Moreover, the AHP method exhibits the lowest RLF probability, whereas the WSM shows the highest. As mentioned, the AHP method emphasizes RSRP, contributing to improved SINR and consequently reducing RLF occurrences. Conversely, the fixed weights utilized by the WSM method for attributes increase the likelihood of RLFs. Additionally, the STD method outperforms the Entropy method because it assigns higher weights to attributes with greater variance. This results in the selection of the highest-ranked alternative as the target, ultimately reducing RLF occurrences.

In contrast, the AHP method exhibits a higher probability of HOPP, while the WSM method shows the lowest probability among the evaluated methods. This disparity is attributed to reasons mentioned above for the AHP and WSM methods. On the other hand, the Entropy method outperforms the STD method in mitigating HOPP occurrences. The implementation of the max-min normalization method in the Entropy weighting technique not only reduces HORs but also mitigates HOPP occurrences. However, the STD method's tendency to assign higher weights to attributes with greater variation results in the more frequent selection of alternatives as the target BS, leading to increased probabilities of both HOPP and HORs. It is essential to note the trade-off between RLF and HOPP/HOR occurrences in the optimization of network performance.

These findings emphasize the significance of choosing a suitable weighting method that aligns with specific performance objectives. It is important to note that there is a trade-off between the weighting methods and performance metrics.

Overall, this paper presents significant findings regarding the performance of various weighting methods and emphasizes the importance of selecting the most suitable method, taking into account specific performance metrics for handover decision-making in LTE-A HetNets. Further investigations can explore the applicability of these methods in different network scenarios and evaluate their performance under varying conditions. Furthermore, it is worth noting that the efficacy and optimization of these methods can be influenced by the inclusion and careful consideration of Handover Control Parameters (HCPs), such as Time-to-Trigger (TTT) and HO Margin (HOM), within the system.

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CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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