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Hybrid Weighted Multiple Attribute Decision Making Handover Method for Heterogeneous Networks

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***Abstract*—Small cell deployment in 5G networks is a promising technology to enhance the capacity and coverage. However, unplanned deployment may cause high interference levels and high number of unnecessary handovers, which in turn result in an increase in the signalling overhead. To guarantee service continuity, minimize unnecessary handovers and reduce signalling overhead in heterogeneous networks, it is essential to properly model the handover decision problem. In this paper, we model the handover decision problem using Multiple Attribute Decision Making (MADM) method, specifically Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), and propose a hybrid TOPSIS method to control the handover in heterogeneous network. The proposed method adopts a hybrid weighting policy, which is a combination of entropy and standard deviation. A hybrid weighting control parameter is introduced to balance the impact of the standard deviation and entropy weighting on the network selection process and the overall performance. Our proposed method show better performance, in terms of the number of frequent handovers and the mean user throughput, compared to the existing methods.**

***Keywords*—**Handover, HetNets, interference, MADM, small cells, TOPSIS, weight.

I. Introduction

THE capacity demand of the cellular network tends to be more than 1000x by end of year 2021 [1]. The existing homogeneous network is insufficient to meet such traffic because of the cost needed to deploy macrocells (MCs). The technology of small cells (SCs) has been implemented to meet the increasing demand of capacity. Networks consisting of both MCs and SCs are defined as heterogeneous networks (HetNets) [2]. The implementation of ultra-dense SCs results in interference and unnecessary handovers issues. The number of handovers is extremely higher in HetNets compared to the homogeneous networks. This can cause high probability of radio link failure (RLF), leading to poor quality of service (QoS) [3]. There have been many works in the literature dealing with the handover (HO) problem. In [4]–[6], we proposed different methods to deal with the HO-related problems in HetNets. This includes the minimization of unnecessary HO, reducing HO failure and load balancing.

MADM techniques deal with the selection of the best alternatives which are characterised according to multiple attributes. The HO decision is usually affected by multiple metrics [7]. Therefore, MADM techniques are natural choice in modelling the HO decision problem.

TOPSIS is regarded as one of the utmost broadly exploited MADM methods. When deployed in wireless network field, TOPSIS is used to elect the target which is closest to the positive ideal solution and farthest from the negative ideal solution. Positive ideal solution relays on the best value for the attributes deployed in decision making, while negative ideal solution relays on the worst attributes [8]. In [9], the authors proposed a TOPSIS method using cost, total bandwidth, network utilization, delay, and jitter when forming the HO decision matrix. In [10], a TOPSIS method is presented to rank the available networks. Many metrics are utilized when building the decision matrix, such as the available bandwidth, cost, and security level. In [11], a TOPSIS technique is deployed to avoid the connection failure in HetNets. User executes HO to the target cell in one of two ways. Initially, once the received power is low, even earlier than the time to trigger expiry. Subsequent, once the received signal from the source cell is adequately higher but the downlink SINR gets less than a threshold. Results reveal that this method minimized the number of HOs, packet loss and increase user mean throughput. However, the use of predefined values to weight the HO metrics could show some deficiency in HO decision due to the large variation in signal power because of user mobility specially for high speed ones in ultra dense SCs scenarios. In [12], we proposed two TOPSIS HO methods exploiting the standard deviation (SD) and entropy weighting techniques separately. The two methods are applied to a two-tier HetNet where it has been found that the entropy-based method is suitable for home-based SCs, while the SD-based method is more suitable for other SC types at the cost of slightly higher complexity in operation. In this paper, the HO decision uses the time of stay (ToS) in the target cell, user angle of movement and the SINR for the target cell. We proposed a method which adopts a hybrid weighting technique motivated by [12]. The new proposal improves the work in [12] by combining two weighting techniques in one technique. Using numerical simulations, the proposed method is compared with the exiting methods in terms of the number of HOs, RLFs and user mean throughput. The contribution of this paper can be listed as follows:

- TOPSIS is utilized to model the HO problem. The proposed method uses the user angle of movement, ToS and SINR to build the HO decision matrix.
- The proposed method combines both standard deviation and entropy weighting techniques, hybrid weighting. Thus, this method is named as hybrid weighted technique for order preference by similarity to an ideal solution (HW-TOPSIS).
- Results revealed that the proposed HW-TOPSIS method has outperformed the existing methods in the literature by reducing the number of HOs and RLF, in addition to improving the mean user throughput.

The rest of the paper is organized as follows. System model is described in Section II. The proposed method's procedures are illustrated in Section III. Section IV gives the proposed weighting techniques. The performance and results analysis are given in

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Section V. Finally, the conclusion is drawn in Section VI.

II. System Model

The system model consists of a two-tier downlink HetNet scenario with a single MC of $500m$ radius and N_{sc} number of SCs with a radius of $100m$ each. Thus, the total number of base stations in the network is N_{bs}. SCs are randomly deployed following uniform distribution. The minimum distance is adjusted to $75m$ between MC and SC sites and $40m$ between SC and SC site [2] ensuring the existence of overlapping between SCs. Users are distributed uniformly in the MC coverage area. Random direction mobility model is deployed for users movement, in which the UE travels in straight line with a constant speed.

A large scale channel is taken into account using the path loss model and shadowing effects. The path loss between the MC and the user is expressed as [13]

$$\delta_{m,k} = 128.1 + 37.6\ \log_{10}(d_{m,k}), \tag{1}$$

where $d_{m,k}$ is the distance between the user and the MC in kilometres. The path loss between the SC and the user is expressed as [14]

$$\delta_{sc_i,k} = 38 + 30\ \log_{10}(d_{sc_i,k}), \tag{2}$$

where $d_{sc_i,k}$ is the distance between the user and SC i in metres. The SINR received from SC i at user k is defined as

$$\gamma^r_{sc_i,k} = \frac{P^r_{sc_i,k}}{\sum_{j=1,j\neq i}^{N_{bs}} P^r_{bs_j,k} + \sigma^2}, \tag{3}$$

while the SINR received from MC at user k is given as

$$\gamma^r_{m,k} = \frac{P^r_{m,k}}{\sum_{j=1,j\neq m}^{N_{bs}} P^r_{bs_j,k} + \sigma^2}, \tag{4}$$

where $P^r_{sc_i,k}$ and $P^r_{m,k}$ are respectively the reference signal received power (RSRP) received from SC i and MC, $P^r_{bs_j,k}$ is the RSRP from the interfering MC/SCs, $\gamma^r_{m,k}$ is the SINR received from MC at user k, $\gamma^r_{sc_i,k}$ is the SINR received from SC i at user k, σ^2 is the noise power, and N_{bs} is the total number of base stations in the network.

As illustrated in Fig. 1, the real ToS, ToS^{real}_k, can be computed as

$$\begin{aligned} ToS^{real}_k &= \frac{\mid \overrightarrow{A_{in}A_{out}} \mid}{V_k} \\ &= \frac{2R_i \cos(\alpha)}{V_k}, \end{aligned} \tag{5}$$

where A_{in}, and A_{out} are respectively the entry and the exit points of the UE to and from base station i, R_i is the radius of the base station, and V_k is the user velocity k.

The following can be obtained from Fig. 1

$$\frac{\mid A_1A_0 \mid}{\sin(180-\alpha)} = \frac{R_i}{\sin(\theta)}, \tag{6}$$

where A_0, and A_1 are respectively the location of base station i, and the previous location of the UE. Equation (6) can be rewritten as

$$\sin(\alpha) = \frac{\mid A_1A_0 \mid \sin(\theta)}{R_i} \tag{7}$$

Thus

$$\cos(\alpha) = \sqrt{1 - \frac{\left(\mid A_1A_0 \mid \sin(\theta)\right)^2}{R_i^2}} \tag{8}$$

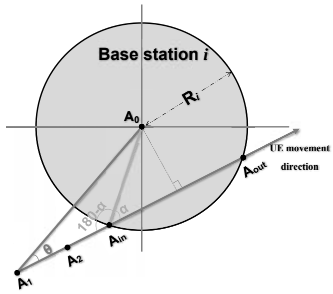

Fig. 1 Time of stay measurement

The angle between base station i and the trajectory of the user, θ, can be computed as

$$\theta = \arccos\left(\frac{\overrightarrow{A_1A_0} \cdot \overrightarrow{A_1A_2}}{\mid \overrightarrow{A_1A_0} \mid \times \mid \overrightarrow{A_1A_2} \mid}\right), \tag{9}$$

where A_2 is the current location of the UE.

Finally, we substitute (8) and (9) in (5) to obtain the real time of stay as

$$ToS^{real}_k = \frac{2R_i\sqrt{1 - \frac{\left(|\overrightarrow{A_1A_0}| \cdot \sin\left(\arccos\left(\frac{\overrightarrow{A_1A_0}\cdot\overrightarrow{A_1A_2}}{|\overrightarrow{A_1A_0}|\times|\overrightarrow{A_1A_2}|}\right)\right)\right)^2}{R_i^2}}}{V_k}. \tag{10}$$

III. Proposed Hybrid Weighted TOPSIS (HW-TOPSIS)

The proposed method uses TOPSIS technique to choose the adequate base station for HO by ranking the candidates. The HO metrics (i.e. attributes) utilized to rank the target cells are: the time of stay (ToS^{real}_k), the user angle of movement (θ) and the SINR of the target cell. The HW-TOPSIS method grants that the chosen cell is suboptimal solution i.e. close to the positive ideal solution and far from the negative ideal solution. Henceforth the cell(s)/base station(s) will be named alternative(s) and the HO decision metric(s) will be named attribute(s). The user has a set of N_{bs} target alternatives $m = \{1, 2, \cdots, N_{bs}\}$, a set of attributes $n = \{1, 2, 3\}$ and weighting vector $\mathbf{w}$. The procedures of HW-TOPSIS method can be summarized as follows:

Step 1: A decision matrix, $\mathbf{D}$, is built by mapping the alternatives against attributes as

$$\mathbf{D} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}, \tag{11}$$

where each row means one alternative and the columns mean their correspondent attributes, $n = 1, \cdots, 3$, $m = 1, 2, \cdots, N_{bs}$, r_{ij} represents the value of the j^{th} attribute for the i^{th} alternative. In this work, $r_{i1} = \theta$, $r_{i2} =$ ToS, and $r_{i3} =$ SINR.

Step 2: Decision matrix normalization using a Square root normalization method as

$$r^{norm}_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^m r_{ij}^2}}\ , \quad r^{norm}_{ij} \in [0, 1], \tag{12}$$

where r^{norm}_{ij} is the j^{th} normalized attribute of the i^{th} alternative.

Step 3: Weighting the normalized matrix to consider the influence of each attribute as in (13). The detailed hybrid weighting computations are illustrated in section IV.

$$\mathbf{D^{n,w}} = \begin{bmatrix} r_{11}^{norm}\cdot w_1 & r_{12}^{norm}\cdot w_2 & r_{13}^{norm}\cdot w_3 \\ r_{21}^{norm}\cdot w_1 & r_{22}^{norm}\cdot w_2 & r_{23}^{norm}\cdot w_3 \\ \vdots & \vdots & \vdots \\ r_{m1}^{norm}\cdot w_1 & r_{m2}^{norm}\cdot w_2 & r_{m3}^{norm}\cdot w_3 \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & d_{m3} \end{bmatrix} \quad (13)$$

$$\text{subject to} \sum_{j\in n} w_j = 1, \quad (14)$$

where d_{ij} is the j^{th} weighted normalized attribute of the i^{th} alternative i.e., $d_{11} = r_{11}^{norm}\cdot w_1$, $d_{12} = r_{12}^{norm}\cdot w_2$ and so on.

Step 4: The weighted normalized decision matrix is utilized to obtain the ideal positive solution (best alternative which has the best attribute values, denoted as $\mathbf{r}^+$) and the ideal negative solution (worst alternative which has the worst attribute values, denoted as $\mathbf{r}^-$) by

$$\begin{aligned}\mathbf{r}^+ &= \left\{(\max_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\min_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-)\right\} \\ &= \left\{d_1^+, d_2^+, d_3^+\right\},\end{aligned} \quad (15)$$

$$\begin{aligned}\mathbf{r}^- &= \left\{(\min_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\max_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-)\right\} \\ &= \left\{d_1^-, d_2^-, d_3^-\right\},\end{aligned} \quad (16)$$

where $\mathbf{j}^+$ is the set with attributes having positive impact, for instance SINR and ToS, and $\mathbf{j}^-$ is the set with attributes having negative impact, for instance θ. Thus, θ is a cost attribute and both ToS and SINR are benefit attributes.

Step 5: Determine the Euclidean distance between every alternative and both the positive and negative ideal solutions as

$$dist^+ = \sqrt{\sum_{j=1}^{n}(D_{ij}^{n,w} - d_j^+)^2}, \ \forall i = 1,\cdots,m \quad (17)$$

$$dist^- = \sqrt{\sum_{j=1}^{n}(D_{ij}^{n,w} - d_j^-)^2}, \ \forall i = 1,\cdots,m \quad (18)$$

Step 6: Network ranking by obtaining the vector **a** to measure the relative closeness of each candidate alternative to the ideal solution as

$$a = \frac{dist^-}{\max(dist^-)} - \frac{dist^+}{\min(dist^+)}, \ \forall i = 1,\cdots,m. \quad (19)$$

In fact, $\forall i = 1,\cdots,m$, $a(i) \le 0$, bigger (a) means the better alternative. When an existing alternative satisfies both of the conditions $\left(\max(dist^-) = dist^-\right)$ and $\left(\min(dist^+) = dist^+\right)$, this means that this alternative is the best one, i.e. it is close to the positive ideal solution and far from the negative ideal solution.

Step 7: Vector **a** is then ranked in descending order and the best alternative (with the highest rank) is chosen as a target (i.e., a HO target cell)

$$\mathrm{HO_{target}} = \arg\max_{i\in m} a(i). \quad (20)$$

IV. Hybrid Attribute Weighting Technique

Attributes weighting represents a very considerable role in HO decision. Therefore, the way of determining the weights is a significant factor for the proposed HW-TOPSIS method. The proposed hybrid weighting technique is based on entropy and standard deviation (SD) weighting techniques. In this section, we first define the entropy and SD techniques. Then, the proposed hybrid technique.

A. Entropy and Standard Deviation Weighting Techniques

The entropy weighting technique accurately computes the amount of decision information that each attribute has in the decision matrix [15]. The entropy technique is a type of objective weighting techniques which calculates the attribute weight according to the relative difference between them. The resultant weight of the attribute is then passed for normalization to get the entropy weight of that attribute [16]. The j^{th} entropy coefficients divergence degree, denoted e_j, can be computed by utilizing the normalized decision matrix as

$$e_j = 1 - c_j, \quad (21)$$

$$\text{where} \ \ c_j = \left[\frac{1}{\ln(n)} \sum_{i=1}^{n} r_{ij}^{norm} \ \ln(r_{ij}^{norm})\right], \quad (22)$$

the term $\frac{1}{\ln(n)}$ is a constant which ensures that the value of coefficient $c_j \in [0,1]$ i.e., $0 \le c_j \le 1$.

The entropy coefficient divergence degree e_j represents the inherent contrast intensity of the attributes. The more divergent the values of r_{ij}^{norm} for attribute j, the higher its corresponding entropy coefficient divergence degree e_j, and the more important the attribute j for HO decision. In other words, this means that if the alternatives have a comparable performance ratings for an attribute, then this attribute has less impact in HO decision. Otherwise, if an attribute j for all alternatives in the decision matrix is the same, then this attribute is ineffective in HO decision since it has no valuable information for the decision maker [17]. Ultimately, the entropy weighting of the j^{th} attribute can be identified as

$$w_j^e = \frac{e_j}{\sum_{j=1}^{n} e_j}, \quad (23)$$

where w_j^e is the final weight of the j^{th} attribute.

The SD weighting technique computes the weights of each attribute in terms of the standard deviation [18]. The SD technique assigns a small weight for identical-valued attribute with respect to all alternatives. For instance, if an attribute has an identical values on all alternatives, then it has no influence on HO decision and therefore, its weight is null. In other words, attributes having high standard deviation are given higher weights and vice versa.

The vector **w** characterises the importance of the attribute. Thus, $w1$, $w2$, and $w3$ are respectively the weights of θ, ToS, and SINR. The weights can be restrained by SD method as

$$w_j^{sd} = \frac{\sigma_j}{\sum_{k=1}^{3} \sigma_k}, \quad (24)$$

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(r_{ij}^{norm} - \mu_j)^2}, \quad (25)$$

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} r_{ij}^{norm}, \tag{26}$$

where σ_j and μ_j are respectively the standard deviation and the mean value of the j^{th} normalized attribute.

B. Hybrid Attributes Weighting

In this subsection, we propose a hybrid weighting technique to obtain the weighting vector **w** used in (13).

The proposed hybrid weighting technique combines the good properties of both entropy and SD weighting techniques by using a specific parameter λ. The hybrid weighting technique determines the weight of each attribute by integrating the SD weight of each attribute with its correspondent entropy weight using the control parameter λ. The introduced parameter, λ, allows to exploit both of SD and entropy weighting techniques with adjustable priority for each technique. The hybrid weighting technique can be expressed using the following

$$w_j^h = \lambda \cdot w_j^e + (1-\lambda) \cdot w_j^{sd}, \tag{27}$$

where λ is a constant parameter which can be used to assign the percentage of the impact of both SD and entropy weighting techniques together. The higher the value of λ means the higher impact in weighting is given to the entropy technique and vice versa. In order to validate and compare the variations in the weighting techniques, we test a numerical example, whose decision matrix is defined as

$$\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccc} \theta & ToS & SINR \end{array} \\ \begin{bmatrix} 80 & 100 & -109 \\ 45 & 20 & -106 \\ 20 & 50 & -81 \\ 5 & 90 & -45 \end{bmatrix} \end{array}$$

where A_i is the i^{th} alternative $\forall i = 1,\cdots,4$.

First, we apply the Square root normalization on the decision matrix

$$\mathbf{D^n} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccc} \theta & ToS & SINR \end{array} \\ \begin{bmatrix} 0.8504 & 0.6901 & 0.6149 \\ 0.4783 & 0.1380 & 0.5937 \\ 0.2126 & 0.3450 & 0.4537 \\ 0.0531 & 0.6211 & 0.2521 \end{bmatrix} \end{array}$$

Then, the weighting vectors for the entropy, SD and hybrid techniques are obtained respectively as

$$\mathbf{w^e} = \begin{bmatrix} 0.0189 & 0.0144 & 0.9667 \end{bmatrix},$$
$$\mathbf{w^{sd}} = \begin{bmatrix} 0.4522 & 0.3310 & 0.2168 \end{bmatrix},$$
$$\mathbf{w^h} = \begin{bmatrix} 0.3222 & 0.2360 & 0.4418 \end{bmatrix}.$$

Visibly, the three methods (entropy, SD and hybrid) assess the attributes with various ranking, i.e., $w_3 > w_1 > w_2$ for entropy, $w_1 > w_2 > w_3$ for SD and $w_3 > w_1 > w_2$ for hybrid, where w_1, w_2 and w_3 are respectively the weights of θ, ToS and SINR.

The entropy method allocates exceptionally high weight for the SINR, nearly 97%, and less weight for θ and ToS, nearly 1.8% and 1.4% respectively. Inversely, the SD method assigns 45%, 33% and 21% weights for θ, ToS and SINR respectively. The hybrid technique assigns more moderate and accurate weights for the attributes, about 32%, 24% and 44% for θ, ToS and SINR respectively. The entropy technique nearly assigns the complete weight to one attribute (i.e., SINR) which is unfavourable, since the ToS and θ attributes are also influential factors in HO decision. The user could receive high SINR from a specific cell but its ToS is very short and its moving direction is not towards the cell (i.e., θ is very large) and hence, giving a higher weight for only SINR is interpreted as a disadvantage of this technique. This problem has been avoided by the SD and hybrid techniques with the hybrid technique distributing the weights more moderately among attributes. The proposed method uses the hybrid weighting technique for measuring the weighting vector **w** and is called HW-TOPSIS and its procedures are described in Algorithm 1. The procedures start by first getting the cells that have an RSRP higher than or equal to a predefined threshold ($RSRP_{th}$). Then, the metrics θ, ToS, and SINR are calculated to form the decision matrix. The normalization is then performed on the decision matrix. After that, the weighting vector **w** is computed using the hybrid weighting technique. The obtained cells from the previous steps are gathered in vector **a**. Finally, the highest ranked cells in vector **a** is selected as HO target.

Algorithm 1 HW-TOPSIS Method

1: **Start procedures**
2: **Obtain metrics**, θ, ToS and SINR for all cells with $RSRP \geq RSRP_{th}$
3: **Built the decision matrix D**
4: **Normalize the decision matrix**
5: Obtain the **weighting vector w** using Hybrid technique
6: **Rank** the cells to obtain vector **a**
7: **Perform HO** to the cell with the **highest rank** in **a**
8: **End procedures**

V. Performance and Results Analysis

The performance of the HW-TOPSIS method is evaluated in terms of number of handovers, RLF and user mean throughput and compared against other two methods, the conventional method, the method in [11] denoted as TOPSIS, which uses a predefined weighting vector with fixed values. Simulation parameters are listed in Table I [19].

TABLE I
SIMULATION PARAMETERS

Parameter	Value
MC radius	500 meters
SC radius	100 meters
Number of SCs	50
Bandwidth	20 MHz
MC transmission power	46 dBm
SC transmission power	30 dBm
MC Shadowing standard deviation	8 dB
SC Shadowing standard deviation	10 dB
UE velocity	{1, 20, 40, 60, 80, 100} km/h
$RSRP_{th}$	-70 dBm
γ_{th}	-8 dB
T310	1 sec

A. Number of Handovers

Fig. 2 shows the total number of HOs per second. Obviously, the conventional method has higher number of HOs compared to TOPSIS and HW-TOPSIS. This is clearly resulted from the fact that the conventional method does not predict the target

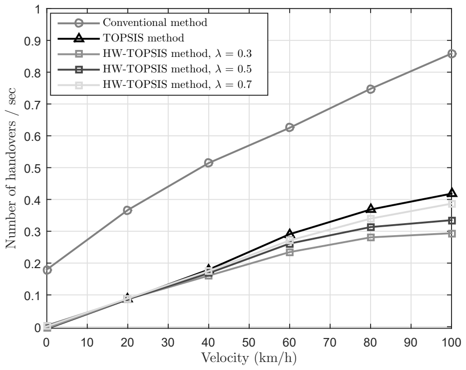

Fig. 2 Number of handovers

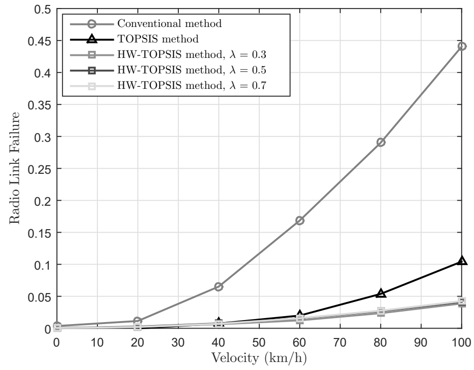

Fig. 3 Radio link failure

cell and it does the HO when the downlink received power from the neighbour cell is offset greater than that of the serving cell for TTT time period. Differently, less number of HOs is noticed in the performance of TOPSIS and HW-TOPSIS methods. The HW-TOPSIS has also outperformed the TOPSIS method, for all λ values, by minimizing the number of HOs due to the hybrid weighting computations which causes a proper assigning of importance to the attributes θ, ToS and SINR, different from TOPSIS method, which gives fixed weights to the attributes. Contrasting fast moving users, slow moving users will not result in a short ToS phenomena, consequently, the number of HOs is lower for slow moving users which explains the gain of realising the ToS criterion. Moreover, the angle criterion removes the base stations that are not in the user's movement direction leading to a fewer number of target base stations, and hence, minimizes the number of unnecessary HOs compared to the other methods.

B. Radio Link Failure

A radio link failure is defined if the HO is initiated to a cell from vector **a** but the SINR of that cell goes below the threshold γ_{th} for a period of time window T310, which is 1 second, as described in [20]. The RLF is depicted in Fig. 3. The RLF increases with the speed for all methods with the conventional method having the higher increase due to the frequent undesired HOs, hence, the HO will be initiated but interrupted before finishing due to the sudden drop in the target cell received power. Both TOPSIS and HW-TOPSIS methods have the lowest RLF with HW-TOPSIS outperforming, for all values of λ, particularly at high speeds due to the early HO to the correctly predicted cell. The low RLF in the HW-TOPSIS method affirms the accuracy of weighting assignment to HO metrics which results into an accurate cell selection. Moreover, the low link failure in HW-TOPSIS method comes from the positive influence of incorporating the angle metric where the users will avert initiating the HO to a cell located away from its movement direction, and hence, the failure will be decreased.

C. User Mean Throughput

The user mean throughout is depicted in Fig. 4. Noticeably, the throughout decreases as the velocity increases for all methods with the conventional method having the highest decrease because of their higher number of unnecessary HOs which causes a lower throughput for the user (since the high speed users will

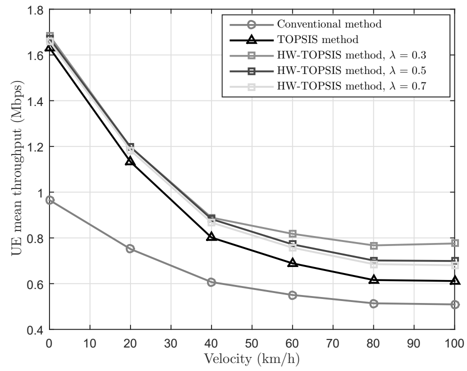

Fig. 4 User mean throughput

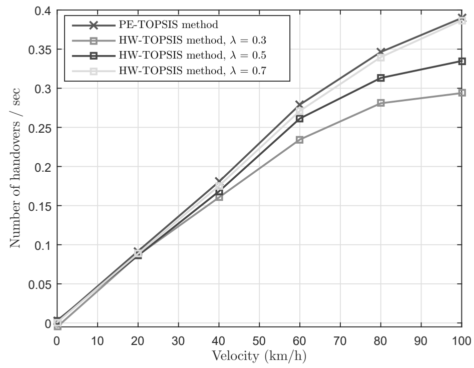

Fig. 5 Number of handovers

cause RLF which results in a poor throughput). The TOPSIS and HW-TOPSIS methods produce higher throughput since they perform the HO upon the proper target prediction with the HW-TOPSIS outperforming TOPSIS method for all values of λ. Higher throughout especially for low speed users reflects the receiving of high SINR at the user side. Therefore, the implementation of SINR metric has the advantage of enhancing the throughput for different velocities.

D. Comparing HW-TOPSIS with PE-TOPSIS

In this subsection we compare the performance of the proposed method, HW-TOPSIS, with that of our previous method PE-TOPSIS, presented in [12]. Fig. 5 depicts that the number of HOs is minimized in HW-TOPSIS method compared to

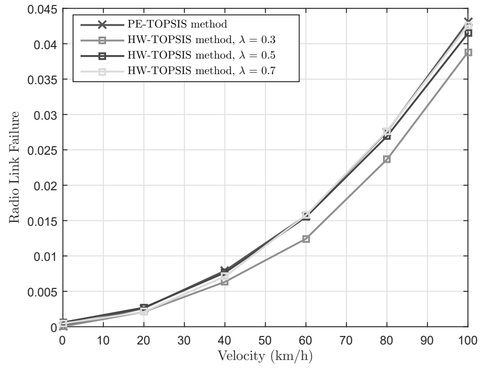

Fig. 6 Radio link failure

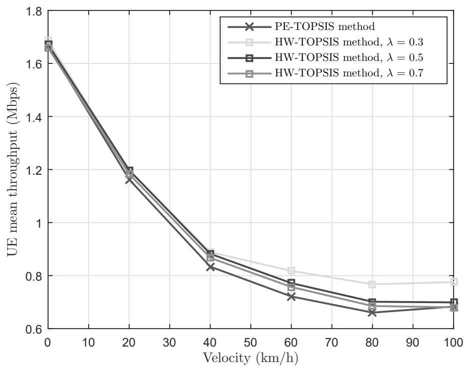

Fig. 7 User mean throughput

PE-TOPSIS. For all values of λ, the HW-TOPSIS method gives less number of HOs. The hybrid weighting technique gives more stable weights to the attributes which in turn causes an efficient alternative selection among the available alternatives. Obviously, from Fig. 5, the influence of the weighting control parameter λ is clear. The lower the value of λ the lower the number of HOs for all velocities.

The RLF is shown in Fig. 6. The HW-TOPSIS method decreases the RLF, which could cause HO failure. The level of increase in the link failure increases with the increase in velocity according to the common sense because the high speed users may leave the coverage area of the cell before finishing the HO process, hence the failure increases. The weighting control parameter λ also shows a clear impact on minimizing the failure.

In Fig. 7, the mean user throughput is depicted. A smaller value of λ in the proposed hybrid weighting technique produces higher achieved throughput for the user.

To further validate the influence of the hybrid weighting technique on the proposed method, we compare the performance in a form of tables. Tables II and III give the numerical results of the PE-TOPSIS and HW-TOPSIS methods when the velocity is 40km/h and 80km/h respectively. The influence of the proposed hybrid weighting technique is obvious at medium and high velocities (e.g., at 40 and 80km/h). The lower the value of the parameter λ the lower the number of HOs, the lower the RLF and the higher the achieved user throughput. For instance, when the velocity is 40km/h, the number of HOs is reduced by 9.38% when the value of λ is changed from 0.7 to 0.3. Additionally, the RLF is reduced by 17.46% in the same case and the user mean throughput is enhanced by 2.54%. The impact of λ is more clear at high velocity (e.g., 80km/h). The number of HOs is reduced by 17% when the value of λ is changed from 0.7 to 0.3. Additionally, the RLF is reduced by 16% in the same case and the user mean throughput is enhanced by 12.9%.

TABLE II
PERFORMANCE ANALYSIS AT 40 KM/H

Method	λ	HOs/sec	RLF	UE throughput(Mbps)
HW-TOPSIS	0.3	0.1605	0.0063	0.889
	0.5	0.1683	0.0076	0.883
	0.7	0.175	0.0074	0.867
PE-TOPSIS		0.19	0.0085	0.815

TABLE II
PERFORMANCE ANALYSIS AT 80 KM/H

Method	λ	HOs/sec	RLF	UE throughput(Mbps)
HW-TOPSIS	0.3	0.282	0.023	0.768
	0.5	0.313	0.027	0.70
	0.7	0.34	0.0274	0.68
PE-TOPSIS		0.363	0.030	0.63

In the proposed hybrid technique, when $\lambda = 0.3$, which means 30% is given to entropy weighing technique and 70% is given to the SD weighting technique, the overall performance is better. However, when $\lambda = 0.7$, which means 70% is given to entropy weighing technique and 30% is given to the SD weighting technique, the overall performance gets worse. On the other hand, when only using the entropy weighting technique, the overall performance is the worst compared to that when using hybrid weighting. This proves the advantage of the proposed hybrid weighting technique which exploits the good properties of both SD and entropy weighting techniques. Furthermore, Fig. 9 depicts the influence of different values of λ on the overall performance when the velocity is fixed at 40km/h. Obviously, lower values of λ give lower number of HOs and RLF but higher throughput compared to higher values of λ. Therefore, we can conclude that selecting a proper value of λ for a network depends on the requirements of the service provider and/or the deployed type of SCs, in addition to the network tolerance for the number of HOs, RLF and complexity.

E. Complexity Analysis

The complexity analysis of the proposed HW-TOPSIS method is tested in this section and compared with that of our two previous methods in [12]. Fig. 8 shows the computational complexity where the total number of floating point operations (flops) is evaluated with different sizes of the decision matrix (i.e., different numbers of SCs). We used the Matlab function defined in [21]. Obviously, the complexity increases linearly with the increase in the number of SCs for all methods. The HW-TOPSIS has slightly higher complexity operations compared to PSD-TOPSIS and PE-TOPSIS methods. Clearly, when the complexity is not an issue in the application, then HW-TOPSIS method would be a better solution at the expense of slightly higher complexity. Additionally, higher complexity means higher energy consumption. Therefore, deploying HW-TOPSIS, PE-TOPSIS or PSD-TOPSIS also depends on the type of SCs. For instance, when home-based SCs are deployed (e.g. femtocells), then the PE-TOPSIS is more preferred due to the limited calculation abilities of the femtocell. On the other hand, when other SC types are used (e.g. picocell), then the PSD-TOPSIS could be the best option. Alternatively, when using multi-tier SCs HetNet, then the HW-TOPSIS can be considered as best option.

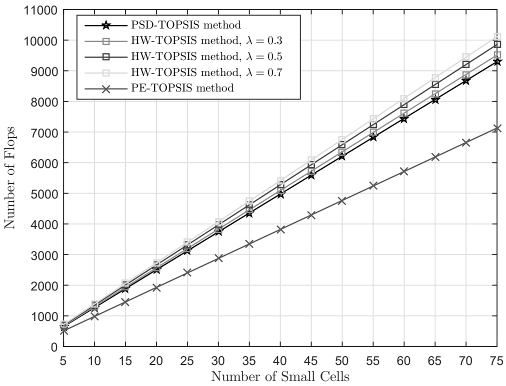

Fig. 8 Complexity Analysis

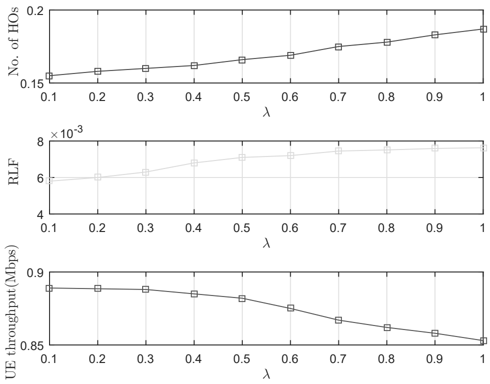

Fig. 9 λ effects on the overall performance at 40 km/h velocity

VI. Conclusion

In this paper, a hybrid weighted MADM TOPSIS method has been presented. The proposed method deploys the TOPSIS technique of ranking the HO candidate cells according to the influence of their attributes. We proposed a hybrid weighted TOPSIS method, HW-TOPSIS, which combines the properties of standard deviation and entropy weighting techniques via a weighting control parameter λ. This method shows better results in enhancing the network performance by minimizing the number of HOs and RLF, in addition to enhancing the mean user throughput. By using lower values of λ, which means that i.e., deceasing the weight given to the entropy and increasing the weight to standard deviation technique, the user mean throughput is enhanced, while the RLF remains low especially for medium and high speeds.

References

[1] A. M. Akhtar, X. Wang, and L. Hanzo, "Synergistic spectrum sharing in 5g hetnets: A harmonized sdn-enabled approach," *IEEE Communications Magazine*, vol. 54, no. 1, pp. 40–47, 2016.

[2] X. Chu, D. López-Pérez, Y. Yang, and F. Gunnarsson, *Heterogeneous Cellular Networks: Theory, Simulation and Deployment*. Cambridge University Press, 2013.

[3] G. T. 36.839, "Evolved universal terrestrial radio access (eutra); mobility enhancements in heterogeneous networks," 2013.

[4] M. Alhabo and L. Zhang, "Unnecessary handover minimization in two-tier heterogeneous networks," in *Wireless On-demand Network Systems and Services (WONS), 2017 13th Annual Conference on*. IEEE, 2017, pp. 160–164.

[5] M. Alhabo, L. Zhang, and N. Nawaz, "A trade-off between unnecessary handover and handover failure for heterogeneous networks," in *European Wireless 2017; 23th European Wireless Conference; Proceedings of*. VDE, 2017.

[6] M. Alhabo, L. Zhang, and O. Oguejiofor, "Inbound handover interference-based margin for load balancing in heterogeneous networks," in *Wireless Communication Systems (ISWCS), 2017 International Symposium on*. IEEE, 2017, pp. 1–6.

[7] N. Nasser, A. Hasswa, and H. Hassanein, "Handoffs in fourth generation heterogeneous networks," *Communications Magazine, IEEE*, vol. 44, no. 10, pp. 96–103, 2006.

[8] C.-H. Yeh, "A problem-based selection of multi-attribute decision-making methods," *International Transactions in Operational Research*, vol. 9, no. 2, pp. 169–181, 2002.

[9] F. Bari and V. C. Leung, "Automated network selection in a heterogeneous wireless network environment," *IEEE network*, vol. 21, no. 1, pp. 34–40, 2007.

[10] B. Bakmaz, Z. Bojkovic, and M. Bakmaz, "Network selection algorithm for heterogeneous wireless environment," in *Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on*. IEEE, 2007, pp. 1–4.

[11] X. Chen, Y. H. Suh, S. W. Kim, and H. Y. Youn, "Reducing connection failure in mobility management for lte hetnet using mcdm algorithm," in *Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), 2015 16th IEEE/ACIS International Conference on*. IEEE, 2015, pp. 1–6.

[12] M. Alhabo and L. Zhang, "Multi-criteria handover using modified weighted topsis methods for heterogeneous networks," *IEEE Access*, vol. 6, pp. 40 547–40 558, 2018.

[13] Q. Europe, "Hnb and hnb-macro propagation models," *3GPP R4–071617, Oct*, 2007.

[14] E. U. T. R. Access, "Radio frequency (rf) requirements for lte pico node b," *Release*, vol. 9, p. V9, 2012.

[15] G.-H. Tzeng and J.-J. Huang, *Multiple attribute decision making: methods and applications*. CRC press, 2011.

[16] L. Wang and G.-S. G. Kuo, "Mathematical modeling for network selection in heterogeneous wireless networksŮa tutorial," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 271–292, 2013.

[17] M. F. Shipley, A. de Korvin, and R. Obid, "A decision making model for multi-attribute problems incorporating uncertainty and bias measures," *Computers & operations research*, vol. 18, no. 4, pp. 335–342, 1991.

[18] Y.-M. Wang and Y. Luo, "Integration of correlations with standard deviations for determining attribute weights in multiple attribute decision making," *Mathematical and Computer Modelling*, vol. 51, no. 1, pp. 1–12, 2010.

[19] E. U. T. R. Access, "Mobility enhancements in heterogeneous networks," 3GPP TR 36.839, Tech. Rep., 2012.

[20] D. Lopez-Perez, I. Guvenc, and X. Chu, "Mobility management challenges in 3gpp heterogeneous networks," *IEEE Communications Magazine*, vol. 50, no. 12, 2012.

[21] MathWorks, "Counting the floating point operations (flops)," 2015. [Online]. Available: https://uk.mathworks.com

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