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Multi-Criteria Handover Using Modified Weighted TOPSIS Methods for Heterogeneous Networks

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ABSTRACT Ultra-dense small cell deployment in future 5G networks is a promising solution to the ever increasing demand of capacity and coverage. However, this deployment can lead to severe interference and high number of handovers, which in turn cause increased signaling overhead. In order to ensure service continuity for mobile users, minimize the number of unnecessary handovers and reduce the signaling overhead in heterogeneous networks, it is important to model adequately the handover decision problem. In this paper, we model the handover decision based on the multiple attribute decision making method, namely Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The base stations are considered as alternatives, and the handover metrics are considered as attributes to selecting the proper base station for handover. In this paper, we propose two modified TOPSIS methods for the purpose of handover management in the heterogeneous network. The first method incorporates the entropy weighting technique for handover metrics weighting. The second proposed method uses a standard deviation weighting technique to score the importance of each handover metric. Simulation results reveal that the proposed methods outperformed the existing methods by reducing the number of frequent handovers and radio link failures, in addition to enhancing the achieved mean user throughput.

INDEX TERMS Heterogeneous networks, handover, small cells, interference, MADM, weight, TOPSIS.

I. INTRODUCTION

The rapid growth of the number of smart mobile devices connected to the wireless network has led to the high data traffic demand. The capacity demand of the cellular network is estimated to be 1000 times higher by year 2020 [1]. The already deployed traditional macrocell (MC) base stations are incapable of coping with this demand because it is very costly to deploy MCs any time anywhere. The concept of small cells (SCs), which are economic small base stations with lower transmit power and radius coverage compared to the MCs, has been introduced to deal with the high capacity demand. The networks consisting of both MCs and SCs are known as heterogeneous networks (HetNets) [2]. The SCs have a great benefits in enhancing the network performance especially for the users at MC edges. Despite their huge benefits, the dense deployment of SCs has led to the problems of interference, and frequent unnecessary handovers. The number of handovers is very high in dense HetNets compared to the homogeneous MC-only networks. This can also lead to high probability of radio link failure. As a consequence, the quality of service (QoS) delivered to the end user is degraded [3]. Therefore, it is necessary to solve these problems when dense SCs are deployed to maximize their benefits. There have been many researches dealing with the problem of handover (HO) in the literature. Xu *et al.* [4] used received signal strength (RSS) and path loss as metric for HO. Window function has been applied to the RSS of both the SC and MC to compensate for the uneven transmit power of both cells. However, the large variation of the path loss may lead to high number of ping-pong HOs. Singoria *et al.* [5] propose a call admission control to reduce the unnecessary HO in SC networks. User velocity, RSS and the time required to maintain the minimum RSS for service continuity are used as HO metrics. Only low speed user are allowed to perform HO to SC. While medium speed users are only permitted to HO to SC when their traffic type is real time traffic such as ongoing phone conversation. In [6], we proposed a method to minimize the number of target SCs and reduce the unnecessary HOs in HetNet. A SC target list is formed by using the distance between the user and the SC in addition to the user's angle of movement. High speed users are prevented from performing the HO to SCs. The results show a good performance in terms of SC list minimization, unnecessary HO reduction, and network throughput improvement. Alhabo *et al.* [7] proposed a method to reduce both of the unnecessary HO and HO failure. A predicted time of stay (ToS) is used to remove SC, which could lead to unnecessary HO or HO failure, from the target HO SC list. The user is handed over to the SC, which provides the sufficient signal to interference plus noise ratio (SINR) and has enough capacity to deliver services. Time threshold and the SINR are also used to find a compromise between the unnecessary HO and HO failure. Results reveal that both of the unnecessary HO and HO failure have been minimized. An inbound HO method for throughput enhancement and load balancing is proposed in [8]. The impact of interference and estimated ToS is used to perform offloading from MC to SC. An inbound HO margin based on serving cell load and interference level is derived so as to accomplish the traffic offloading. Results show that this method has reduced the unnecessary HO and outage probability in addition to enhancing the achieved throughput for both the user and the network.

The multiple attribute decision making (MADM) deals with the selection of the best alternatives which are characterised based on multiple attributes. Basically, all of the MADM methods have the following characteristics:

Alternatives: sometimes called options or candidates. All of the alternatives are ranked based on certain criteria and the best one is nominated as candidate.

Attributes: also named metrics or criteria. Multiple attributes are taken into account when selecting the alternative.

Decision matrix: the MADM problem is formulated as a matrix whose rows represent the alternatives and columns represent the attributes of each alternative.

Weighting of attributes: every attribute must be weighted to measure the importance of them.

Normalization: because different attributes have different unit of measurement, hence, the normalization is applied so that the attributes have same scale.

The HO decision can be taken by considering different metrics [9]. Therefore, the MADM techniques can be a good solution to model and solve the HO decision problem. In this work, the HO decision takes into considerations the time of stay in the target cell, user angle of movement and the SINR for the target cell.

The selection of the attributes (HO metrics) is a crucial factor for making the HO decision, especially in ultra-dense SCs environment. The advantages of the handover decision criteria can be explained as follows:

Signal to interference plus noise ratio (SINR): the small cells are usually deployed in an unplanned manner where they share the spectrum with macrocell causing a severe interference and eventually results in poor Quality of Service. The achievable data rate of a mobile device is a function of SINR. Therefore, the best performance cannot be achieved if only the received signal strength (RSS) is used as handover criterion. Therefore, in this paper, we take the interference in the network into consideration by using SINR as a selection criterion.

Time of Stay (ToS): the short association of the user to the base station can be considered as an unnecessary handover. Therefore, the predicted time of stay which is an indication of the time that a user may stay in the coverage area of the target base station will help making a decision with reduced chance to handover to a base station and stay for a short time. This will eventually improve the service experienced by the end user and reduce the signalling overhead.

The user angle of movement with respect to the target cell (θ): the user can have some neighbour small cells that offer good communication channel in terms of SINR but these small cells may locate in an opposite direction of the user's movement. Therefore, it is not recommended to perform the handover to such small cells because this may cause unnecessary handover and lead to high signalling overhead. For this reason, we use the user angle of movement with respect to the small cell as one of the decision criteria to reduce the number of target base stations.

Giving fixed weights for the attributes is inefficient strategy because this may lead to improper cell selection and can result in either unnecessary HO or HO failure which eventually will reduce the throughput and increase the signalling overhead. Therefore, we deploy two weighting techniques that compute the attribute weight based on the actual values of these attributes and for all alternatives. The three criteria which take into account the most influential factors are used in TOPSIS base station selection and weighted using two techniques, the entropy and standard deviation. When the moving speed or angles change, the weighting technique assign different weights for handover criteria. In other words, if any of the metrics has no significant influence on the handover decision making, then the weighting techniques will assign a poor weight for this metric and vice versa. In this way, the best target base station can always be selected in the presence of mobility.

In general, the selection of the best alternative among the available ones is widely adopted in wireless sensor networks research field through the use of TOPSIS method. However, in the field of heterogeneous networks (specifically for ultra-dense small cells), the TOPSIS method is rarely investigated. Moreover, the few works available are dealing with base station selection for static users [10] and do not consider the handover due to the user mobility which is a big challenge in future 5G networks. To the best of our knowledge, the exploitation of entropy and standard deviation weighting techniques (for handover metrics weighting), which are considered as an objective weighting techniques that assign very small weights to the attributes with small influence on decision making, in TOPSIS method is also not considered in the literature.

In this work, a modified weighted TOPSIS methods are proposed. We deployed the entropy weighting technique for attributes weighting. We also adopt the standard deviation weighting method to weight the importance of HO metrics of each MC and SC in the heterogeneous network. The HO metric with the higher deviation variation, compared to the mean value, will obtain larger weight value. In other words, this HO metric will have a higher impact in HO decision making compared to other HO metrics. To the best of our knowledge, both of the SD and entropy weighting techniques have not been applied on HO problem in ultra-dense SCs heterogeneous networks. Using numerical simulations, the proposed methods' performance is compared against other exiting methods in terms of the number of HOs, radio link failures and user mean throughput.

We proposed two TOPSIS methods, one of them uses entropy weighting to weight the attributes (named PE-TOPSIS) and the second one uses the standard deviation weighting technique (named PSD-TOPSIS). The PSD-TOPSIS shows better performance but higher computational complexity. On the other hand, PE-TOPSIS shows lower complexity but worse performance. As we know, there are different small cells with different sizes and transmit power, and hence, different capabilities. For example, the femtocells have small capabilities in terms of size and transmit power compared to the picocells. We draws a conclusion that when the complexity is not an issue in the application, then the PSD-TOPSIS method would be a good solution i.e., it can be used in picocell base stations. On the other hand, the PE-TOPSIS method can be used for femtocells.

Upper-case boldface letters are used to represent matrices and lower-case boldface are used to represent vectors. The major contribution of this paper can be summarized as follows:

- The well-known MADM technique, TOPSIS, is used to model the HO problem. Two methods are proposed and both of them use the user angle of movement, ToS and SINR to form the HO decision matrix.
- The first method weights the attributes via entropy weighting technique, and hence named as (PE-TOPSIS).
- The second proposed method uses the standard deviation weighting technique to assign weights to the attributes (HO metrics) and hence, named as proposed weighted technique for order preference by similarity to an ideal solution (PSD-TOPSIS).
- Results revealed that the proposed methods PE-TOPSIS and PSD-TOPSIS have outperformed the existing methods in the literature by reducing the number of HOs and radio link failure, in addition to enhancing the achieved mean user throughput.
- Based on the complexity of calculations, we suggest using the PE-TOPSIS method for low power SCs (e.g. residential femtocells) and the PSD-TOPSIS method for other types of SCs (e.g. picocells).

The rest of the paper is organized as follows. Section II presents the related work. The system model is given in section III. The proposed methods' procedures are illustrated in section IV. Section V gives the proposed weighting techniques. The performance and results analysis are given in section VI. Finally, the conclusion and future work are drawn in section VII.

II. RELATED WORKS

MADM techniques are widely adopted recently in making decisions for multiple criteria problems. One of the most widely used MADM method is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS method's principle, in wireless network field, is to select the target which is closest to the positive ideal solution and farthest from the negative ideal solution. Positive ideal solution is based on the best value for the attributes used in decision making. While negative ideal solution is based on the worst attributes values [11]. In the field of network selection, many researches in the literature have been accomplished by using TOPSIS method to solve the HO decision making. Bari and Leung [12] proposed a TOPSIS method taking into account cost, total bandwidth, network utilization, delay, and jitter when building the HO decision matrix. Another research paper in [13], a TOPSIS method is proposed to rank the available networks. Different parameters are used when forming the decision matrix, such as the available bandwidth, cost, and security level. Chen *et al.* [14] proposed a TOPSIS based method to reduce the connection failure in heterogeneous networks. The user performs HO to the target cell in either two ways. First, when the received power is very low, even before the time to trigger expires so as to avoid radio link failure. Second, when the received signal from the serving cell is high enough but the downlink SINR drops below a predefined threshold. Results show that this method reduce the number of HOs, packet loss and increase user mean throughput. However, the use of predefined value for weighting the HO metrics could show some deficiency in HO decision due to the large variation in signal power because of user mobility specially for fast moving ones in dense SCs scenarios.

III. SYSTEM MODEL

In this work, as shown in Fig.1, we consider a two-tier downlink HetNet scenario consisting of a single MC of 500m radius and N_{sc} number of SCs with a radius of 100m each. Thus, we have a total number of N_{bs} base stations in the network. SCs are deployed randomly following uniform distribution. Both tiers are deployed with the same carrier frequency. The minimum distance between MC site and SC sites is set to 75m and the SC to SC site distance is set to 40m [2], which ensures an overlapping between SCs. Users are distributed uniformly in the MC coverage area and they move in a random direction with a constant speed. In this mobility model, the UE moves in straight line with a constant speed. It goes to a selected direction $[0, 2\pi]$ to the boundary. Upon completing the movement by reaching the boundary, the UE pauses and decides to move to another direction and travels to complete a second movement. This process is independently repeated until the simulation is finished. Which means that the UE has different angle of movement during the simulation. In this case, the UE angle of movement is measured with regards to the coordinates of the base stations at each period of time, so it is not constant. This movement direction, i.e., angle θ, is used to compute the time of stay and it is different with respect to different base stations.

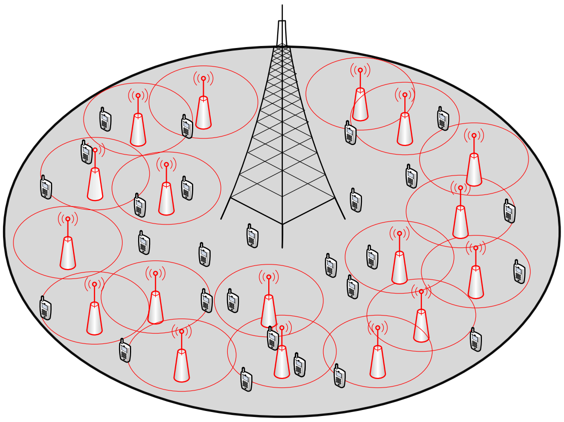

FIGURE 1. HetNet system model.

For the sake of clarity, we define a list of abbreviations as depicted in table 1.

TABLE 1. List of abbreviations.

Abbreviation	Definition
5G	Fifth Generation
HetNets	Heterogeneous Networks
HO	Handover
MADM	Multiple Attribute Decision Making
MC	Macrocell
NCH	Network Controlled Handover
PE-TOPSIS	Proposed Entropy Technique for Order Preference by Similarity to an Ideal Solution
PSD-TOPSIS	Proposed Standard Deviation Technique for Order Preference by Similarity to an Ideal Solution
RSRP	Received Signal Received Power
RSS	Received Signal Strength
SD	Standard Deviation
SC	Small Cell
SINR	Signal to Interference plus Noise Ratio
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
ToS	Time of Stay
TTT	Time To Trigger
UE	User Equipment
QoS	Quality of Service

A. CHANNEL MODEL

A large scale channel is considered using the path loss model and shadowing effects. The path loss between the MC and the user is defined as in [15] by

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

where $d_{m\to ue_k}$ is the distance between the user and the MC base station in kilometres. The path loss between the SC and the user is defined as in [16] by

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

where $d_{sc_i\to ue_k}$ is the distance between the user and SC i in metres.

The SINR from SC i and MC received at user k can respectively be expressed as

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

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

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

B. TIME OF STAY MEASUREMENT

As depicted in Fig.2, the real ToS, $ToS^{real}_{ue_k}$, can be measured as

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

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 base station radius, and V_k is the velocity of user k.

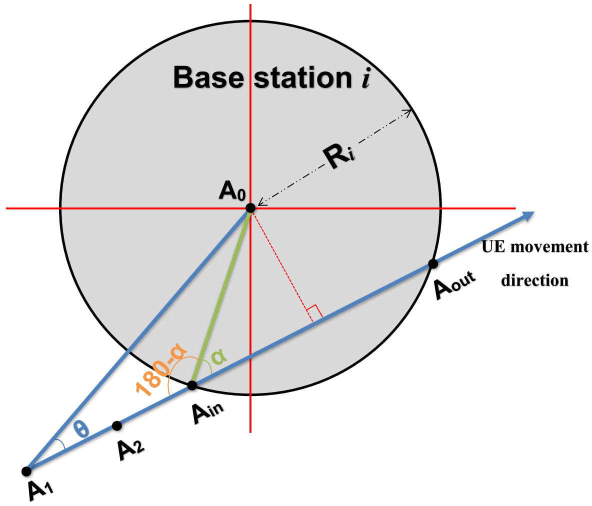

FIGURE 2. Time of stay measurement.

We can get the following from Fig.2

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

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

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

Therefore

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

The angle between the UE trajectory and the base station i, θ, can also be calculated 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 get the real time of stay as

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

IV. PROPOSED WEIGHTED TECHNIQUES FOR ORDER PREFERENCE BY SIMILARITY TO AN IDEAL SOLUTION

The proposed methods adopt one of the well known MADM techniques, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), to select the proper target cell for HO by ranking the available neighbouring candidate cells. The attributes (i.e. HO metrics) used to rank the target cells are: the time of stay ($ToS_{ue_k}^{real}$), the user angle of movement (θ) and the SINR of the target cell.

The HO decision is based on choosing a proper alternative (i.e. base station) among the available set of alternatives. The proposed methods grant that the selected HO target cell is suboptimal solution i.e. near the positive ideal solution and far from the negative ideal solution. Henceforth the base station(s) will be called alternative(s) and the HO decision metric(s) will be called attribute(s). The user has a set of N_{bs} target alternatives $m = \{1, 2, \cdots, N_{bs}\}$ with a set of attributes $n = \{1, 2, 3\}$ and attributes weighting vector $\mathbf{w}$. We can present our proposed methods' procedures as follows:

Procedure 1: The decision matrix, $\mathbf{D}$, is formed by mapping the alternatives against the attributes as shown

$$\mathbf{D} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ a_{31} & a_{32} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}, \tag{11}$$

where the each row represents one alternative, and the columns represent their correspondent attributes, $n = 1, \cdots, 3$, $m = 1, 2, \cdots, N_{bs}$, a_{ij} represents the value of the j^{th} attribute (HO metric) for the i^{th} alternative (base station). In this paper, $a_{i1} = \theta$, $a_{i2} = \text{ToS}$, and $a_{i3} = \text{SINR}$.

Procedure 2: The decision matrix is then normalized using a Square root normalization method as described in (12)

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

where a_{ij}^{norm} is the j^{th} normalized attribute of the i^{th} alternative. Which means that each element in the decision matrix $\mathbf{D}$ is divided by its correspondent column squared-elements sum. Thus, we can write the normalized decision matrix, $\mathbf{D^n}$, as

$$\mathbf{D^n} = \begin{bmatrix} \frac{a_{11}}{\sqrt{\sum_{i=1}^{m} a_{i1}^2}} & \frac{a_{12}}{\sqrt{\sum_{i=1}^{m} a_{i2}^2}} & \frac{a_{13}}{\sqrt{\sum_{i=1}^{m} a_{i3}^2}} \\ \frac{a_{21}}{\sqrt{\sum_{i=1}^{m} a_{i1}^2}} & \frac{a_{22}}{\sqrt{\sum_{i=1}^{m} a_{i2}^2}} & \frac{a_{23}}{\sqrt{\sum_{i=1}^{m} a_{i3}^2}} \\ \frac{a_{31}}{\sqrt{\sum_{i=1}^{m} a_{i1}^2}} & \frac{a_{32}}{\sqrt{\sum_{i=1}^{m} a_{i2}^2}} & \frac{a_{33}}{\sqrt{\sum_{i=1}^{m} a_{i3}^2}} \\ \vdots & \vdots & \vdots \\ \frac{a_{m1}}{\sqrt{\sum_{i=1}^{m} a_{i1}^2}} & \frac{a_{m2}}{\sqrt{\sum_{i=1}^{m} a_{i2}^2}} & \frac{a_{m3}}{\sqrt{\sum_{i=1}^{m} a_{i3}^2}} \end{bmatrix}. \tag{13}$$

Procedure 3: The normalized matrix is weighted in this step so as to take into account the importance of each attribute. The detailed weighting calculations are presented in sections V-B and V-A. Thus, the weighted normalized decision matrix can be expressed as

$$\mathbf{D^{n,w}} = \begin{bmatrix} a_{11}^{norm} \cdot w_1 & a_{12}^{norm} \cdot w_2 & a_{13}^{norm} \cdot w_3 \\ a_{21}^{norm} \cdot w_1 & a_{22}^{norm} \cdot w_2 & a_{23}^{norm} \cdot w_3 \\ a_{31}^{norm} \cdot w_1 & a_{32}^{norm} \cdot w_2 & a_{33}^{norm} \cdot w_3 \\ \vdots & \vdots & \vdots \\ a_{m1}^{norm} \cdot w_1 & a_{m2}^{norm} \cdot w_2 & a_{m3}^{norm} \cdot w_3 \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \\ \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & d_{m3} \end{bmatrix} \tag{14}$$

$$\text{subject to} \sum_{j \in n} w_j = 1, \tag{15}$$

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

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

$$\mathbf{a}^+ = \left\{(\max_{i \in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\min_{i \in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-)\right\} = \left\{d_1^+, d_2^+, d_3^+\right\}, \tag{16}$$

$$\mathbf{a}^- = \left\{ (\min_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\max_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-) \right\} = \left\{ d_1^-, d_2^-, d_3^- \right\}, \tag{17}$$

where $\mathbf{j}^+$ is the set with the attributes having positive impact (i.e., the higher value the better) such as SINR and ToS, and $\mathbf{j}^-$ is the set with the attributes having negative impact (i.e., the lower value the better) such as θ. The best alternative value for the attributes θ, ToS and SINR are respectively $\min(\theta)$, $\max(ToS)$ and $\max(SINR)$. On the other hand, the worst alternative for the attributes are respectively $\max(\theta)$, $\min(ToS)$ and $\min(SINR)$. Hence, θ is considered as a cost attribute and both ToS and SINR are considered as benefit attributes.

Procedure 5: Compute the Euclidean distance between each alternative and both the positive and negative ideal solutions as shown below

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

$$dist^- = \sqrt{\sum_{j=1}^{n} (D_{ij}^{n,w} - d_j^-)^2}, \quad \forall i = 1, \cdots, m \tag{19}$$

Procedure 6: In this step, the ranking network vector, $\mathbf{r}$, is obtained so as to measure the relative closeness of each candidate alternative to the ideal solution, as shown

$$r = \frac{dist^-}{dist^+ + dist^-}, \quad \forall i = 1, \cdots, m. \tag{20}$$

According to [17], it has been shown that in some situations the above equation in (20) cannot ensure that the optimal alternative is having the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution at the same time. Therefore, the formula in (20) can be replaced by the revised closeness as in (21), which computes the extent to which the optimal alternative closes to the positive ideal solution and far from the negative ideal solution, that is

$$r = \frac{dist^-}{\max(dist^-)} - \frac{dist^+}{\min(dist^+)}, \quad \forall i = 1, \cdots, m. \tag{21}$$

Indeed, $\forall i = 1, \cdots, m$, $r(i) \leq 0$, bigger r 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 which is close to the positive ideal solution and far away from the negative ideal solution.

Procedure 7: The resulted vector from the previous step is then ranked in descending order and the best alternative (with the highest rank) from $\mathbf{r}$ vector is selected as a target (i.e., the HO target base station)

$$\mathrm{HO}_{\mathrm{target}} = \arg\max r(i). \tag{22}$$

V. ATTRIBUTE WEIGHTING MEASUREMENTS

Attributes weighting represents a very significant role in HO decision making. Thus, the way of determining the weights is a crucial factor for the proposed methods. Different techniques have been proposed to deal with the weights. We present two weighting techniques in this section, namely the entropy and standard deviation weighting techniques. We also validate and compare the differences between the two techniques using a numerical example in the subsection V-C.

A. ENTROPY ATTRIBUTES WEIGHTING

The entropy weighting technique measures the uncertainty in the data by using the probability theory. This means that if the data distribution is broad then the uncertainty is higher. On the other hand, if the data distribution is sharply peaked then the uncertainty is lower. The entropy weighting technique precisely calculates the amount of decision information that each attribute has in the decision matrix [18]. The entropy technique is a type of objective weighting techniques which measures the attribute weight based on the relative difference between them. The resulted weight of the attribute is then normalized to obtain the entropy weight of that attribute [19]. The j^{th} entropy coefficients divergence degree, denoted e_j, can be measured using the normalized decision matrix

$$e_j = 1 - c_j, \tag{23}$$

$$\text{where } c_j = \left[\frac{1}{\ln(n)} \sum_{i=1}^{n} a_{ij}^{norm} \ln(a_{ij}^{norm}) \right], \tag{24}$$

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

The entropy coefficient divergence degree e_j represents the inherent contrast intensity of the attributes (i.e., HO metrics). The more divergent the values of a_{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 similar performance ratings for a certain attribute, then this attribute has less influence in HO decision making. On the other hand, if an attribute j for all alternatives in the decision matrix is identical, then this attribute is not useful in HO decision making because it has absolutely no useful information for the decision maker [20]. For example, for a given attribute j, when all elements a_{ij}^{norm} are the same, then the coefficient $c_j \approx 1$ which means that $e_j \approx 0$ and hence, the weight of this attribute becomes zero as well. This means that this attribute has no effect on the HO decision.

Finally, the entropy weighting of the j^{th} attribute is expressed as

$$w_j^e = \frac{e_j}{\sum_{j=1}^{n} e_j}, \tag{25}$$

where w_j^e is the final weight of the j^{th} attribute using the entropy weighting technique. The entropy weighting technique is not affected by the range of different attributes values because it uses the normalized attributes (i.e., a_{ij}^{norm}) for weight calculation [21].

B. STANDARD DEVIATION ATTRIBUTES WEIGHTING

The proposed method also deploys the standard deviation (SD) weighting technique [22] so as to rate the importance of the attributes for each cell in the network. The SD weighting technique measures the weights of each attribute in terms of the standard deviation.

The SD weighting technique gives a small weight for an attribute if the value of this attribute is identical for all available alternatives. For example, if an attribute has an equal values on all available alternatives, then it has no significant impact on HO decision making and hence, its weight is null. In other words, attributes with small standard deviation are given smaller weights and vice versa.

The weighting vector $\mathbf{w}$ represents the importance of the attribute (HO metrics). Thus, $w1$, $w2$, and $w3$ are respectively the weights of θ, ToS, and SINR. The weights can be calculated using SD technique as

$$w_j^{sd} = \frac{\sigma_j}{\sum_{k=1}^{3} \sigma_k}, \tag{26}$$

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(a_{ij}^{norm} - \mu_j)^2}, \tag{27}$$

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} a_{ij}^{norm}, \tag{28}$$

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

C. NUMERICAL EXAMPLE

To validate and compare the differences between the weighting techniques, we examine a numerical example, whose decision matrix is given 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, the decision matrix is normalized by Square root normalization method as

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

Then, we can obtain the weighting vector for the entropy and SD techniques respectively as

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

It is clear that the entropy and SD techniques evaluate the three attributes with different ranking, i.e., $w_3 > w_1 > w_2$ for entropy and $w_1 > w_2 > w_3$ for SD, where w_1, w_2 and w_3 are respectively the weights of θ, ToS and SINR.

The entropy technique gives very high weight for the SINR, about 97%, and fewer weights for θ and ToS, about 1.8% and 1.4% respectively. Unlike the entropy technique, the SD technique assigns more moderate and accurate weights for the attributes 45%, 33% and 21% for θ, ToS and SINR respectively.

The entropy technique nearly gives the whole weight to one attribute (i.e., SINR) which is undesirable because the ToS and θ attributes are also significant factors for HO decision. The user may receive high SINR from a certain cell but its ToS is very short and its moving direction is away from the cell (i.e., θ is very large) and hence, assigning a higher weight for only SINR is considered as a drawback of this technique which will result in an increase in the number of unnecessary HOs and leads to throughput reduciton. These problems have been avoided by the SD technique by distributing the weights more positively among attributes.

Thus, we now have two proposed methods. The first method utilizes the entropy weighting technique to find the weighting vector $\mathbf{w}$ and is named as PE-TOPSIS. The second one uses the SD weighting technique for measuring the weighting vector $\mathbf{w}$ and is named as PSD-TOPSIS. The procedures of the proposed methods PE-TOPSIS and PSD-TOPSIS are illustrated in Fig.3. The procedures begin by first obtaining the cells that have a downlink RSRP greater than or equal to the threshold ($RSRP_{th}$). This step is essential to reduce the number of alternatives in the decision matrix and hence, reducing the computational complexity. For each of the obtained cells, the parameters θ, ToS, and SINR are measured to build the decision matrix. Then, the normalization of the decision matrix is applied. After that, the weighting vector $\mathbf{w}$ is calculated using the entropy weighting technique for PE-TOPSIS method and standard deviation weighting technique for PSD-TOPSIS method. The resulted cells from the previous steps are combined in vector $\mathbf{r}$. Finally, the HO target is the cell with highest order in vector $\mathbf{r}$.

VI. PERFORMANCE AND RESULTS ANALYSIS

The performance of the PE-TOPSIS and PSD-TOPSIS methods is evaluated in terms of number of handovers, radio link failure and user mean throughput and compared against other three methods, the conventional method, the network controlled HO method (NCH) in [23] and the method in [14] denoted as TOPSIS, which uses a predefined weighting vector with fixed values. Simulations parameters are listed in table 2 [24].

According to [25], the density of the number of nodes (here SCs) in a given coverage area can be obtained by using the definition of the density metric, D_{sc}, as

$$D_{sc} = \frac{|\, N_{sc} \,|\, \pi R_{sc}^2}{\pi R_m^2}, \tag{29}$$

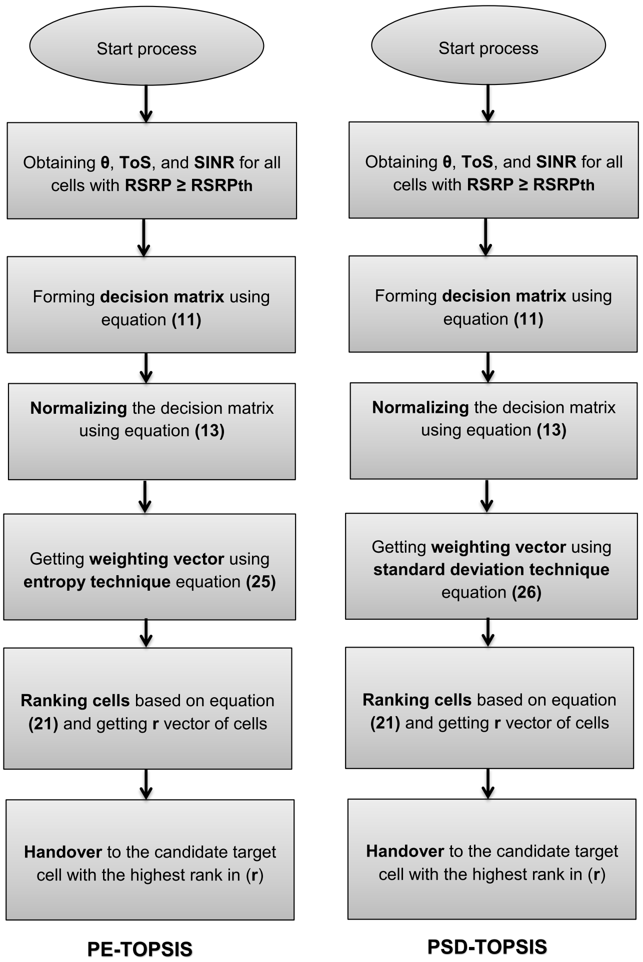

FIGURE 3. Procedures of PE-TOPSIS and PSD-TOPSIS.

TABLE 2. 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

where R_{sc} and R_m are respectively the SC and MC radius. The denominator represents the area of the umbrella base station i.e., the MC coverage area. Thus, if the SC density metric D_{sc} is equal to 1, this means that the deployment of the SCs covers the whole area of the MC coverage area. While a higher than 1 value means that the SCs are covering the whole area of MC and an overlapping is ensured among the SCs. We set up the number of SCs to 50, which means that $D_{sc} \approx 2$ and hence, the dense SCs scenario is achieved.

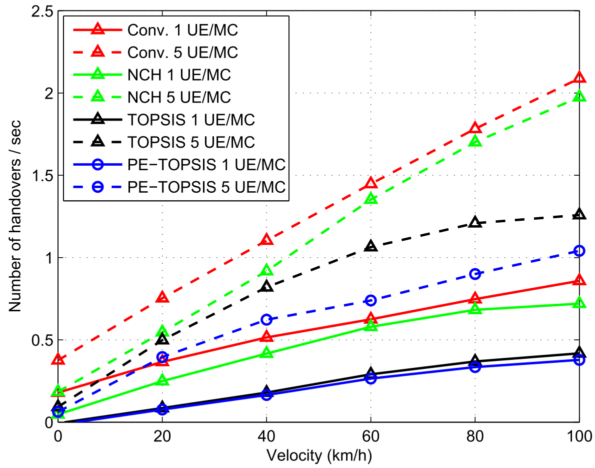

FIGURE 4. Number of handovers.

First, we only compare the PE-TOPSIS with the conventional, NCH and TOPSIS methods.

A. NUMBER OF HANDOVERS

Fig.4 depicts the total number of HOs per second. Two different scenarios are shown, when the density of the users are 1 and 5 per one MC. For all methods, the lower the density of the users the lower the number of HOs for all velocities. It is clear that the conventional and NCH methods have higher number of HOs compared to TOPSIS and PE-TOPSIS. This is because that both methods do not predict the target cell for HOs and they respectively perform the HO when the downlink received power from the neighbour cell is offset greater than that of the serving cell for TTT period of time and if the SINR is below the SINR threshold for NCH method. On the other hand, the TOPSIS and PE-TOPSIS have less number of HOs compared to the other two methods. The PE-TOPSIS has also outperformed the TOPSIS method by reducing the number of HOs due to the modified entropy weighting calculations which leads to proper assigning of importance to the HO metrics θ, ToS and SINR. Unlike the TOPSIS method which assigns a fixed weights for the HO metrics. Unlike the high speed users, the low speed users will not cause a short time of stay phenomena, therefore, the number of HOs is lower for low speed users which clarify the advantage of incorporating the ToS criterion. Additionally, the angle criterion omits the base stations that are not in the user's movement direction resulting in a fewer number of target base stations, and hence, reduce the number of unnecessary handovers compared to the competitive methods.

The percentage of each type of HO compared to the total number of HOs is presented in Fig.5. These percentage have been taken for three types of user velocity, low at 20km/h, medium at 60km/h and high at 100km/h. For the case of outbound HO (i.e., SC to MC HO), both the conventional and NCH methods have the higher percentages of HO and these percentages grow as the user velocity increases. On the other hand, TOPSIS and PE-TOPSIS methods have lower percentages of HOs with the PE-TOPSIS having less percentage than that of the TOPSIS. It is obvious from Fig.5 that the PE-TOPSIS has eliminated the outbound HO for low speed user, hence, low speed users are preferred to stay connected to SC rather than performing HO to MC. For the case of inbound HO (i.e., MC to SC HO), all of the four methods have an instantaneous increase in the HO percentage with the increase in user velocity with the PE-TOPSIS method having a slight drop at high speed due to the HO target prediction which reduces the unnecessary HO to SC for high speed users. For the case of inter-SC HO (i.e., SC to SC HO), all methods also show an instantaneous increase in the HO percentage as the velocity increases due to the high density of SCs. It is clear that PE-TOPSIS has lower HO percentage than that of the TOPSIS at high speed because the proper HO target prediction of PE-TOPSIS let the high speed users occasionally perform HO to SC (when the SINR of MC is not sufficient) so as to reduce the radio link failure which may lead to HO failure.

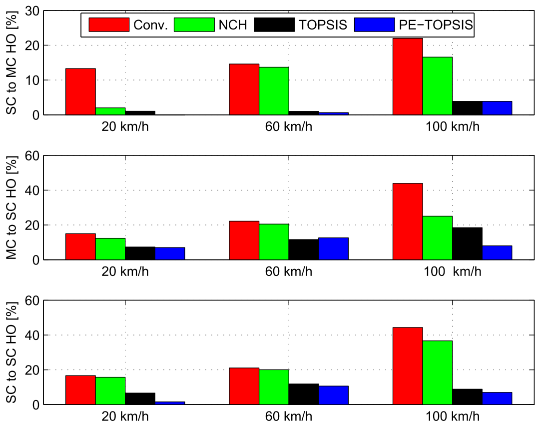

FIGURE 5. The percentage of handover frequency.

B. RADIO LINK FAILURE

A radio link failure is declared if the HO is initiated to the target cell from vector **r** but the SINR of that cell drops below the threshold γ_{th} for a period of time window T310, which is 1 second, as defined in [26]. The radio link failure is depicted in Fig.6. The higher the speed the higher the radio link failure for all methods. The conventional method yields higher failure due to the frequent HOs as the velocity increases, hence, the HO will be initiated but interrupted before completion due to the sudden drop in the target cell received power at the user side. The NCH method has lower failure compared to the conventional method because it performs the HO when the SINR of the serving cell drops below a predefined threshold. Both the TOPSIS and PE-TOPSIS methods have the lowest radio link failure with the PE-TOPSIS outperforming specially at high speeds due to the early HO to the correctly predicted HO target cell. The low radio link failure in the PE-TOPSIS method emphasizes the accuracy of weighting assignment to the HO metrics which leads to an accurate cell selection compared to the other methods. Additionally, the low link failure in PE-TOPSIS method comes from the positive influence of utilizing the angle criterion where the users will avoid initiating the HO to the base station that are located away from it is movement direction, and hence, the failure will be reduced.

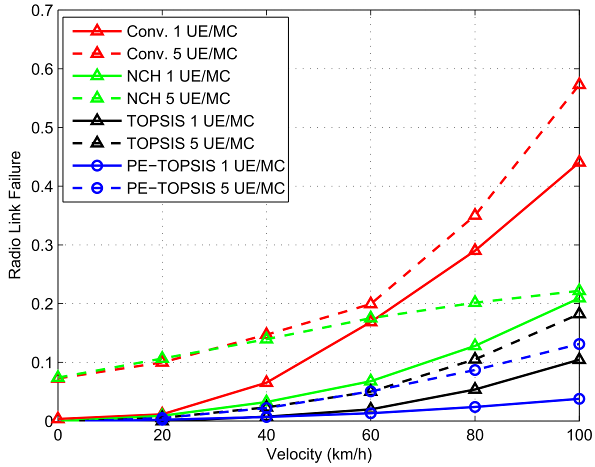

FIGURE 6. Radio link failure.

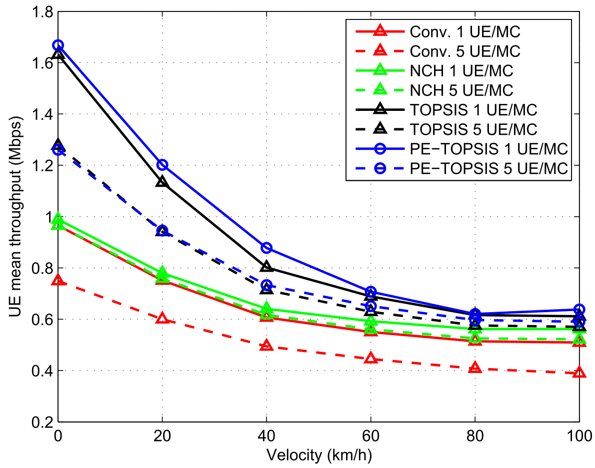

FIGURE 7. User mean throughput.

C. USER MEAN THROUGHPUT

Fig.7 shows the user mean throughput for the four methods. All methods have dropped in the mean user throughput as the velocity increase. The conventional and NCH methods have the lowest throughput compared to the other two methods because of their higher number of unnecessary HOs which results in producing a lower throughput for the user (since the high speed users will result in radio link failure which leads to poor throughput gain). The TOPSIS and PE-TOPSIS methods produce higher throughput because they perform the HO upon the proper target prediction with the PE-TOPSIS outperforming the TOPSIS method. Higher throughout especially for low speed users reflects the receiving of high SINR at the

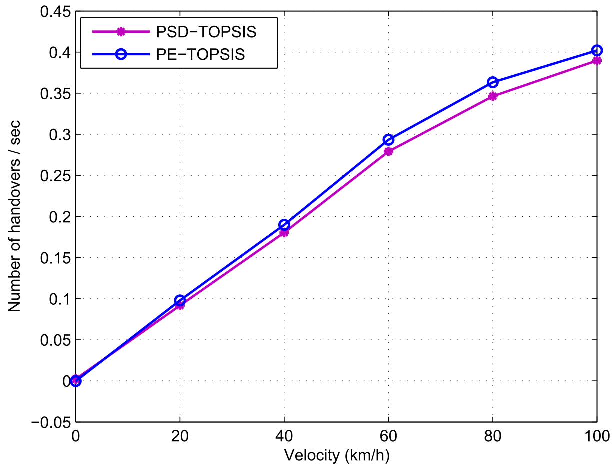

FIGURE 8. Number of handovers.

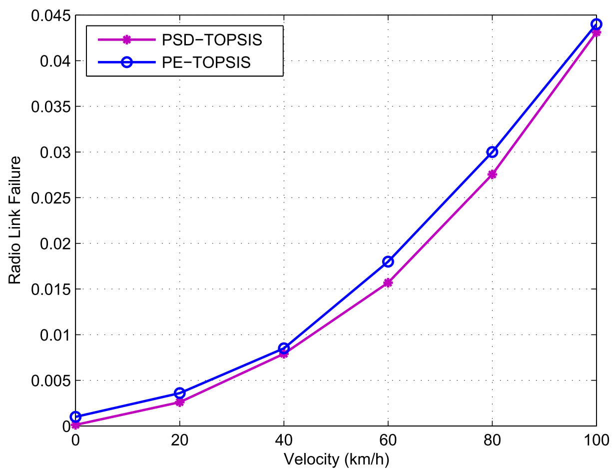

FIGURE 9. Radio link failure.

user side. Therefore, the incorporation of SINR criterion has the advantage of improving the throughput at all velocities.

D. COMPARING PE-TOPSIS AND PSD-TOPSIS

In this subsection we compare the performance of PE-TOPSIS with that of the PSD-TOPSIS methods in terms of the number of HOs, radio link failure, user mean throughput and complexity of calculations.

Fig.8 shows that the number of HOs has been reduced in PSD-TOPSIS method compared to PE-TOPSIS. For all velocities, the PSD-TOPSIS method produces less number of HOs. The SD weighting technique provides more stable weights to the attributes which in turn leads to an efficient alternative selection among the available options.

The radio link failure is depicted in Fig.9. The PSD-TOPSIS method reduces the radio link failure, which may cause HO failure. The level of increase in the link failure increases with the increase in user velocity according to the common sense because the fast moving users may leave the coverage area of the cell before completing the HO process, hence the failure increases.

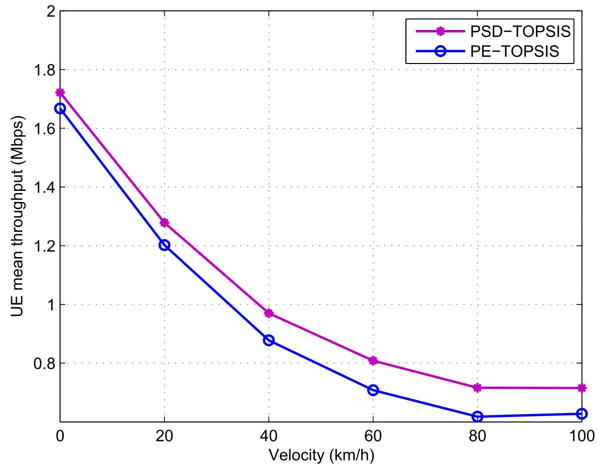

FIGURE 10. User mean throughput.

In Fig.10, the mean user throughput is illustrated. As expected the PSD-TOPSIS method produces higher achieved throughput for the user.

For the sake of clarity, we did not compare the proposed PSD-TOPSIS method with the conventional, NCH or TOPSIS because those methods have already been outperformed by our proposed method PE-TOPSIS.

To further conclude the impact of the weighting techniques on the proposed methods, we compare the performance in a form of tables. Tables 3, 4 and 5 give the numerical results of the PE-TOPSIS and PSD-TOPSIS methods when the velocity is 20km/h, 40km/h and 80km/h respectively.

TABLE 3. Performance analysis at 20 km/h.

Method	HOs/sec	RLF	UE throughput(Mbps)
PE-TOPSIS	0.100	0.0038	1.20
PSD-TOPSIS	0.0917	0.00263	1.28

TABLE 4. Performance analysis at 40 km/h.

Method	HOs/sec	RLF	UE throughput(Mbps)
PE-TOPSIS	0.19	0.0085	0.86
PSD-TOPSIS	0.17	0.0078	0.97

TABLE 5. Performance analysis at 80 km/h.

Method	HOs/sec	RLF	UE throughput(Mbps)
PE-TOPSIS	0.365	0.030	0.15
PSD-TOPSIS	0.346	0.0276	0.71

We can see from the tables that the PSD-TOPSIS method has outperformed PE-TOPSIS at all velocities. For instance, when the velocity is 20km/h, the number of HOs is reduced by 9%. Furthermore, the radio link failure is reduced by 30.7% in the same case. At a velocity of 80km/h, the number of HOs is reduced by approximately 5.2% for PSD-TOPSIS compared to PE-TOPSIS. Furthermore, the radio link failure is minimized by 8% in the same case and the user mean throughput is enhanced by 78.8%.

When using the entropy weighting technique the overall performance is getting worse (but still better than that of the TOPSIS, NCH and the conventional methods) compared to that when using SD weighting technique. This proves the advantage of the SD over the entropy weighting technique in distributing the weights between the attributes and hence, gives a better performance in terms of reducing the number of HOs and radio link failures in addition to enhancing the user mean throughput.

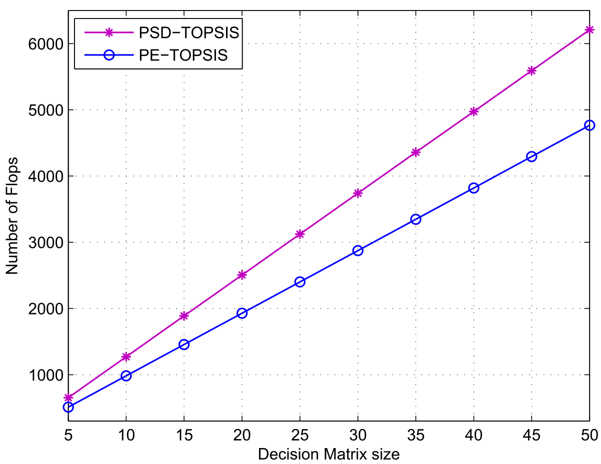

FIGURE 11. **Complexity analysis.**

To further analyze the benefits of the proposed methods, PE-TOPSIS and PSD-TOPSIS, we evaluate the complexity of both methods. Fig.11 depicts the computational complexity of the proposed methods. This is done by evaluating the two methods in terms of the total number of floating point operations (flops) with different sizes of the decision matrix (i.e., different densities of SCs). We used the Matlab function defined in [27] which scans and parses each line of the simulation code and counts the number of flops. As can be noticed from Fig.11, the computational complexity increases linearly with the increase in the size of the decision matrix for both methods. The PSD-TOPSIS method has slightly higher complexity operations compared to the PE-TOPSIS. In fact, as the size of the decision matrix increases the difference between the two methods in terms of complexity increases. We conclude that, when the complexity is not an issue in the application, then the PSD-TOPSIS method would be a good solution. Otherwise, the PE-TOPSIS method is an alternative at the expense of less accuracy on attributes weight assignment, and hence, higher HO and link failure levels in addition to less achieved throughput.

Furthermore, higher complexity means higher energy consumption. Therefore, deploying PE-TOPSIS or PSD-TOPSIS also depends on the capability of the SCs. For example, when residential SCs are deployed (e.g. femtocells), then the PE-TOPSIS is more preferred due to the limited calculation capabilities 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.

VII. CONCLUSION AND FUTURE WORK

In this paper, modified weighted MADM TOPSIS methods have been presented. The proposed methods exploit the TOPSIS principle of ranking the HO candidate cells based on their attributes and the weights of each attribute. The final HO destination cell is selected when it is close to positive ideal solution and far from the negative ideal solution. In the first method, PE-TOPSIS, we deploy the entropy weighting technique to weight the attributes. This method shows a good performance in reducing the number of HOs and radio link failures and enhancing the achieved user throughput compared to the NCH, TOPSIS and conventional methods. The second proposed method, PSD-TOPSIS, deploys the standard deviation weighting technique to scale the importance of each attribute for all HO candidate cells. As the results show, our proposed PSD-TOPSIS method reached low number of HOs and low radio link failure, while higher mean user throughput is achieved compared to the existing methods. This method shows even better results in enhancing the network performance by reducing the number of HOs and radio link failure, in addition to increasing the mean user throughput owing to the accurate weight distribution between the attributes. Furthermore, we compare the performance of PE-TOPSIS and PSD-TOPSIS in terms of complexity and suggest to choose the method based on the size and capability of calculations of the SCs. For smaller size SCs, the PE-TOPSIS is more suitable, otherwise, the PSD-TOPSIS is an alternative solution.

As a future work, we intend to investigate the influence of different normalization techniques on the network performance, in addition to studying the phenomena of what so called network ranking abnormality in MADM methods.

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