Dynamic Multi-Attribute Network Selection Algorithm for Vertical Handover Procedures over Mobile Ad Hoc Networks

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***Abstract*—The Vertical Handover and the related *Network Selection* process play a fundamental role in supporting reliable communications over MANETs. The goal of the *Network Selection* is to determine the Radio Access Network (RAN) that a Mobile Node (MN) has to use among several available RANs. This decision process finds out the RAN that fits the MN requirements and has to provide the decision as rapidly as possible. A computationally heavy *Network Selection* algorithm can impact the whole handover process because it waits until the selection is carried out. This waste of time can have negative consequences in the quality of communications. The main contribution of this paper is the definition of a new *Network Selection* algorithm based on a different formulation of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method found in the literature, called Dynamic-TOPSIS (D-TOPSIS). It is aimed at performing the same selection of the TOPSIS but with a significant reduction of necessary computational load. Finally, the numerical results highlight the execution time reduction obtained by applying the D-TOPSIS with respect to the standard algorithm, and other *Network Selection* techniques usually applied within Vertical Handover Processes.**

***Index Terms*—*Network Selection*, Vertical Handover, Multi Attribute Decision Making, Mobile Ad Hoc Networks.**

I. Introduction

THE mobile communication field is constantly evolving and new technologies and standards are currently available. As a consequence, a multitude of heterogeneous Radio Access Networks (RANs) are often available and assure ubiquitous communications to Mobile Nodes (MNs) independently of their positions. A device with multiple network interfaces is able to access to a network services while it is moving. So the challenge is to select the RAN, among the available ones, that fits MN performance requirements accordingly to the so called Always Best Connected (ABC) paradigm, firstly defined in [1].

A peculiar and important family of mobile networks are the so called *Mobile Ad Hoc Networks* (MANETs) [2]. They are self-configuring networks for the communication among MNs, which are free to move independently in any direction, and will therefore change their (radio) links to other devices, frequently. A requirement of MNs that belong to such a network is the capability to dynamically select the RAN that they have to use and to execute the handover which is a process aimed at enabling the MN to change the RAN in use.

In more detail, two different types of handovers are defined: *i)* **horizontal handover**, when the RANs involved in the operation employ the same radio technology or *ii)* **vertical handover** when the MN selects a RAN in a set of them characterised by different radio technologies. According to the IEEE 802.21 Standard [3] aimed at facilitating the interoperability of different radio access technologies, the function that triggers the handover execution is the *Network Selection* aimed at choosing the RAN that an MN has to use.

Within mobile scenarios, an MN have usually limited computational and energy capacities. As a consequence, as reported in [4], the *Network Selection* problem has stringent time constraint. In practice, an algorithm for the *Network Selection* has to match the MN requirements in terms of communications performance (e.g., packet loss, delay and jitter) and, simultaneously, to limit the number of operations, and the time, necessary to carry out the selection. Indeed, a computationally heavy *Network Selection* algorithm can negatively impact the whole handover process because it has to weight until the selection is completed. It implies an undesired waste of time. The contribution of this paper concerns the proposal of a novel *Network Selection* algorithm able to carry out the RAN selection process with a limited computational load. The rational under the proposal of this paper starts from the assumption that, even if the mobile scenario is highly dynamic, some characteristics of the available RANs remain constant until the MN is inside the related coverage areas. In other words, some metrics often considered in the RAN selection process (such as the monetary cost of the RAN, its level of security and the energy consumption) assume values independent of the position of the MN.

Indeed, as presented in [5] the metrics (or parameters) can be classified in three groups: static, dynamic and semi-dynamic. Starting from this classification, a new version of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) algorithm, called Dynamic-TOPSIS (D-TOPSIS), aimed at reducing the number of operations required to select the network, is presented in this paper. The new formulation of the TOPSIS algorithm does not modify the performance of the algorithm because both versions generate the same selection as confirmed by the obtained numerical results.

The rest of the paper is organized as follows: Section II surveys the state of the art regarding the *Network Selection* problem; in Section III are described the TOPSIS algorithm and the D-TOPSIS. The simulative scenario, developed to evaluate in terms of performance the proposed algorithm and to compare it with other algorithms, is described in Section IV-A, while the numerical results of the execution time and of the performance comparison are discussed in Section IV-B. Finally the conclusions are drawn in Section V.

II. The State of the Art

Several works about the *Network Selection* can be found in the literature. A first group of algorithms, called in this paper *mono-attribute*, chooses the network, among the available ones, by considering only one specific metric (also said *attributes*). These algorithms have a low computational complexity and a low execution time because the RAN is selected by optimizing only the considered metric. On the other hand, they may provide unsatisfactory performance in several scenarios because the choice could not be the optimal one from an extended viewpoint, which takes into account more performance metrics and parameters.

A widely used approach is the so called RSSI Based [6] [7]: in this case the MN measures the Received Signal Strength Indicator (RSSI) from the Points of Access (PoAs), such as WiFi Access Points (APs) or cellular Radio Base Stations (RBS), of all the available RANs and chooses the RAN with the highest RSSI. These algorithms are largely used within horizontal handover procedures but can be used also for the vertical handover.

A further group of algorithms, called *multi-attribute*, considers more than one performance metric during the selection of the RAN. These metrics are, for example, the RSSI, the Available Capacity, the Packet Loss Rate, the Packet Delay, the Energy (or Power) Consumption and the Monetary Cost (MC). The task of the *Network Selection* algorithm, implemented within a decision making function, also called Decision Maker (DM), is to determine the RAN, also said *alternative*, that assures the best compromise among the considered metrics, according to a certain policy.

According to [8] and [9] among the others, the **Simple Additive Weight** (SAW) algorithm assigns a value, often called cost, to each *alternative*, computed as the sum of the normalized value of each considered *attribute*. Weights are applied to each *attribute* to differentiate their importance and are positive if the *attribute* must be minimized or negative if it must be maximized. As a consequence the selected RAN is the one with the lowest cost.

Similarly in the **Weighted Product Method** (WPM) algorithm [10], the cost is obtained by multiplying the value of each *attribute*. No normalization is needed and the weights are applied as exponent of the *attribute* values. Again the selected RAN is the one that determines the lowest cost.

A further family of algorithms is the **Fuzzy Logic Based**. Fuzzy Logic is a many-valued logic derived from fuzzy set theory in which the variables may have a truth value that ranges in a degree range between 0 and 1. Fuzzy Logic is able to model non-linear functions in a compact set of arbitrary accuracy and is used to solve many problems such as real time and automatic control, data classification and decision analysis. Concerning the problem of the *Network Selection* many papers (such as [11] and [12]) present a combination of Fuzzy Logic theory with *multi-attribute* algorithms.

Finally the **Technique for Order of Preference by Similarity to Ideal Solution** (TOPSIS) algorithm selects the *alternative* (i.e., the RAN) that simultaneously minimizes and maximizes the distance, in Euclidean terms, respectively between the Positive Ideal Solution and the Negative Ideal Solution. More details about this algorithm are described in Section III because it represents the standard version of the proposed new formalisation of the algorithm and, as a consequence, the starting point of the D-TOPSIS.

III. The proposed *Network Selection* algorithm

The proposed algorithm is a modification of the well known TOPSIS, defined in [13] among the others, already applied for *Network Selection* procedures as in [14], [15] and [16] as well as in other fields [17]. It enables to obtain the same results by the DM (i.e., it selects the same RAN) and, simultaneously, a significant reduction of the number of operations necessary to determine the solution.

A. TOPSIS

TOPSIS considers all the *alternatives* (i.e., all the available RANs) defined by the values assumed by the considered *attributes*. The *i-th alternative* is defined by the vector $A_i = (x_{i1}, \cdots, x_{ij} \cdots, x_{in})$ for $i \in [1, m]$ where n and m are respectively the number of *attributes* and the number of available *alternatives*. As reported in [13], the TOPSIS approach can be geometrically modelled with m points in a n-dimensional space. As a consequence, it is possible to apply the Euclidean Norm to compute the distance between each *alternative* and a reference point. This algorithm is composed of several successive steps as reported in the following:

- Calculation of the weighted normalized *attribute* values (1):

$$v_{ij} = w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

  for each $i = 1, \cdots, m$ *alternative*, for each $j = 1, \cdots, n$ considered *attribute*. w_j is the weigh associated to the j-th *attribute*, which must be selected by respecting the condition $\sum_{j=1}^{n} w_j = 1$.

- Identification of the Positive (A^*) and the Negative (A^-) Ideal Solution, shortly PIS and NIS respectively, as reported in (2).

$$\begin{aligned} A^* &= (v_1^*, \cdots, v_j^* \cdots, v_n^*) = \\ &= \Big((\max_i v_{ij} | j \in J_1), (\min_i v_{ij} | j \in J_2) | i = 1, \cdots, m \Big) \\ A^- &= (v_1^-, \cdots, v_j^- \cdots, v_n^-) = \\ & \Big((\min_i v_{ij} | j \in J_1), (\max_i v_{ij} | j \in J_2) | i = 1, \cdots, m \Big) \end{aligned} \tag{2}$$

  where J_1 represents the set of positive *attributes*, that needs to be maximized, and J_2 represents the set of negative *attributes* that needs to be minimized.

- Calculation of the Separation Measures (SMs): to evaluate the distance between *alternatives* and ideal point (i.e., the Separation Measures), the Euclidean Norm is applied, as reported in (3).

$$S_i^* = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^*)^2}; \quad for \quad i = 1, \cdots, m$$
$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}; \quad for \quad i = 1, \cdots, m \tag{3}$$

- Calculation of the Similarity Index (SI): for the i-th *alternative*, A_i, the SI is calculated as $C_i = S_i^-/(S_i^- + S_i^*)$. The values are in the range $[0 - 1]$, where $C_i = 0$ if the *alternative* coincides with the NIS (i.e., $A_i = A^-$) and $C_i = 1$ if if the *alternative* coincides with the PIS (i.e., $A_i = A^*$). It means that the best *alternative* is the one with the highest similarity index associated.

B. D-TOPSIS

The new formulation of the TOPSIS algorithm is called Dynamic-TOPSIS (D-TOPSIS). The RAN selection at the generic step t, which coincides with a given instant, takes in consideration the decision performed in the previous step $t - 1$. In more detail, the *attributes* at a generic step t, used to evaluate the i-th *alternative*, are divided into two groups: the *static attributes* $\mathbf{s}_i(t)$ and the *dynamic attributes* $\mathbf{d}_i(t)$. In particular, the static attributes for each *alternative* maintain constant their values at each t step, when the *Network Selection* is performed. So for the i-th *alternative* the value of each static *attribute* at the step t is equal to the value of the same *attribute* at $t - 1$. In practice $\mathbf{s}_i(t) = \mathbf{s}_i(t - 1)$. Consequently, it is possible to modify the formulation of the TOPSIS algorithm as described in the following. Supposing the *Network Selection* performed, periodically, each T seconds (i.e., the selection at the step $t + 1$ is taken T seconds after the selection at the step t) and defining the i-th *alternative* as in (4):

$$\mathbf{A}_i(t) = (\mathbf{s}_i(t-1), \mathbf{d}_i(t)) = (s_{i,1}(t-1), \cdots, s_{i,j}(t-1), \cdots, s_{i,n_s}(t-1), d_{i,j}(t), \cdots, d_{i,j}(t), \cdots, d_{i,n_d}(t)) \tag{4}$$

n_s and n_d represent respectively the number of static and dynamic *attributes*.

The basic idea of the new version of the algorithm is to apply the standard version of the TOPSIS each time the set of available RANs changes (i.e., the MN enters or leaves a new RAN). Then the results obtained are saved and reused for each successive selection in which the D-TOPSIS is applied, until the set of available RANs does not change again (i.e., MN enters or leaves another RAN). In other words, the following steps, necessary to perform the selection, are different depending on the number of available *alternatives* at the instant t ($m(t)$). In practice, if $m(t) = m(t - 1)$ the dynamic version of the algorithm is used, while, if this condition is not verified, the standard version of the algorithm is employed.

In order to define D-TOPSIS it is worth noting that the distance between the NIS and the i-th *alternative* at the t-th instant is determined by the two components $S_{ij}(t)$ and $D_{ij}(t)$ with $j = [1, \cdots, n]$, called in this work *Partial Distances*, that must be calculated for each *alternative* and for each *attribute* during each execution of the TOPSIS algorithm. Being $S_{ij}(t) = S_{ij}(t - 1)$, it is not necessary to calculate the value of this parameter. It obviously reduces the number of the operations needed to carry out the RAN selection. Moreover this reduction becomes larger if the considered number of static *attributes* or the number of *alternatives* increase.

D-TOPSIS is composed of the following phases:

- Calculation of the weighted normalized values of the static and dynamic *attributes* (5):

$$N(s_{ij}(t)) = \begin{cases} N(s_{ij}(t-1)); & if \;\; m(t) = m(t-1) \\ w_j \dfrac{s_{ij}(t)}{\sqrt{\sum_{i=1}^{m(t)} s_{ij}(t)^2}}; & else \end{cases}$$
$$i = 1, \cdots, m(t); \; j = 1, \cdots, n_s;$$
$$N(d_{ij}(t)) = w_j \frac{d_{ij}(t)}{\sqrt{\sum_{i=1}^{m(t)} d_{ij}(t)^2}}$$
$$i = 1, \cdots, m(t); \; j = 1, \cdots, n_d; \tag{5}$$

- Identification of the Positive $A^*(t)$ and the Negative $A^-(t)$ Ideal Solution

$$A^*(t) = \begin{cases} (\mathbf{s}^*(t-1), \mathbf{d}^*(t)); & if \;\; m(t) = m(t-1) \\ (\mathbf{s}^*(t), \mathbf{d}^*(t)); & else \end{cases} \tag{6}$$

where

$$\begin{aligned} \mathbf{d}^*(t) &= \left(d_1^*(t), \cdots, d_j^*(t), \cdots, d_{n_d}^*(t)\right) = \\ &= \left((\max_i d_{ij}(t) | j \in J_{d_1}), (\min_i d_{ij}(t) | j \in J_{d_2}),\right. \\ \mathbf{s}^*(t) &= \left(s_1^*(t), \cdots, s_j^*(t), \cdots, s_{n_s}^*(t)\right) = \\ &= \left.(\max_i s_{ij}(t) | j \in J_{s_1}), (\min_i s_{ij}(t) | j \in J_{s_2})\right) \end{aligned} \tag{7}$$

$$A^-(t) = \begin{cases} (\mathbf{s}^-(t-1), \mathbf{d}^-(t)); & if \;\; m(t) = m(t-1) \\ (\mathbf{s}^-(t), \mathbf{d}^-(t)); & else \end{cases} \tag{8}$$

where

$$\begin{aligned} \mathbf{d}^-(t) &= \left(d_1^-(t), \cdots, d_j^-(t), \cdots, d_{n_d}^-(t)\right) = \\ &= \left((\min_i d_{ij}(t) | j \in J_{d_1}), (\max_i d_{ij}(t) | j \in J_{d_2}),\right. \\ \mathbf{s}^-(t) &= \left(s_1^-(t), \cdots, s_j^-(t), \cdots, s_{n_s}^-(t)\right) = \\ &= \left((\min_i s_{ij}(t) | j \in J_{s_1}), (\max_i s_{ij}(t) | j \in J_{s_2})\right) \end{aligned} \tag{9}$$

In (7) and (9) J_{s_1} and J_{d_1} are respectively the sets of positive static and dynamic *attributes*, that needs to be maximized, while J_{s_2} and J_{d_2} are, respectively, the sets of negative static and dynamic *attributes* that needs to be minimized.

- Calculation of the *Partial Distance* for all the *attributes* between each *alternative* and the Ideal Solutions as in (10) and (11).

$$
\begin{aligned}
&D^*_{ij}(t) = \left|d_{ij}(t) - d^*_j(t)\right| \\
&i = 1, \cdots, m(t);\ j = 1, \cdots, n_d; \\
&S^*_{ij}(t) = \begin{cases} S^-_{ij}(t-1); & if\ \ m(t) = m(t-1) \\ \left|s_{ij}(t) - s^*_j(t)\right|; & else \end{cases} \\
&i = 1, \cdots, m(t);\ j = 1, \cdots, n_s;
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
&D^-_{ij}(t) = \left|d_{ij}(t) - d^-_j(t)\right| \\
&i = 1, \cdots, m(t);\ j = 1, \cdots, n_d; \\
&S^-_{ij}(t) = \begin{cases} S^-_{ij}(t-1); & if\ \ m(t) = m(t-1) \\ \left|s_{ij}(t) - s^-_j(t)\right|; & else \end{cases} \\
&i = 1, \cdots, m(t);\ j = 1, \cdots, n_s;
\end{aligned} \tag{11}
$$

- Calculation of the Separation Measures (SMs) as reported in (12):

$$
\begin{aligned}
&M^*_i(t) = \sqrt{\sum_{j=1}^{n_s}(S^*_{ij}(t))^2 + \sum_{j=1}^{n_d}(D^*_{ij}(t))^2} \\
&M^-_i(t) = \sqrt{\sum_{j=1}^{n_s}(S^-_{ij}(t))^2 + \sum_{j=1}^{n_d}(D^-_{ij}(t))^2} \\
&i = 1, \cdots, m(t);
\end{aligned} \tag{12}
$$

- Calculation of the Similarity Index as $C_i(t) = M^-_i(t)/(M^-_i(t) + M^*_i(t))$. Clearly, also for the D-TOPSIS the highest Similarity Index identifies the best *alternative*.

Starting from the described phases, the reduction of the number of necessary operations is obvious. In practice, applying the D-TOPSIS for each *alternative*, it is not necessary to calculate both values of the *Partial Distances* for the static *attributes*. These values are stored during the last execution of the standard TOPSIS and simply loaded during the execution of the D-TOPSIS. Only the *Partial Distances* referred to the dynamic *attributes* must be calculated in order to compute the Separation Measures and the Similarity Index.

IV. Performance Investigation

A. The Reference Scenario

The scenario taken as reference in this paper is composed by a remote host that communicates with an MN that is moving along a rectilinear trajectory with a speed equal to 3 [m/s] (pedestrian speed). A UDP traffic flow that is transmitted by a remote host to an MN. Three different types of RANs are considered: UMTS, with a single cell that covers the whole area, WiMAX, with again a single cell and eight WiFi cells. The *Network Selection* is performed periodically each $T = 5$ [s]. Each simulation duration is set equal to 500 [s].

The metrics considered during the RAN selection process are four: the Received Signal Strength Indicator, (*RSSI*), measured by the MN, the Capacity that the network reserves to the MN (*C*), the Monetary Cost (*MC*) paid by the user to use the network and the Power Consumption (*P*) of the MN. Obviously, the first two *attributes* are positive while the others are negative. It is worth noticing that, according with [5], *C*, *MC* and *P* are static *attributes* while *RSSI* is a dynamic *attribute*, computed as a function of the distance between the MN and the PoA of the RAN in use. So $n_s = 3$ and $n_d = 1$. Together with TOPSIS and D-TOPSIS, seven RANs selection algorithms are considered. Four are *single-attribute* approaches and each of them is focused only on the optimization of one of the considered *attributes*: *i)* Received Signal Strength Indicator based ($RSSI$), *ii)* Available Capacity (AC), *iii)* Monetary Cost (MC) and *iv)* Power Consumption (PC).

The simulated scenario adopted has been developed through the Network Simulator 2 (*ns-2*). The dimension and the position of the coverage areas of each access network are randomly set in each simulation. The values of the considered *attributes* vary in each executed simulation, over the range reported in Table I. In Table I, the Monetary Cost is only an indicative number that ranks the network from the cheapest, which as *MN* $= 1$, to the most expensive (*MN* $= 10$).

TABLE I
Range value of the *attribute* considered

Parameters	Range Value
Power Consumption	[0,16 - 0,22] w
Monetary Cost	[1-10]
Wi-Fi Capacity	[1 - 20] Mbps
Wi-Max Capacity	2 Mbps
UMTS Capacity	0.384 Mbps

B. The Simulative Results

The numerical results obtained through a simulative campaign are presented and discussed in this section. In particular, the results are grouped into two sets. The first one is aimed at highlighting the improvement assured by the D-TOPSIS, with respect to the standard TOPSIS, in terms of execution time, maintaining the same selection results. The second set reports a comparison between the performance obtained by the D-TOPSIS and by the other considered algorithms. Moreover, also a comparison in terms of execution time is discussed considering again the aforementioned algorithms.

1) Execution Time Comparison: In this subsection are analysed the execution time of TOPSIS and D-TOPSIS: these quantities identify the measurement of the time needed to perform a single execution of the two considered version of the algorithm. Figure 1 shows two different quantities: on the left ordinate axis is plotted the difference in the execution time between the two different versions of the TOPSIS algorithm, while on the right it is plotted the percentage of the execution time reduction of the D-TOPSIS with respect to the TOPSIS. Both the quantities are considered for a different number of *alternatives* (i.e., available RANs), in a range limited by two, that obviously represents the minimum number of necessary *alternatives* needed to perform the *Network Selection*, and ten, that is the number of network that are considered in the

simulative scenario.
It is possible to view that the difference between the execution times of the two versions of the TOPSIS algorithm increases if the number of *alternatives* (i.e., the available RANs) increases. On the contrary, the reduction of the execution time in percentage is constantly between 70% and 75% independently of the number of *alternatives*. In practice, these results demonstrate that the execution time reduction is independent of the number of available *alternatives* in the considered range.

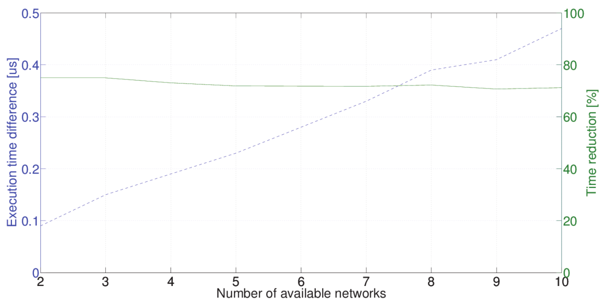

Fig. 1. Execution times of TOPSIS and D-TOPSIS and percentage of execution time reduction of D-TOPSIS over different number of *alternatives*

In Figure 2 are shown the execution time for all the considered *Network Selection* algorithms for a different number of RANs. It is worth noticing that nine *Network Selection* algorithms are defined in this section but only six of them are reported in Figure 2. Indeed, the four *single-attribute* algorithms implement the same operations and differs each other only for the *attributes* considered during the selection process. Consequently their execution times are substantially the same. For this reason the *single-attribute* line in Figure 2 identifies the execution time of all the aforementioned *single-attribute* algorithms. It is possible to view in Figure 2 D-TOPSIS is the second fastest algorithm among the considered algorithms; the only one that is faster is the single attribute group, as previously said in II. The algorithms that belong to this group are computationally lighter with respect to the *multi-attribute* approaches and select the network considering a single parameter. On the other hand these algorithms gives poor results and a sub-optimal selection as highlighted in the next subsection.
The execution time of the standard TOPSIS has intermediate performance while the fuzzy algorithm is the slowest algorithm because it implements several operations during the so called *fuzzyfication* and the *defuzzyfication* phases. The results highlight the advantage assured by the D-TOPSIS in terms of execution time, not only with respect to the standard TOPSIS but also with respect to all the other *multi-attribute Network Selection* algorithms.
Finally, it is possible noticing that the differences between the execution times increase if the number of *alternatives* increase. For example, if $m = 10$ the D-TOPSIS execution time is equal to 1.9 [μs], while for the TOPSIS standard is 6.6 [μs] and for the F-SAW is 7 [μs].

C. Performance analysis

Figure 3 represents the time in which each network is used by the MN for both versions of the TOPSIS algorithm. It

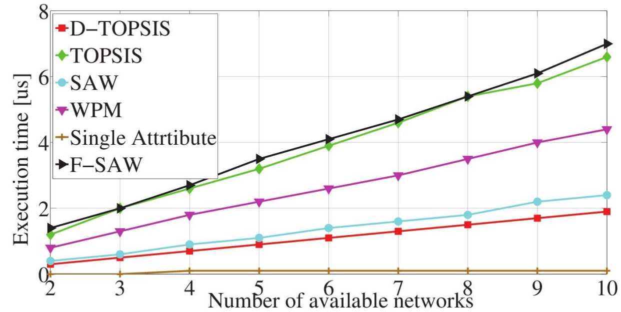

Fig. 2. Distance of the i-th *alternative* from the Negative Ideal Solution

is worth noticing that for each available network the time of usage is the same. It means that both algorithms perform the same selection in each period so confirming the concepts proposed in Section III: D-TOPSIS is a modification of the TOPSIS algorithm that enables a great reduction in the execution time but, at the same time, converges on the same solution.
Some further considerations can be done regarding the time of use of each network. The UMTS network is the most used, for more than 150 [s] over 500 [s] of simulation. This happens because this network has the biggest coverage area with respect to the others. On the contrary, all the WiFi networks are not used for a long time, between 30 [s] and 40 [s], even if they assure better performance with respect to the UMTS, because they have small coverage areas.

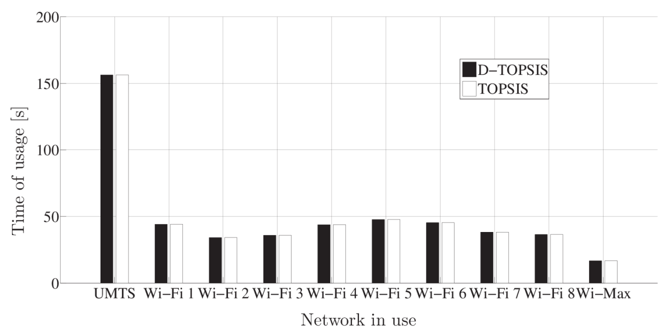

Fig. 3. Distance of the i-th *alternative* from the Negative Ideal Solution

As demonstrated also in a previous work by the same authors [14] the TOPSIS assure a compromise between the considered metrics because of it selects the *alternative* that simultaneously minimize and maximize the distance with the positive and the negative ideal solution, respectively. Table II confirms this result.
Six performance metrics are adopted to evaluate the *Network Selection* algorithms: *i)* Received Signal Strength Indicator ($RSSI$) expressed in $[dBW]$, *ii)* Capacity (C), in $[bps]$, that the RAN in use assigns to the MN to transmit the UDP traffic flow, *iii)* Monetary Cost (MN) paid for the use of the RAN, *iv)* Power consumption (P) of the MN, expressed in $[W]$, *v)* packets Delay (D) calculated as the difference between the packet transmission time and the time in which the packet is received by the MN in $[s]$, and *vi)* number of handover executed by the MN (H). The first two metrics are positive, while the other are negative; the best *Network*

Selection algorithm is the one that obtain the best compromise between the considered performance metrics.

In Table II are reported the values of each performance metric for each considered algorithm, obtained through the aforementioned simulative campaign. The *multi-attribute* algorithms assure better performance with respect to the single-attribute ones because of they consider simultaneously several *attributes* during the selection process. Among the multi-objective approaches the best performance compromise is obtained by the TOPSIS and D-TOPSIS approaches.

TABLE II
PERFORMANCE METRICS VALUES FOR EACH CONSIDERED ALGORITHM

Algorithm	$RSSI$	C	D	MC	P	H
RSSIb	-85.7433	6.5653	0.027	5.9416	0.2769	11.9026
Cb	-93.5383	11.1978	0.0256	5.9366	0.2680	6.3938
MCb	-94.8021	5.5567	0.0291	3.720	0.269	4.5663
Pb	-95.5913	5.4112	0.0296	6.0384	0.2202	4.6415
SAW	-88.3951	8.752	0.0261	5.1704	0.2639	11.8141
F-SAW	-85.7758	6.7033	0.0271	5.8946	0.2745	12.0796
WPM	-86.5028	8.1367	0.0261	5.5028	0.2704	13.4115
TOPSIS	-93.137	10.6647	0.0259	5.1205	0.2691	13.3141
D-TOPSIS	-93.137	10.6647	0.0259	5.1205	0.2691	13.3141

V. CONCLUSIONS

The execution time reduction is a fundamental requirement for the *Network Selection* algorithms in order to limit the waste of time in the overall handover process. As a consequence, the limitation of the number of operations is an important challenge in the definition of new algorithms. In this paper a new version of the well known TOPSIS algorithm, called D-TOPSIS, is presented. It requires a limited number of operations and, at the same time, converge on the same selection. The numerical results confirm the reduction of the execution time of the D-TOPSIS. Moreover the results highlight that, among the *multi-attribute* decision making algorithms for RAN selection, both TOPSIS versions assure satisfactory performance, selecting the network that represents the best compromise among the considered metrics.

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