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Conference Paper · October 2008

DOI: 10.1145/1454659.1454671 · Source: DBLP

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ABSTRACT
Current mobile terminals are often equipped with several network interfaces, which may be of different access technologies, both wireless and cellular. It is possible to select dynamically the best interface according to different attributes such as the interface characteristics, user preferences and/or application preferences … MADM is an algorithmic approach suitable to realize a dynamic interface selection with multiple alternatives (interfaces) and attributes (interface characteristics, user preferences …). In this paper, we propose the Distance to ideal Alternative (DiA) algorithm to help terminal to select dynamically the best interface and deals with the ranking abnormalities of the TOPSIS method and the ranking identification of the SAW and WP method. Simulation results in are presented to validate the DiA algorithm.

Categories and Subject Descriptors
I.5.2 [**Pattern Recognition**]: Design Methodology – *Classifier design and evaluation.*

General Terms
Algorithms, Performance, Reliability.

Keywords
Multi-interface mobile terminal, interface selection, MADM approach, decision making.

1. INTRODUCTION
The foreseen evolutions of the next generation of mobile networks are expected to be an evolution of UMTS and CDMA2000 standards, and to capitalize on a large number of wireless networks based on IEEE standards : 802.11, .15, .16, .20, .21, .22, also known as branding names Wi-Fi, WiMedia, WiMAX, Wi-MAX Mobile, Wi-RAN.

Each access technology has specific characteristics in terms of coverage area and technical characteristics (bandwidth, QoS …) and provides diverse commercial opportunities for the operators.

MobiWac'08, October 30-31, 2008, Vancouver, BC, Canada.

It seems likely that these various technologies have to coexist and, from then, solutions of integration and interoperability will be necessary to deal with the technological diversity.

Solutions of integration allow a network operator to reduce the risks of introducing a new technology and provide the users a ubiquitous access to a large range of services.

Mobile terminals are expected to have several radio interfaces providing the possibility to communicate simultaneously through the different interfaces and choose the "best" interface according to several parameters such the application characteristics, the user preferences, the networks characteristics, the operator policies, tariff constraints.

In our work, we tackle the interface selection issue where the mobile terminal equipped with several interfaces has to select at any time the best interface or the best access technology according to interface and network characteristics, user preferences, application quality of service requirements, operators' policies, etc.

Interface selection is a "decision making" problem with multiple alternatives (interfaces) and attributes (interface characteristics, user preferences …). Various approaches [1] [2] [3] [4] have been proposed for decision making and interface selection, Multiple Attribute Decision Making (MADM) is one of the most promising approach [5] [6] [7] [8].
MADM includes many methods such as SAW (Simple Additive Weighting), WP (Weighting Product) [9], and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [10]. SAW calculates the overall score of alternatives by the weighted sum of all attribute values. The overall score in WP is a product of the weighted values made across the attributes. The fundamental premise of TOPSIS is that the best alternative should have the shortest relative distance to the positive ideal solution (made up of the best value for each attribute regarding the alternatives) and the negative ideal solution (made up of the worst value of each attribute regarding the alternatives).

In this paper, we propose *the distance to ideal alternative (DiA)* algorithm belonging to the MADM category which aims to select the best interface while ensuring no ranking abnormalities, that is the removal of an alternative does not influence the ranking order of the alternatives and improving the ranking identification problem that allows to distinguish easily the alternative ranks and select the best alternative.

This paper is organized as follows. Section 2 presents background and related works to the interface selection issue; the MADM algorithms are presented and analyzed. In section 3, we present the DiA algorithm comparing to TOPSIS and SAW. Simulation results are presented in section 4 to validate the DiA approach and demonstrate that DiA outperforms MADM algorithms. Section 5 concludes this paper with further work.

2. BACKGROUND AND RELATED WORK

In cellular networks, when a mobile terminal moves away from a base station the signal level degrades and there is a need to switch to another base station. The mechanism by which an ongoing connection between the mobile terminal and its correspondent is transferred from one point of access to the fixed network to another is called handover or handoff.

Handoff techniques have been well studied and deployed in cellular systems and are of a great deal of importance in the wireless systems.

A horizontal handoff is made between two networks that use the same technology and interface. Vertical handoff occurs when the mobile terminal moves between two different networks of different technologies. In the simplest context, a vertical handover involves at least two different network interfaces.

Traditionally, the handover decision, especially in case of horizontal handovers, is made purely according to radio signal strength (RSS) thresholds and hysteresis values as input parameters. However, these parameters are not able to present the whole performance of the network.

A decision for vertical handoff which consists in choosing the "best" interface may depend on several parameters such as network conditions, application types, power requirements, terminal conditions, user preferences, security, cost and quality of service parameters.

The interface selection challenge is to determine the most favorable trade-off among all these metrics.

There are many approaches to support the interface selection.

Cost function [1] approach is based on a measurement of the cost obtained by selecting a particular interface. The interface which has the minimum cost is the best interface. The cost function is defined by the sum of some normalized form of each parameter.

In profit function-based approach, each interface is associated with a profitability function. The function defined in [2] is evaluated as the difference between a profit and a cost to select interface. The algorithm considers the input data coming from two different sources: the bandwidth gain and the handoff cost. Although, this method cannot deal with a multi-criteria interface selection, profit functions can be combined with other methods for interface selection.

The policy-based approach [3] is different from the mathematical function based approaches in the sense that, in this approach, there is no procedure to rank interfaces. The interface is selected when it matches a specific policy. A set of policies can be defined and used to describe users/applications/operators needs and rights. The decision makers have to define all possible cases (policy rules). The approach is not really dynamic for interface selection procedure.

The MADM is an algorithmic approach suitable to realize a dynamic interface selection with multiple alternatives (interfaces) and attributes (interface characteristics, user preferences …).

A MADM problem is formulated as follows:

$$A= \{A_i, i=1, 2,\dots, n\} \quad (1)$$

is a set of a finite number of alternatives which represents the possible interfaces the mobile terminal supports.

$$C= \{C_j, j=1, 2,\dots, m\} \quad (2)$$

is a set of attributes such as the interface characteristics, application characteristics or user preferences, (e.g. signal strength, bit rate, power consumption, price, coverage, delay constraints, security, …)

The weight vector w= {w_1, w2,…, wm} represents the relative importance of these attributes.

An MADM problem can be represented by a matrix as shown in Table I.

Table I. MADM matrix

	C_1 (w_1)	C_2 (w_2)	.	.	C_m (w_m)
A_1	x_{11}	x_{12}	.	.	x_{1m}
A_2	x_{21}	x_{22}	.	.	x_{2m}
.	.	.	.	.	.
.	.	.	.	.	.
A_n	x_{n1}	x_{n2}	.	.	x_{nm}

2.1 SAW

The SAW approach is probably the well-known method of MADM. In the SAW approach, the overall score of an interface is determined by the weighted sum of all attribute values. The score of each interface (or alternative) is obtained by adding the normalized contributions from each value x_{ij} multiplied by the assigned importance weight w_j. The selected interface is then:

$$SAW^* = \max_i \sum_{j=1}^{m} x_{ij} \times w_j \quad (3)$$

2.2 WP

This approach is similar to SAW but the attribute values of each interface (or alternative) are x_{ij} in power w_j and the overall score is a product of the values made across the attributes. The selected interface is then:

$$WP^* = \max_i \prod_{j=1}^{m} x_{ij}^{\,w_j} \quad (4)$$

2.3 TOPSIS

TOPSIS is an algorithm widely used for mobile terminal interface selection based on multiple attributes. The approach is based upon the concept that the chosen alternative should have the relative shortest distance to the ideal solution.

The TOPSIS alternative calculation includes several steps:

- *Step 1:* Construct the normalized decision matrix. Each element r_{ij} of the Euclidean normalized decision matrix R can be calculated as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad (5)$$

- *Step 2:* Construct the weighted normalized decision matrix. This matrix V is calculated by multiplying each column of the matrix R with its associated weight w_i.

$$V = \begin{bmatrix} v_{11} & . & . & v_{1m} \\ . & . & v_{ij} & . \\ . & . & . & . \\ v_{1n} & . & . & v_{nm} \end{bmatrix}$$

$$= \begin{bmatrix} r_{11} * w_1 & . & . & r_{1m} * w_m \\ . & . & r_{ij} * w_i & . \\ . & . & . & . \\ r_{n1} * w_1 & . & . & r_{nm} * w_m \end{bmatrix} \quad (6)$$

- *Step 3:* Determine ideal and negative-ideal solutions:

$$A^+ = \max_j v_{ij} = \left[v_1^+, v_2^+, \ldots, v_i^+, \ldots, v_m^+\right] \quad (7)$$

$$A^- = \min_j v_{ij} = \left[v_1^-, v_2^-, \ldots, v_i^-, \ldots, v_m^-\right] \quad (8)$$

- *Step 4:* The distance between alternatives are measured using the m-dimensional Euclidean distance.

The distance between each alternative and the positive ideal solution is:

$$S_j^+ = \sqrt{\sum_{i=1}^{m} (v_{ij} - v_i^+)^2} \quad (9)$$

The distance between each alternative and the negative ideal solution is:

$$S_j^- = \sqrt{\sum_{i=1}^{m} (v_{ij} - v_i^-)^2} \quad (10)$$

- *Step 5:* Calculate the relative closeness to the ideal solution:

$$C_j = \frac{S_j^-}{S_j^- + S_j^+} \quad (11)$$

- *Step 6:* Rank the preference order. A set of alternatives can now be ranked according to the decreasing order of C_j

2.4 Comparative Study of SAW, WP and TOPSIS

In [14], we presented a performance comparison of SAW, WP and TOPSIS algorithms. The comparative study allowed us to highlight and identify the limitations of each MADM algorithm influencing the decision making for interface selection.

TOPSIS suffers from "ranking abnormality" problem, SAW and WP provide less accuracy in identifying the alternative ranks.

The "ranking identification" problem in SAW happens especially when the attribute values of alternatives are not much different. The overall scores of alternatives are similar leading to confusion in the decision making as stated above.

Additionally to the "identification problem", the WP algorithm penalizes the alternatives with poor attribute values. This influences the overall score of alternative. Moreover, if some values of the constraint factor are equal to zero (e.g. the connection is free of charge), the overall score of alternative is equal to zero. In this situation, a decision can not be made.

There are many factors influencing the ranking abnormality of TOPSIS. When one of the alternatives is removed from the candidates list, the calculation of the weighted normalized decision values of V matrix (see equation 6) will change and the best and worst values for each of the attributes (see equation 7, and 8) will change also. TOPSIS calculates the m-dimensional Euclidean distance of attributes from the respective positive ideal and negative ideal values (as described in equation 9, 10).

When an alternative is removed, the Euclidean distance calculation for each alternative will be based on the new positive ideal and new negative ideal values and this distance changes non-uniformly with the alternatives. Therefore, the relative closeness to the ideal solution based on these new distance values will change non-uniformly and, as a result, the calculation of the preference order Cj (see equation 11) can provide a different ranking order than the prior one.

3. THE DiA ALGORITHM

In this section, we present the DiA algorithm which aims at selecting the best interface while ensuring no ranking abnormality problem and provide a good accuracy in identifying the alternative ranks.

To avoid the limitation of TOPSIS, DiA calculates the Manhattan distance[1] (in the m-dimensional space) to the positive and negative ideal attributes instead of the Euclidean distance in TOPSIS. This allows these distances to change uniformly when an alternative is removed out of the list of candidates. Moreover, the positive ideal alternative (PIA) which has the minimum distance to the positive ideal attribute and maximum distance to the negative ideal attribute is determined and the best "actual" alternative has the shortest distance to the PIA instead of the relative closeness to the ideal solution in TOPSIS.

The DiA algorithm is based on the following principles.

As TOPSIS, DiA determines the positive and negative ideal alternative attribute values of each attribute. These are the maximum and minimum values of attribute in each column of the MADM matrix.

$$a_i^+ = \max_j [v_{ij}] \quad (12)$$

$$a_i^- = \min_j [v_{ij}] \quad (13)$$

While TOPSIS uses the positive ideal solution values to calculate in the m-dimensional space the Euclidean distance between the solutions and the ideal solution, DiA uses the Manhattan distance to calculate the distance between the attribute values and the positive and negative ideal values of each attribute.

$$D^+{}_j = \sum_{i=1}^{m} \left| v_{ij} - a^+{}_i \right| \quad (14)$$

$$D^-{}_j = \sum_{i=1}^{m} \left| v_{ij} - a^-{}_i \right| \quad (15)$$

Then, DiA considers the minimum value of D^+ and maximum value of D^-.

[1] Manhattan distance is also known as rectilinear distance, L1 distance, or city blocks distance. It is the distance between two points measured along axes at right angles [13].

$$\min D^{+} = \min D_j^{+} = \min_j \sum_{i=1}^{m} \left| v_{ij} - a^{+}{}_i \right| \quad (16)$$

$$\max D^{-} = \max D_j^{-} = \max_j \sum_{i=1}^{m} \left| v_{ij} - a^{-}{}_i \right| \quad (17)$$

If we consider the (D^+, D^-) plane, the point ($\min D_i^+$, $\max D_i^-$) is defined as the "positive ideal alternative" (PIA) (see Figure 1).

The best alternative has the shortest distance to the PIA. This absolute distance is calculated as follow.

$$R_j = \sqrt{(D_j^{+} - \min(D^{+}))^2 + (D_j^{-} - \max(D^{-}))^2} \quad (18)$$

The alternative having the smallest R_j value has the shortest distance to the PIA.

In the following, we will show that DiA has no ranking abnormality compared to TOPSIS.

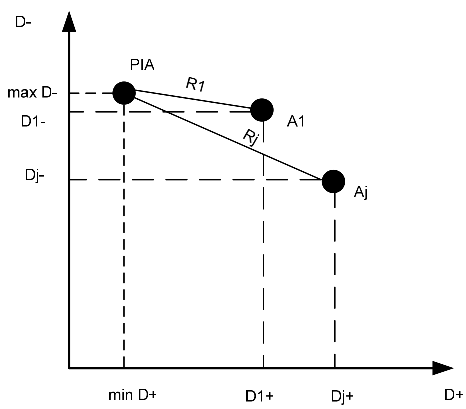

Figure 1. The D^+ , D^- plane.

If we consider a ranking order of the alternatives as follows (e.g. the best alternative is A_1 and the worst alternative is A_n)

$$A_1 > A_2 > \ldots > A_j > \ldots > A_n \quad (19)$$

We have the following distances to the PIA associated to the alternatives.

$$R_1 < \ldots < R_j < \ldots < R_n \quad (20)$$

Now, we suppose that an alternative (e.g. A_j) including one of the positive ideal attribute value (e.g. $a_k^{+(old)}$) in the k^{th} column of the MADM matrix is removed. The distances to the negative ideal attribute of alternatives D_j^- are not changed.

We can find a new positive ideal attribute value in the k^{th} column (e.g. $a_k^{+(new)}$).

The new value of the positive ideal attribute is smaller than the previous one.

$$a_k^{+(old)} > a_k^{+(new)} \quad (21)$$

The distance between the new and previous positive ideal attributes is d (where d is constant).

$$\left| a_k^{+(new)} - a_k^{+(old)} \right| = d \quad (22)$$

The Manhattan distances of all attribute values to the positive ideal attribute value in the k^{th} column before and after removing an alternative are respectively:

$$D^{+old}{}_{ik} = \left| v_{ik} - a_k^{+(old)} \right| \quad (23)$$

$$D^{+new}{}_{ik} = \left| v_{ik} - a_k^{+(new)} \right| \quad (24)$$

We have:

$$\left| D^{+new}{}_{ik} - D^{+old}{}_{ik} \right| = \left| a_k^{+(new)} - a_k^{+(old)} \right| = d \quad (25)$$

Therefore, the distance between all attribute values to the new positive ideal attributes will decrease uniformly with distance d.

$$\left| D_i^{+(new)} - D_i^{+(old)} \right| = \left| \sum_{j=1}^{m} D_{ij}^{+new} - \sum_{j=1}^{m} D_{ij}^{+old} \right|$$

$$= \left| D^{+new}{}_{ik} - D^{+old}{}_{ik} \right| = d \quad (26)$$

We can conclude also that the new minimum value of D^+ decreases uniformly also with a distance d compared to the old minimum value of D^+

$$\left| \min(D^{+(new)}) - \min(D^{+(old)}) \right| = d \quad (27)$$

Thus, the old distance to the old PIA of the alternative i (e.g. R_i^{old}) is equal to the new distance to the new PIA (new R_i^{new}).

$$R_i^{new} = \sqrt{(D_i^{+(new)} - \min(D^{+(new)}))^2 + (D_i^{-} - \max(D^{-}))^2}$$
$$= \sqrt{((D_i^{+(old)} - d) - (\min(D^{+(old)}) - d))^2 + (D_i^{-} - \max(D^{-}))^2}$$
$$= R_i^{old} \quad (28)$$

This shows that the distances to the PIA of all alternatives are unchanged ($R_1 < \ldots < R_{j+1} < \ldots < R_n$), and thus, the ranking order of alternatives is unchanged ($A_1 > A_2 > \ldots > A_{j+1} > \ldots > A_n$).

If the removed alternative includes one of negative ideal attributes, all distances D_j^- of the alternatives to negative ideal alternative will increase uniformly with the same distance. As analyzed above, the distance to the PIA is also unchanged. Therefore, the ranking order of alternatives is also unchanged

The DiA algorithm is not subject to the ranking abnormality problem and outperforms TOPSIS algorithm.

In the following, we tackle the accuracy of the alternative ranking identification and we will easily demonstrate that DiA provides better accuracy than SAW.

In SAW, the difference of ranking values between two alternatives (e.g. two alternatives A_k and A_t), is calculated as the subtraction of two overall score SAW_k and SAW_t.

$$SAW_k - SAW_t = \sum_{j=1}^{m}(x_{kj} - x_{tj}) \times w_j = \sum_{j=1}^{m}(v_{kj} - v_{tj}) \quad (29)$$

In DiA, the difference between D^+_k and D^+_t is

$$D^+{}_k - D^+_t = \sum_{i=1}^{m}(a_j^+ - v_{ik}) - \sum_{i=2}^{m}(a_j^+ - v_{ik})$$

$$D^+{}_k - D^+_t = \sum_{i=1}^{m}(v_{ik} - v_{it}) \quad (30)$$

The difference between D^-_k and D^-_t

$$D^-{}_k - D^-_t = \sum_{i=1}^{m}(v_{ik} - a_j^-) - \sum_{i=2}^{m}(v_{it} - a_j^-)$$

$$D^-{}_k - D^-_t = \sum_{i=1}^{m}(v_{ik} - v_{it}) \quad (31)$$

Then

$$\left|SAW_k - SAW_t\right| = \left|D_k^+ - D_t^+\right| = \left|D_k^- - D_t^-\right| \quad (32)$$

The difference of ranking values in DiA is the distance between two alternatives (e.g. two alternatives A_k and A_t) is calculated as follow:

$$R_{kt} = \sqrt{(D_k^+ - D_t^+)^2 + (D_k^- - D_t^-)^2}$$

$$= \sqrt{2(SAW_k - SAW_t)^2} \quad (33)$$

We have:

$$\left|R_{kt}\right| > \left|SAW_k - SAW_t\right| \quad (34)$$

Therefore, we can conclude that the difference of ranking values in DiA is larger than in SAW.

Considering WP, it is hard to prove analytically that DiA provides better accuracy than WP. However, the simulation results presented in section 4 demonstrate that DiA outperforms WP as well as SAW.

In the following, we summarize the main steps of DiA algorithm:

- *Step 1:* Construct the normalized decision matrix R. Each element r_{ij} of the Euclidean normalized decision matrix R can be calculated as equation 5.

- *Step 2:* Construct the weighted normalized decision matrix. This matrix *V* is calculated by multiplying each column of the matrix *R* with its associated weight w_i (see equation 6).

- *Step 3:* Determine positive and negative ideal attribute values of the alternatives (see equation 7, 8).

- *Step 4:* Calculate the Manhattan distance to the positive and negative attribute.

$$D^+{}_j = \sum_{i=1}^{m}\left|v_{ij} - a^+{}_i\right| \quad (35)$$

$$D^-{}_j = \sum_{i=1}^{m}\left|v_{ij} - a^-{}_i\right| \quad (36)$$

- *Step 5:* Determine the "positive ideal alternative" (PIA) which has minimum D^+, and maximum D^-.

$$PIA = \left\{\min(D_j^+), \max(D_j^-)\right\} \quad (37)$$

- *Step 6:* The distance of an alternative to the PIA is calculated as follow:

$$R_i = \sqrt{(D_i^+ - \min(D_i^+))^2 + (D_i^- - \max(D_i^-))^2} \quad (38)$$

A set of alternatives can now be ranked according to the increasing order of R_i

4. PERFORMANE COMPARISON

In this section, we present the simulation results and performance comparison of the three MADM decision algorithms: SAW, WP, TOPSIS, and DiA. The simulations are carried out using MATLAB.

In the first simulation, we calculate the overall score of SAW and WP, the relative closeness to the ideal solution of TOPSIS and the distance to the PIA of DiA. This simulation allows determining the ranking order of the algorithms related to interface characteristics and selection criteria considered in the simulation.

In the second simulation, we focus on the ranking abnormality problem. The ranking abnormality happens when the low ranking alternative is removed from the candidate list; the ranking order of the alternatives changes. A robust MADM algorithm ensures that the best alternative does not change when an alternative which is not the best is removed or replaced by another alternative. Therefore, if an algorithm suffers from the ranking abnormality problem, the ranking order is not stable.

In the third simulation, we measure the difference of the ranking values of each algorithm. In SAW and WP, the ranking values are the overall score values of alternatives.

In DiA, the distance to the PIA is the raking value of DiA.

The difference of ranking value between two alternatives corresponds to the subtraction of two ranking values. When this difference is small, it is very difficult to identify which alternative is better. This may lead confusion in the decision making. The difference of ranking values between alternatives of the algorithms allows determining the accuracy of the algorithms in identifying the alternative ranks.

In the simulation, we consider five attributes associated to five network interfaces (UMTS, 802.11b, 802.11a, 802.11n, and 4G). The attributes are: packet jitter, packet delay, utilization, packet loss, and cost per byte for each network as presented in Table II. These attributes represent two main criteria: QoS parameters and user's preferences. The attribute list can be expanded depending on the interface selection objectives.

The Packet Jitter (J): is a measure of the average delay variation within the access system. It can be measured in milliseconds.

The Packet delay (D): measures the average delay variation within the access system. It can be measured in milliseconds.

Utilization (U): is a measure of the current utilization of the access network or the wireless link. It can be expressed in percentage.

The Packet Loss (L): is a measure of the average packet loss rate within the access system over a considerable duration of time. It can be expressed in packet losses per million packets.

The Cost (CB): is the cost of the access network. (cent/byte).

Table II. The attribute parameters

	J (ms)	**D (ms)**	**U (%)**	**L (per 10^6)**	**CB (cent/ byte)**
Network #1 UMTS	50	400	10	100	100
Network #2 802.11b	25	200	20	20	20
Network #3 802.1a	15	100	20	15	10
Network #4 802.11n	30	150	40	20	5
Network #5 4G	20	100	20	15	30

The attribute values of all algorithms are normalized by the Euclidean normalization method. We choose this normalization method since it provides the highest ranking consistency [11].

In the simulation, we consider a weight vector for which the cost is significantly important compared to any QoS parameters for the candidate interface to be selected. Therefore, the cost per byte is given a very high weight.

$$w = [0.05\ \ 0.05\ \ 0.15\ \ 0.05\ \ 0.7]$$

4.1 Simulation 1

In this simulation, we calculate the ranking order of alternatives by using the SAW, WP, TOPSIS and DiA algorithms. Table III presents the overall score of SAW and WP, the relative closeness to the ideal solution of TOPSIS and the distance to PIA of DiA.

Table III. The ranking order of SAW, WP, TOPSIS, and DiA

	SAW	**WP**	**TOPSIS**	**DiA**
Network #1	0,154 Rank #5	0,923 Rank #5	0,052 Rank #5	0,987 Rank #5
Network #2	0,745 Rank #3	0,994 Rank #4	0,833 Rank #3	0,149 Rank #3
Network #3	***0,851 Rank #1***	***0,998 Rank #1***	***0,947 Rank #1***	***0 Rank #1***
Network #4	0,799 Rank #2	0,997 Rank #2	0,904 Rank #2	0,073 Rank #2
Network #5	0,734 Rank #4	0,995 Rank #3	0,748 Rank #4	0,166 Rank #4

The results show that the ranking order of the alternatives is the same for three algorithms SAW, TOPSIS and DiA. The ranking order is $Network_{\#3}$, $Network_{\#4}$, $Network_{\#2}$, $Network_{\#5}$ and $Network_{\#1}$.

The ranking order of WP is $Network_{\#3}$, $Network_{\#4}$, $Network_{\#5}$, $Network_{\#2}$ and $Network_{\#1}$.

The ranking order of WP is different from the ranking order of SAW, TOPSIS and DiA related to $Network_{\#5}$ and $Network_{\#2}$. The reason is that WP (see equation 4) penalizes the alternative having worse attributes than the other alternatives. In this situation, the ranking order of $Network_{\#2}$ is lower than $Network_{\#5}$ since $Network_{\#2}$ has poor QoS attribute values compared to $Network_{\#5}$.

However, $Network_{\#2}$ has a higher ranking order than $Network_{\#5}$ in SAW, TOPSIS and DiA.

Although $Network_{\#2}$ has poor QoS attributes, its cost with the very high weight is better than $Network_{\#5}$. WP did not make a good decision in ranking the $Network_{\#5}$ and $Network_{\#2}$ when it considers only the poor attributes.

Note that SAW, WP, TOPSIS and DiA algorithms provide the same best alternative (e.g. $Network_{\#3}$).

4.2 Simulation 2

In this simulation, we focus on the ranking abnormality problem and the "robustness" of the algorithms to removal of interfaces related to the interface ranking order.

We then remove an alternative (i.e. $Network_{\#1}$) from the alternatives candidate list. Table IV presents the overall score of SAW and WP, the relative closeness to the ideal solution of TOPSIS and the distance to PIA of DiA.

Table IV. The ranking order of SAW, WP, TOPSIS, and DiA

	SAW	**WP**	**TOPSIS**	**DiA**
Network #1	------	------	------	------
Network #2	0,455 Rank#3	0,968 Rank#4	0,397 Rank#3	0,335 Rank #3
Network #3	***0,693 Rank#1***	***0,986 Rank#1***	0,805 Rank#2	***0 Rank #1***
Network #4	0,651 Rank#2	0,984 Rank#2	***0,856 Rank#1***	0,081 Rank #2
Network #5	0,380 Rank#4	0,973 Rank#3	0,142 Rank#4	0,441 Rank #4

In this situation, the results show that a removal of an alternative causes a change in the ranking order of TOPSIS. The ranking order of SAW, WP and DiA remains the same. In particular, the top ranked alternative in TOPSIS has changed (from *Network#3* to *Network#4*).

We continue removing an alternative (i.e. *Network#5*) from the alternatives candidate list.

The results, in Table V, show that the ranking order in SAW, WP and DiA is always stable, but the top ranked alternative in TOPSIS has changed from $Network_{\#4}$ to $Network_{\#3}$.

In Table III, all algorithms determine that $Network_{\#3}$ is the best interface since it has the best QoS attribute values and the cost is not very high. $Network_{\#1}$ is the worst interface because it has the worst QoS and cost attribute values.

When we remove the worst interface (i.e. $Network_{\#1}$) out of the candidates list, this does not influence the ranking order of other interfaces of SAW, WP and DiA. However, the best interface in TOPSIS changes (i.e. from $Network_{\#4}$ to $Network_{\#4}$ in Table IV). When another worst interface (i.e. $Network_{\#5}$) is removed, the best interface in TOPSIS also changes (see Table V).

Table V. The ranking order of SAW, WP, TOPSIS, and DiA

	SAW	WP	TOPSIS	DiA
Network #1	------	------	------	------
Network #2	0,456 Rank#3	0,968 Rank#3	0,412 Rank#3	0,513 Rank#3
Network #3	***0,694 Rank#1***	***0,986 Rank#1***	***0,838 Rank#1***	***0 Rank#1***
Network #4	0,636 Rank#2	0,983 Rank#2	0,851 Rank#2	0,111 Rank#2
Network #5	------	------	------	------

The simulation results highlight the ranking abnormality problem of TOPSIS and show that SAW, WP and DiA provide a more efficient behavior in this situation.

4.3 Simulation 3

In this simulation, we compare DiA to SAW and WP by measuring the difference of ranking values of three algorithms. This difference allows distinguishing the ranking order and selecting easily the best alternative.

We consider the ranking values measured by SAW, WP and DiA in Table III to calculate the difference of ranking values.

Figures 2, 3 and 4 show the difference of ranking values of all algorithms. We measure the difference of ranking values between rank#1 and rank#2 (i.e. Diff(R1-R2) in figures 2, 3 and 4), rank#2 and rank#3 (i.e. Diff(R2-R3)), rank#3 and rank#4 (i.e. Diff(R3-R4)), and rank#4 and rank#5 (i.e. Diff(R4-R5)) of all algorithms. The results show that the difference of ranking values in SAW is larger than WP and the difference of ranking values in DiA is lager than SAW and WP.

DiA has the largest difference of ranking values and allows more accuracy in identifying the ranks between the alternatives compared to SAW and WP.

To provide results applicable to a wide range attribute values, we conduct a simulation that does not only consider the attribute values in the previous simulations.

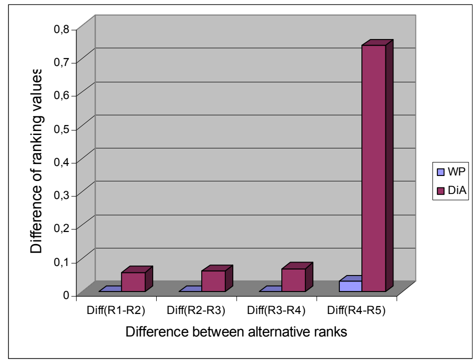

Figure 2. The difference of ranking values of WP and DiA

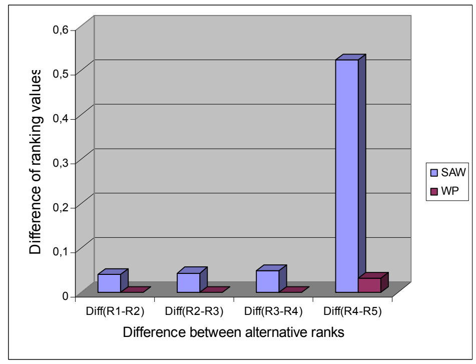

Figure 3. The difference of ranking values of WP and SAW

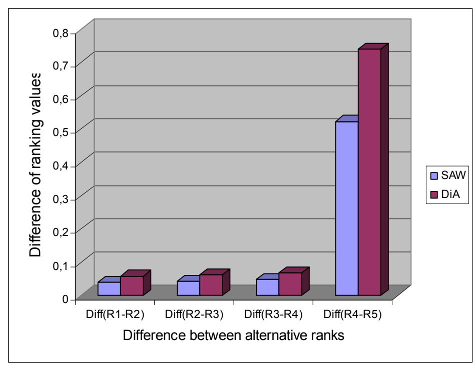

Figure 4. The difference of ranking values of SAW and DiA

The simulation generates random decision matrices with alternatives A_i (i=1,2,3,4) and attributes C_j(j=1,2,3,4). The decision matrix is normalized by using the Euclidean normalization. To obtain an unbiased result, the following settings are used in the simulation.

-10000 decision matrices are generated randomly for each simulation

-For each data range, the process was repeated 10 times and the average is noted in the final result table

-The data range for four attributes (C_1,C_2,C_2,C_4) were 1-10, 1-100,1-1000, 1-10000 respectively.

Figures 5, 6 and 7 depict the average difference of ranking values in 10000 times of simulation. The results show that the same conclusion can be made, DiA is more accurate than SAW and WP, it shows a larger difference of ranking values.

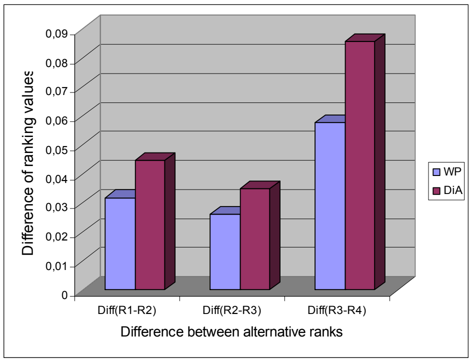

Figure 5. The difference of ranking values of WP and DiA

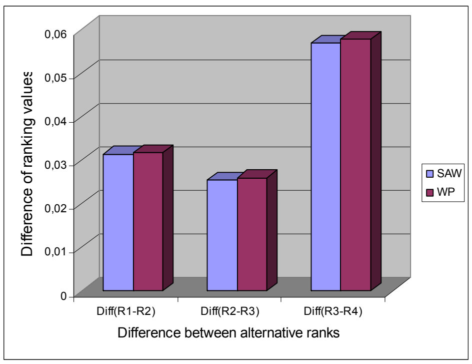

Figure 6. The difference of ranking values of SAW and WP

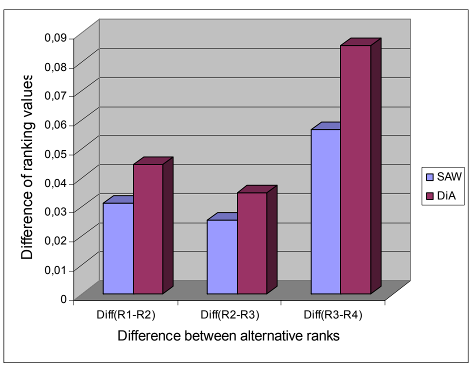

Figure 7. The difference of ranking values of SAW and DiA

5. CONCLUSION

In this paper, we propose an algorithm to select the best alternative (interface) based on multiple attributes.

Our solution improves the limits of the MADM approach, particularly SAW, WP and TOPSIS algorithms. The simulation results validated our proposal and demonstrate that DiA outperforms the ranking abnormality of TOPSIS and the difference of ranking values of SAW and WP.

DiA algorithm is implemented as part of an overall framework that we develop to allow a mobile terminal to use simultaneously multiple interfaces [12]. This allows to take advantage of fault-tolerance/redundancy, load sharing (data-striping), and interface selection capabilities provided by the multi-homing capacity of a multi-interface mobile terminal.

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