An Evidential Approach for Network Interface Selection in Heterogeneous Wireless Networks

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***Abstract*—When several networks (e.g., Wi-Fi, UMTS, and LTE) cover the same region, the mobile terminals that are equipped with multiple network interfaces provide the possibility for mobile end-users to select their believed best network. This is known as the network selection problem, which is a decision making problem with multiple criteria (network conditions, service requirements, terminal characteristics, and user needs). Many network selection solutions using different mathematical theories have been proposed in the literature to allow the best connectivity for applications, users, and terminals. Unfortunately, most approaches for the network selection do not make effective selection decisions, since they are vulnerable to the uncertainty and imprecision related to network state information. In this paper, we investigate the belief functions theory to devise an efficient lightweight uncertainty-aware network interface selection scheme. We provide analytical studies and simulation experiments to demonstrate the efficiency of the proposed solution.**

***Index Terms*—Heterogeneous Wireless Networks, Network Interface Selection, Belief functions theory.**

I. Introduction

Mobile users run different kind of services over Internet (e.g., video steaming, interactive video gaming, etc.). These services have different requirements in terms of Quality of Service (QoS). In Heterogeneous Wireless Networks (HWNs), different Radio Access Technologies (RATs) with different characteristics (e.g., UMTS, LTE-A, and WiFi) can cover the same region, and the terminals that are equipped with multiple interfaces can be always best connected by dealing with this heterogeneity, where mobile users switch among different available networks and select the one that best fulfills their needs. Being always best connected involves the selection of an optimal network that best satisfies the service needs at anytime and anywhere, known as the network selection problem.

The selection of an optimal network can be static or dynamic. Static network selection is based on filtering rules of policies set used as input in the Operating System. Dynamic network selection is the main challenge in HWNs, where the selection process depends on multiple criteria such as application requirements, terminal capacities, user needs, and network conditions. However, the network criteria are commonly dynamic and their information could be imprecisely gathered, which imposes great difficulties on network selection.

The network selection decision can be made based on the information of the parameters that have an influence on the decision making such as delay, throughput, jitter, and cost. In addition, the network selection decision can be made by the terminal in terminal-centric approaches, or by the network in network-centric approaches. Many approaches using different mathematical theories have been proposed in the literature for network selection problem including fuzzy logic, game theory, combinatorial optimization, Multi-Attribute Decision Making (MADM), Markov chain, data mining, utility theory, and Dempster-Shafer theory.

Unfortunately, most approaches for the network selection do not make effective selection decisions, since they are vulnerable to the uncertainty and imprecision related to network state information. In this paper, to deal with uncertain information, we propose a comprehensive solution for the network interface selection problem that is based on the belief functions theory. We employ belief function correction mechanisms, and use conflict-aware combination rules to deal with complex scenarios that exhibit highly conflicting beliefs. The proposed approach uses a conflict-aware combination rules such as CREC [1] in order to improve the decision making process and avoid selection of a less desirable network interface.

The main contribution of this work is the design and evaluation of an uncertainty-aware network interface selection scheme. More precisely, this paper makes the following specific contributions. First, we present a review of recent and most used methods for the network selection problem. Second, we discuss briefly the belief functions theory providing some comprehensive examples. Third, we present our uncertainty-aware network interface selection scheme. Finally, we present and discuss obtained results.

The remainder of the paper is organized as follows. Section II looks at the related work. Section III introduces the background of belief functions theory, while Section IV details our proposed solution. Experiments results are presented and discussed in Section V. Finally, Section VI concludes the paper and discusses some future directions.

II. Related work

As mentioned above, when dealing with the network interface selection problem, the imperfection associated with information must be incorporated into any interface selection scheme that aims to provide a complete and accurate solution. The representation and management of the imperfection associated with information can be done using mathematical formalisms such as fuzzy sets theory [2] in the case of imprecise data, or Probability theory [3] in the case of uncertain data.

Probability theory has been widely used to deal with uncertainty that impinges information related the network interface selection problem. In [4], the authors used a probabilistic approach for users' network selection in HWNs, which is a network-centric approach that accounts for users' mobility, the price charged, and the QoS provided by the network operator for a given radio access technology (RAT).

Authors in [5], proposed a fuzzy logic based approach as the core of the network interface selection system, where it was used to deal with imprecise information of dynamic parameters. However, the adjustment of the values of these parameters can lose precision.

In utility theory [6], the objective is to obtain the overall utility of each candidate network, and the one with the largest utility value is selected as the best. The utilities of all criteria are evaluated and adjusted by a functionality, and then combined in order to have a global utility for each candidate network. Nevertheless, the adjustment can be imprecise.

In the cost function [7], the objective is to select the network with the lowest cost, where the cost caused by the utilization of each network is computed based on its availability in the vicinity of the user. However, it is difficult to calculate the cost of some criteria.

In [8], a Markov Decision Process (MDP) based approach has been proposed for network selection problem, the goal is to optimize the network selection decisions by maximizing the overall expected reward of a connection. However, the MDP-based scheme considers a group of consecutive decisions and combines them to have one decision, which can result in a delay in the decision making.

In [9], a permutation based approach has been proposed for similar purpose, the main idea is to prioritize all candidate networks in the permutation without considering their availability. At the decision time, the best network is the first available one in the permutation. The permutation-based scheme computes the total costs of all permutations, which can cause a delay in the network selection process.

In [10], a game theory based approach has been proposed for network selection problem, the objective is to balance benefits between players, where the mobile users are the players in the game, and the transmission rates at which VoIP traffic is received are the strategies. Players in the game are seeking to maximize their gains by choosing from different strategies. The gain of each user is represented by an utility function. The utility function role is to map the wireless characteristics (e.g., loss rate and delay) into the Mean Opinion Score (MOS) which represents a measure for voice quality. The authors' conclusion was that having free users, the game can reach equilibrium close to optimal, but the equilibrium is very unfair.

In combinatorial optimization such as Knapsack model [11], the main idea is to allocate services to networks. The network selection problem is mapped to Multiple Choice Multiple Dimension Knapsack (MMKP) with multiple knapsacks problem, where services are mapped to the items, and each network is mapped to a knapsack. Also, the resource constraints of network are mapped to the resource constraints (i.e. volume) of the knapsack, and the user utility is mapped to the gain resulted by the items placed into the knapsacks. Further, the service cost in a network is mapped to the weight of an item in a knapsack, and the service utility in a network is mapped to the gain of an item in a knapsack. The objective is to maximize the total gain without exceeding the maximum volume of any of the knapsacks.

In [12], a data mining based approach has been proposed for network selection problem, where status of available interfaces, data profile (priority and quantity), and user preferences (cost, mobility, and energy) are considered in the decision making process. The k-NN algorithm extracts the parameters incoming from the application and compares them with the parameters of entries (records) in the predefined training set for all available networks in order to identify the k most similar records. The comparison can be done by calculating the Euclidean distance, where the k most similar records are those with the shortest distance. The obtained distances are weighted and arranged in descending order, then the first k weights are selected, and the vote vf is computed for each network in the set of k weights. The network with the highest value of vf is selected as the best.

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [13] is a widely adopted Multi-Attribute Decision Making (MADM) method for network interface selection. However, TOPSIS suffers from rank reversal phenomenon, e.g., if a low ranking network is disappeared or a new network is discovered, then the order of the higher-ranking networks will change abnormally, which leads to the selection of a less desirable network. Authors in [14] combined TOPSIS with utility function to tackle rank reversal problem and provide best network selection, where TOPSIS was used to rank the candidate networks based on their scores with the highest being the best, and the utility function was used to compute the normalized value of each parameter.

Although, Probability theory has been widely used, it has many limitations such as the representation epistemic uncertainty. Recently, many attempts apply the belief functions theory (BFT) to cope with complicated scenarios during network selection. Wang and LI [15] used BFT for network selection problem, where for each single parameter, all candidate networks are judged with different masses (degrees of belief), where the belief reflects the satisfactory extents for each candidate network from the view point of this specific parameter. In case of multiple-criteria, one network will have multiple judgments; one belief from the view point of each parameter. To obtain one judgment that reflects a comprehensive satisfactory rate for that network, all the masses are combined together using the Dempster's rule of combination. The candidate network with the highest combined mass is selected as the best. In [16], a BFT based approach has been proposed for similar purpose, where it was combined with Analytic Hierarchy Process (AHP). BFT was used to deal with the parameters that are unrelated to service and have an influence on the network interface selection decisions.

The above-discussed approaches have opted for a straightforward application of the BFT. They totally ignore complex scenario, such as the presence of highly conflicting beliefs, which could yield to counterintuitive results. The incompleteness of previous works motivates our research presented here. In the next sections, we summarize the key concepts of the BFT, and show how it can be wisely used to handle the network interface selection problem.

III. Brief outline of the belief functions theory

In this section, we discuss the BFT. For each relevant concept discussed, we give an example related to the interface selection problem.

A. Frame of discernment

In a BFT-based reasoning system, the frame of discernment is a fundamental concept. The BFT represents a problem domain by a set called the Frame of Discernment (FoD) Θ which is the set of possible states of the system.

$$\Theta = \{\theta_1 \ldots \theta_k \ldots \theta_N\} = \bigcup_{k=1}^{N} \{\theta_k\}$$

Θ must be exhaustive and mutually exclusive in the sense that the system is certainly in one, and only one, state $\theta_k \in \Theta$. The elements of the power set 2^Θ are called *hypotheses*.

Example 1: Let consider an interface selection problem where 3 interfaces are available, namely: WiFi, UMTS, and WiMAX. In this case, the FoD $\Theta = \{\mathrm{WiFi}, \mathrm{UMTS}, \mathrm{WiMAX}\}$.

B. Basic belief assignment

The central element of the BFT is the basic belief assignment (bba). A bba is a function m (mass function) from the power set 2^Θ to $[0, 1]$ satisfying:

$$\begin{aligned} m(\emptyset) &= 0 \\ m(A) &\geq 0, \ \forall\, A \subseteq \Theta \\ \sum_{A:A\subseteq\Theta} m(A) &= 1 \end{aligned} \tag{1}$$

The basic belief mass (*bbm*) $m(A)$ is the part of belief that supports A and does not support any strict subset of A [17]. If $m(A) > 0$, the subset $A \subseteq \Theta$ is called a *focal set* of m.

A *bbm* can be committed to either a singleton or a subset of Θ. This property makes BFT more expressive than probability theory.

Example 2: Let us return to Example 1. If the user has no preferences at all (total ignorance). This could be modeled by the following bba:

$$m(\{\mathrm{WiFi}\}) = 0,\ m(\{\mathrm{UMTS}\}) = 0,\ m(\{\mathrm{WiMAX}\}) = 0$$
$$m(\{\mathrm{WiFi}, \mathrm{UMTS}\}) = 0,\ m(\{\mathrm{UMTS}, \mathrm{WiMAX}\}) = 0,$$
$$m(\{\mathrm{WiFi}, \mathrm{WiMAX}\}) = 0,$$
$$m(\{\mathrm{WiFi}, \mathrm{UMTS}, \mathrm{WiMAX}\}) = 1$$

It is worth pointing out that the same information could be modeled using the Probabilistic theory, as follows:

$$p(\{\mathrm{WiFi}\}) = \frac{1}{3},\ p(\{\mathrm{UMTS}\}) = \frac{1}{3},\ p(\{\mathrm{WiMAX}\}) = \frac{1}{3}$$

However, if the user has the same preference for all available interfaces. This could be modeled by the following bba:

$$m(\{\mathrm{WiFi}\}) = \frac{1}{3},\ m(\{\mathrm{UMTS}\}) = \frac{1}{3},\ m(\{\mathrm{WiMAX}\}) = \frac{1}{3}$$
$$m(\{\mathrm{WiFi}, \mathrm{UMTS}\}) = 0,\ m(\{\mathrm{UMTS}, \mathrm{WiMAX}\}) = 0,$$
$$m(\{\mathrm{WiFi}, \mathrm{WiMAX}\}) = 0$$
$$m(\{\mathrm{WiFi}, \mathrm{UMTS}, \mathrm{WiMAX}\}) = 0$$

Using the Probabilistic theory for the same example, we have:

$$p(\{\mathrm{WiFi}\}) = \frac{1}{3},\ p(\{\mathrm{UMTS}\}) = \frac{1}{3},\ p(\{\mathrm{WiMAX}\}) = \frac{1}{3}$$

From the above-described example, we observe that when a bbm is committed to a subset that has more than one element, it is explicitly stating that there is not enough information to distribute this belief more precisely among the individual elements in the subset. In particular, the total belief is assigned to Θ when there is no evidence about Θ at all. In contrast, probability theory lacks this ability by dividing the total belief equally among elements of Θ (principle of Insufficient Reason). Furthermore, probability theory do not distinguish between equiprobabilities and total ignorance.

C. Belief and plausibility functions

Two other evidential functions can be used to represent an agent's belief. The belief function (Bel) represents the belief assigned to an event $A \subseteq \Theta$ given the available evidence. It is obtained by summing all the basic belief masses $m(B)$ for $B \subseteq A, B \neq \emptyset$. We have:

$$Bel(A) = \sum_{B:\emptyset\neq B\subseteq A} m(B),\ \forall A \subseteq \Theta, A \neq \emptyset \tag{2}$$

where $Bel(\emptyset) = 0$, and $Bel(\Theta) = 1$. The dual of Bel, called plausibility function Pl is defined as:

$$Pl(A) = \sum_{X\subseteq\Theta:X\cap A\neq\emptyset} m(X),\ \forall A \subseteq \Theta \tag{3}$$

The quantity Pl is thus equal to the sum of the basic belief masses assigned to propositions that are not in contradiction with A. It corresponds to the maximum degree of support that could be given to A, if further evidence becomes available.

Other functions have been defined such as the *commonality function* Q which is generally used as a technical device to simplify proofs of computational theorems. Shafer [18] showed that a one-to-one correspondence exists between mass, belief, plausibility and commonality, meaning that given any one of m, Bel, Pl or Q, the other three can be calculated. Thus, a body of evidence in any of the four forms may be called a belief function since Bel is uniquely determined and can be recovered.

Example 3: Table I shows an example of the connection between mass, belief, and plausibility functions.

TABLE I
THE CONNECTION BETWEEN MASS, BELIEF, AND PLAUSIBILITY FUNCTIONS

$A \subseteq \Theta$	$m(A)$	$Bel(A)$	$Pl(A)$
$\emptyset$	0	0	0
WiFi	0.35	0.35	0.56
UMTS	0.25	0.25	0.45
WiMAX	0.15	0.15	0.34
WiFi, UMTS	0.06	0.66	0.85
WiFi, WiMAX	0.05	0.55	0.75
UMTS, WiMAX	0.04	0.44	0.65
WiFi, UMTS, WiMAX	0.1	1.0	1.0

D. Combination

When several pieces of evidence are obtained through distinct sources (agents) over the same FoD Θ, new evidence representing the consensus of those disparate opinions can be obtained through the combination operation. Many combination rules have been proposed such as the conjunctive rule of combination (also referred to as the unnormalized Dempster's rule), the disjunctive rule of combination, Yager's rule, Inagaki's unified combination rule; Zhang's center combination rule; and Dubois and Prade's disjunctive pooling rule [19]. For instance, if m_1 and m_2 are two mass functions on Θ representing two pieces of evidence from independent sources, the conjunctive combination (denoted by $m^{\Theta}_{1 \bigcirc\!\!\!\!\cap\, 2}$) is calculated from the aggregation of m_1 and m_2 in the following manner:

$$m^{\Theta}_{1 \bigcirc\!\!\!\!\cap\, 2}(C) = \sum_{A \subseteq \Theta, B \subseteq \Theta : A \cap B = C} m_1(A) \cdot m_2(B) \quad \forall C \subseteq \Theta \quad (4)$$

Example 4: Let consider two sources of information m^{Θ}_{delay} and $m^{\Theta}_{bandwidth}$ over the same FoD Θ, where:

$$m^{\Theta}_{bandwidth}(u) = \begin{cases} 0.1 & \text{if } u = \text{WiFi}, \\ 0.3 & \text{if } u = \text{UMTS}, \\ 0.6 & \text{if } u = \text{WiMAX}, \\ 0 & \text{otherwise.} \end{cases}$$

$$m^{\Theta}_{delay}(u) = \begin{cases} 0.35 & \text{if } u = \text{WiFi}, \\ 0.5 & \text{if } u = \text{UMTS}, \\ 0.15 & \text{if } u = \text{WiMAX}, \\ 0 & \text{otherwise.} \end{cases}$$

The combination of the above mass functions using the Dempster's rule gives:

$$m^{\Theta}_{bandwidth \bigcirc\!\!\!\!\cap\, delay}(u) = \begin{cases} 0.1273 & \text{if } u = \text{WiFi}, \\ 0.5455 & \text{if } u = \text{UMTS}, \\ 0.3273 & \text{if } u = \text{WiMAX}, \\ 0 & \text{otherwise.} \end{cases}$$

E. Decision Making

The typical problem-solving scenario using the evidence theory is to gather bodies of evidence and represent them as belief functions, combine these belief functions with Dempster's rule (or other combination rules), and then select the hypothesis best supported by the combined evidence. Pignistic probability [20], Bel and Pl are the measures provided by the BFT to make the selection. For instance equation (5) shows how the pignistic transformation is computed:

$$BetP(A) = \sum_{B \subseteq \Theta} \frac{|A \cap B|}{|B|} \frac{m(B)}{1 - m(\emptyset)}, \ \forall A \subseteq \Theta \quad (5)$$

Example 5: Let us return to Example 4. To decide on the best interface to select, we could compute the maximum of the belief, the plausibility or the pignistic probability. If we consider the maximum of the pignistic probability, we have:

$$BetP(u) = \begin{cases} 0.1273 & \text{if } u = \text{WiFi}, \\ 0.5455 & \text{if } u = \text{UMTS}, \\ 0.3273 & \text{if } u = \text{WiMAX}. \end{cases}$$

Thus, we could decide that the UMTS interface is the best one.

IV. The Evidence-Based Network Interface Selection Scheme

The main idea of our proposal is to translate all interface selection-related information (network conditions, service requirements, terminal characteristics, and user needs) to mass functions. Then, combine these mass functions with a conflict-aware combination rule (such as CREC), and finally, select the best interface using a decision rule (such as the maximum of pignisitic probability). Figure 1 shows the global architecture for our evidence-based network interface selection scheme.

Some parameters such as user needs could be translated to one mass function. For instance, if the user has no preferences at all, this could be modeled by a vacuous belief function $m(\Theta) = 1$. Other parameters such as network conditions necessarily yield to several mass functions. Indeed, when considering the network conditions, the network interface selection problem is formulated as follows:

	C_1	C_2	...	C_m
	w_1	w_2	...	w_m
I_1	v_{11}	v_{12}	...	v_{1m}
I_2	v_{21}	v_{22}	...	v_{2m}
...				
I_n	v_{n1}	v_{n2}	...	v_{nm}

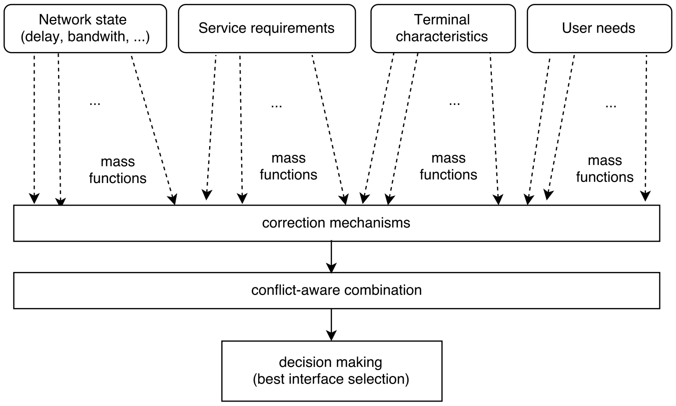

Fig. 1. Evidence-based interface selection global architecture.

where $I = \{I_i, i = 1, 2, ..., n\}$ is a set of finite number of alternatives which represents the possible interfaces that the mobile terminal supports (e.g. WiFi, UMTS, WiMAX, etc.). $C = \{C_i, i = 1, 2, ..., m\}$ is a set of attributes against which the alternatives have to be judged. The weight vector $w = \{w_i, i = 1, 2, ..., m\}$ represents the relative importance of these attributes. In the sequel, we first discuss how to translate network conditions into mass functions.

A. Step 1: Normalization

We apply the normalization procedure, for the upward criteria (e.g., throughput), the largest value is the best and the lowest value is the worst, the normalized value r_{ij} is obtained by:

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}$$

For the downward criteria (e.g., delay, loss rate, and cost), the lowest value is the best and the largest value is the worst, r_{ij} is computed as follows:

$$r_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{j=1}^{m} \frac{1}{x_{ij}}}$$

B. Step 2: Evidence construction

As the objective is to select the best interface among the possible interfaces of the mobile terminal, we define the frame of discernment (FoD) as the set $\Theta = \{I_1, I_2, ..., I_n\}$. To translate the collected and processed data into belief functions, we proceed as follows: each single attribute will be considered as an expert that will judge the available network interfaces. Therefore, a mass function m_{C_i} will be associated with each criterion C_i. The different masses attributed to the interfaces reflect the satisfactory extent from the viewpoint of this specific expert (i.e. criterion).

It is worth pointing out that if other sources of information are considered, such as terminal characteristics and user needs, mass functions will be associated also to these sources.

C. Step 3: Weighted mass functions

In practice, different applications assign different weights to the considered attributes or criteria. In contrary to all BFT-based approaches above-discussed that ignore completely this issue, we consider the weights of different criteria. For that, we exploit the discounting operation, which transfers a part of the mass to the FoD, i.e. the total ignorance.

The weight w assigned to each criterion is used to discount its corresponding belief function, i.e. to weaken the information provided by that criterion. The resulting mass function is a new *bba* denoted by m^w, defined as:

$$m^w(A) = wm(A) \text{ for } A \subset \Theta$$

$$m^w(\Theta) = (1 - w) + wm(\Theta)$$

D. Step 4: Evidence combination

One of the (hidden) assumptions of previous works mentioned in Section II is the absence of highly conflicting beliefs. In fact, these works use the original Dempster's combination rule, which produce counterintuitive results in the presence of highly conflicting beliefs. Let us consider an example of interface selection where $\Theta = \{I_1, I_2, I_3\}$. Assume that we have two mass functions, the first one m_1 is associated to criterion C_1, and the second one m_u is related to the user needs, where: $m_1(I_1) = 0.9$, $m_1(I_2) = 0.1$, and $m_u(I_2) = 0.1$, $m_u(I_3) = 0.9$. By applying the Dempster's rule, we obtain the following result: $m_{1 \circledcap u}(I_2) = 1$.

From the above example, it is clear that any decision rule will inevitably lead to the selection of interface I_2, which is quite surprising. Indeed, intuitively it is more likely that interface I_1 or I_3 get selected, but definitively not I_2 as it has the lowest belief in both mass functions. This counterintuitive result is known as the Zadeh's paradox.

In our proposed solution, we use conflict-aware combination rules such as CREC [1], Murphy's rule [21], or PCR6 [22]. Table II shows that results obtained when applying these combination rules to the previous example.

TABLE II
COMPARISON OF THE COMBINED MASS RESULTS

	Focal element		
Combination rule	I_1	I_2	I_3
CREC	0.4455	0.1090	0.4455
PCR6	0.4860	0.0280	0.4860
Murphy's	0.4880	0.0241	0.4880
Dempster's	0	1	0

Besides the Dempster's rule, all other conflict-aware rules give quite similar and intuitive result. Indeed, a low belief of interface I_2 acquires the lowest value after combination, whereas high belief values of interface I_1 and I_3 do not vanish into zero as in Dempster's rule.

The CREC rule exhibits several interesting properties such as certainty convergence [1], and it will be considered in the remainder of this paper.

E. Step 5: Decision making

As explained in Section III, different criteria could be considered for a decision rule. The main idea is to select the hypothesis best supported by the combined evidence. The maximum of the belief, the plausibility or the pignistic probability are generally considered in the literature. Let consider an example of interface selection where $\Theta = \{I_1, I_2, I_3\}$, with the following mass functions: $m_1(I_1) = 0.6$, $m_1(\Theta) = 0.4$, and $m_2(I_2) = 0.6$, $m_2(\{I_1, I_2\}) = 0.4$.

TABLE III
COMPARATIVE RESULTS FOR DECISION MAKING

	Decision criterion					
	$Bel(.)$		$Pl(.)$		$BetP(.)$	
	Interfaces					
Combination rule	I_1	I_2	I_1	I_2	I_1	I_2
CREC	0.3333	0.2756	0.7244	0.6667	0.5111	0.4533
PCR6	0.4200	0.4200	0.5800	0.5800	0.5000	0.5000
Murphy's	0.4024	0.4024	0.5976	0.5976	0.4919	0.4919
Dempster's	0.3750	0.3750	0.6250	0.6250	0.5000	0.5000

The obtained results show that excepting the CREC rule, all other combination rules cannot provide a clear decision using the maximum of one of the three criteria: credibility, plausibility, or pignistic probability. In fact, for both interfaces I_1 and I_2, we have the same values for each criterion. However, using the CREC rule, a clear and straightforward decision could be made while using any decision rule, as we have different values on the focal elements: I_1 and I_2.

V. Performance evaluation

In our simulation tool, we consider 5 types of networks (LTE, UMTS, WiMAX, 802.11b, and 802.11g) with 4 criteria defined with intervals, which represent the possible values that each network parameters could have, as illustrated in Table IV.

TABLE IV
SCENARIO 1

Networks	Delay [ms]	Loss rate [%]	Throughput [Mbps]	Cost [c/MB]
LTE	50 - 100	0 - 2	5 - 50	2 - 8
UMTS	50 - 100	0 - 2	0.5 - 2	20 - 40
WiMAX	50 - 120	0 - 2	1 - 10	2 - 5
802.11b	50 - 200	0 - 4	0.1 - 5	0 - 1
802.11g	50 - 200	0 - 4	1.5 - 8	0 - 1

We randomly generate a matrix with several networks. First, we randomly select a type of network (LTE, UMTS, etc.), then for each parameter we randomly choose a value from the corresponding interval. Table V resumes the obtained values.

Let consider the following weights associated to a particular application, w(Delay)=0.2; w(Loss rate)=0.1; w(Throughput)=0.2; and w(Cost)=0.5. By applying the above-mentioned Steps 1, 2 and 3, we obtain the mass functions shown on Table VI.

TABLE V
SCENARIO 1: PARAMETERS

Network	Delay	Loss Rate	Throughput	Cost
	ms	%	Mbps	c/MB
LTE	75	1	25	8
UMTS	52	1	2	30
WiMAX	55	1	8	4
802.11b	90	1	2	0.2
802.11g	130	2	4	1

TABLE VI
SCENARIO 1: ASSOCIATED MASS FUNCTIONS

	LTE	UMTS	WiMAX	802.11b	802.11g	Θ
m_{delay}	0.0383	0.0553	0.0522	0.0319	0.0221	0.8
m_{lossRate}	0.0222	0.0222	0.0222	0.0222	0.0111	0.9
m_{cost}	0.0039	0.0010	0.0078	0.1560	0.0312	0.8
$m_{\text{throughput}}$	0.3049	0.0244	0.0976	0.0244	0.0488	0.5

To rank the five available interfaces, we apply Steps 4 and 5. Obtained results are presented in Table VII, supported with comparisons with TOPSIS [13]. $BetP$ are obtained pignistic probabilities.

TABLE VII
SCENARIO 1: OBTAINED RESULTS

Network	Our scheme		TOPSIS [13]
	$BetP(.)$	Rank	Rank
LTE	0.2183	**1**	**1**
UMTS	0.1896	5	5
WiMAX	0.1979	3	2
802.11b	0.2035	2	3
802.11g	0.1907	4	4

For this scenario, the two approaches give quit similar results. Both approaches choose LTE as the best network interface, which offers the best performance in terms of throughput with a low cost. Furthermore, UMTS is selected as the worst, because it is very low in throughput and very high in cost. Remember that for this example, the cost is the most influential criterion on the decision making process.

In scenario 1, there is no high conflict among the mass functions. To highlight one of the advantages of our scheme, we consider more complex scenarios exhibiting medium and high conflicted mass functions, as detailed on Table VIII. It should be noted that suggested scenarios 2 and 3 are strictly hypothetical.

We run our scheme and Wang and Li [15] approach on the two scenarios 2 and 3. Obtained interfaces ranking are presented in Table IX. To ensure fair comparison, in this simulations we do not consider weights since Wang and Li [15] ignore them.

In both scenarios 2 and 3, our scheme still produces an intuitive ranking as expected. Indeed, we can easily remark that the best selected interfaces are indeed best supported with body of evidence. This is not the case for Wang and Li [15]

TABLE VIII
SCENARIOS 2 AND 3: ASSOCIATED MASS FUNCTIONS

	LTE	UMTS	WiMAX	802.11b	802.11g
			Scenario 2		
m_{delay}	0.6	0.1	0.1	0.1	0.1
m_{lossRate}	0.2	0.6	0.05	0.1	0.05
m_{cost}	0.06	0.03	0.78	0.01	0.14
$m_{\text{throughput}}$	0.2	0.7	0.05	0.04	0.01
			Scenario 3		
m_{delay}	0.5	0.25	0.24	0.005	0.005
m_{lossRate}	0.2	0.4	0.05	0.3	0.05
m_{cost}	0.1	0.1	0.1	0.6	0.1
$m_{\text{throughput}}$	0.04	0.06	0.1	0.1	0.7

TABLE IX
SCENARIOS 2 AND 3: OBTAINED RESULTS

	Scenario 2		**Scenario 3**	
Network	Our scheme	Wang and Li [15]	Our scheme	Wang and Li [15]
LTE	2	1	3	2
UMTS	1	2	4	1
WiMAX	3	3	5	3
802.11b	5	5	1	4
802.11g	4	4	2	5

scheme that produces counterintuitive result clearly visible in scenario 3.

VI. CONCLUSION AND FURTHER WORK

In this paper, a new efficient lightweight uncertainty-aware network interface selection approach was proposed. To deal with the uncertainty and imprecision related to network state information, the proposed approach is based on the belief functions theory, where network conditions, service requirements, terminal characteristics, and user needs are all translated to mass functions. Weights were considered by exploiting belief function correction mechanisms, and conflict-aware combination rules were used to handle complex scenarios. Analytical studies and simulation results show the effectiveness of the proposed method.

Our motivation for the future work is to benefit from the advantages provided by the multi-homed terminal. This latter is equipped with several interfaces; hence it becomes possible to use simultaneously the various available network interfaces and not simply to switch from one to another. We will devise a new approach for flow/interface association that uses belief functions theory to deal with uncertainty related to network state information, and considers the Quality of Experience (QoE) by making use of users' feedback in decisions process. The user may place different QoE demands on different flows. Thus, in order to ensure the best QoE, the approach should be able to dynamically distinguish data flows based on preset user's demands and feedback, and make appropriate flow/interface association accordingly in order to maximize the system performance.

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