An evidential and context-aware recommendation strategy to enhance interactions with smart spaces

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Abstract. This work describes a novel strategy implementing a context-aware recommendation system. It has been conceived to offer an intelligent selection of micro-services used to orchestrate networks of smart objects taking into account users' needs and preferences. The recommendation offering dynamically evolves depending on users' micro-service management patterns and users' context. The complete system has been designed within Dempster-Shafer evidential theory framework, ensuring uncertainty support both at context acquisition and at recommendation configuration level.

Keywords: Dempster-Shafer evidential theory; context-aware services; recommendation systems; smart spaces; smart objects

1 Introduction

The concept of *smart space* is becoming popular to describe intelligent environments able to satisfy their inhabitant needs. In brief, smart spaces can be considered as a set of coordinated smart objects coexisting in the same environment. Our previous works (e.g., [1]) address smart objects coordination in an environment where *(i)* smart objects are able to publish their capabilities and *(ii)* users may configure cooperative smart object *behaviours*. These *behaviours* are constructed and evaluated from the user's personal mobile device in the form of Event-Condition-Action (ECA) rules (e.g., 'IF *I'm approaching home* AND *no one is there* THEN *turn the heater on*'). This smart object orchestration approach empowers the user to configure his/her personal set of ECA rules, enabling the emergence of a 'shared behaviours market'. This proposal faces several challenges, some of them related to the delivery of a satisfactory user experience. In particular, in a near future, smart spaces may be densely populated by a great number of smart objects, each of them offering several capabilities and with different ways of combining them. This potential environment may overwhelm the user when trying to personalize a smart space and encourages the appearance of new techniques to filter the available information and adapt it to the user's particular needs.

Thus, this paper proposes a context-based information filtering mechanism to enhance interactions with smart spaces. It specifically proposes a novel strategy for recommending already developed *behaviours* (i.e., ECA rules) used to orchestrate networks of smart objects. Dempster-Shafer evidential theory (DSET from now on) capabilities for handling uncertainty and ignorance are exploited in order *(i)* to model user context acquisition process, *(ii)* to map user context and *behaviours* to recommend and *(iii)* to quantify *behaviours* usage patterns. A contextual update strategy is also proposed in order to dynamically adapt the recommendation offering according how the users consume those *behaviours*.

Section 2 reviews the relation between DSET and context-aware recommendation systems. An overview of DSET and how it can be exploited for recommendation purposes is the focus of Section 3. The recommendation mechanism is deeply described in Section 4 . Section 5 focuses on the contextual update of the recommendation. Finally, Section 6 analyses some preliminary validation tests and Section 7 offers some conclusions and anticipates future works.

2 Related research

Regarding the techniques for supporting recommendation, and beyond the classical differences between content-based and collaborative recommenders, the relatively new field of context-aware recommender systems is deeply covered in [3], where several techniques are mentioned for implementing model-based recommendations, i.e., predictive models for calculating the probability with which the user chooses a certain type of item in a given context (e.g., support vector machines or Bayesian classifiers). As a generalization of the Bayesian probability theory, DSET extends uncertainty support, e.g., by explicitly representing ignorance in the absence of information, by offering a simple mechanism for evidence propagation or by a limited reliance on training data [4][5]. However, it is difficult to find in the literature references to systems implementing DSET mechanisms for supporting recommendations. It is necessary to search within the decision making area in order to find researches implementing DSET-based intelligent selections mechanisms. Most of them are based on payoff matrices, built by experts, linking several states of nature to different alternatives and where the knowledge of the state of nature is captured in terms of a belief mass function (a DSET concept explained in Section 3.1) [6]. Based on this idea, our work also proposes to model the quantification of the relation between that state of nature (*context* in our case) and the alternatives (e.g., *items* to recommend) adopting the concept of evidential mappings: an extension of the DSET where belief mass functions are used to represent uncertain relationships [7]. Evidential mappings have been used for location and activity estimation (e.g., [4][5]) but, as far as we are concerned, no research has been conducted in order to exploit this technique for recommendation purposes.

3 Motivation: enhancing smart space personalization

Fig. 1 outlines a generic smart space to be personalized by means of the definition of ECA rules working on the capabilities offered by the sensors integrated into different smart objects. The user is able to deal with different kinds of entities in his/her daily life: physical objects (smart or not), services (real or virtual) and other people. Beyond dynamic context information acquired from sensors, semi-static information about the user is also available in the form of a personal profile.

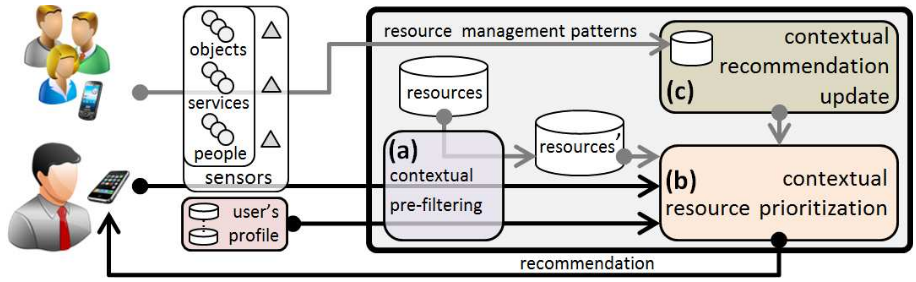


Fig. 1. Evidential recommendation service overview

Both, the information acquired from sensors and that stored in the personal profile are inputs of a recommendation system aiming at making a context-based selection of already developed ECA rules used to personalize the smart space (let denote these set of rules as 'resources'). The recommendation process involves two different phases: *(i)* a contextual pre-filtering mechanism (Fig. 1.a; not covered in this paper) implementing an intelligent selection of the resources to take part in *(ii)* a multidimensional recommender in charge of making a contextual prioritization of resources (Fig. 1.b). The relation between the user context and the resources to recommend is dynamically built and constantly updated taking into account the context of the users when manipulating (create, execute, share, delete, (de)activate, download or modify) the resources (Fig. 1.c).

Basically, the proposed system has to deal with uncertain information when handling the information acquired from sensors (inherently uncertain entities with some reliability associated [8]) and when defining the relation between context and resources to recommend (which an expert may not be unequivocally certain about). Thus, the recommendation system has been built following a DSET approach, whose capabilities for handling uncertainty and ignorance are next detailed.

3.1 Dempster-Shafer evidential theory

DSET was originally developed from Dempster's research and later completed by Shafer [9]. It offers a mathematical method for handling subjective beliefs (evidences) over a set of hypotheses $\Omega = \{h_1, h_2, \ldots, h_N\}$, called *frame of discernment*, that has to be exhaustive and with mutually exclusive elements.

Uncertainty assignation is performed in DSET by means of a *belief mass function* $m(\cdot)$. This distribution can assign evidence to any combination of elements in Ω, i.e., $m : 2^{\Omega} \rightarrow [0,1]$. It should also satisfy that $m(\emptyset) = 0$ and $\sum\limits_{\forall A_i | A_i \in 2^{\Omega}} m(A_i) = 1$.

$m(A)$, with $A \in 2^{\Omega}$, represents the proportion of all relevant and available evidence that supports the claim that the hypothesis A is true, offering no information about the evidence assigned to any subset of A. Evidence assigned to singletons constitutes more precise knowledge than evidence assigned to other subsets of Ω.

A belief mass function $m(\cdot)$ on the frame of discernment Ω generates two other set functions also defined on 2^{Ω}: *belief* $Bel(\cdot)$ and *plausibility* $Pls(\cdot)$. $Bel(\cdot)$, defined as $Bel : 2^{\Omega} \rightarrow [0,1]$, is a measure of the (total) evidence certainly assigned to a hypothesis (e.g., A). It represents our confidence that A or any subset of A is true: $Bel(A) = \sum_{\forall B_i | B_i \subseteq A} m(B_i)$. $Pls(\cdot)$ is also defined as $Pls : 2^{\Omega} \rightarrow [0,1]$. It is a measure of the evidence that could be possibly assigned to A, that is, evidence assigned to any hypothesis consistent with A (i.e., any hypotheses not contradicting A): $Pls(A) = \sum_{\forall B_i | A \cap B_i \neq \emptyset} m(B_i)$. Some authors (not everyone) interpret $Bel(\cdot)$ and $Pls(\cdot)$ functions as a kind of lower and upper bounds of a probability function (in fact, the interval between these two functions is known as *belief interval* $[Bel(\cdot), Pls(\cdot)]$).

DSET also provides a method to combine the measures of evidence from independent sources: the *Dempster's rule of combination* [10]:

$$(m_1 \otimes m_2)(A) = \frac{\sum\limits_{\forall B,C | B \cap C = A} m_1(B) \cdot m_2(C)}{1 - \sum\limits_{\forall B,C | B \cap C = \emptyset} m_1(B) \cdot m_2(C)} \tag{1}$$

3.2 Evidential mappings

Elements of different frames of discernment can be related through an *evidential mapping*, i.e., a causal link among elements of two frames in the form of mass functions. An evidential mapping Γ^* from frame Ω_E (representing known evidences) to frame Ω_H (representing hypothesis to calculate) is called a Complete Evidential Mapping (CEM) if it assigns to each subset of Ω_E a set of 'subset-mass pairs' from Ω_H (i.e., $\Gamma^*(E_i) = \{(H_1, g(E_i \rightarrow H_1)), \ldots, (H_M, g(E_i \rightarrow H_M))\}$). A deep analysis regarding evidential mappings can be found in [7]. Then, a piece of evidence on Ω_E can be propagated to Ω_H through an evidential mapping as follows:

$$m_H(H_j) = \sum_{i=1}^{M} m_E(E_i) \cdot g(E_i \rightarrow H_j) \tag{2}$$

Next Section explores how evidential mappings are exploited in order to support sensor-based context acquisition and contextual recommendation.

4 Recommendation service description

4.1 Sensors evidential modelling

In general, sensors are to be modelled by means of Γ_i^S CEM. It relates the evidences Ω_{S^i} a sensor offers over a context variable and the real status of that variable Ω_{V^i} (index i identifies each sensor). In this work sensors are considered to be evidential, i.e., they estimate reality in the form of a belief mass function $m_{S^i}(\cdot)$, that can be used in (2), together with Γ_i^S, in order to calculate $m_{V^i}(\cdot)$.

Example 1. Table 1.a exemplifies a CEM modelling the estimates obtained from a location system with 3 possible symbolic locations $\{a, b, c\}$. For instance, Γ_{loc}^S states that *'if the location sensor estimates that the user is located at "c", then the user is actually located at "b" or "c" with an evidence of 0.1 and ...'*. It is worth noting that this sensor modelling includes ignorance modelling at evidence level in the form of the belief mass assigned to combinations of the singletons within Ω_{S^i}.

(a)

	$m_{S^{loc}}$	Γ_{loc}^S	context hypotheses $\Omega_{V^{loc}}$							
			∅	a	b	c	ab	ac	bc	abc
sensor evidences $\Omega_{S^{loc}}$	0.0	∅	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	0.8	a	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.5
	0.0	b	0.0	0.1	0.6	0.0	0.1	0.0	0.0	0.2
	0.0	c	0.0	0.0	0.0	0.7	0.0	0.1	0.1	0.1
	0.0	ab	0.0	0.1	0.1	0.0	0.8	0.0	0.0	0.0
	0.0	ac	0.0	0.2	0.0	0.1	0.0	0.7	0.0	0.0
	0.0	bc	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.1
	0.2	abc	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
			↓	↓	↓	↓	↓	↓	↓	↓
		$m_{V^{loc}}$ (6)	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.6

(b)

	$m_{V^{loc}}$	Γ_{loc}^R	resource prioritization hypotheses Ω_R							
			∅	r_1	r_2	r_3	r_1r_2	r_1r_3	r_2r_3	$r_1r_2r_3$
context evidences $\Omega_{V^{loc}}$	0.0	∅	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	0.4	a	0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.1
	0.0	b	0.0	0.0	0.2	0.0	0.4	0.0	0.2	0.2
	0.0	c	0.0	0.1	0.0	0.3	0.6	0.0	0.0	0.0
	0.0	ab	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
	0.0	ac	0.0	0.0	0.3	0.0	0.3	0.3	0.0	0.1
	0.0	bc	0.0	0.0	0.0	0.1	0.0	0.0	0.9	0.0
	0.6	abc	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
			↓	↓	↓	↓	↓	↓	↓	↓
		$m_{R^{loc}}$ (6)	0.0	0.0	0.36	0.0	0.0	0.0	0.0	0.64

Table 1. Example of CEMs modelling **(a)** a location sensor and **(b)** a context-resource recommendation

4.2 Evidential decision making

Context-resource evidential mapping. An evidential decision making process, aiming at offering a context-prioritized list of resources, is also built from another set of CEMs (Γ_i^R). In this case, the evidential mapping links each context variable Ω_{V^i} modelled according a belief mass function obtained from the above mentioned sensor modelling process (m_{V^i}) with a common frame of discernment $\Omega_R = \{r_1, r_2, ..., r_N\}$ representing resources to recommend.

Once again, (2) can be used in order to calculate $m_{R^i}(\cdot)$, i.e., the partial belief mass function representing evidences regarding how to prioritize the resources taking only into account the context provided by $m_{V^i}(\cdot)$.

Example 2. Table 1.b shows Γ^R_{loc}, the CEM representing the relation between the possible locations of a user ($\Omega_{V^{loc}}$) and the resources to be prioritized (only 3 resources are considered in this example: $\{r_1, r_2, r_3\}$). For instance, it states that *'if the user is located at "c", then the resources "r_1" or "r_2" should be recommended with an evidence of 0.6 and ...'*. This example also covers ignorance modelling at mapping level, this time in the form of evidence assigned to $g(E_i \rightarrow \Omega_R) \forall i$ mappings.

Evidential fusion. At this point, partial information on how to distribute the resource recommendation taking into account different types of context (i.e., the complete set of partial $m_{R^i}(\cdot)$ belief assignment functions) is aggregated using Dempster's rule of combination (1) obtaining $m_{R^*}(\cdot)$.

Evidential prioritization strategy. $m_{R^*}(\cdot)$ can be considered as a score rating the suitability of each resource (or set of resources) taking into account the complete set of available context. Remembering the definition of belief mass function from Section 3.1, it has to be noted that the complete suitability assigned to a resource, e.g., r_i, is not included just in $m_{R^*}(\{r_i\})$, but also (partially) in the belief mass assigned to other subsets of Ω_R, e.g., in $m_{R^*}(\{r_i, r_j\})$, $m_{R^*}(\{r_i, r_j, r_k\})$, etc. $Bel(\cdot)$ and $Pls(\cdot)$ functions provide complementary approaches for calculating the complete resource recommendation suitability in the form of a belief interval $[Bel_{R^*}(\cdot), Pls_{R^*}(\cdot)]$.

Although other techniques do exist, resource recommendation has been developed in this work applying a Minimax Regret Approach (MRA) [11] to the set of belief intervals describing each resource. MRA assures optimality in a worst case scenario, being able to detect the resource that minimizes the maximum difference of expected evidence among the complete set of resources (3)(4).

$$q(r_i) = \max_{\forall j \neq i} [Pls_{R^*}(r_j)] - Bel_{R^*}(r_i) \tag{3}$$

$$Q(\Omega_R) = \arg\min_{\forall i} [q(r_i)] \tag{4}$$

The iterative algorithm in Fig. 2 exploits (3) and (4) in order to obtain an ordered ranking of resources. $\overline{Q_{R^*}}$ vector, initially empty, represents the ordered list of resources to be calculated. The algorithm iteratively applies MRA (3)(4) to Θ. Although Θ is initially composed by the complete set of resources ($\Theta = \Omega_R$), the most suitable resource calculated $Q(\Theta)$ is removed from Θ at each iteration in order to apply MRA only to the rest of resources and then iteratively calculate the recommendation order.

5 Evidential mapping contextual update

Besides acquiring user context for recommendation purposes, sensor data can be used to quantify user's patterns in resource management. This resource management information can be exploited in order to dynamically update CEMs

Input: $[Bel_{R^*}(r_i), Pls_{R^*}(r_i)]\ \forall r_i \in \Omega_R$

$\Theta = \Omega_R$
$\overline{Q_{R^*}}$ *is empty*
while $|\Theta| \neq 0$
  for all $r_i \in \Theta$
    $q(r_i) = \max_{\forall j \neq i}[Pls_{R^*}(r_i)] - Bel_{R^*}(r_i)$ (3)
  end for
  $Q(\Theta) = arg\, \min_{\forall i}[q(r_i)]$ (4)
  $\overline{Q_{R^*}} = [\overline{Q_{R^*}}, Q(\Theta)]$
  $\Theta = \Theta \backslash Q(\Theta)$
end while

Output: $\overline{Q_{R^*}}$

Fig. 2. Belief interval based recommendation algorithm

modelling context-resource mappings Γ_i^R, being then able to offer recommendations correlated with the real manipulation of resources.

Γ_i^R update is dynamically computed taking into account single user's resources management. Then, the particular behaviour of individual users regarding resource management (and his/her particular context) is used to update the global recommendation used for every user (Γ_i^R). Information regarding resource management operations is also modelled as evidential information obtained from in-device sensors installed in the user mobile device.

Matrix $\mathbb{M}_{jk}^i$ stores evidential information on how user u_i manages resource r_j at a specific moment. Individual resource management is modelled by assigning evidences over the frame of discernment covering the complete set of management operations $\Omega_L = \{l_1, ..., l_L\}$ (k index in $\mathbb{M}_{jk}^i$ is used to reference each element in 2^{Ω_L}), so $\sum_{\forall k} \mathbb{M}_{jk}^i = 1$. Each time $\mathbb{M}_{jk}^i$ is modified (i.e., each time a particular user manipulates in any sense a resource) user context would be also stored in $\mathbb{S}_{jk}^i$ matrix. $\mathbb{S}_{jk}^i$ assigns evidences over Ω_{V^j}, i.e., evidences supporting the fact that context variable V^j is in state s_k for user u_i ($\sum_{\forall k} \mathbb{S}_{jk}^i = 1$).

Then, in order to contextualize resources management, the joint (i.e., multidimensional) belief mass function $\mathbb{U}_{jkmn}^i$ is constructed using (5), assigning evidences over the product frame $\Omega_{U_m} = \Omega_L \times \Omega_{V^m}$. $\mathbb{U}_{jkmn}^i$ represents a way of quantifying how a particular management operation $k \in 2^{\Omega_L}$ over a resource r_j is distributed among the different states s_n of different context variables V^m for a given user u_i (with $\sum_{\forall k,n} \mathbb{U}_{jkmn}^i = 1$). Finally, resource management information, stored in different $\mathbb{U}_{jkmn}^i$ matrices (one per user), is aggregated using (6), also verifying that $\sum_{\forall k,n} \mathbb{U}_{jkmn}^T = 1$.

$$\mathbb{U}_{jkmn}^i = \mathbb{M}_{jk}^i \cdot \mathbb{S}_{mn}^i \tag{5}$$

$$\mathbb{U}^T_{jkmn} = \frac{1}{N_U} \sum_{\forall i} \mathbb{U}^i_{jkmn} \quad (6)$$

Γ_i^R dynamic update is performed applying the corresponding update factor α_{ijk} to each of its elements each time $\mathbb{U}^T_{jkmn}$ is modified , i.e., $g_{\Gamma_i^R}(j \to k) = \alpha_{ijk} + g'_{\Gamma_i^R}(j \to k)$, where $g'_{\Gamma_i^R}(j \to k)$ represents the value assigned to each element in Γ_i^R before recommendation update. α_{ijk} is obtained from $\mathbb{U}^T_{jkmn}$ by means of (7).

$$\alpha_{ijk} = \sum_{m=1}^{\left|2^{\Omega_L}\right|-1} x_m {\cdot} \mathbb{U}^T_{kmij} \quad (7)$$

x_m in (7) are integer values (positives or negatives) associated to each element in 2^{Ω_L}; they are used to quantify to which extend each kind of resource manipulation should make $g_{\Gamma_i^R}(j \to k)$ evolve from its previous value $g'_{\Gamma_i^R}(j \to k)$. Thus, (7) aggregates the effect of different management operations in the recommendation into a single value (α_{ijk}). It is easy to see that $\alpha_{ijk} > 0$ leads to increasing $g_{\Gamma_i^R}(j \to k)$, $\alpha_{ijk} < 0$ results in decreasing it and no update in the recommendation is obtained for $\alpha_{ijk} = 0$.

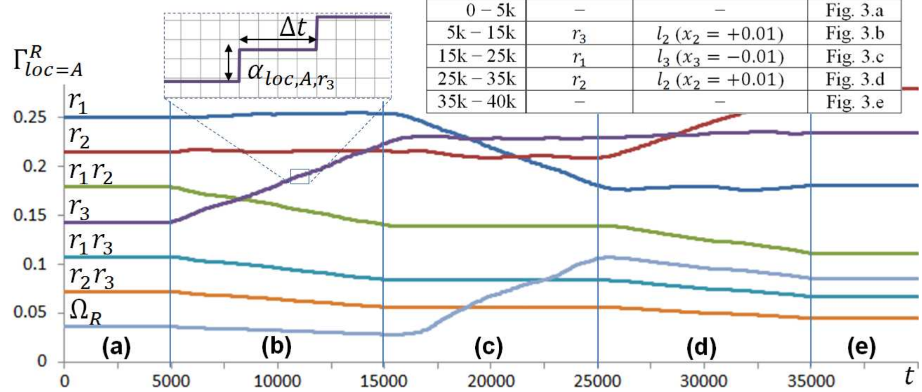
6 Recommendation update: tests and evaluations

In order to check the contextual update of the recommendation, a simulation scenario has been built. It is composed of 10 users able to perform 2 different management operations ($l_2 = \{download\}$ and $l_3 = \{delete\}$) over a set of 3 resources (i.e., 3 different ECA rules configuring each of them some kind of *behaviour* for the smart space). The recommendation is updated taking into account 2 context variables representing 7 symbolic locations and 4 temporal parts of the day (*morning*, $afternoon$, *evening* and *night*) respectively.

Starting from a random recommendation ($\Gamma_i^R; \forall i$) and contextual usage matrix ($\mathbb{U}^i_{jkmn}; \forall i$), users perform different management operations over several resources each Δt; all these operations are performed in the same context in order to test how the recommendation evolves (see Fig. 3's configuration table for simulation details).

Fig. 3.b depicts a scenario where users tend to perform operation $l_2 = \{download\}$ over resource r_3. It verifies that, for the particular context of *'being located in roomA'*, this resource increases its recommendation (i.e., $g_{\Gamma^R_{loc}}(A \to r_3)$) as $x_2 > 0$. The new mass assigned to r_3 recommendation leads to proportionally decrease the mass assigned to non-singletons values in Ω_R. A zoom is also presented in order to highlight Δt and context-dependent variable α_{ijk}. Equivalently, Fig. 3.c represents an intensive use of operation $l_3 = \{delete\}$ over r_1. As this operation has associated a negative impact on the recommendation ($x_3 < 0$), then the recommendation score associated to r_1 is decreased. In this case this decrement is compensated by increasing total ignorance (Ω_R). Fig.

3.d represents other operation-resource pair as defined in Fig. 3's configuration table. No operations are held in Fig. 3.a and Fig. 3.e.



Δt	100 seconds		
context	$V_{loc}, s_A \equiv$ '*user located in roomA*'		
user	different at each Δt ($u_1, \dots, u_{10}, u_1, \dots, u_{10}, \dots$)		
t	**resource**	**operation**	**graph**
0 – 5k	–	–	Fig. 3.a
5k – 15k	r_3	l_2 ($x_2 = +0.01$)	Fig. 3.b
15k – 25k	r_1	l_3 ($x_3 = -0.01$)	Fig. 3.c
25k – 35k	r_2	l_2 ($x_2 = +0.01$)	Fig. 3.d
35k – 40k	–	–	Fig. 3.e

Fig. 3. Recommendation update simulation configuration details and graph

7 Conclusions and future works

This paper describes a novel strategy implementing context-aware recommendations of micro-services for smart spaces personalization. Both, the phase designed to calculate micro-services priority and the one in charge of updating the recommendation according user's micro-service management patterns are supported by DSET in order to ensure uncertainty support at different levels. Simulation tests have been executed in order to functionally validate the strategy.

Some future works are already planned for enhancing the recommendation process. For example, in this work just instantaneous events are considered as possible management operations to be applied to the resources and we are already working on also being able to deal with other types of operations involving temporal durations. Besides, recommendation update for a particular management operation is quantitatively equal for any kind of context, but future extensions may consider context-dependant update factors (i.e., making x_m in (7) contextual). In a more abstract perspective it can be argue that neither context nor resources to recommend are in this work related; hierarchically modelling these entities (using semantic technologies, for instance) may lead to improvements in the recommendation [3] (e.g., instead of recommending single resources, it could be possible to recommend types of resources). Furthermore, the system presented may be considered user-context-driven in the sense that only the context of the user is the one able to modify the recommendation, but resources also have their own context (e.g., expiration date) and then new functions for modifying the recommendation may appear based on this fact. Another issue to enhance in the update recommendation process is related to the fact that it always leads in decrementing belief mass associated to combination of resources (except for total ignorance Ω_R; see r_1r_2, r_1r_3 and r_2r_3 in Fig. 3) and only a system administrator may change this tendency. Based on the idea of Shafer's partition technique [7], we are already working in a new definition of $\mathbb{M}^i_{jk}$ in order to let the system change this kind of uncertainty automatically.

Finally, we are also planning to deploy this recommendation service in a real scenario. In this sense, it would be interesting to apply it to solve other recommendation problems within the smart space domain (e.g., for supporting intelligent selection of interfaces).

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