Method for embedding context-sensitive information on "communicating textiles" via Fuzzy AHP

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Abstract. The amount of data output in our environment is increasing each day, and the development of new technologies constantly redefines how we interact with information. In the context of PLM (Product Lifecycle Management), it is not uncommon to use intelligent products to ensure an information continuum all along the product life cycle (e.g. for traceability purposes). However, it is not that easy to identify what information should be stored on the product. To answer this question, this paper proposes a data dissemination process to select context-sensitive information from the database, that must be stored/replicated on the product (especially if the product is made of "communicating material"). Our approach uses the fuzzy AHP theory for aggregating points of view from different actors. The data dissemination process is then applied on a case study to embed context-sensitive information on a "communicating textile".

Keywords: Product lifecycle management, Data dissemination, Fuzzy AHP, Decision theory, Intelligent product

1. Introduction

1.1. Intelligent products

Challenges and opportunities arise with concepts such as the Internet of Things (IoT) and ubiquitous/pervasive computing [23]. Through these concepts, real-world objects are linked with the virtual world. Thus, connections are not just people to people or people to computers, but people to things and most strikingly, things to things. During its product life cycle (PLC), a product moves through numerous companies and a variety of core business sectors. Technical, semantic and organizational interoperability between these companies is not always ensured, thereby contributing to information loss. Considering the product as an information vector (to which information can be linked) should contribute to improved interoperability throughout its PLC [12]. Research has been conducted on intelligence in objects [12,14], i.e., products that carry their own information and intelligence. These are also referred to as intelligent or communicating products. However, information is often deported through a network and these solutions do not help to identify the information that must be stored on the product. Indeed, some products are only given an identifier (e.g., via an RFID tag) that provides a network pointer to a linked database and a decision-making software agent [14]. It should be noted that these products have limitations in some respects [13]:

– *Discrete reading*: it is necessary to read a specific zone of the product,

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– *Risk of tag damage*: if the unique RFID tag is damaged, all information related to the product will therefore be lost,
– *Problem of information transfer*: when a product is transformed (e.g., cut), some resulting parts will not contain information,
– *Small memory capacity*: RFID tags currently available are memory constrained.

After many years of considering a communicating product as a physical product associated with an informational product (realized via auto-identifying technologies such as RFID), we have proposed a new paradigm, which changes drastically the way we see the material. The concept was first proposed by Thomas [18] and aims to give the ability to the material to be intrinsically and wholly communicating, as discussed in [8,9]. The powerful and futuristic idea behind this concept is to imagine that the material is communicating at the cellular/molecular level. Obviously, this vision is far from being possible today, especially due to the technological limitations, but some current research seems to be great on promises. For instance, in [9], a prototype of "communicating textile" was designed in which a huge quantity of RFID μtags is spread. Although current technologies do not allow building a "communicating material" up to the molecular level, the designing of new solutions, methods providing new services to users may be addressed. For instance, a product made of "communicating material" could have special abilities like data storage, copy/redundancy/backup information solutions.

Nonetheless, there are still some open questions. These include a specification for the information to be gathered, stored and distributed over the PLC, how information should be managed during the PLC, the linkage of new hardware and software systems with current systems [13]. To address some of these matters, this paper develops a data dissemination process to allocate information between databases and "communicating products". This process is described in the next section.

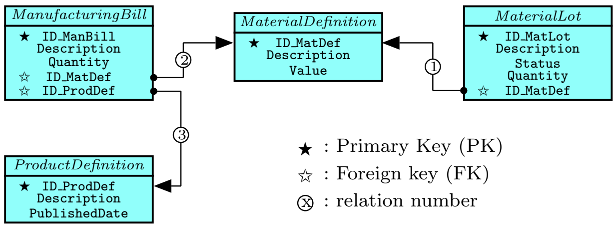
1.2. Data dissemination process

The data dissemination process proposed in this paper consists of three steps:

– Process step 1 implements the database system architecture of each actor/company taking place on the PLC. Many studies exists that can help designers to choose the most suitable systems according to their expectations and the application constraints [15],
– Process step 2 selects data appropriate to the expected situation from the database system (i.e., the data that should be stored on the product) thanks to an indicator of relevance which gives the degree to which information might be useful for the subsequent actors (e.g. manufacturers, recyclers) and activities,
– Process Step 3 deals with the storage of the data selected in the previous step on the product (made of "communicating material") and with their retrieval. In our study, we propose to use the "communicating textile" developed in [9]. When the product is read again (after having stored data on it), data retrieved from the product can be updated in the database thanks to classical protocols (e.g. synchronous/asynchronous protocols) [15].

This paper mainly focuses on Process step 2 and 3. During its life cycle, a product moves through numerous companies to various core business sectors. The information relevance is therefore dependent upon a variety of factors at each stage of the PLC such as the user concerns, the product environment, etc. An approach relying on a Logical Data Model (LDM) is developed by Chan and Roddick [2] to select context-sensitive information by formalizing the relationship between context and data. This approach assesses the relevance of all data items, from all tables. Fig. 1(a) shows a part of a LDM, where one entity corresponds to a relational table as depicted with the entity/table `MaterialDefinition` in Fig. 1(b). The attributes listed in each entity correspond to the table columns and each row is referred to as a tuple. For instance, `MaterialDefinition` has 3 attributes and 4 tuples. One data item corresponds to one table cell (*cf.* Fig. 1(b)).

The Chan and Roddick's model uses the notion of priorities which are numerical values (either supplied or generated via observation and experimentation) assigned using a multicriteria evaluation. The higher the relevance value, the higher the necessity that this data item should be stored on the product. In our context, only product-related



(a) Example of a Logical Data Model (LDM)

	1 (★)	2	3
	ID_Material	Description	Value
1	MDWP0	Wood plank with a nominal"...	$4m$ of...
2	MDP-B	Textile with a high developed...	$3mm$...
3	MD06 0.2	Textile which is provided... 0.05	15°C 0.36
4	MDH-V1	Vehicle headrests which conf...	2 × ...

This corresponds to the data item noted $T_{MD\{3,1\}}$
The relevance value of $T_{MD\{3,1\}}$ is equal to 0.2

(b) Table *MaterialDefinition* & data item relevance

Fig. 1. View of a Logical Data Model (LDM) and a relational table

information is assessed[1]. For instance, in Fig. 1(b), only tuple 3 is assessed (see dashed background) and the relevance value of the data item located at row 3, column 1, noted $T_{MD}\{3, 1\}$, is equal to 0.2. Finally, data items are classified in order of relevance (e.g. $T_{MD}\{3, 3\}$ is the most relevant with a value of 0.36). The approach proposed by Chan and Roddick has been applied in our previous work [7] but their model does not offer possibilities to take into account several opinions and may turn out to be inappropriate to our context. Indeed, at a given moment of the PLC, several experts are concerned by selecting information that must be stored on the product, therefore generating different points of view. All points of view are legitimate and must be taken into account. Accordingly, this paper proposes an approach which combines the use of the analytic hierarchy process (AHP) with the fuzzy logic. AHP enables to handle the multi-criteria decision making (MCDM) problem while fuzzy logic enables to aggregate multiple points of view.

Section 2 introduces different approaches used to handle MCDM problems and justify the use of fuzzy AHP. Section 3 details the stages that compose our fuzzy AHP method. Finally, the data dissemination process is applied on a case study in section 5 in order to embed context-sensitive information on a "communicating textile".

2. Fuzzy AHP/ANP and related work

There are a number of publications existing in the literature which use MCDM methods such as AHP (analytic hierarchy process), ANP (analytic network process), TOPSIS (technique for order preference by similarity to ideal situation), ELECTRE to solve the selection problem [5]. There are no better or worse techniques, but some techniques better suit to particular decision problems than others do [26].

AHP/ANP methods have been widely used in the literature to handle the MCDM problems [19]. These methods, originally proposed by Saaty [16], have the advantage to organize the critical aspects of the problem in a hierarchical structure, similar to a tree, thus facilitating the decision making process. In these methods, decision makers use linguistic variables rather than expressing their judgments in the form of exact numeric values, which make them usually feel more confident and facilitates the valuation process. Moreover, the use of AHP/ANP does not involve cumbersome mathematics, thus it is easy to understand and it can effectively handle both qualitative and quantitative data [26]. The ANP extends the AHP to problems with dependencies and feedback among the criteria by using a "super matrix" approach [16]. Like AHP, pairwise comparisons in ANP are performed in a matrix framework, and a local priority vector can be determined as an estimate of the relative importance of the elements being compared[2], but in the case of interrelated criteria, a network replaces the hierarchy. In this study, we make the assumption that no dependencies among criteria occur, and we therefore propose to implement the AHP method. Nonetheless, we highlight in conclusion that some interdependencies among criteria might be identified and, accordingly, the applica-

[1] An algorithm to identify all product-related tuples from the database is developed in [7].

[2] It consists in deriving weights from a pairwise comparison matrix.

tion of ANP should be examined in future work so as to compare the results with those of this paper.

Although AHP facilitates the decision making process, some shortcomings can be noted [24] such as (i) it does not take into account the uncertainty associated with the mapping of human judgment to a number, (ii) it does not integrate an aggregation mechanism to allow the expression of multiple points of view, (iii) the ranking of the AHP method is rather imprecise. To overcome these problems, several researchers integrate fuzzy theory with AHP [20].

Fuzzy set theory, introduced by Zadeh [25], mimics human reasoning in its use of approximate information to generate decisions. It was designed to mathematically represent uncertainty and vagueness and provide formalized tools for dealing with the imprecision intrinsic to many problems. This formalization is gradual rather than crisp. In a classical set $\mathcal{A}$, an element belongs entirely or not to $\mathcal{A}$. In a fuzzy set $\tilde{A}$, an element has a degree of membership in $[0, 1]$.

The earliest work in fuzzy-AHP appeared in [20] in which triangular fuzzy numbers were compared according to their membership functions. Later, [3] introduced a new approach for handling fuzzy AHP, with the use of triangular fuzzy numbers for pairwise comparison scale and the use of the extent analysis method (FEAHP). Many researchers have attempted to use and to develop fuzzy AHP for selecting and solving problems. One of the significant literature surveys is presented in [19]. Compared with the other MCDM methods, the use of fuzzy AHP methodology offers a number of benefits. Firstly, the other MCDM method experiences difficulty in capturing uncertain and imprecise judgment of experts [4]. Fuzzy AHP can overcome such inability by handling linguistic variables. Secondly, some factors are non-physical and qualitative, measuring qualitative factors by using fuzzy numbers instead of using crisp numbers helps both making decisions easier and obtaining more realistic results, therefore the fuzzy methodology is an excellent tool to handle qualitative assessments [26]. As the AHP method, fuzzy AHP has been employed in numerous sectors such as political [11], hospital [1] or still in the transportation sector [21].

Existing approaches for fuzzy AHP weight derivation can be classified into two categories:

- approaches which derive a set of fuzzy weights from a fuzzy pairwise comparison matrix,
- approaches which derive a set of crisp weights from a fuzzy pairwise comparison matrix.

Our study relies on the second category which includes the FEAHP method [3]. Since fuzzy weights are not as easy to compute as crisp ones, the literature survey made by [22] shows that the vast majority of the fuzzy AHP applications uses FEAHP for simplicity of calculation [21]. Based on this review, our attention has turn to FEAHP which is, in part, implemented and described in the next section.

3. Process step 2: Computation of data item relevances using fuzzy AHP

In our study, fuzzy AHP consists of 5 stages as depicted in Fig. 2:

1. breakdown the MCDM problem into a hierarchical structure: criteria/alternatives,
2. collection & aggregation of information to determine: i) fuzzy sets of alternatives with respect criteria, ii) the criteria importance,
3. creation of the fuzzy judgment matrix $\tilde{A}$,
4. computation of the fuzzy performance matrix $\tilde{H}$ by synthesizing $\tilde{A}$ with criteria importance,
5. alternative ranking: necessity of aggregating the alternative multi-criteria performance in a fuzzy vector $\tilde{\mathcal{R}}$ and then, to rank alternatives.

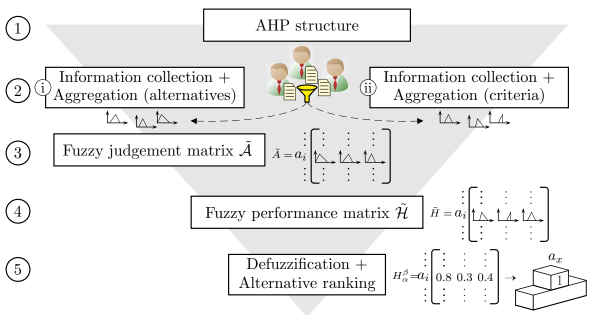


Fig. 2. Fuzzy AHP consisting of 5 stages

These five stages are respectively detailed in section 3.1 to 3.5. To make the understanding easier, a scenario is considered in the rest of the paper whose parts are preceded by the symbol "☞". This scenario relies on 19 entities which come from

Table 1
Main notations used in the paper

Notations	Description
$\mathcal{T}$	set of tables in the database. Let t be a table $\in \mathcal{T}$, a data item from t is noted $\mathrm{T}_t\{u, v\}$ where u corresponds to the row/instance and v to the column/attribute
l	alternative l (i.e. a data item l) in the AHP structure, with $l = \{1, 2, .., n\}$
C_x	abbreviation for the criterion x with $x = \{e, c, m, s\}$ (e: Enumeration, c: Contextual, s: Data Size, m: Model-based)
G_i	abbreviation for a group of entity i defined in the LDM, with $i = \{1, 2, .., Z\}$
D^p	decision maker p with $p = \{1, 2, .., p_{max}\}$; p_{max} varies according to the criterion x
$\tilde{\phi}_x(l)$	fuzzy score (i.e. triangular fuzzy number) of the alternative l with respect to criterion x
$\tilde{\phi}_c(\mathrm{G}_i)$	fuzzy score (i.e. triangular fuzzy number) representing the relative importance of group G_i over the other groups
$\tilde{\phi}(\mathrm{C}_x)$	fuzzy score (i.e. triangular fuzzy number) representing the relative importance of criterion C_x over the other criteria
$\tilde{A}$	fuzzy judgement matrix which gives all alternative fuzzy scores with respect to all criteria
$\tilde{H}$	fuzzy performance matrix synthesizing the decision matrix $\tilde{A}$ and the fuzzy weight vector $\tilde{\phi}(\mathrm{C}_x)\ \forall\ x = \{e, c, m, s\}$
H_α^β	crisp performance matrix which gives the crisp performance score of all alternatives with respect to all criteria under a degree of confidence α and a risk level β
$R_\beta^\alpha(l)$	the final crisp score which indicates the relevance of the alternative l. The higher the relevance value, the higher the necessity that the data item l should be stored on the product

the LDM of the B2MML standard[3]. Fig. 1(a) illustrates 4 of the 19 entities.

3.1. Stage 1: AHP structure

Our MCDM problem is broken down into the hierarchical structure depicted in Fig. 3. The alternatives are the data items (*cf.* level 3) which must be assessed and ranked in term of relevancy (*cf.* level 1). Four criteria are defined at level 2: *Enumeration*, *Contextual*, *Data Size* and *Model-Based* which are respectively abbreviated C_e, C_c, C_s, C_m and are detailed in stage 2 (next section).

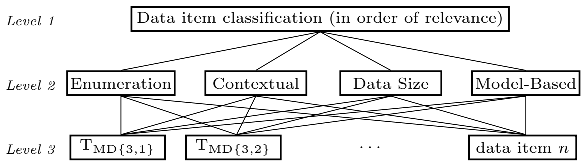


Fig. 3. General architecture of the hierarchy

3.2. Stage 2: Information collection and expert's point of view aggregation

This section details how a decision maker evaluates each alternative with respect to each criterion (C_e, C_c, C_s, C_m) and how he evaluates the criteria importance. In our study, there are $p_{\max}$ experts who give their evaluation in a criterion ($p_{\max}$ may vary according to the criterion). The main notations used in this paper are synthesized in Table 1.

3.2.1. Enumeration - C_e

Through this criterion, the user may enumerate information he judges important to store on the product. To do so, each decision maker p enumerates attributes from tables. Let t a table from the database ($t \in \mathcal{T}$) and v an attribute of t. If the attribute v is enumerated by an expert p, the crisp enumeration score $s^p(v, t) = 1$, otherwise 0, as noted in equation 1. Then, all decision makers' opinion $s^p(v, t)$ are aggregated in equation 2 through a triangular fuzzy number $\tilde{s}(v, t)$. Since an attribute corresponds to a column of a table, which in turn, consists of one or many data items, therefore, if a data item l belongs to v, its fuzzy score with respect to the criterion C_e, noted $\tilde{\phi}_e(l)$, will therefore be equal to $\tilde{s}(v, t)$.

$$s^p(v,t) = \begin{cases} 1 & \text{enumerated} \\ 0 & \text{not enumerated} \end{cases}, \ \forall\ p = \{1..p_{\max}\} \qquad (1)$$

$$\tilde{s}(v,t) = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \left[\begin{array}{ccc} \min(s^p(v)) & \frac{\sum_{p=1}^{p_{\max}} s^p(v)}{p_{\max}} & \max(s^p(v)) \end{array} \right] \end{array} \qquad (2)$$

➫ Two decision makers D^1, D^2 enumerate respectively the attributes listed in Table 2. By applying equations 1 and 2, the triangular fuzzy number of each attribute of each table t is com-

[3] B2MML is meant to be a common data format to link business enterprise applications with manufacturing enterprise applications.

puted. Let `MaterialDefinition` be the table t and `Value` be the attribute v. Table 2 shows that D^1 enumerates v (i.e. $s^1(v,t)=1$) and D^2 does not enumerate v (i.e. $s^2(v,t)=0$). $\tilde{s}(v,t)$ can therefore be computed as in equation 3.

$$\begin{array}{rl} & \quad\; L \qquad\qquad M \qquad\quad U \\ \tilde{s}(v,t) = & \left[\min(0,1) \quad \frac{0+1}{2} \quad \max(0,1)\right] \\ = & [0\ 0.5\ 1] \quad v = \texttt{Value} \in \texttt{MaterialDefinition} \end{array} \tag{3}$$

Table 2

"Table attributes" enumerated by D^p

D^p	Table Name (t)	Enumerated attributes (v)
D^1	`MaterialLot`	{`IDLot`, `Quantity`}
	`MaterialDefinition`	{`IDMatDef`, `Value`}
	`ProductSegment`	{`IDProdSeg`, `Duration`, `Unit`}
	`ProductionOrder`	{`IDProdOrd`, `StartTime`, `EndTime`}
D^2	`MaterialLot`	{`IDLot`, `Quantity`}
	`ProductSegment`	{`IDProdSeg`, `Description`}

Let us consider the data item $T_{MD}\{3,3\}$ (*cf.* Fig. 1) as the alternative l. Since $T_{MD}\{3,3\}$ belongs to the attribute `Value`, its fuzzy score with respect to C_e, noted $\tilde{\phi}_e(l)$, will therefore be equal to $\tilde{s}(v,t)=[0,0.5,1]$.

3.2.2. Contextual - C_c

The previous criterion allows users to specify information that must be stored on the product. However, they could omit important information. Indeed, they might not be aware of all the data needed by the downstream actors (along the PLC). As a result, a new criterion referred to as *contextual* - C_c is integrated in order to moderate and to balance C_e. First, let us note that a multitude of information systems exist over the PLC (e.g. ERP, PDM, MES) which are not concerned by the same data (i.e. the same entities from the LDM). The idea is to identify specific "entity groups" through the LDM according to, for instance, the information systems and, therefore, to evaluate their importance over the PLC. In our study, each decision maker p performs pairwise comparisons between entity groups as in equation 4, with z the number of groups defined trough the LDM. The importance of entity group i over entity group j evaluated by the decision maker p is noted s_{ij}^p. This evaluation is based on the 1 to 9-point scale from [17]: $\{1,3,5,7,9\}$. s_{ij}^p=1 means that groups i and j are equal in importance and s_{ij}^p=9 means that group i is strongly favored over j. Then, all crisp scores s_{ij}^p are aggregated through a triangular fuzzy number, noted $\tilde{s}_{ij}$, in equation 5. Equation 6 is finally applied in order to acquire a unique fuzzy score (triangular fuzzy number) $\tilde{\phi}_c(G_i)$ for each entity group i. $\tilde{\phi}_c(G_i)$ actually indicates the relative importance of information involves in G_i. If a data item l is contained in a table included in G_i, its fuzzy score with respect to C_c, noted $\tilde{\phi}_c(l)$, is therefore equal to $\tilde{\phi}_c(G_i)$.

$$\begin{array}{cc} & \begin{array}{ccc} G_1 & \cdots & G_z \end{array} \\ \begin{array}{c} G_1 \\ \vdots \\ G_z \end{array} & \begin{bmatrix} 1 & \cdots & s_{1z}^p \\ \vdots & \ddots & \vdots \\ s_{z1}^p & \cdots & 1 \end{bmatrix} \end{array}, s_{ji}^p = \begin{cases} s_{ij}^p & i=j \\ (s_{ij}^p)^{-1} & i \neq j \end{cases} \tag{4}$$

$$\begin{array}{rl} & \qquad L \qquad\qquad\quad M \qquad\qquad\quad U \\ \tilde{s}_{ij} = & \left[\min(s_{ij}^p) \quad \frac{\sum_{p=1}^{p_{\max}} s_{ij}^p}{p_{\max}} \quad \max(s_{ij}^p)\right] \end{array} \tag{5}$$

$$\tilde{\phi}_c(G_i) = \frac{\sum_{j=1}^{z} \tilde{s}_{ij}}{\sum_{k=1}^{z}\sum_{j=1}^{z} \tilde{s}_{kj}} \tag{6}$$

➫ In our case study, the experts cluster the 19 entities in 4 groups as detailed in Table 3. The *Equipment* and *Personal data groups* report information about equipments and persons which/who are somehow related to the product (e.g. equipments used for manufacturing it). The *Product* and *Production data groups* relate respectively information about the product composition (e.g. raw material) and operations (e.g. production rule). Two decision makers D^1, D^2 perform the pairwise comparison matrices as given in equation 7. For instance, D^1 strongly favors information from G_1 over G_2 ($s_{12}^1=9$), while D^2 favors slightly G_1 on G_2 ($s_{12}^2=3$). Therefore, the vector $\tilde{s}_{12}$ can be determined as in equation 8. All vectors $\tilde{s}_{ij}$ $\forall\ i,j=\{1,2,3,4\}$ are synthesized in equation 9. The importance value $\tilde{\phi}_c(G_i)$ of each group i is then computed as detailed with $\tilde{\phi}_c(G_1)$ in equation 10[4]. Since a triangular fuzzy set $\tilde{\phi}_c(G_i)$ represents the preference of all experts about storing on the product information belonging to G_i

[4]Let $\tilde{\mathcal{A}}=[a,b,c]$ and $\tilde{\mathcal{B}}=[d,e,f]$ be two fuzzy numbers:

- $\tilde{\mathcal{A}} \oplus \tilde{\mathcal{B}} = [a+d, b+e, c+f]$
- $\tilde{\mathcal{A}} \otimes \tilde{\mathcal{B}} = [a\times d, b\times e, c\times f]$
- $\frac{\tilde{\mathcal{A}}}{\tilde{\mathcal{B}}} = [\frac{a}{f}, \frac{b}{e}, \frac{c}{d}]$

Table 3

LDM entities grouped according to the type of information

Product data group (G_1)	Personal data group (G_2)	Production data group (G_3)	Equipment data group (G_4)
`MaterialLot`	`Person`	`ProductionOrder`	`Equipment`
`MaterialDefinition`	`PersonClass`	`ProductSegment`	`EquipmentClass`
`MaterialClass`	`ActualPersonSegment`	`ProductDefinition`	`EquipmentSegmentSpecificat`°
`ManufacturingBill`	`PersonSegmentSpecificat`°	`SegmentRequirement`	`ActualEquipmentSegment`
`ActualMaterialLot`		`SegmentResponse`	
`MaterialSegmentSpecificat`°			

then, the higher the triangular fuzzy numbers, the higher the importance/necessity. Accordingly, it can be observed that information from the entity groups G_1 and G_3 are more important compared to information from G_2 and G_4.

Let us consider $\mathrm{T}_{\mathrm{MD}}\{3,3\}$ as the alternative l. Since $\mathrm{T}_{\mathrm{MD}}\{3,3\}$ belongs to `MaterialDefinition`, which is a table included in G_1, its fuzzy score with respect to C_c, noted $\tilde{\phi}_c(l)$, will therefore be equal to $\tilde{\phi}_c(\mathrm{G}_1) = [0.29, 0.52, 0.97]$.

$$\mathrm{D}^1 = \begin{array}{c} \\ \mathrm{G}_1 \\ \mathrm{G}_2 \\ \mathrm{G}_3 \\ \mathrm{G}_4 \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{G}_1 & \mathrm{G}_2 & \mathrm{G}_3 & \mathrm{G}_4 \end{array} \\ \begin{bmatrix} 1 & 9 & 5 & 5 \\ \frac{1}{9} & 1 & \frac{1}{5} & 1 \\ \frac{1}{5} & 5 & 1 & 3 \\ \frac{1}{5} & 1 & \frac{1}{3} & 1 \end{bmatrix} \end{array}, \ \mathrm{D}^2 = \begin{bmatrix} 1 & 3 & 5 & 3 \\ \frac{1}{3} & 1 & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{5} & 3 & 1 & \frac{1}{5} \\ \frac{1}{3} & 3 & 5 & 1 \end{bmatrix} \quad (7)$$

$$\tilde{s}_{12} = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \min(9,3) & \frac{9+3}{2} & \max(9,3) \end{bmatrix} \end{array} \quad (8)$$

$$= [3\ 6\ 9]$$

$$\begin{bmatrix} [1,1,1] & [3,6,9] & [5,5,5] & [3,4,5] \\ [\frac{1}{9},\frac{2}{9},\frac{1}{3}] & [1,1,1] & [\frac{1}{5},\frac{4}{15},\frac{1}{3}] & [\frac{1}{3},\frac{2}{3},1] \\ [\frac{1}{5},\frac{1}{5},\frac{1}{5}] & [3,4,5] & [1,1,1] & [\frac{1}{5},\frac{8}{5},3] \\ [\frac{1}{5},\frac{4}{15},\frac{1}{3}] & [1,2,3] & [\frac{1}{3},\frac{8}{3},5] & [1,1,1] \end{bmatrix} \quad (9)$$

$$\tilde{\phi}_c(\mathrm{G}_1) = \frac{[1,1,1] \oplus [3,6,9] \oplus \ldots \oplus [3,4,5]}{[1,1,1] \oplus \ldots \oplus [\frac{1}{3},\frac{8}{3},5] \oplus [1,1,1]} \quad (10)$$

$$= [0.29, 0.52, 0.97]$$

$$\tilde{\phi}_c(\mathrm{G}_2) = [0.04, 0.07, 0.13]$$

$$\tilde{\phi}_c(\mathrm{G}_3) = [0.11, 0.22, 0.44]$$

$$\tilde{\phi}_c(\mathrm{G}_4) = [0.06, 0.19, 0.45]$$

3.2.3. Data Size - C_s

This criterion favors the storage of information on the product according to the data size. Since products are often memory-constrained, the data relevance should decrease when the data size increases. Such a behavior can be obtained via equation 11, with b the size in bytes of a data item l and k a constant adjusted by an expert p. Fig. 4 shows two functions according to the data size b and for two different k. It can be observed that the smaller k is, the bigger the data authorized to be stored on the product is (e.g., the expert who fixes $k = 1.08$ does not wish to store on the product data > 60 bytes).

$$k^{-b} \qquad k \in \mathbb{R}_+ \ ; b \in \mathbb{N}_+ \quad (11)$$

The coefficient k must be adjusted by each expert p as in equation 12. Then, all coefficients s_k^p are aggregated through a triangular fuzzy number, noted $\tilde{s}_k$ in equation 13. The fuzzy score of an alternative l with respect to C_s, noted $\tilde{\phi}_s(l)$, is therefore computed in equation 14.

$$s_k^p = k \quad (12)$$

$$\tilde{s}_k = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \min(s_k^p) & \frac{\sum_{p=1}^{p_{\max}} s_k^p}{p_{\max}} & \max(s_k^p) \end{bmatrix} \end{array} \quad (13)$$

$$\tilde{\phi}_s(l) = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \tilde{s}_k\,(U)^{-d} & \tilde{s}_k\,(M)^{-d} & \tilde{s}_k\,(L)^{-d} \end{bmatrix} \end{array} \quad (14)$$

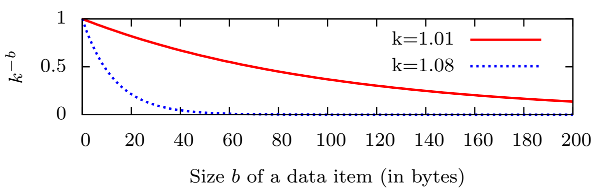


Fig. 4. Adjustment of k performed by an expert p

➫ A unique expert D^1 adjusts the coefficient k to specify if large data items are favored or not. D^1 decides to fix k at 1.08, as shown in equation 15, to get the function behavior depicted in Fig. 4. Let us consider $\mathrm{T}_{\mathrm{MD}}\{3,3\}$ as the alternative l. The fuzzy score of alternative l with respect to C_s, noted $\tilde{\phi}_s(l)$, is therefore computed via equations 16 and 17. The power value in equation 17 is equal to -4 because the size of $T_{MD}\{3,3\}$ is equal to 4 bytes (one ASCII character occupies 1 byte).

$$s_k^1 = 1.08 \tag{15}$$

$$\tilde{s}_k = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \min(1.08) & \frac{1.08}{1} & \max(1.08) \end{bmatrix} \end{array} = [1.08\ 1.08\ 1.08] \tag{16}$$

$$\tilde{\phi}_s(l) = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} 1.08^{-4} & 1.08^{-4} & 1.08^{-4} \end{bmatrix} \end{array} \tag{17}$$

3.2.4. Model-based - C_m

This criterion is based on the relationships implied through the LDM. Chan and Roddick [2] explain that the shorter the distance between tables, the higher the data correlation. In our context, the network pointer carried by the product refers to a given table of the database (i.e. from the LDM) which is called "product table". This table is at the centre of our concerns and thus, the data relevance would decrease as the modeled distance between the product table and a distant table increases. The distance corresponds to the shortest path (i.e. the number of relations which separate them). Let, for instance, `MaterialLot` be the product table in Fig. 1(a) and `ManufacturingBill` be the distant table. The distance between both tables equals 2 (relations ①-②). Once again, the expert can adjust his preference about storing distant data on the product through the same equation than previously, as detailed in equation 18 with d the distance and k a constant adjusted by the expert p.

$$k^{-d} \qquad k \in \mathbb{R}_+ \ ; \ d \in \mathbb{N}_+ \tag{18}$$

In this case, the lesser the coefficient k, the more distant information is favored. It is therefore necessary to study the entire LDM to fix k (depending on the maximal distance through the LDM). The fuzzy score of an alternative l with respect to C_m, noted $\tilde{\phi}_m(l)$, is also obtained through equations 12 to 14.

➫ Two decision makers D^1, D^2, adjust the coefficient k. Since the model is not so large (maximum distance through the LDM equals 18), they respectively fix k at 1.08 and 2 as in equation 19. Let us consider the data item $T_{MD}\{3,3\}$ as the alternative l. The fuzzy score of alternative l, noted $\tilde{\phi}_m(l)$ is obtained via equations 20 and 21. The power value in equation 21 is equal to -1 because the table containing $T_{MD}\{3,3\}$ is distant of 1 relation from the product table[5].

$$s_k^1 = 1.08 \qquad s_k^2 = 2 \tag{19}$$

$$\tilde{s}_k = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \min(1.08, 2) & \frac{1.08+2}{2} & \max(1.08, 2) \end{bmatrix} \end{array} = [1.08\ 1.09\ 2] \tag{20}$$

$$\tilde{\phi}_m(l) = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} 2^{-1} & 1.09^{-1} & 1.08^{-1} \end{bmatrix} \end{array} \tag{21}$$

3.2.5. Criteria importance

Experts specify the criteria importance via pairwise comparisons as in the Contextual criterion. Each decision maker D^p performs the pairwise comparison matrix given in equation 22. Then, all decision maker's grades are integrated in the fuzzy vector $\tilde{s}_{ij}$ in equation 23. Finally, equation 24 is applied in order to acquire a unique fuzzy score/fuzzy vector $\tilde{\phi}(C_x)$ which represent the relative importance of criterion x.

$$\begin{array}{c|cccc} & C_e & C_c & C_s & C_m \\ \hline C_e & 1 & s_{ec}^p & s_{es}^p & s_{em}^p \\ C_c & s_{ce}^p & 1 & s_{cs}^p & s_{cm}^p \\ C_s & s_{se}^p & s_{sc}^p & 1 & s_{sm}^p \\ C_m & s_{me}^p & s_{mc}^p & s_{ms}^p & 1 \end{array} \quad s_{ji}^p = \begin{cases} s_{ij}^p & i = j \\ (s_{ij}^p)^{-1} & i \neq j \end{cases} \tag{22}$$

$$\tilde{s}_{ij} = \begin{array}{c} \begin{array}{ccc} L & M & U \end{array} \\ \begin{bmatrix} \min(s_{ij}^p) & \frac{\sum_{p=1}^{p_{\max}} s_{ij}^p}{p_{\max}} & \max(s_{ij}^p) \end{bmatrix} \end{array} \tag{23}$$

$$\tilde{\phi}(C_x) = \frac{\sum_{j=\{e,c,m,s\}} \tilde{s}_{xj}}{\sum_{k=\{e,c,m,s\}} \sum_{j=\{e,c,m,s\}} \tilde{s}_{kj}} \tag{24}$$

➫ The evaluation of the importance between each criterion x is performed via pairwise comparisons but only the resulting importances (triangular fuzzy vectors) of the four criteria are given in equation 25. The results show that the criterion C_e is the most important at this moment of the PLC. In other words, the experts give freedom to the user to decide what information must be stored on the product.

[5] In our study, the network pointer carried by the product refers to `MaterialLot` which is therefore considered as the product table.

$$\tilde{\phi}(\mathrm{C}_e) = [0.41, 0.53, 0.71]\,;\tilde{\phi}(\mathrm{C}_c) = [0.21, 0.28, 0.37] \quad (25)$$

$$\tilde{\phi}(\mathrm{C}_s) = [0.07, 0.11, 0.18]\,;\tilde{\phi}(\mathrm{C}_m) = [0.05, 0.07, 0.1]$$

3.3. Stage 3: Fuzzy judgement matrix $\tilde{A}$

After getting all alternative fuzzy scores with respect to all criteria, the fuzzy judgment matrix $\tilde{A}$ is formed as in equation 26, where $\tilde{\phi}_x(l)$ denotes the fuzzy judgement score of alternative l with respect to criterion x.

$$\tilde{A} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{C}_e & \mathrm{C}_c & \mathrm{C}_s & \mathrm{C}_m \end{array} \\ \begin{bmatrix} \tilde{\phi}_e(1) & \tilde{\phi}_c(1) & \tilde{\phi}_s(1) & \tilde{\phi}_m(1) \\ \tilde{\phi}_e(2) & \tilde{\phi}_c(2) & \tilde{\phi}_s(2) & \tilde{\phi}_m(2) \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{\phi}_e(n) & \tilde{\phi}_c(n) & \tilde{\phi}_s(n) & \tilde{\phi}_m(n) \end{bmatrix} \end{array} \quad (26)$$

➫ All along the scenario considered in the previous section, the fuzzy scores of $\mathrm{T_{MD}}\{3,3\}$ with respect to C_e, C_c, C_s and C_m have been computed, which are respectively equal to:

$$\tilde{\phi}_e(\mathrm{T_{MD}}\{3,3\}) = [0, 0.5, 1]$$

$$\tilde{\phi}_c(\mathrm{T_{MD}}\{3,3\}) = [0.29, 0.52, 0.97]$$

$$\tilde{\phi}_s(\mathrm{T_{MD}}\{3,3\}) = \left[1.08^{-4}, 1.08^{-4}, 1.08^{-4}\right]$$

$$\tilde{\phi}_m(\mathrm{T_{MD}}\{3,3\}) = \left[2^{-1}, 1.09^{-1}, 1.08^{-1}\right]$$

3.4. Stage 4: Fuzzy performance matrix $\tilde{H}$

At this stage, only fuzzy scores of alternatives with respect to criteria are taken into account, without considering the relative importance of criteria. As a result, we synthesize the fuzzy matrix $\tilde{A}$ with the criteria importance in a fuzzy performance matrix $\tilde{H}$. The fuzzy performance score $\tilde{h}_x(l)$ consists in multiplying the fuzzy set $\tilde{\phi}_x(l)$ by the criterion importance itself $\tilde{\phi}(\mathrm{C}_x)$ as in equation 27. Finally, the fuzzy performance matrix $\tilde{H}$ is obtained as depicted in equation 28.

$$\tilde{h}_x(l) = \tilde{\phi}_x(l) \otimes \tilde{\phi}(\mathrm{C}_x) \quad (27)$$

$$\tilde{H} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{C}_e & \mathrm{C}_c & \mathrm{C}_s & \mathrm{C}_m \end{array} \\ \begin{bmatrix} \tilde{h}_e(1) & \tilde{h}_c(1) & \tilde{h}_s(1) & \tilde{h}_m(1) \\ \tilde{h}_e(2) & \tilde{h}_c(2) & \tilde{h}_s(2) & \tilde{h}_m(2) \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{h}_e(n) & \tilde{h}_c(n) & \tilde{h}_s(n) & \tilde{h}_m(n) \end{bmatrix} \end{array} \quad (28)$$

➫ The equation 29 details the calculations of $\tilde{h}_e(\mathrm{T_{MD}}\{3,3\})$ and $\tilde{h}_c(\mathrm{T_{MD}}\{3,3\})$.

$$\begin{aligned} \tilde{h}_e(\mathrm{T_{MD}}\{3,3\}) &= \tilde{\phi}_e(\mathrm{T_{MD}}\{3,3\}) \otimes \tilde{\phi}(\mathrm{C}_e) \quad (29) \\ &= [0, 0.5, 1] \otimes [0.41, 0.53, 0.71] \\ &= [0, 0.265, 0.71] \\ \tilde{h}_c(\mathrm{T_{MD}}\{3,3\}) &= \tilde{\phi}_c(\mathrm{T_{MD}}\{3,3\}) \otimes \tilde{\phi}(\mathrm{C}_c) \\ &= [0.29, 0.52, 0.97] \otimes [0.21, 0.28, 0.37] \\ &= [0.061, 0.146, 0.359] \end{aligned}$$

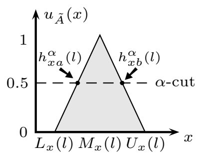
3.5. Stage 5: Defuzzification/Alternative ranking

This stage aims at ranking alternatives according to their fuzzy sets. To do so, defuzzification is first applied to transform each fuzzy set into a crisp value. Then, alternatives are ranked by considering the crisp values based on the TOPSIS method [6]. Defuzzification and TOPSIS methods are respectively presented in section 3.5.1 and 3.5.2.

3.5.1. Defuzzification step

Defuzzification is executed (i) by using the α-cut method on the fuzzy performance matrix $\tilde{H}$ and (ii) by taking into account the risk index β to compute the crisp performance matrix H^{α}_{β}.

i. The α-cut level of an alternative l, noted $h^{\alpha}_{x}(l)$, is computed via equations 14 to 16. $h^{\alpha}_{xa}(l)$ and $h^{\alpha}_{xb}(l)$ denotes respectively the left and right point of the level of the triangle as shown in Fig. 5 ($0 \leq \alpha \leq 1$). The α-cut value reflects the degree of confidence of the decision makers when they subjectively evaluate alternative and criteria scores for the MCDM problem. If decision makers set up a high degree of confidence, it means that they have gathered enough knowledge to support their decisions.



$$h^{\alpha}_{xa}(l) = L_x(l) + \alpha\left(M_x(l) - L_x(l)\right) \quad (14)$$

$$h^{\alpha}_{xb}(l) = U_x(l) - \alpha\left(U_x(l) - M_x(l)\right) \quad (15)$$

$$h^{\alpha}_{x}(l) = [h^{\alpha}_{xa}(l) \;\; h^{\alpha}_{xb}(l)] \quad (16)$$

Fig. 5. α-cut on each fuzzy performance score $\tilde{h}_{lx}$

ii. In our approach, the risk index β is applied as a defuzzifier. The crisp performance matrix H^{α}_{β} is calculated in equation 18 based on equation 17, where $h^{\alpha}_{x\beta}(l)$ denotes the crisp performance score of alternative l with respect to the criterion C_x under a degree of confidence α and a risk level β. In equation 17, when β continuously increases, the crisp performance score progressively approaches the left point of the interval. A risk index $\beta = \{0, 0.5, 1\}$ respectively indicates an optimistic, moderate and pessimistic viewpoint of the decision maker choice.

$$h^{\alpha}_{x\beta}(l) = \beta h^{\alpha}_{xa}(l) + (1-\beta) \times h^{\alpha}_{xb}(l) \tag{17}$$

$$H^{\alpha}_{\beta} = \begin{array}{c c} & \begin{array}{cccc} C_e & C_c & C_m & C_s \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_n \end{array} & \begin{bmatrix} h^{\alpha}_{e\beta}(1) & h^{\alpha}_{c\beta}(1) & h^{\alpha}_{m\beta}(1) & h^{\alpha}_{s\beta}(1) \\ h^{\alpha}_{e\beta}(2) & h^{\alpha}_{c\beta}(2) & h^{\alpha}_{m\beta}(2) & h^{\alpha}_{s\beta}(2) \\ \vdots & \vdots & \vdots & \vdots \\ h^{\alpha}_{e\beta}(n) & h^{\alpha}_{c\beta}(3) & h^{\alpha}_{m\beta}(n) & h^{\alpha}_{s\beta}(n) \end{bmatrix} \end{array} \tag{18}$$

3.5.2. Alternative ranking

In TOPSIS, the ideal solution $h^{\alpha+}_{x\beta}$ and the negative ideal solution $h^{\alpha-}_{x\beta}$ are respectively defined as the best and the worst crisp performance scores among all alternatives on a criterion, as specified in equation 19. Subsequently, the distance between the ideal and the negative ideal solution for each alternative is respectively calculated in equations 20 and 21, where $S^{\alpha+}_{\beta}(l)$ and $S^{\alpha-}_{\beta}(l)$ represent the distances between the crisp performance scores $h^{\alpha}_{x\beta}(l)$ of an alternative l with respect to all criteria C_x and all the ideal and negative ideal solutions $h^{\alpha+}_{x\beta}$, $h^{\alpha-}_{x\beta}$, respectively.

$$h^{\alpha+}_{x\beta} = \max_{l=1..n}\left(h^{\alpha}_{x\beta}(l)\right) \quad h^{\alpha-}_{x\beta} = \min_{l=1..n}\left(h^{\alpha}_{x\beta}(l)\right) \tag{19}$$

$$S^{\alpha+}_{\beta}(l) = \sqrt{\sum_x \left(h^{\alpha}_{x\beta}(l) - h^{\alpha+}_{x\beta}\right)^2} \quad l = 1, 2, .., n \tag{20}$$

$$S^{\alpha-}_{\beta}(l) = \sqrt{\sum_x \left(h^{\alpha}_{x\beta}(l) - h^{\alpha-}_{x\beta}\right)^2} \quad l = 1, 2, .., n \tag{21}$$

A prior alternative has a longer distance to the negative ideal solution and a shorter distance to the ideal solution. Consequently, the relative closeness to the ideal solution for each alternative can be formulated as in equation 22, where $R^{\alpha}_{\beta}(l)$ denotes the final performance score. The larger the score $R^{\alpha}_{\beta}(l)$, the more relevant the alternative l. All alternatives/data items can therefore be ranked from the more relevant to the less relevant.

$$R^{\alpha}_{\beta}(l) = \frac{S^{\alpha-}_{\beta}(l)}{S^{\alpha+}_{\beta}(l) + S^{\alpha-}_{\beta}(l)} \quad l = 1, 2, .., n \tag{22}$$

3.6. Synthesis

In resume, when the machine/operator needs to store data on the product, the relevance of each data item from the database is computed thanks to the fuzzy AHP method. Data items are then ranked in order of relevance and information of the highest relevance/importance is therefore stored on the product thanks to the process step 3 which is detailed in the next section

4. Data item storage/retrieval using "communicating materials": Process step 3

As mentioned in the introduction, a prototype of a "communicating textile" was designed in our previous work [9], throughout which a large quantity of RFID μtags are spread (up to 1500μtags/m^2). This "communicating textile" is shown in Fig. 6. In this section, an appropriate architecture combined with a protocol of communication is developed to disseminate data items all over the material and then, to retrieve them.

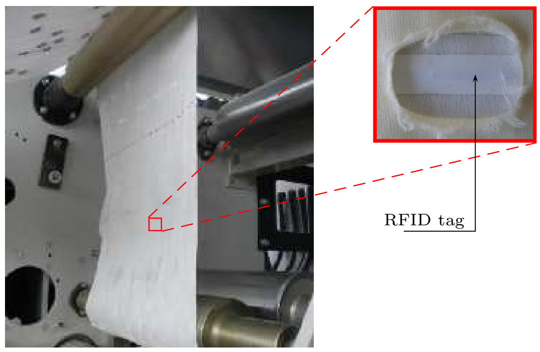


Fig. 6. Prototype "communicating textile" designed in [9]

As the RFID tags are memory-constrained, the idea is to split the set of data items among several tags. Fig. 7 depicts the architecture that must be implemented for storing the list of data items (identified thanks to process step 2) all over the "communicating textile" (split thanks to process step 3). A specific application protocol, named *splitting protocol*, is developed in [10] to split the data items. Indeed, a RFID tag may store more or less information according to the technology and, therefore, one data item may require more memory space than that available in a unique tag. This header enables to know in what order data items have been split.

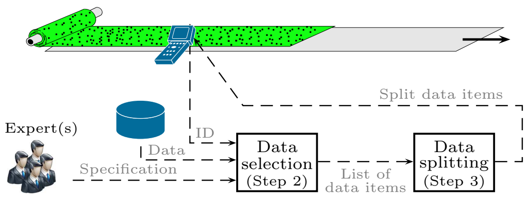


Fig. 7. Global communication architecture

The next section presents the case study in which process step 2 (fuzzy AHP method) and process step 3 are applied so as to disseminate relevant information over the "communicating textile".

5. Case study: Dissemination of information using a "communicating textile"

All along section 3, we detailed the set of computations needed to determine the fuzzy performance matrix $\tilde{H}$ (see equations 28 and 29). Then, H^{α}_{β} and $R^{\alpha}_{\beta}(l)$ are calculated based respectively on equations 17-18 and equations 19 to 22 with $\alpha = 0.85$ (decision makers judge they have gathered enough knowledge to overcome uncertainty in their evaluations) and $\beta = 0.2$ (reasonable to match the real situation). Let us remind ourselves that the higher the final score $R^{\alpha}_{\beta}(l)$, the more relevant the data item l. The results about the relevance $R^{\alpha}_{\beta}(l)$ of all data items (i.e. alternatives) are commented in section 5.1. Section 5.2 gives insight into the way data items are split on the "communicating textile" and then, rebuilt when reading.

5.1. Results about data relevance: Process step 2

Fig. 8(a) provides the resulting *list* of data items (which are product related data items) ordered from the highest relevant $R^{\alpha}_{\beta}(l)$ to the smallest. The two more relevant data items come from `MaterialLot` ($R^{\alpha}_{\beta}(l) = 0.8232$ and 0.6524) and the 3^{rd} is $\mathrm{T_{MD}}\{3,3\}$. Due to the large amount of data items included in the *list* (225 alternatives), the results are presented in the form of diagrams (whisker diagram and pie chart).

First, let us look at the whisker diagram in Fig. 8(b). For each table $t \in \mathcal{T}$ is given the min, the 1^{st}-3^{rd} quartile, the median and the max $R^{\alpha}_{\beta}(l)$ of the set of data items included in the *list* and belonging to t. We can see that the most relevant data items come from `MaterialLot` (which includes the two first data items of the *list*), but also from `MaterialDefinition`, `ProductSegment` and `ProductionOrder`. This is due to the fact that attributes from these four tables have been enumerated by the decision makers (*cf.* Table 2). We can see that D^1 and D^2 enumerate the same two attributes in `MaterialLot`, which explains why this table stands out among the other tables. Moreover, note that these four tables are included in G1 and G3 and that the experts, concerned by C_c, have highly recommended to select information from both groups (*cf.* vectors in equation 10).

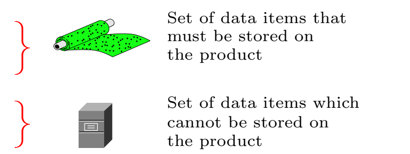
In our scenario, it is not possible to embed more than the first 155 data items from the *list* because the product memory is limited (as highlighted in Fig. 8(a)). The pie chart in Fig. 8(c) shows the percentage of data items among the 155 which belong to each entity group. We can observe that 49% (i.e. $\approx$ 75 data items out of 155) are included in tables clustered in G3 and 38% in tables clustered in G1. This is largely due to the choices made in the enumeration and contextual criteria as explained previously. In this respect, these results meet the expert specifications. The *list*, the whisker diagram and the pie chart are displayed to the user and can be used as decision-support tools. The last step consists in storing the first 155 data items on the product thanks to the process step 3 which is the subject of the following section.

5.2. Data Storage and retrieval: Process step 3

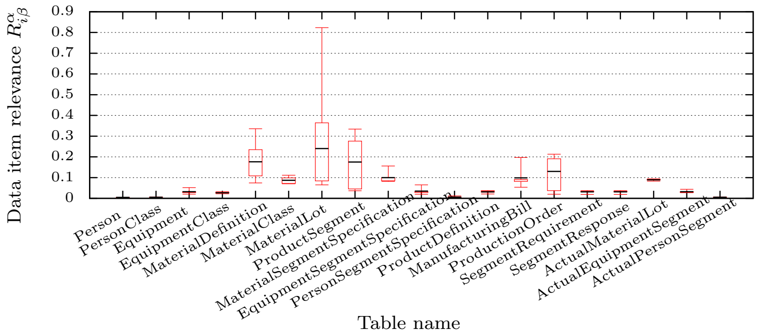
In our case study, the "communicating textile" designed in [9] (see Fig. 6) is used to store the first 155 data items from the *list*. Only two data items from the table `MaterialDefinition` must be stored on the product, namely $\mathrm{T_{MD}}\{3,1\}$ and $\mathrm{T_{MD}}\{3,3\}$ as shown in Fig. 9, because $\mathrm{T_{MD}}\{3,2\}$ got the 199^{th} rank (i.e. > 155). Fig. 9 exemplified the splitting process of these two data items in addition to the remaining 153 others, where the protocol header developed in [10] is added to each resulting piece of data item (gray background). These pieces of data items can therefore be stored/disseminated among the RFID tags.

The "communicating textile" continues its life cycle, and let us assume that a downstream user read the information carried by that one. The 155 data items stored in the "communicating textile" are retrieved, rebuilt, and then displayed

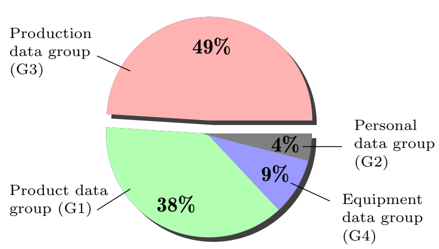
Rang l	Table Name	Attribute Name	Primary Key	Cell Value	$R^{\alpha}_{\beta}(l)$
1^{st}	MaterialLot	Quantity	LPB61	50	0.8232
2^{th}	MaterialLot	IDMaterialLot	LPB61	LPB61	0.6524
3^{rd}	MaterialDefinition	Value	MD06	15°C	0.3639
...	...			...	...
		Product storage limit: 155^{th}			
...	...			...	...
224^{th}	EquipmentClass	Description	ECBSM01	Bonding machi...	0.0036
225^{th}	PersonClass	Description	PCPLW01	Worker Line...	0.0029



(a) List of data items ordered from the highest relevant to the smallest. The relevance of the data item l is given by $R^{\alpha}_{i\beta}$.



(b) Result of the data item's relevance in a whisker diagram



(c) Result in form of a pie chart

Fig. 8. Results of the data item's relevance

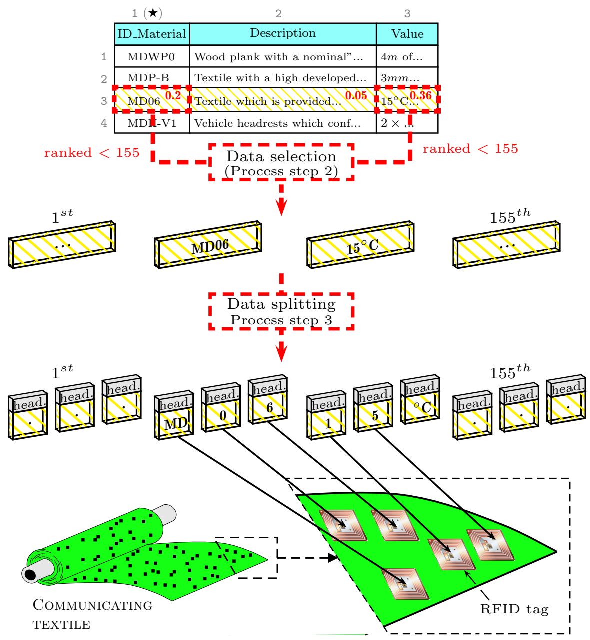


Fig. 9. Illustration of the *splitting protocol*

on a mobile device via an application software (JAVA programming). The software actually recomposes all tables based on the set of data items retrieved from the material, enabling users to view each table and product-related tuples. For example, Fig. 10 shows the unique tuple of `MaterialDefinition` which has been rebuilt. This is the "product-related tuple" and more exactly, the data items $T_{MD}\{3,1\}$ and $T_{MD}\{3,3\}$ which were included in the first 155^{th} data items of the *list*. In this example, the software cannot displayed $T_{MD}\{3,2\}$ (see Fig. 10) which may lead to unanswerable queries. Based on the application software, many services can be programmed: e.g. queries may be directly performed via the JAVA software without requiring access to the database.

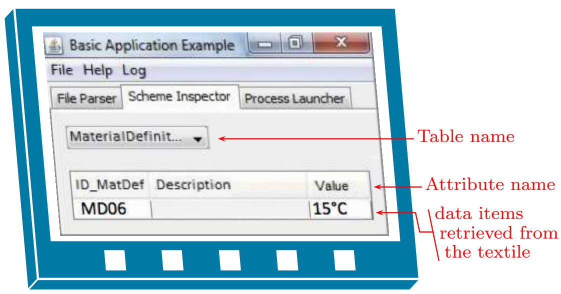


Fig. 10. Display of tuples related to `MaterialDefinition`

6. Conclusion

In the framework of the product life cycle management, it is not uncommon to use intelligent/communicating products for ensuring an information continuum over the product life cycle - PLC (e.g. for traceability purposes). If one considers the product as an information vector (on which information could be stored), it would contribute to improve interoperability all along its life cycle. However, it is not that easy to identify, at a given stage of the PLC, what information should be stored on the product. To answer this question, a data dissemination process is developed in this paper to select context-sensitive information from the database and to store/replicate it on the product.

The approach proposed in this paper uses the fuzzy AHP theory for aggregating points of view from different actors/experts. An assumption is made about independencies among criteria, as required in AHP. Currently, no strong dependencies have been clearly identified among our criteria, even if some may be sensed. Indeed, since the product is memory-constrained, the number of enumerated data might, for instance, impact the maximal data size allowed to be stored on the product. Further experiments should therefore confirm or reveal such interdependencies, which cannot be captured by AHP. Accordingly, in future work, the application of ANP will be examined and results compared with those of this paper.

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