Group fuzzy AHP approach to embed relevant data on "communicating material"

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Abstract

The amount of data output into our environment is increasing each day, and the development of new technologies constantly redefines how we interact with information. In the context of product life cycle management, it is not uncommon to use intelligent products to ensure an information continuum throughout the product life cycle (e.g., for traceability purposes). Integrating intelligence and information into products themselves is now possible through numerous technologies (RFID, communicating materials). However, these technologies currently have low memory capacities (several kilobytes or megabytes), whereas to product databases are becoming larger and larger (several gigabytes or terabytes). As a result, a data dissemination process is required to determine the relevant information that should be stored on the product. This paper proposes a multiple-criteria decision-making (MCDM) method based on a fuzzy Analytical Hierarchy Process (fuzzy AHP). This method is context-aware and supports the aggregation of opinions from a group of experts. An application is proposed to embed context-sensitive information in a "communicating textile".

Keywords: Fuzzy AHP, Group decision-making, Opinion aggregation, Data dissemination, Intelligent product

1. Introduction

Intelligent Products have been introduced as a concept for transforming physical products into autonomous actors that can optimize their operations, use, and other behavior in order to fulfill their "mission", which may depend on their current context [1, 2, 3]. For instance, an intelligent vehicle can continuously monitor its own state and environment to optimize the power delivered versus fuel consumption, while simultaneously monitoring itself for upcoming faults and necessary maintenance [4]. Similarly, an intelligent shipment might optimize its own transportation with the mission of arriving at its destination on time and with the lowest possible cost. Modern vehicles contain powerful processors and various means of communication, whereas shipments are usually limited to Radio Frequency Identification (RFID) or barcode technologies. Intelligent Products can be classified according to many different criteria and frameworks, such as the one proposed in [3], in which a classification based on the three criteria of "aggregation level of intelligence", "location of intelligence", and "level of intelligence" is proposed.

After many years of considering a communicating product to be a physical product associated with an informational product (realized via auto-identifying technologies such as RFID [2, 5]), a new paradigm has been proposed in our previous work [6] that drastically changes the way in which one interacts with the material. The concept aims to provide the ability for the material to be intrinsically and wholly communicating. In this work, it is not necessary to know how such a material could be achieved. We just have to accept, as a hypothesis, that all of the material of the product is communicating and is able both to embed/convey data and to communicate it with its environment (see [7, 6] for more information). A product made of communicating material could therefore have special abilities, such as data storage and copy/redundancy/backup information on all or part of the product. Obviously, this vision is far from being possible today, mainly because of technological limitations, but the current research in

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this field is promising. In [6], a prototype of a communicating textile is designed, in which a large quantity of RFID μtags is spread throughout the textile.

In this paper, communicating materials are considered, and the communicating textile prototype is reused. For such materials, an important challenge is to determine the information that should be stored in/on the product during the product life cycle (PLC). Indeed, many new information systems have been brought to market, yielding the opportunity to work more efficiently internally and externally with customers, suppliers, and partners. The linkage of product-related information to the product itself throughout its PLC may therefore improve product visibility, data interoperability between companies, and data sustainability [8, 9, 10]. Indeed, accessing the appropriate product-related information at any moment and in any location is essential (e.g., a car may need to be repaired in any part of the world) because when data are difficult to access, users may prefer to re-invent them rather than searching and waiting to gain access [11]. However, it is not that easy to identify what information needs be stored on the product at a given stage of the PLC [12]. To address this issue, this paper develops a solution based on a multicriteria decision-making (MCDM) method to identify the appropriate data for the expected situation.

Section 2 first explains why the data selection problem is an MCDM problem. Then, a discussion is presented that identifies the most appropriate approach to address our data selection problem, and it is concluded that the fuzzy AHP (Analytical Hierarchy Process) best suits to it. From this discussion, a new approach to aggregating opinions from a group of experts is developed in section 3 based on the fuzzy set theory. The different stages that compose our "group" fuzzy AHP method are then detailed in section 4. The group fuzzy AHP is put into practice in section 5; context-sensitive information is embedded in the "communicating textile" designed in our previous work. Finally, the approach to aggregating opinions that is developed in this paper is compared with existing approaches in section 6.

2. Method to handle the data selection problem

2.1. Criteria for data selection

During its PLC, a product moves through numerous companies with various core business sectors and many information systems. The information required is dependent on a variety of factors at each stage of the PLC, such as the user concerns, the product environment, the company core business, and the application features [11]. Hence, at each stage of the PLC, business actors may decide to store information on the communicating material by extracting relevant data from the company's database. Thus, they may wonder how to measure this relevance.

A number of research studies within the framework of distributed database systems (DDBSs) consider the data distribution problem [13]. However, few works on DDBSs propose methods that are sensitive to the context of use of the database and the semantics of the data [14, 15]. Among these works, Chan and Roddick [16] proposed an approach that relies on a database, whose Logical Data Model (LDM) is known, to select context-sensitive information by formalizing the relationship between context and data. This approach assesses the relevance of all information using a multicriteria evaluation based on 8 weighted criteria expressing the context of use. A relevance value for each piece of information is then computed based on a weighted sum. Finally, a higher relevance value indicates a greater need to store this information on the product.

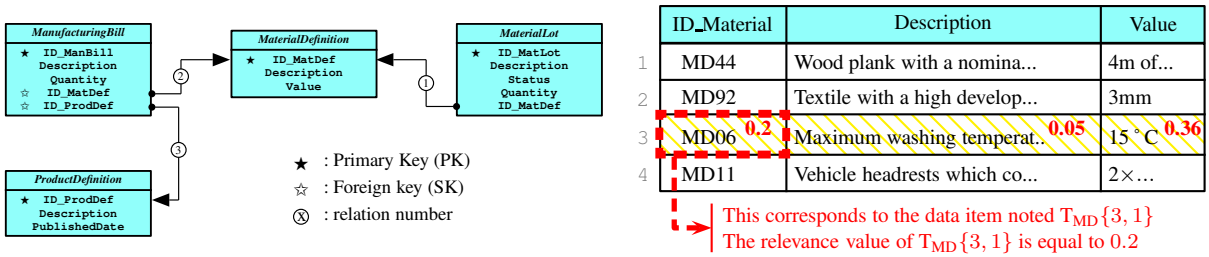
Figure 1 shows part of an LDM in which one entity corresponds to a relational table, as depicted in Figure 1(b) with `MaterialDefinition`. The attributes listed for each entity correspond to the table columns, each row is referred to as a tuple, and a table cell is called a data item. In this example, `MaterialDefinition` has 3 attributes and 4 tuples (i.e., 12 data items). In the approach developed by Chan and Roddick, the relevance is actually computed for each data item from each relational table. In Figure 1(b), the relevance value of the data item located at row 3, column 1, noted as[1] $T_{MD}\{3, 1\}$, is equal to 0.2.

To tackle the data selection problem throughout the PLC, we consider three of the eight criteria defined by Chan and Roddick:

1. *Enumeration* (C_e): this criterion allows the user to enumerate the information that he considers important to be stored on the product,

2. *Contextual* (C_c): experts may not be aware of all of the data needed by the downstream actors of the PLC and could omit important classes of information. Indeed, several information systems exist over the PLC, e.g., CAD (Computed-Aided Design), PDM (Product Data Management), and CRM (Customer Relationship Management),

[1] Such a notation is used in the rest of the paper to symbolize the different data items. In this example, MD is used as the abbreviation of `MaterialDefinition`.



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

(b) Relational table *MaterialDefinition* & Data item relevance

Figure 1: View of a Logical Data Model (LDM) and a relational table

which are not concerned with the same data (i.e., the same entities from the LDM). The importance of the entities should therefore change according to the location of the product in the PLC [17]. This criterion involves groups of experts drawn from a consortium of networked enterprises or from standards organizations, and it aims to assess the importance of different groups of information in the LDM according to the PLC phases,

3. *Data Size* (C_s): this criterion favors the storage of information on the product according to the data item size. Because products are often memory-constrained compared with classic databases, the data relevance should decrease when its size increases [16, 18].

Moreover, unlike Chan and Roddick's approach, which assesses all data items from all tables, only tuples related to the individual product (i.e., the product in question) are assessed in our study. An algorithm is developed in [6] to identify such tuples from the database. In this paper, these tuples are referred to as "product-related tuples". For instance, in Figure 1(b), only tuple 3 is identified as a product-related tuple (represented with a dashed background), and thus, only this tuple is assessed in terms of relevancy (not tuples 1, 2, and 4). Finally, data items are ranked, and in this case, $T_{MD}\{3,3\}$ is the most relevant among the three data items with a relevance of 0.36.

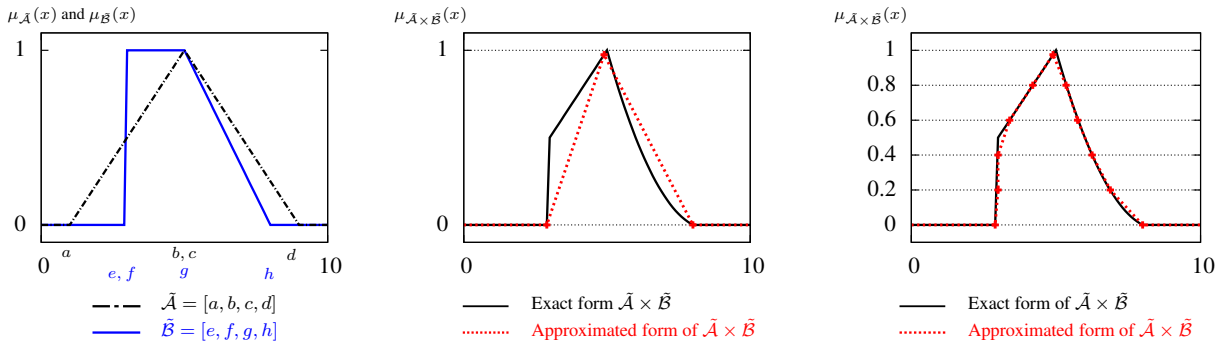
2.2. *Choice of the MCDM method*

Chan and Roddick's model has several limitations. First, it does not offer the possibility to consider different expert opinions. Moreover, it does not allow one to consider the uncertainty associated with human judgment. Consequently, this approach may turn out to be inappropriate according to the context of the study. With regard to our problem of data selection, several experts give their opinion at a given stage of the PLC (see C_c). Each opinion is legitimate and must be considered. Accordingly, the set of opinions must be formalized in accordance with a mathematical theory and then synthesized using a suitable aggregation method.

Numerous studies have used MCDM methods, such as the AHP (Analytical Hierarchy Process), ANP (Analytical Network Process), TOPSIS (technique for order preference by similarity to an ideal situation), and ELECTRE [19]. There are no better or worse techniques, but some techniques are better suited to particular decision problems than others [20]. For instance, in our study, it is necessary to implement an MCDM method that meets our requirements (i.e., consideration of group opinion, uncertainty,...).

AHP methods have been widely used in the literature to handle MCDM problems [21]. These methods, originally proposed by Saaty [22], have the advantage of organizing the critical aspects of the problem in a hierarchical structure, thus facilitating the decision-making process. In these methods, experts use linguistic variables rather than expressing their judgments in the form of exact numeric values, which usually makes them feel more confident and facilitates the valuation process. Moreover, the use of the AHP does not involve cumbersome mathematics; thus it is easy to understand, and it can effectively handle both qualitative and quantitative data [23, 20]. To tackle the problem of incomplete and vague information arising from the environment (e.g., human judgment, data from sensors), numerous scholars have proposed combining fuzzy set theory with the AHP, which has become known as the fuzzy AHP.

The fuzzy set theory, introduced by Zadeh [24], mimics human reasoning in its use of approximate information and uncertainty to generate decisions. It was specifically designed to mathematically represent uncertainty and vagueness to provide formalized tools for handling the imprecision that is intrinsic to many problems. This



(a) Trapezoidal fuzzy set $\tilde{\mathcal{A}}$ and $\tilde{\mathcal{B}}$ (b) $\tilde{\mathcal{A}} \times \tilde{\mathcal{B}}$ approximated by a triangular fuzzy set (c) $\tilde{\mathcal{A}} \times \tilde{\mathcal{B}}$ approximated by 6 α-cuts

Figure 2: Multiplication of two fuzzy sets using two approximation methods

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 $\tilde{\mathcal{A}}$, an element has a degree of membership in $[0, 1]$. The kernel of a fuzzy set $\tilde{\mathcal{A}}$ is defined as the set of elements whose membership degree is equal to 1, as formalized in equation 1, and the support of a fuzzy set $\tilde{\mathcal{A}}$ is defined as the set of elements whose membership degree is different from 0 (see equation 2) [25].

$$\text{kernel}\left(\tilde{\mathcal{A}}\right) = \{x \in \mathcal{X} | \, \mu_{\tilde{\mathcal{A}}}(x) = 1\} \tag{1}$$

$$\text{support}\left(\tilde{\mathcal{A}}\right) = \{x \in \mathcal{X} | \, \mu_{\tilde{\mathcal{A}}}(x) > 0\} \tag{2}$$

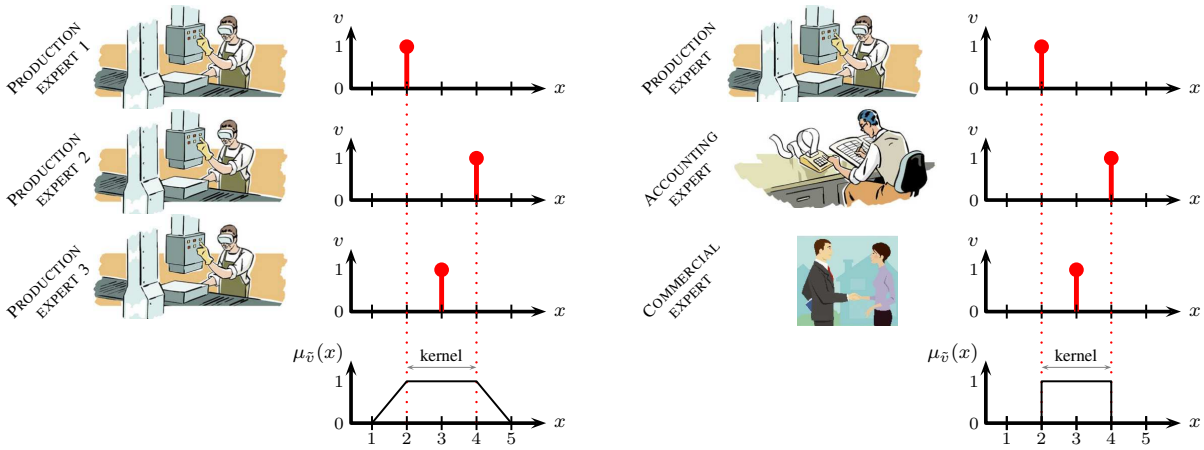
By combining the advantages of both the AHP and fuzzy set theory, the fuzzy AHP is an excellent tool to handle qualitative assessments [20]. As with the AHP method, the fuzzy AHP has been used in various sectors, including political [26], social [27], environmental [28], and product development [23, 29, 30]. Most of the work uses fuzzy sets to model the uncertainty [31, 32]. The literature survey made by [33] shows that the vast majority of the fuzzy AHP applications use the fuzzy extended AHP (FEAHP) for simplicity [34, 35, 36]. Based on this review, our attention has turned to the FEAHP [37] or, to be more exact, to a variant proposed by Deng [38], which is an improvement over the original FEAHP. Indeed, the FEAHP is mainly criticized because of the mechanism used when conducting the computation of weights. Wang et al. [39] explained that the use of the possibility degree in this mechanism can lead to untrue weights and therefore to wrong decisions. The approach of Deng does not use the same weight computation mechanism and seems to be free of the drawbacks described by Wang et al. [39]. To make a clear distinction between the original and the variant FEAHP, the term "Deng's Fuzzy AHP" is used throughout the paper rather than the FEAHP.

2.3. *Adaptation of Deng's Fuzzy AHP to the context of use*

In this paper, Deng's Fuzzy AHP is adapted because the original computation mechanism and the data modeling do not exactly fit our context expectations. First, the original approach uses triangular fuzzy numbers to perform the pairwise comparison needed in the AHP. However, the shape of the fuzzy number is highly related to the semantics of the information. As a result, triangular fuzzy numbers are not always appropriate for modeling information. For instance, in our study, fuzzy numbers are customized based on an aggregation method that combines the set of expert opinions in appropriate fuzzy forms. These forms are not triangular but are instead trapezoidal or rectangular. Section 3 introduces the aggregation method and such customizations. In the literature, some authors develop methods to perform pairwise comparisons using other shapes, such as trapezoidal fuzzy sets [40, 41, 42, 20].

Moreover, in Deng's Fuzzy AHP, computations on fuzzy numbers are made by only using the limit values of the kernel and the support, which is a rough approximation of the exact resulting fuzzy set. Let us illustrate this problem with two fuzzy sets $\tilde{\mathcal{A}}$ and $\tilde{\mathcal{B}}$ as given in Figure 2(a). Figure 2(b) provides the result of the multiplication of $\tilde{\mathcal{A}}$ and $\tilde{\mathcal{B}}$ where the exact form corresponds to the full line and the approximate form to the dotted line. It can be observed that a part of the information is lost when using only the limit values. Another possible representation of fuzzy sets is the use of crisp intervals, so-called α-cuts. Computations on α-cuts preserve the form of the membership function as shown in Figure 2(c). However, the membership function must be sampled as there are α-cut levels [41].

As a result, Deng's Fuzzy AHP is adapted as follows:



(a) Expert consensus a

(b) Expert consensus b

Figure 3: Aggregation techniques considering two types of expert panels/groups

- the shape of fuzzy numbers, which are used in pairwise comparisons, are obtained via clear semantic rules,
- computations on fuzzy sets are done with the use of α-cuts to preserve information. One hypothesis of this work is to consider that preserving the form of fuzzy sets should help obtain a more precise ranking of the alternatives. Let us note that 11 α-cut levels are used in our study: $\alpha \in \{0, 0.1, 0.2, \ldots, 0.9, 1\}$.

3. Proposition of an aggregation method based on fuzzy set theory

The objective of aggregation is to combine individual sources of information into an overall resource in an appropriate manner so that the final result of aggregation can account for all of the individual contributions [43, 44, 45]. When conflicts occur among experts, an effective way to manage the conflict involves assigning weights to the experts (i.e., by assessing their quality). Such operations are usually performed in the framework of probability theory [46]. The probabilistic approach, although it has proven its worth, is once again ill-suited to model vague opinions and limits the choice of aggregation methods, as claimed by Destercke et al. [47]. Uncertainty theories such as fuzzy set theory make it possible to overcome these limits [48]. Many fuzzy set theory proposals have been developed in recent years [49, 50, 45]. According to [47], an aggregation method can be characterized by one of the three behaviors itemized below. Let us consider a parameter v on a domain $\mathcal{X}$ to be estimated. Two experts e_1 and e_2 give their opinion $e_1(v) = A$ and $e_2(v) = B$ with $A, B \subseteq \mathcal{X}$. Let $\bowtie$ be the aggregation operator:

- *conjunctive behavior*: $e_1(v) \bowtie e_2(v) \subseteq A \cap B$. The result is more certain than the expert's opinion and can be used when the opinions are not conflicting (i.e., $e_1(v) \bowtie e_2(v) \neq \emptyset$),
- *disjunctive behavior*: $e_1(v) \bowtie e_2(v) \supseteq A \cup B$. The result is less accurate than it was previously, but all opinions are taken into account. In fact, the disjunction represents the case in which the modeler does not want to choose among the expert opinions, which might be conflicting,
- *"counting" behavior*: The result corresponds to a statistical view of the opinions. A counting behavior could actually be defined at the interface between the disjunctive and the conjunctive results.

In practice, it makes sense to adapt the aggregation method according to the context. The accuracy and the nature of the aggregated result depends on both the presence of conflicts and the available knowledge on the expert quality. In the PLC, experts who evaluate alternatives and criteria may originate from the same or different core business(es). Two situations involving expert points of view may be identified:

a) *same point of view*: experts originate from the same core business and their concerns about the product are similar. As a result, these experts have the same point of view when evaluating a parameter.

Figure 3(a) shows an example of three experts in production control, i.e., e_1, e_2, and e_3, provide a crisp evaluation of parameter v on the same scale, $\mathcal{X} = \{1, 2, 3, 4, 5\}$,

b) *different points of view*: experts originate from distinct core businesses, and their concerns about the product are different. As a result, these experts do not have the same point of view when evaluating information. Figure 3(b) shows an example of three experts from three distinct core businesses: e_1 - expert in production control, e_2 - expert in accounting, and e_3 - expert in commercial business. They also provide a crisp evaluation of parameter v on the same scale, $\mathcal{X} = \{1, 2, 3, 4, 5\}$,

All of the expert points of view are legitimate and must be considered. Accordingly, choosing conjunctive behavior for the aggregation is not suitable; rather, disjunctive or perhaps even counting should be used. In this sense, a new approach for aggregating multiple points of view from a group of experts is developed based on the fuzzy set theory. This approach aims at aggregating crisp evaluations formulated by the experts through suitable fuzzy set modeling. To consider all expert points of view, the aggregation method proceeds by aggregating their evaluations through an information continuum, namely, a fuzzy interval in which all points of view form the kernel, as illustrated in Figure 3(a) and 3(b). In case *a)* in which experts have the same point of view, the target value might be located outside the kernel because of the small numbers of experts considered (a new expert could give an evaluation outside the interval). As a result, the support is extended with a linear slope (i.e., the values decrease when the distance from the kernel increases) as shown in Figure 3(a). In case *b)*, in which experts have different points of view, the fuzzy interval is not extended because the addition of a new evaluation would mean that a point of view (i.e., a core business) has been omitted. In this study, we make the assumption that all core businesses are known at a given stage of the PLC.

The next section details the different stages of the group fuzzy AHP method. For each criterion evaluation, the suitable aggregation is implemented, depending on the category of points of view of the experts solicited in each criterion.

4. Data item relevance using the group fuzzy AHP

Our group fuzzy AHP method relies on Deng's Fuzzy AHP and consists of five stages as depicted in Figure 4:

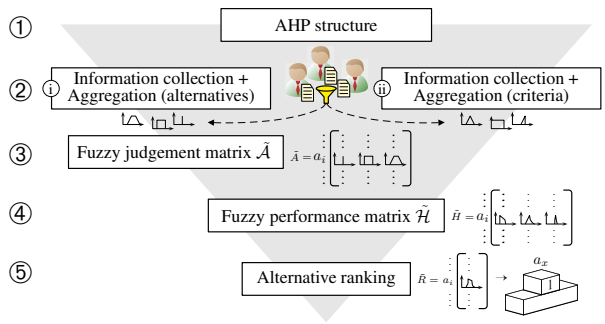


Figure 4: Group fuzzy AHP consisting of 5 stages

1. breakdown of the MCDM problem into a hierarchical AHP structure: definition of criteria & alternatives,
2. collection and aggregation of the expert evaluations regarding *i)* the evaluations of alternatives with respect to criteria, and *ii)* the evaluations of the importance of criteria. In both cases, the evaluations are aggregated in suitable fuzzy sets,
3. creation of the fuzzy judgment matrix $\tilde{A}$: this matrix is built based on the fuzzy sets of alternatives with respect to each criterion (fuzzy sets arising from stage 2),
4. computation of the fuzzy performance matrix $\tilde{H}$: this matrix is built by synthesizing $\tilde{A}$ with the relative criteria importances (importances arising from stage 2),
5. alternative ranking: multi-criteria performance of alternatives must be aggregated in a fuzzy vector $\tilde{\mathcal{R}}$, and then alternatives must be ranked.

These five stages are respectively detailed in sections 4.1 to 4.5. To make the approach easy to understand, a scenario is considered in the rest of the paper whose parts are preceded by the symbol "✎". This scenario relies on 19 entities that come from the LDM of the B2MML standard. B2MML (Business To Manufacturing Markup Language) is meant to be a common data format to link business enterprise applications with manufacturing enterprise applications. Figure 1(a) illustrates 4 of them.

4.1. Stage 1: AHP structure

Our MCDM problem is broken down into the AHP structure depicted in Figure 5. The alternatives are the data items (*cf. Level 3*) that must be assessed and ranked in terms of relevancy to be stored on the communicating

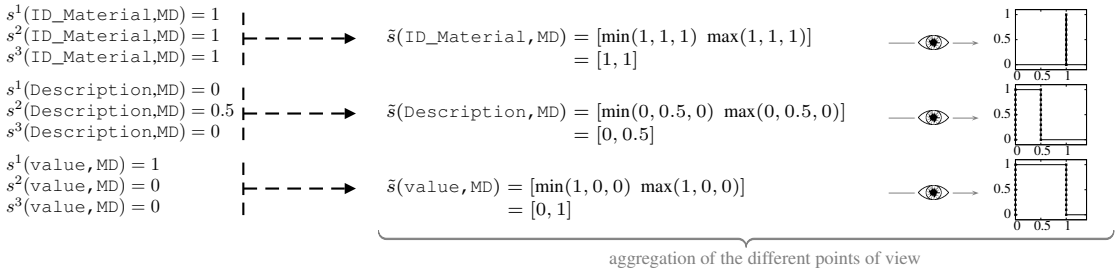


Figure 6: Expert evaluations related to *Enumeration* and fuzzy opinion aggregation

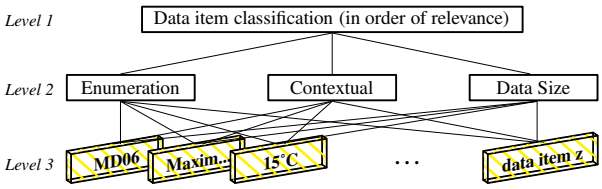


Figure 5: General architecture of the hierarchy

material (*cf. Level 1*). The three criteria introduced in section 2.1 take place at *Level 2* and are detailed in the next stage.

4.2. Stage 2: Information collection and aggregation of expert points of view

Sections 4.2.1 to 4.2.3 explain the three criteria (C_e, C_c, C_s), how the experts evaluate each alternative with respect to each criterion, and how these evaluations are aggregated. Section 4.2.4 provides the same details but regarding the evaluations of the criteria importance. The main variables used in this paper are given in Table 1.

4.2.1. Enumeration - C_e

This criterion allows the user to enumerate the information that he considers important to store on the product. To do so, each expert e_p enumerates certain attributes from tables. Let t be a table from the database ($t \in \mathcal{T}$) and v be an attribute of t. If the attribute v is enumerated by e_p, the crisp enumeration score $s^p(v,t) = 0.5$ or 1 (depending on the preference intensity, as formulated in equation 3). Experts may come from different areas (e.g., production, shipping) and may therefore want to store different information on the product because of their different concerns. Accordingly, the aggregation method defined in consensus b is used (*cf.* Figure 3(b)) to aggregate the set of opinions as formalized in equation 4. Finally, the score of a data item $a_l \in v$ with respect to C_e, denoted by $\tilde{\phi}_e(a_l)$, is equal to $\tilde{s}(v,t)$.

$$s^p(v,t) = \begin{cases} 1 & \text{enumerated (useful attribute)} \\ 0.5 & \text{enumerated (interesting attribute)} \\ 0 & \text{not enumerated (useless attribute)} \end{cases} \quad (3)$$

$$\tilde{s}(v,t) = [\min(s^p(v,t)) \max(s^p(v,t))] \quad (4)$$

✎ Table 2 shows the attributes enumerated by three experts e_1, e_2 and e_3. The preference intensities formulated by each expert for the attributes are also presented. For instance, e_1 judges information from the attribute `Quantity` of the table `MaterialLot` as "useful" because he gives it a preference of 1 (noted `Quantity`+*1* in Table 2). e_2 judges the same attribute to be "useless" because he does not enumerate it. Attributes not enumerated by experts are not presented in Table 2, but they take the value of 0. The aggregation of the three expert opinions regarding each attribute, from each table is then performed based on Equation 4. Figure 6 shows the aggregation steps and the fuzzy sets resulting from the aggregation for the three attributes of `MaterialDefinition` (i.e., `ID_Material`, `Description` and `value`), based on the preferences expressed by experts in Table 2. The fuzzy scores of data items $T_{MD}\{3,1\}$, $T_{MD}\{3,2\}$, $T_{MD}\{3,3\}$ with respect to C_e, which are noted $\tilde{\phi}_e(T_{MD}\{3,1\})$, $\tilde{\phi}_e(T_{MD}\{3,2\})$, and $\tilde{\phi}_e(T_{MD}\{3,3\})$, are respectively equal to $\tilde{s}(\texttt{ID\_Material}, \texttt{MD})$, $\tilde{s}(\texttt{Description}, \texttt{MD})$, and $\tilde{s}(\texttt{value}, \texttt{M})$ because they belong to these three attributes.

4.2.2. Contextual - C_c

This criterion more globally evaluates the information that should be selected than with C_e. Indeed, experts may not be aware of all of the data needed by the downstream actors in the PLC and could omit important information. There is thus a need to identify important data with regard to the global PLC. This evaluation cannot be focused on individual data items but should instead focus on a group of tables. Accordingly, the

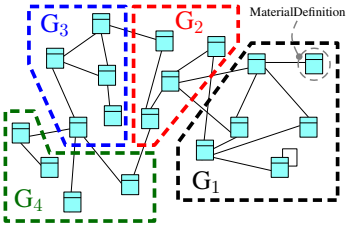
Table 1: Variable definitions

	Variables	Description
Classical sets & Crisp scores	$\mathcal{T}$	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.
	a_l	represents an alternative l (i.e., a data item l) in the AHP structure, with $l = \{1, 2, .., n\}$.
	e_p	represents an expert p with $p = \{1, 2, .., p_{\max}\}$; $p_{\max}$ varies according to the criterion x.
	C_x	abbreviation for the criterion x with $x = \{1, 2, .., m\}$. In our study, three criteria are defined in this study, namely: C_e, C_c, C_s.
	G_i	abbreviation for an entity group i defined in the LDM, with $i = \{1, 2, .., z\}$.
	k	coefficient $\in \mathbb{R}_+$ used to favor the storage of information on the product according to the data item size (in C_s).
	α	crisp interval of a fuzzy set, so-called α-cut (11 α-cuts are used in our study: $\alpha \in \{0, 0.1, 0.2, \ldots, 0.9, 1\}$).
	$x^{\blacklozenge}$	represents the center of gravity (CoG) of a fuzzy set. $x^{\blacklozenge}_{-}$ and $x^{\blacklozenge}_{+}$ are respectively the inferior and superior approximations of the CoG which are calculated based on the α-cut levels.
	$\overline{r^{\alpha}}, \underline{r^{\alpha}}$	respectively indicate the minimal and the maximal values of the α-cut on the x-axis.
	$\Delta_{\mathrm{Y}} r^{\alpha}$	corresponds to the level difference (y-axis) between the α-cut and $\alpha + 1$-cut levels.
	L	list of product-related data items ordered from the most relevant to the lowest (ordered according to their CoG $x^{\blacklozenge}$)
Fuzzy score	$\tilde{s}(v, t)$	fuzzy score representing the aggregation of the crisp evaluations provided by each expert e_p (with $p = \{1, .., p_{\max}\}$) in C_e. The crisp evaluation is noted $s^p(v, t)$ and indicates the preference intensity, expressed by e_p, about storing on the product information related to attribute v of table t.
	$\tilde{s}_k$	represents the aggregation of the crisp evaluations provided by each expert e_p (with $p = \{1, .., p_{\max}\}$) in C_s. The crisp evaluation is noted s^p_k and corresponds to the value of coefficient k, adjusted by e_p.
	$\tilde{s}_{ij}$	fuzzy score representing the aggregation of pairwise comparisons between element i and j of the pairwise matrix, performed by all experts. A pairwise comparison between element i and j performed by an expert e_p is noted s^p_{ij} (with $p = \{1, .., p_{\max}\}$). Aggregation is based on rules from Table 3.
	$\tilde{\phi}(\mathrm{G}_i)$	fuzzy score representing the relative importance of entity group G_i over the other groups. It can be decomposed in intervals, on the basis of α-cuts, as $\phi^{\alpha}(\mathrm{G}_i)$.
	$\tilde{\phi}(\mathrm{C}_x)$	fuzzy score representing the relative importance of criterion C_x over the other criteria. It can be decomposed in intervals, on the basis of α-cuts, as $\phi^{\alpha}(\mathrm{C}_x)$.
	$\tilde{\phi}_x(a_l)$	fuzzy score of alternative a_l with respect to criterion x, without considering the relative importance of criterion x .
	$\tilde{h}_x(a_l)$	fuzzy score of alternative a_l with respect to criterion x, by considering the relative importance of criterion x.
Fuzzy matrix/vector	$\tilde{G}$	fuzzy matrix synthesizing all fuzzy scores $\tilde{s}_{ij}$ (i and $j = \{1, 2, .., z\}$) regarding pairwise comparisons between entity groups.
	$\tilde{\Phi}_G$	fuzzy vector synthesizing all fuzzy scores $\tilde{\phi}(\mathrm{G}_i)$, with $i = \{1, 2, .., z\}$.
	$\tilde{\rho}$	fuzzy matrix synthesizing all fuzzy scores $\tilde{s}_{ij}$ (i and $j = \{1, 2, .., m\}$) regarding pairwise comparisons between criteria.
	$\tilde{\Phi}_{\rho}$	fuzzy vector synthesizing all fuzzy scores $\tilde{\phi}(\mathrm{C}_x)$, with $x = \{1, 2, .., m\}$.
	$\tilde{A}$	fuzzy judgment matrix synthesizing all fuzzy scores $\tilde{\phi}_x(a_l)$ (i.e., the importance of criteria is not considered yet).
	$\tilde{H}$	fuzzy performance matrix which synthesizes the judgment matrix $\tilde{A}$ and the fuzzy vector $\tilde{\Phi}_{\rho}$ (i.e., the importance of criteria is now considered).
	$\tilde{R}$	fuzzy vector after multi-criteria aggregation (i.e., after having aggregated scores from the performance matrix $\tilde{H}$).

Table 2: "Table attributes" enumerated by e_1, e_2, and e_3

	Table name (t)	Enumerated attributes (v)+*Preference*
e^1	`MaterialLot`	`IDLot`+*1*; `Quantity`+*1*
	`MaterialDefinition`	`IDMaterial`+*1*; `Value`+*1*
	`ProductSegment`	`IDProdSeg`+*1*; `Duration`+*1*; `Unit`+*0.5*
	`ProductionOrder`	`IDProdOrd`+*1*; `StartTime`+*1*; `EndTime`+*1*
e^2	`MaterialDefinition`	`IDMaterial`+*1*; `Description`+*0.5*
e^3	`MaterialLot`	`Status`+*0.5*
	`MaterialDefinition`	`IDMaterial`+*1*
	`ProductSegment`	`IDProdSeg`+*0.5*; `Description`+*0.5*

main idea is to cluster all entities of the LDM needed by the same information systems in "entity groups". Figure 7(a) illustrates the definition of four entity groups in an LDM. Experts then perform pairwise comparisons among these groups to indicate the utility for the current and downstream actors of the PLC to obtain access to information from the different groups. In our study, each expert e_p performs pairwise comparisons among entity groups as in equation 5, with z being the number of groups. The importance of entity group G_i over group G_j, evaluated by e_p, is denoted by s^p_{ij}. This evaluation is based on the 1- to 9-point scale from Saaty [51]: $\{1, 3, 5, 7, 9\}$. $s^p_{ij} = 1$ means that G_i and G_j are of equal importance and $s^p_{ij} = 9$ means that G_i is strongly favored



(a) Entity groups in the LDM

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

(b) 19 entities clustered in 4 groups

Figure 7: Definition of entity groups in the LDM required in the *Contextual* criterion

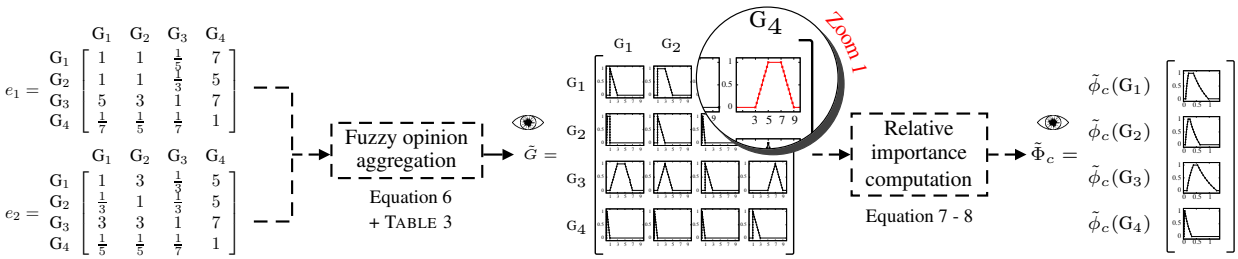


Figure 8: Pairwise comparisons between entity groups; Aggregation; Computation of their relative importance

over G_j.

$$\begin{array}{c} \\ G_1 \\ \vdots \\ G_z \end{array} \begin{array}{c} \begin{array}{ccc} G_1 & \cdots & G_z \end{array} \\ \begin{bmatrix} 1 & \cdots & s^p_{1z} \\ \vdots & \ddots & \vdots \\ s^p_{z1} & \cdots & 1 \end{bmatrix} \end{array}, s^p_{ji} = \begin{cases} 1 & i = j \\ \frac{1}{s^p_{ij}} & i \neq j \end{cases} \quad (5)$$

For this criterion, experts who provide to the evaluations are drawn from domains related to the information systems involved in the PLC and thus have the same point of view on the question. Accordingly, all crisp scores s^p_{ij} are aggregated via the aggregation method defined in consensus b. A fuzzy set, denoted by $\tilde{s}_{ij}$ is therefore defined based on the rules given in Table 3. Two assumptions are made: (A_1) experts agree with the sense of the importance of either $G_i > G_j$ or $G_i < G_j$; (A_2) evaluations are performed using Saaty's scale. Matrix $\tilde{G}$ in Equation 6 synthesizes all fuzzy sets. Finally, the relative importance of each group G_i, denoted by $\tilde{\phi}(G_i)$, is computed based on the basis of 11 α-cuts[3] in Equation 7. These relative importances are ultimately synthesized in a fuzzy vector $\tilde{\Phi}_G$, as in equation 8. If a data item a_l is contained in a table belonging to G_i, its fuzzy score with respect to C_c, denoted by $\tilde{\phi}_c(a_l)$, is thus equal to $\tilde{\phi}(G_i)$.

$$\tilde{G} = \begin{array}{c} \\ G_1 \\ \vdots \\ G_z \end{array} \begin{array}{c} \begin{array}{ccc} G_1 & \ldots & G_z \end{array} \\ \begin{bmatrix} \tilde{s}_{11} & \ldots & \tilde{s}_{1z} \\ \vdots & \ddots & \vdots \\ \tilde{s}_{z1} & \ldots & \tilde{s}_{zz} \end{bmatrix} \end{array} \quad (6)$$

$$\phi^\alpha(G_i) = \frac{\sum_{j=1}^{z} G^\alpha(i,j)}{\sum_{k=1}^{z}\sum_{j=1}^{z} G^\alpha(k,j)} \quad \forall\, \alpha = \{0, 0.1, .., 1\} \quad (7)$$

$$\tilde{\Phi}_G = [\tilde{\phi}(G_1), \ldots, \tilde{\phi}(G_i), \ldots, \tilde{\phi}(G_z)] \quad (8)$$

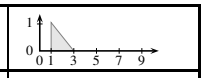
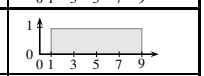
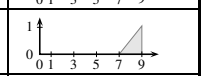
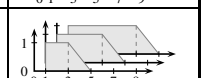
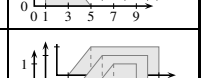
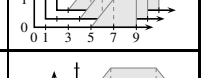
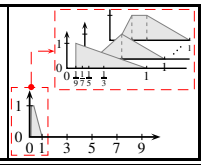
✎ The experts cluster the 19 entities into four groups as detailed in Figure 7(b). The *Equipment* and *Personal data groups* report information about equipment and people which/who are somehow related to the product (e.g., equipment used for its manufacturing). The *Product* and *Production data groups* relate respectively information about the product composition (e.g., raw material) and operations (e.g., production processes). Two experts e_1 and e_2 perform the pairwise comparison matrices, as given in Figure 8. For instance, e_1 highly favors G_1 over G_4 ($s^1_{14} = 7$) and e_2 gives an importance slightly below ($s^2_{14} = 5$). The aggregation of the opinions of e_1 and e_2 is then performed based on the rules

[2]In Table 8, the letter q is used instead of $p_{\max}$ for space purposes.

[3]Let $\mathcal{A}^\alpha = [a, b]$ and $\mathcal{B}^\alpha = [c, d]$ be the α-cut of two fuzzy numbers $\tilde{\mathcal{A}}$ and $\tilde{\mathcal{B}}$ respectively:

- $(\mathcal{A} \oplus \mathcal{B})^\alpha = \mathcal{A}^\alpha \oplus \mathcal{B}^\alpha = [a + c, b + d]$
- $(\mathcal{A} \otimes \mathcal{B})^\alpha = \mathcal{A}^\alpha \otimes \mathcal{B}^\alpha = [a \times c, b \times d]$
- $\left(\frac{\mathcal{A}}{\mathcal{B}}\right)^\alpha = \frac{\mathcal{A}^\alpha}{\mathcal{B}^\alpha} = [\frac{a}{d}, \frac{b}{c}]$

Table 3: Construction of the fuzzy sets related to the pairwise comparison matrix

n°	Condition[2]	Membership f.	Description	Illustration (👁)
	Aggregation of the evaluations $G_i > G_j$ are built via the following rules:			
1	$\min_{p\in\{1..q\}}(s_{ij}^p) = 1 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = 1$	$\tilde{s}_{ij} = [1\ 1\ 1\ 3]$	Experts agree on the equivalence of groups i and j and on $G_i > G_j$ (to respect assumption A_1). The fuzzy interval is therefore limited to 1 and is extended to 3.	
2	$\min_{p\in\{1..q\}}(s_{ij}^p) = 1 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = 9$	$\tilde{s}_{ij} = [1\ 1\ 9\ 9]$	Experts agree on $G_i > G_j$. However, aggregation leads to total uncertainty about the importance. To respect assumption A_2, the fuzzy interval $[1; 9]$ is defined.	
3	$\min_{p\in\{1..q\}}(s_{ij}^p) = 9 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = 9$	$\tilde{s}_{ij} = [7\ 9\ 9\ 9]$	Experts agree on $G_i > G_j$. To respect the assumption A_2, the fuzzy interval is bounded to 9 and is extended to the graduation immediately inferior to x (i.e., 7).	
4	$\min_{p\in\{1..q\}}(s_{ij}^p) = 1 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = x \quad x = 3, 5, 7$	$\tilde{s}_{ij} = [1\ 1\ x\ (x{+}2)]$	Experts agree on $G_i > G_j$. However, aggregation leads to partial uncertainty about the importance. To respect assumption A_2, the fuzzy interval $[1; x]$ is defined and is extended to the graduation superior to x (i.e., 5, 7 or 9).	
5	$\min_{p\in\{1..q\}}(s_{ij}^p) = x \quad \max_{p\in\{1..q\}}(s_{ij}^p) = 9 \quad x = 3, 5, 7$	$\tilde{s}_{ij} = [(x{-}2)\ x\ 9\ 9]$	The experts agree on $G_i > G_j$. However, aggregation leads to partial uncertainty about the importance value. To respect assumption A_2, the fuzzy interval $[x; 9]$ is defined and is extended to the graduation inferior to x.	
6	$\min_{p\in\{1..q\}}(s_{ij}^p) = x_1 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = x_2 \quad x_1, x_2 = 3, 5, 7$	$\tilde{s}_{ij} = [(x_1 - 2)\ x_1\ (x_2 + 2)]$	The experts agree on $G_i > G_j$. However, aggregation leads to partial uncertainty about the importance value. To respect the assumption A_2, the fuzzy interval $[x_1; x_2]$ is defined and is extended to the graduation immediately inferior to x_1 and immediately superior to x_2.	
	Aggregation of the evaluations $\tilde{s}_{ji}$ are deducted from the evaluations $G_i > G_j$ via the following rule:			
8	$\min_{p\in\{1..q\}}(s_{ij}^p) = x_1 \quad \max_{p\in\{1..q\}}(s_{ij}^p) = x_2 \quad x_1, x_2 = 1, 3, 5, 7, 9$	$\tilde{s}_{ji} = [\frac{1}{9}\ \frac{1}{x_2}\ \frac{1}{x_1}\ 1]$	In classical methods, $\tilde{s}_{ji} = (\tilde{s}_{ij})^{-1}$. For simplicity, we propose that the bounds of the fuzzy interval $\tilde{s}_{ji}$ are equal to the reciprocal to the extreme values of S, namely : $\frac{1}{9}$ and 1, whatever the values of x_1 and x_2. This reduces the number of possibilities that, initially, do not significantly affect the final result because the fuzzy intervals $\tilde{s}_{ji}$ are defined in $]0; 1]$ and the intervals $\tilde{s}_{ij}$ in $]1; 9]$.	

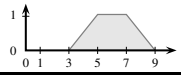
n°	Condition	Membership f.	Illustration (👁)
	Aggregation of the evaluations $G_i > G_j$ are built via the following rules:		
6	$\min_{p\in\{1,2\}}(s_{14}^p) = \min(5, 7) = 5 \quad \max_{p\in\{1,2\}}(s_{14}^p) = \min(5, 7) = 7$	$\tilde{s}_{14} = [(5 - 2)\ 3\ 5\ (7 + 2)] = [3\ 5\ 7\ 9]$	

Figure 9: Aggregation computation of the elements $s_{14}^1 = 7$ and $s_{14}^2 = 5$ given in Figure 8

given in Table 3. Figure 9 details the aggregation computation related to these two elements (i.e., s_{14}^1 and s_{14}^2) based on the appropriate rule from Table 3. The resulting fuzzy set $\tilde{s}_{14}$ (illustrated in Figure 9) is emphasized by Zoom 1 in Figure 8. Finally, the relative importance of each group G_i is computed using Equation 7 and is synthesized in $\tilde{\Phi}_G$ in Figure 8. Because the fuzzy set $\tilde{\phi}_c(G_i)$ represents the preference for storing information belonging to G_i on the product, a higher fuzzy number indicates higher information relevance. Accordingly, it can be observed that information from G_3 and G_1 is more important compared with information from G_2 and G_4. In this scenario, `MaterialDefinition` $\in G_1$. As a result, fuzzy sets of $T_{MD}\{3, 1\}$, $T_{MD}\{3, 2\}$, and $T_{MD}\{3, 3\}$ with respect to C_c, denoted by $\tilde{\phi}_c(T_{MD}\{3, 1\})$, $\tilde{\phi}_c(T_{MD}\{3, 2\})$, and $\tilde{\phi}_c(T_{MD}\{3, 3\})$ are equal to $\tilde{\phi}_c(G_1)$.

4.2.3. *Data Size - C_s*

This criterion favors the storage of information on the product according to the data item size. Because products are often memory-constrained, the data relevance should decrease when its size increases. Such a behavior can be obtained via equation 9, with `size`(a_l) being the size in bytes of the data item a_l and k being a constant adjusted by the expert. Figure 10 shows, for two different k, the score functions according to the data size. A smaller k means that larger pieces of data are authorized to be stored on the product (e.g., an expert who fixes $k = 1.08$ almost excludes data items > 40 bytes).

$$k^{-\texttt{size}(a_l)} \qquad k \in \mathbb{R}_+^* \,;\, \texttt{size}(a_l) \in \mathbb{N}_+ \tag{9}$$

The coefficient k must be adjusted by each expert e_p as in equation 10 (denoted by s_k^p). As discussed previously, experts may have different points of view on

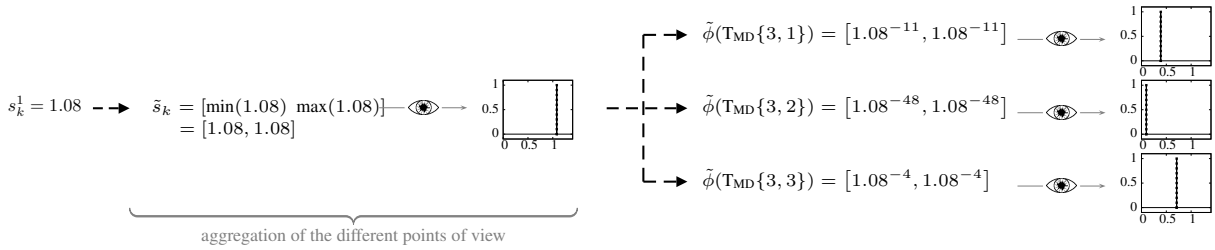


Figure 11: Fuzzy opinion aggregation related to *Data Size*

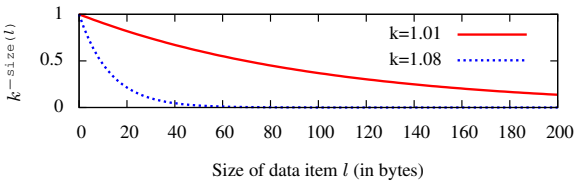


Figure 10: Adjustment of k performed by e_p

this criterion and may adjust k differently. Let us consider an expert e_1, who is interested in a large quantity of data (e.g., e_1 enumerates many attributes) and an expert e_2, who is interested in a small quantity. As a result, e_1 may intend to store small data items on the product to obtain a "complete/diversified" view of the quantity, whereas e_2 wants to authorize the storage of large data items (i.e., $s_k^1 > s_k^2$). Accordingly, all coefficients s_k^p are aggregated via the aggregation method defined in consensus b, giving rise to a fuzzy number $\tilde{s}_k$, as formalized in equation 11. The fuzzy score of an alternative a_l with respect to C_s, denoted by $\tilde{\phi}_s(a_l)$, is therefore computed in equation 12.

$$s_k^p = k \tag{10}$$

$$\tilde{s}_k = [\min(s_k^p)\ \max(s_k^p)],\ \forall\ p = \{1, ..., p_{\max}\} \tag{11}$$

$$\tilde{\phi}_s(a_l) = \tilde{s}_k^{-\mathtt{size}(a_l)} \tag{12}$$

✎ For this criterion, let us consider a unique expert e_1 who adjusts the coefficient k to 1.08 to neglect data items > 40 bytes (*cf.* Figure 10). The resulting fuzzy set corresponds to a single value equal to 1.08, as shown in Figure 11. The fuzzy sets of $\mathrm{T_{MD}}\{3,1\}$, $\mathrm{T_{MD}}\{3,2\}$, and $\mathrm{T_{MD}}\{3,3\}$ with respect to C_s, denoted by $\tilde{\phi}_s(\mathrm{T_{MD}}\{3,1\})$, $\tilde{\phi}_s(\mathrm{T_{MD}}\{3,2\})$, and $\tilde{\phi}_s(\mathrm{T_{MD}}\{3,3\})$ are computed in Figure 11, where $\mathtt{size}(\mathrm{T_{MD}}\{3,1\})) = 11$, $\mathtt{size}(\mathrm{T_{MD}}\{3,2\})) = 48$, and $\mathtt{size}(\mathrm{T_{MD}}\{3,3\})) = 4$. The power in $\tilde{\phi}_s(\mathrm{T_{MD}}\{3,3\}) = \left[1.08^{(-4)}, 1.08^{(-4)}\right]$ is equal to 4 because it is a character string "`15˚C`" and 1 ASCII character is encoded by 1 byte.

4.2.4. *Criteria importance*

In the AHP method, every criterion is weighted. Experts specify the criteria importance via pairwise comparisons as in the *Contextual* criterion. Each expert fills the pairwise comparison matrix given in equation 13.

$$\begin{array}{c} \\ \mathrm{C}_1 \\ \vdots \\ \mathrm{C}_m \end{array} \begin{array}{c} \begin{array}{ccc} \mathrm{C}_1 & \cdots & \mathrm{C}_m \end{array} \\ \begin{bmatrix} 1 & \cdots & s_{1m}^p \\ \vdots & \ddots & \vdots \\ s_{m1}^p & \cdots & 1 \end{bmatrix} \end{array},\ s_{ji}^p = \begin{cases} 1 & i = j \\ \frac{1}{s_{ij}^p} & i \neq j \end{cases} \tag{13}$$

Then, all crisp scores s_{ij}^p are aggregated in a fuzzy set noted $\tilde{s}_{ij}$, based on the rules given in Table 3. Matrix $\tilde{\rho}$ in equation 14 synthesizes all fuzzy sets. Finally, the relative importance of each criterion C_x is computed in Equation 15 based on 11 α-cuts (one α-cut denoted by $\phi^\alpha(\mathrm{C}_x)$) and gives rise to a fuzzy set $\tilde{\phi}(\mathrm{C}_x)$. These importances are synthesized in a fuzzy vector $\tilde{\Phi}_\rho$ in equation 16.

$$\tilde{\rho} = \begin{array}{c} \\ \mathrm{C}_1 \\ \vdots \\ \mathrm{C}_m \end{array} \begin{array}{c} \begin{array}{ccc} \mathrm{C}_1 & \ldots & \mathrm{C}_m \end{array} \\ \begin{bmatrix} \tilde{s}_{11} & \ldots & \tilde{s}_{1m} \\ \vdots & \ddots & \vdots \\ \tilde{s}_{m1} & \ldots & \tilde{s}_{mm} \end{bmatrix} \end{array} \tag{14}$$

$$\phi^\alpha(\mathrm{C}_x) = \frac{\sum_{j=1}^m \rho^\alpha(x,j)}{\sum_{k=1}^m \sum_{j=1}^m \rho^\alpha(k,j)}\ \ \forall\ \alpha = \{0, 0.1, .., 1\} \tag{15}$$

$$\tilde{\Phi}_\rho = [\tilde{\phi}(\mathrm{C}_1), \ldots, \tilde{\phi}(\mathrm{C}_x), \ldots, \tilde{\phi}(\mathrm{C}_m)] \tag{16}$$

✎ The evaluation of the criteria importance is performed via pairwise comparisons by two experts e_1, e_2 as given in Figure 12. It can be observed that both experts favor C_e over the other criteria. For instance, e_1 and e_2 highly favor C_e over C_s ($s_{14}^1 = 7$ and $s_{14}^2 = 7$). Figure 13 details the aggregation computation related to these two elements (s_{13}^1 and s_{13}^2) based on the appropriate rule from Table 3. The resulting fuzzy set $\tilde{s}_{13}$ (illustrated in Figure 13) takes place in the matrix $\tilde{\rho}$ in

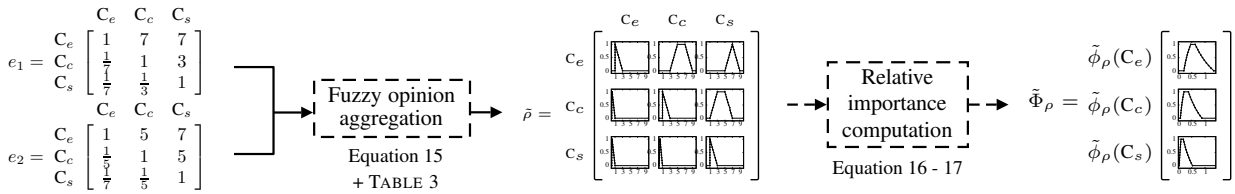


Figure 12: Pairwise comparisons between criteria; Aggregation; Computation of their relative importance

n°	Condition	Membership f.	Illustration (👁)
	Aggregation of the evaluations $G_i > G_j$ are built via the following rules:		
6	$\min_{p\in\{1,2\}}(s^p_{13}) = \min(7,7) = 7$ $\quad \max_{p\in\{1,2\}}(s^p_{13}) = \min(7,7) = 7$	$\tilde{s}_{13} = [(7-2)\ 7\ 7\ (7+2)] = [5\ 7\ 7\ 9]$	

Figure 13: Aggregation computation of the elements $s^1_{13} = 7$ and $s^2_{13} = 7$ given in Figure 12

Figure 12 (*cf.* row 1, column 3). Finally, the relative importance of each criterion C_x is computed using Equation 15 and is synthesized in $\tilde{\Phi}_\rho$ in Figure 12. The resulting fuzzy sets in $\tilde{\Phi}_\rho$ meet the wishes of the experts because C_e is the most important at this PLC stage. In other words, the experts give freedom to users to determine which information must be stored on the product.

4.3. Stage 3: Fuzzy judgment matrix $\tilde{A}$

After obtaining all alternative scores with respect to all criteria, the fuzzy judgment matrix $\tilde{A}$ is built as shown in equation 17, where $\tilde{\phi}_x(a_l)$ denotes the fuzzy set of alternative a_l with respect to criterion x.

$$\tilde{A} = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_m \end{array} \\ \begin{bmatrix} \tilde{\phi}_1(a_1) & \tilde{\phi}_2(a_1) & \dots & \tilde{\phi}_m(a_1) \\ \tilde{\phi}_1(a_2) & \tilde{\phi}_2(a_2) & \dots & \tilde{\phi}_m(a_2) \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{\phi}_1(a_n) & \tilde{\phi}_2(a_n) & \dots & \tilde{\phi}_m(a_n) \end{bmatrix} \end{array} \tag{17}$$

✎ Throughout the scenario considered in the previous section, the scores of $T_{MD}\{3,1\}$, $T_{MD}\{3,2\}$, and $T_{MD}\{3,3\}$ with respect to C_e, C_c, and C_s have been computed, which are respectively synthesized in $\tilde{A}$ in Figure 14.

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

At this stage, only the scores of alternatives with respect to the criteria are considered, without accounting for relative importance of the criteria. As a result, the fuzzy matrix $\tilde{A}$ is combined with the criterion importance $\tilde{\Phi}_\rho$ in a fuzzy performance matrix $\tilde{H}$, as given in equation 18, where each element $\tilde{h}_x(a_l)$ is computed using equation 19.

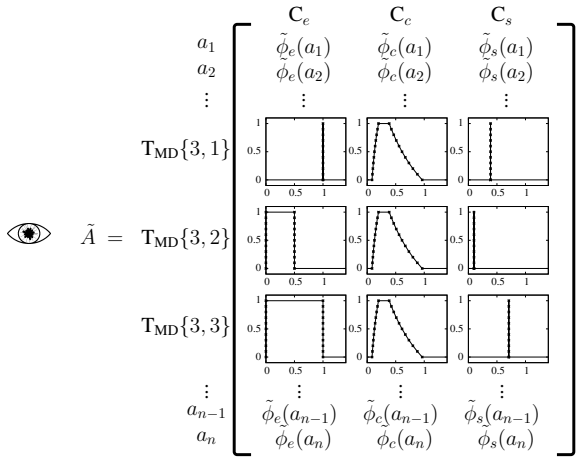


Figure 14: Fuzzy judgment matrix $\tilde{A}$

$$\tilde{H} = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_m \end{array} \\ \begin{bmatrix} \tilde{h}_1(a_1) & \tilde{h}_2(a_1) & \dots & \tilde{h}_m(a_1) \\ \tilde{h}_1(a_2) & \tilde{h}_2(a_2) & \dots & \tilde{h}_m(a_2) \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{h}_1(a_n) & \tilde{h}_2(a_n) & \dots & \tilde{h}_m(a_n) \end{bmatrix} \end{array} \tag{18}$$

$$\tilde{h}_x(a_l) = \tilde{\phi}_x(a_l) \otimes \tilde{\phi}_\rho(C_x) \tag{19}$$

✎ The matrix $\tilde{H}$ in our scenario is computed and depicted in Figure 15. The multiplication related to $\tilde{h}_e(T_{MD}\{3,1\})$ is also illustrated in this figure.

4.5. Stage 5: Alternative ranking

This section aims to rank alternatives according to their evaluations. Until then, each alternative has one fuzzy set with respect to every criterion, giving a total

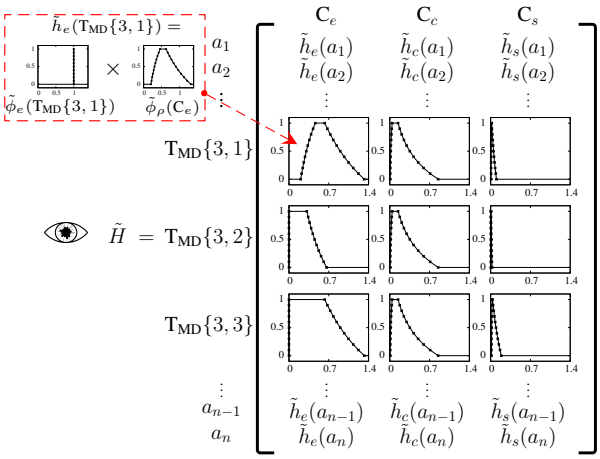


Figure 15: Fuzzy performance matrix $\tilde{H}$

of three fuzzy sets by alternative (*cf.* Figure 15). As Grabish et al. [52] explain, two operating modes can be implemented for multi-criteria alternative ranking:

- AC mode (Aggregate-then-Compare): all fuzzy sets of a given alternative l (i.e., m fuzzy sets) are aggregated, thus giving rise to a unique fuzzy set for each alternative. Then, all alternatives are compared based on this unique fuzzy set (i.e., n fuzzy sets are compared) to obtain the final ranking,

- CA mode (Compare-then-Aggregate): all fuzzy sets of a given criterion x (i.e., n fuzzy sets) are compared, thus giving rise to an alternative ranking for each criterion. Then, all alternative rankings are aggregated (i.e., m aggregation) to obtain the final ranking of alternatives,

In our approach, we decided to implement the AC mode. The operators of aggregation and comparison are respectively introduced in sections 4.5.1 and 4.5.2.

4.5.1. Aggregation operator

The method developed in this paper proceeds similar to Deng's Fuzzy AHP and sums the four fuzzy sets related to each alternative based on their α-cuts, as formalized in equation 20. The resulting fuzzy sets are synthesized in the fuzzy vector $\tilde{R}$ as in equation 21.

$$r^{\alpha}(a_l) = \sum_{x \in \{1,\ldots,m\}} h_x^{\alpha}(a_l) \quad \forall\, \alpha = \{0, 0.1, \ldots, 1\} \tag{20}$$

$$\tilde{R} = \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_n \end{array} \begin{bmatrix} \tilde{r}(a_1) \\ \tilde{r}(a_2) \\ \vdots \\ \tilde{r}(a_n) \end{bmatrix} \tag{21}$$

✎ Figure 16 provides the fuzzy vector $\tilde{R}$ that contains the fuzzy sets resulting from the multi-criteria aggregation regarding the alternatives $\mathrm{T_{MD}}\{3,1\}$, $\mathrm{T_{MD}}\{3,2\}$ and $\mathrm{T_{MD}}\{3,3\}$. The addition that is made to obtain $\tilde{r}(\mathrm{T_{MD}}\{3,1\})$ is also illustrated.

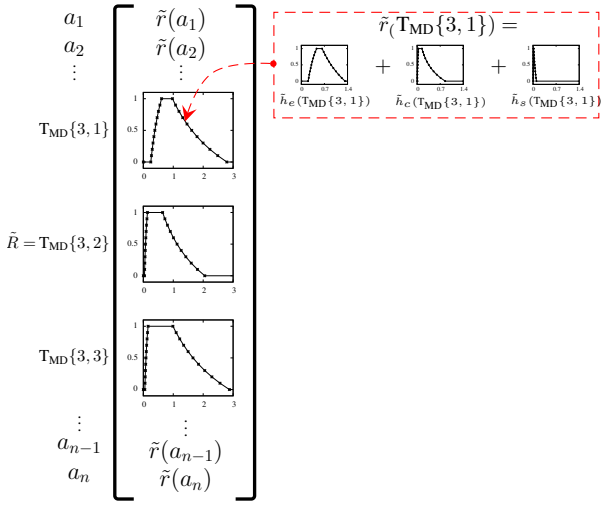
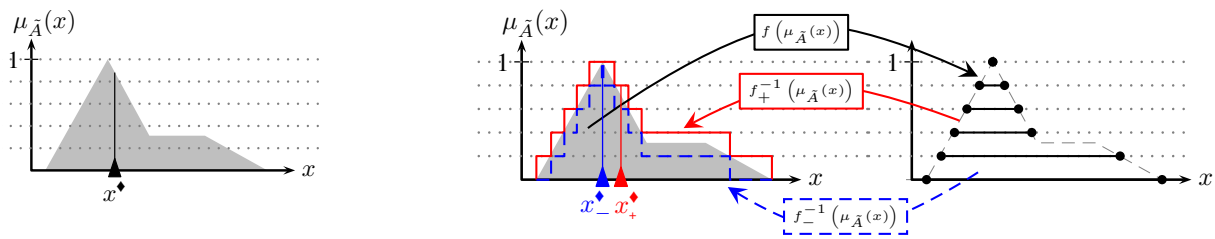


Figure 16: Fuzzy vector $\tilde{R}$

4.5.2. Comparison operator

Various approaches can be implemented to allow a comparison to be made [53]. Some approaches have been suggested that rank fuzzy numbers based on their α-level sets. Chen and Klein [54] suggest an index of differences based on α-cuts, fuzzy subtraction operations and area measurements. Dubois and Prade introduce the averaging level cuts (ALC) method [55], which uses a defuzzification procedure by averaging the α-cuts. According to [56], the most popular defuzzification methods are the center of gravity (CoG, or centroid) method [57] and the mean of maximum (MoM) method. The authors explain that the CoG is more accurate for representing a fuzzy set of any shape but that its computation can be difficult and time consuming. MoM is less time consuming, but in some cases, it may misrepresent the original fuzzy set. Because encompassing the shape of the alternative's fuzzy set is very important in our study, our attention has turned to CoG methods.



(a) Computation of Yager's index

(b) Computation of Yager's index based on α-cuts levels

Figure 17: CoG computation: superior and inferior approximation

In our study, the initial approach proposed by Yager [57] is used for ranking alternatives according to their α-cut levels. This technique computes an index for each fuzzy set that is used to compare and to rank alternatives. This index is a crisp value located on the x-axis, denoted by $x^{\blacklozenge}$, and is computed in equation 22.

$$x^{\blacklozenge} = \frac{\int \mu_{\tilde{\mathcal{A}}}(x) \times x \, dx}{\int \mu_{\tilde{\mathcal{A}}}(x) \, dx} \tag{22}$$

However, because our approach uses α-cut representations, as illustrated in Figure 17(b) (see the arrow annotated $f\left(\mu_{\tilde{A}}(y)\right)$), where $\mu_{\tilde{A}}(y)$ is the fuzzy set and f is the sampling function (6 α-cuts are considered in this example), the integral of equation 22 is turning into a sum over the α-cut levels. Regarding the α-cut, one considers an inferior and a superior approximation of the original fuzzy set, as shown in Figure 17(b) (see the arrows annotated as $f_{-}^{-1}\left(\mu_{\tilde{A}}(y)\right)$ and $f_{+}^{-1}\left(\mu_{\tilde{A}}(y)\right)$, respectively). Accordingly, the CoG index can be calculated either for the inferior or superior approximation in equations 23 and 24 respectively, which are denoted by $x_{-}^{\blacklozenge}$ and $x_{+}^{\blacklozenge}$, with m representing the number of α-cuts ($\alpha = \{\underbrace{0}_{\alpha_0}, \ldots, \underbrace{0.9}_{\alpha_{m\text{-}1}}, \underbrace{1}_{\alpha_m}\}$ in our case), $\overline{r^{\alpha}}$ and $\underline{r^{\alpha}}$ respectively indicating the minimal and the maximal values of the α-cut on the x-axis, and $\Delta_Y r^{\alpha}$ corresponding to the level difference (y-axis) between the α-cut and $\alpha + 1$-cut levels. These notations are detailed in Figure 18, in which the CoG of $\tilde{r}(\mathrm{T_{MD}}\{3,1\})$ is computed based on the superior approximation ($x_{+}^{\blacklozenge} = 1.089$).

$$x_{-}^{\blacklozenge} = \frac{\sum\limits_{\alpha=\{\alpha_1 \ldots \alpha_m\}} \left[\frac{\underline{r^{\alpha}} + \overline{r^{\alpha}}}{2} \cdot \Delta_Y r^{\alpha} \right]}{\sum\limits_{\alpha=\{\alpha_1 \ldots \alpha_m\}} \Delta_Y r^{\alpha}} \tag{23}$$

$$x_{+}^{\blacklozenge} = \frac{\sum\limits_{\alpha=\{\alpha_0 \ldots \alpha_{m\text{-}1}\}} \left[\frac{\underline{r^{\alpha}} + \overline{r^{\alpha}}}{2} \cdot \Delta_Y r^{\alpha} \right]}{\sum\limits_{\alpha=\{\alpha_0 \ldots \alpha_{m\text{-}1}\}} \Delta_Y r^{\alpha}} \tag{24}$$

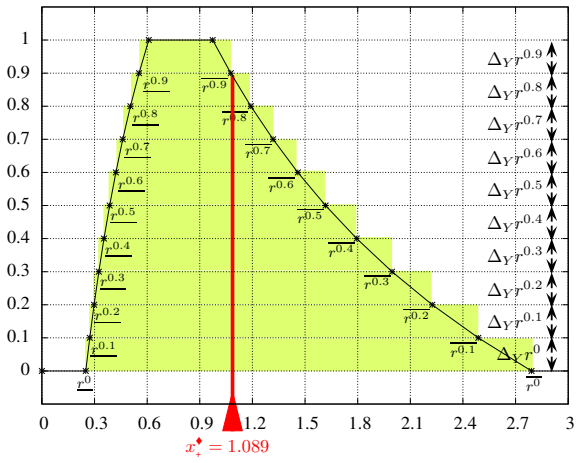


Figure 18: Superior COG computation related to $\mathrm{T_{MD}}\{3,1\}$

✎ The CoG based on the superior approximation is thus computed for each alternative as depicted in Figure 19. It can be concluded that the CoG of $\mathrm{T_{MD}}\{3,1\}$ is higher than the CoG of both $\mathrm{T_{MD}}\{3,2\}$ ($x_{+}^{\blacklozenge} = 0.672$) and $\mathrm{T_{MD}}\{3,3\}$ ($x_{+}^{\blacklozenge} = 0.966$). $\mathrm{T_{MD}}\{3,1\}$ thus receives a better ranking (*cf.* podium in Figure 19) and is stored with priority on the product. Finally, the list of data items is stored on the "communicating material" from most relevant to less relevant until no memory is available.

4.6. Synthesis

In summary, when the machine/operator needs to store data on the product, the relevance of each product-related data item from the database is computed using the group fuzzy AHP method. Data items are then

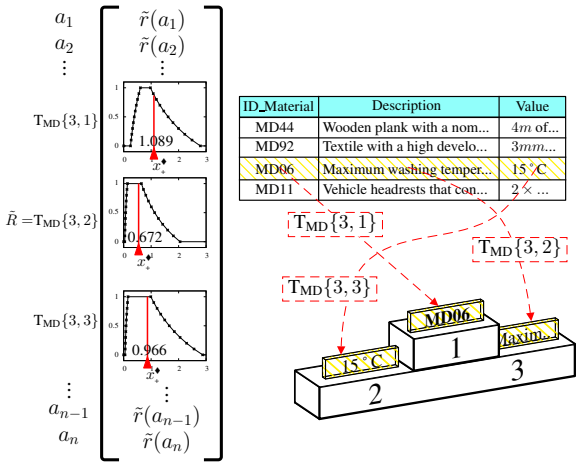


Figure 19: Alternative ranking according to the superior CoG ($x_+^\blacklozenge$)

ranked in order of relevance and information of the highest relevance is stored on the product depending on the available memory space.

5. Application: Information dissemination using a "communicating textile"

5.1. Data item relevance

The set of computations related to the three alternatives/data items $T_{MD}\{3,1\}$, $T_{MD}\{3,2\}$ and $T_{MD}\{3,3\}$ have been presented throughout section 4. In our scenario, approximately 500 product-related data items are ranked (representing $\approx$ 30 Mbytes). In this section, results for the final ranking of all data items are commented on, and then a brief view of how data items are split over the "communicating textile" is presented.

Figure 20(a) provides the resulting list (noted L) of product-related data items ordered from the most relevant to the least relevant (i.e., ordered according to their CoG of superior approximation: $x_+^\blacklozenge$). The two most relevant data items come from the table `MaterialLot` and have relevances of 0.9907 and 0.9839 respectively. The third item is $T_{MD}\{3,3\}$. Due to the large number of data items included in L (498, to be exact), only statistical results in the form of diagrams are presented (whisker diagram and pie chart). First, let us examine the whisker diagram in Figure 20(b). For each table $t \in \mathcal{T}$, the min, the 1st-3rd quartile, the median, and the max relevance of the set of data items belonging to t are given. We can see that the most relevant data items come from `MaterialLot` (which includes the two first data items of L) and from `MaterialDefinition`, `ProductSegment`, and `ProductionOrder`. The attributes from these four tables have been enumerated by the experts e_1, e_2, and e_3 in C_e (see Table 2), and C_e is the most important criterion at this stage of the PLC (see Figure 12). Moreover, one can note that these four tables are included in G_1 and G_3 and that the experts, concerned by C_c, have highly recommended selecting information from both groups (*cf.* vectors in Figure 8).

The "communicating textile" designed is shown in Figure 21(a). As mentioned, the product-related data items are stored on the product from the most relevant to the least relevant, until no more memory is available. In our study, no more than the first 70 data items could be stored on the communicating textile (representing $\approx$ 4Mbytes when the entire list L represents $\approx$ 30Mbytes). The pie chart in Figure 20(c) shows the percentage of data items among the 70 that come from each entity group. For instance, 61% (i.e., $\approx$ 43 of the 70 data items) are included in tables for G_3, and 37% are included in tables for G_1. It can be noted that no information related to the personal data group (i.e., G_2) is embedded in the product, which is largely because of the choices made in the enumeration and contextual criteria. In this respect, these results meet the expert specifications (note that L, the whisker diagram, and the pie chart are always displayed to the user and are used as decision-support tools). The "communicating textile" is then used to store the first 70 data items. In previous work, the tools necessary to disseminate/split data items over a communicating material have been developed. Figure 21(b) illustrates how the data item $T_{MD}\{3,3\}$ is split and then stored on different RFID μtags. In short, a specific protocol header is added to each resulting piece of data item (header represented by the gray background) to determine in what order information is split, and then each "piece+header" is stored among the RFID tags (see Figure 21(b)).

5.2. PLC benefits

With the communicating textile, any actor in a downstream PLC stage is able to retrieve the information preliminarily stored on the communicating textile. Figure 22 illustrates such a scenario considering an typical PLC that consists of three main phases: Beginning of Life (BoL), including design and production, Middle of Life (MoL), including use and maintenance, and End of Life (EoL), including recycling and disposal [10]. A writing phase (described in section 5.1) is defined in BoL and a user (in MoL) then reads and reconstitutes the set of product-related tuples after reading the material. For this to happen, software has been developed, from which a screenshot is given in Figure 22. It shows

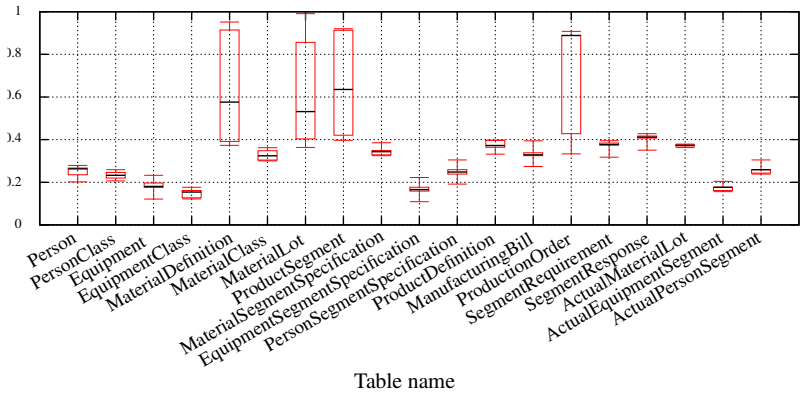
Rang a_l	Table Name	Attribute Name	Primary Key	Cell Value	Relevance
1st	MaterialLot	Quantity	LPB61	50	**0.9907**
2nd	MaterialLot	IDMatLot	LPB61	LPB61	**0.9839**
3rd	MaterialDefinition	Value	MD06	15˚C	**0.9516**
...	...	...	...	...	...
...	...	...	...	...	...
70th	MaterialClass	Value	MCHC3019	Blue/Red	**0.5758**
71th	SegmentResponse	Start Time	PSR0002	10:05:00	**0.5314**
...	...	...	...	...	...
...	...	...	...	...	...
497th	EquipmentClass	Description	ECBSM01	Bonding m...	**0.1541**
498th	PersonClass	Description	PCPLW01	Worker L...	**0.1562**

Set of data items that must be stored on the product

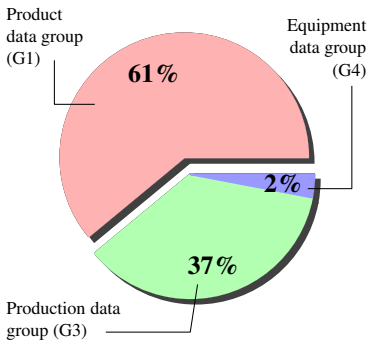
Product storage limit : 70th

Set of data items which cannot be embedded on the product

(a) List of data items ordered from the highest relevant to the lowest

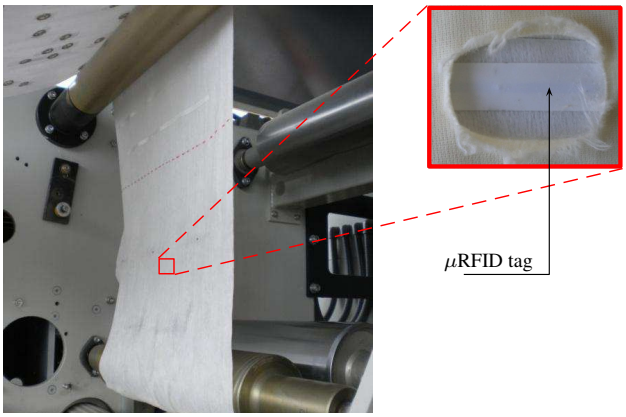


(b) Result of the data item's relevance in form of whisker diagram

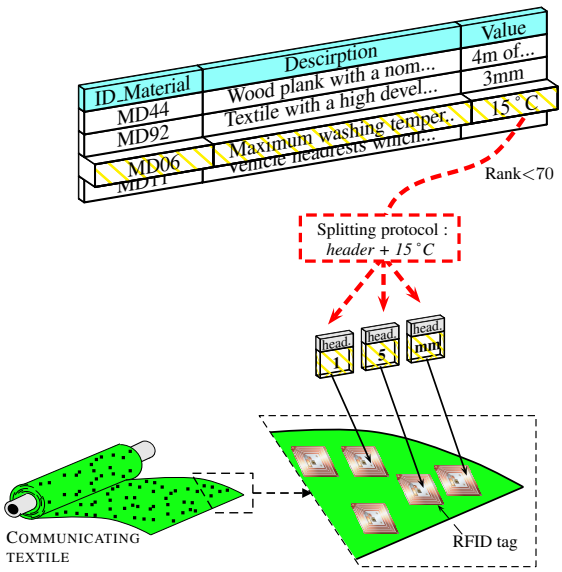


(c) Result in form of a pie chart

Figure 20: Results of the data item's relevance



(a) Communicating textile prototype



(b) *Splitting protocol*

Figure 21: Prototype of "communicating textile" being designed and illustration of the *splitting protocol*

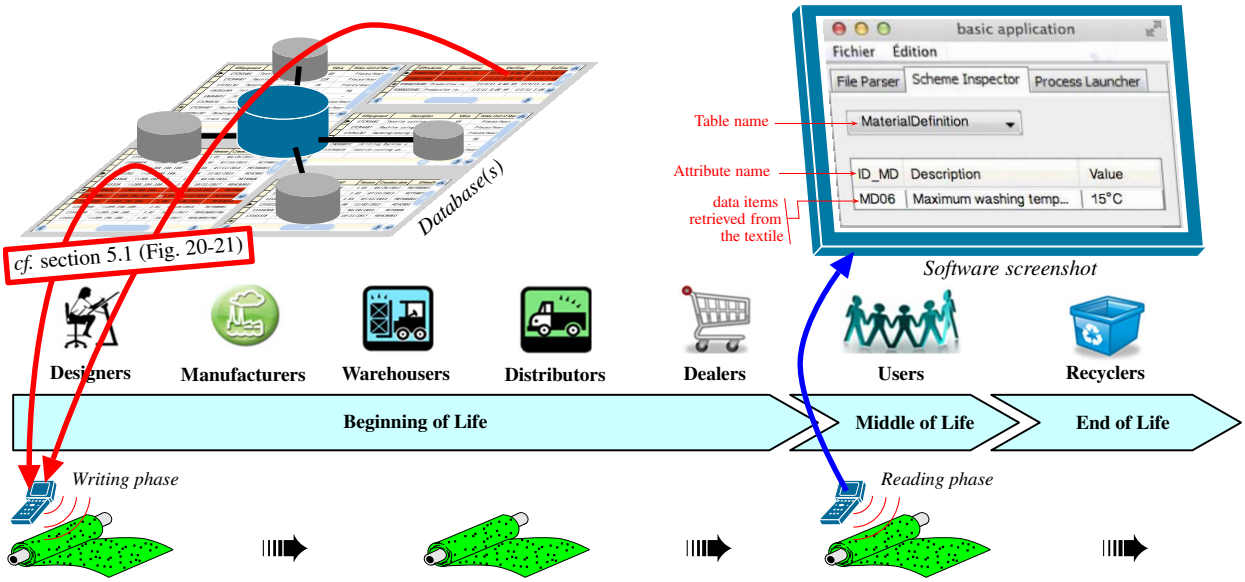


Figure 22: Writing & Reading phases in the PLC – Software screenshot when displaying tuples retrieved from the communicating material

that tuple 3 of `MaterialDefinition` is reconstituted and displayed to the user. In this scenario, such information is helpful to the user to adjust (manually or automatically) the washing program [58, 12].

The data dissemination process introduced in this paper is, to our knowledge, the first that consider PLC criteria to select the information that is to be stored on a manufactured product. In this respect, it contributes to improving data visibility and sustainability throughout the PLC, thus advancing the $CL_2M^{\circledR}$ concept (Closed-Loop Lifecycle Management) [59, 7]. Our data dissemination process is even more groundbreaking because information is split and spread all over the material, thus enabling solutions of copy/redundancy/backup of the information on all or parts of the product. This is particularly important when a product undergoes physical transformations. With classical products (e.g., a product fitted with a unique RFID tag), the pieces resulting from the transformation no longer have the ability to communicate, whereas in our case, they do. Tajima [60] emphasizes the significant proportion of defective tags and false reads with classical products, which has been as high as 20-50% in some pilot projects. Pushing the communicating material paradigm to its extreme, the material should be able to make its own decisions according to the events occurring in its environment. For instance, it could make the decision to propagate/replicate specific data onto different material parts knowing that a physical transformation is scheduled, thereby avoiding data loss. Another example would be to hide information in adversarial environments. Such strategies will be addressed in further work. Other benefits could be identified with regard to the PLC, but the main focus of the paper is on comparing our aggregation method with existing ones, which is presented in section 6.

6. Comparison of aggregation operators

This section presents a comparative study of our proposal with two existing aggregation operators. As stated in section 3, the intended behavior of the aggregation method should be disjunctive or counting rather than conjunctive. For that purpose, one aggregation method based on probability theory (to obtain a *counting* behavior) and another method based on the fuzzy set theory (to obtain a *disjunctive* behavior) are compared with our proposal (*disjunctive* behavior). To detail each method, let us consider the evaluations of parameter v performed by five experts on a domain $\mathcal{X} = \{1, 2, 3, 4, 5\}$ as follows: $e_1(v) = 2$, $e_2(v) = 4$, $e_3(v) = 1$, $e_4(v) = 4$, and $e_5(v) = 4$ (see frame 2 in Figure 23). The three aggregation methods are as follows:

- *Saaty* method [51] (counting behavior): the aggregation operator $\bowtie$ is the average of the expert assessments, as illustrated in frame 3 in Figure 23 with $\bar{v} = \frac{e_1(v)+e_2(v)+e_3(v)+e_4(v)+e_5(v)}{5} = \frac{2+4+1+4+4}{5} = 3$,
- *Deng* method [38] (disjunctive behavior): the aggregation operator $\bowtie$ consists of integrating the ex-

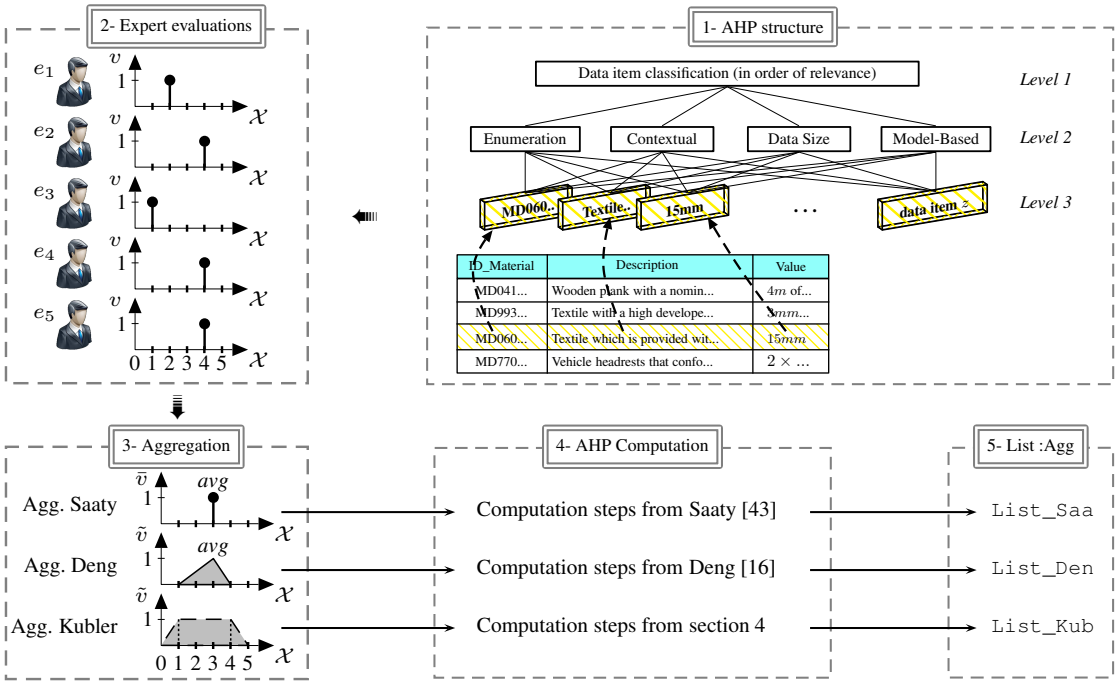


Figure 23: Illustration of the 3 methods of aggregation of expert opinions based on the scenario of data dissemination

pert opinions through a triangular fuzzy set $\tilde{v}$. The kernel of this set is equal to the average evaluation, and uncertainty is added in a decreasing manner from this value (i.e., until reaching the minimal and maximal opinions formulated by the experts), as depicted in Figure 23. This representation tends to mean that the " best/correct" evaluation is considered as the average evaluation and that uncertainty arises from the set of evaluations.

- *Kubler* method (disjunctive behavior – paper proposal): the aggregation operator $\bowtie$ consists of integrating all expert opinions through a uniform fuzzy set, as described in section 3. In the resulting fuzzy set, all opinions are of equal importance, unlike the two previous aggregation methods.

At the end of the process (i.e., after the computations steps; *cf.* frame "4-AHP Computation"), the list L of data items ordered from the most relevant to the lowest is produced by each aggregation method (similar to the list presented in Figure 20(a)), denoted respectively `List_Saa`, `List_Den`, and `List_Kub` in Figure 23 (*cf.* frame "5-List:Agg").

6.1. Comparison process

The assessment of each aggregation method is performed by determining the level of satisfaction of each expert with regard to the aggregation result. To do this, for each method (i.e., Saaty, Deng, Kubler), a performance indicator is defined based on the *similarity* between the aggregated list (e.g., `List_Saa`) and the list resulting from the specification of a single expert k when using the same method (the list is noted, in this case, `List_Saa:`e_k). Figure 24 gives the example in which only the opinion provided by expert 4 about parameter v is considered by each aggregation method (*cf.* frame 2, 3, 4), thus generating three lists: `List_Saa:`e_4, `List_Den:`e_4 and `List_Kub:`e_4. Ultimately, if the degree of *similarity* between `List_Saa:`e_k and `List_Saa` is higher than that between `List_Kub:`e_k and `List_Kub`, the aggregation method proposed by Saaty better satisfies expert k than our aggregation method.

The *Jaccard similarity coefficient* ([61]) can be used to measure such the *similarity* between two distinct lists A and B. It is defined as in equation 25, i.e., the size of the intersection of the lists divided by the size of the union of the lists. In our study, the union size is equal to the number of data items n. A *Jaccard similarity coefficient* goes from 0 (no common data items) to 1 (identical lists).

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{n} \tag{25}$$

Let A, B and C be three lists consisting of five data

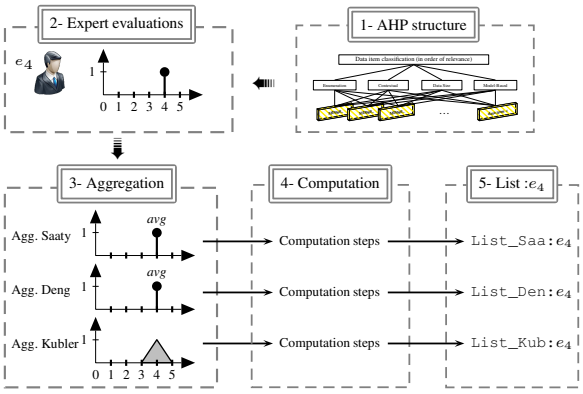


Figure 24: Aggregation operators considering a single expert

items {D1, .., D5}, where each data item receives a final rank, as illustrated in Figure 25. In this example, two *Jaccard similarity coefficients* $J(A, B)$ and $J(A, C)$ are calculated. Both coefficients are equal because the intersections $|A \cap B|$ and $|A \cap C|$ have the same cardinality.

	A	B	C
D1	1	1	7
D2	2	2	6
D3	3	3	1
D4	4	6	2
D5	5	7	3

$$J(A, B) = \frac{|A \cap B|}{n} = \frac{|1,2,3|}{|1,2,3,4,5|} = \frac{3}{5}$$

$$J(A, C) = \frac{|A \cap C|}{n} = \frac{|1,2,3|}{|1,2,3,4,5|} = \frac{3}{5}$$

Figure 25: Computation of *Jaccard similarity coefficients*

In our data dissemination process, data items are ordered from the highest relevance to the lowest. It could be worthwhile to define a *similarity coefficient* that would consider the rank (our attention to similarities at the beginning of the lists is more important). To do so, let us define L_q to be a sublist of L, where L_q consists of data items from rank 1 to q ($q \leq n$). It is then possible to compute a *progressive similarity coefficient* $J_q(A, B)$, as in equation 26.

$$J_q(A, B) = J(A_q, B_q) \tag{26}$$

Figure 26 details the evolution of the *Jaccard progressive coefficients* $J_q(A, B)$ and $J_q(A, C)$ for all $q = \{1, 2, ..., 5\}$, based on lists A, B, and C from Figure 25.

The *progressive Jaccard coefficients* are thus computed for each aggregation method, thus reflecting the evolution of the expert satisfaction. Let us note that considering the expert to be entirely satisfied when the aggregation list is identical to the expert's list is a strong assumption because the expert's list is considered as a correct expression of his opinion. Figure 27 illustrates that $p_{\max}$ *progressive Jaccard coefficients* (curves) are

$$\begin{aligned}
J_1(A, B) &= \frac{|A_1 \cap B_1|}{1} = 1.00 & J_1(A, C) &= \frac{|A_1 \cap C_1|}{1} = 0.00 \\
J_2(A, B) &= \frac{|A_2 \cap B_2|}{2} = 1.00 & J_2(A, C) &= \frac{|A_2 \cap C_2|}{2} = 0.00 \\
J_3(A, B) &= \frac{|A_3 \cap B_3|}{3} = 1.00 & J_3(A, C) &= \frac{|A_3 \cap C_3|}{3} = 0.33 \\
J_4(A, B) &= \frac{|A_4 \cap B_4|}{4} = 0.75 & J_4(A, C) &= \frac{|A_4 \cap C_4|}{4} = 0.50 \\
J_5(A, B) &= \frac{|A_5 \cap B_5|}{5} = 0.60 & J_5(A, C) &= \frac{|A_5 \cap C_5|}{5} = 0.60
\end{aligned}$$

Figure 26: Computation of *Jaccard progressive coefficients*

obtained using the aggregation method, with $p_{\max}$ representing the number of experts (graph entitled *similarity with each expert*). In this example, 5 curves are plotted because 5 experts are considered (see Figure 23); each list consists of n data items.

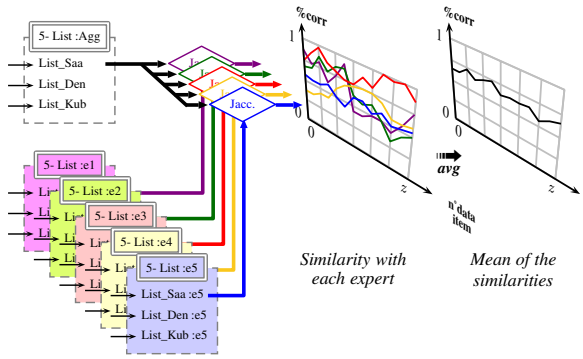


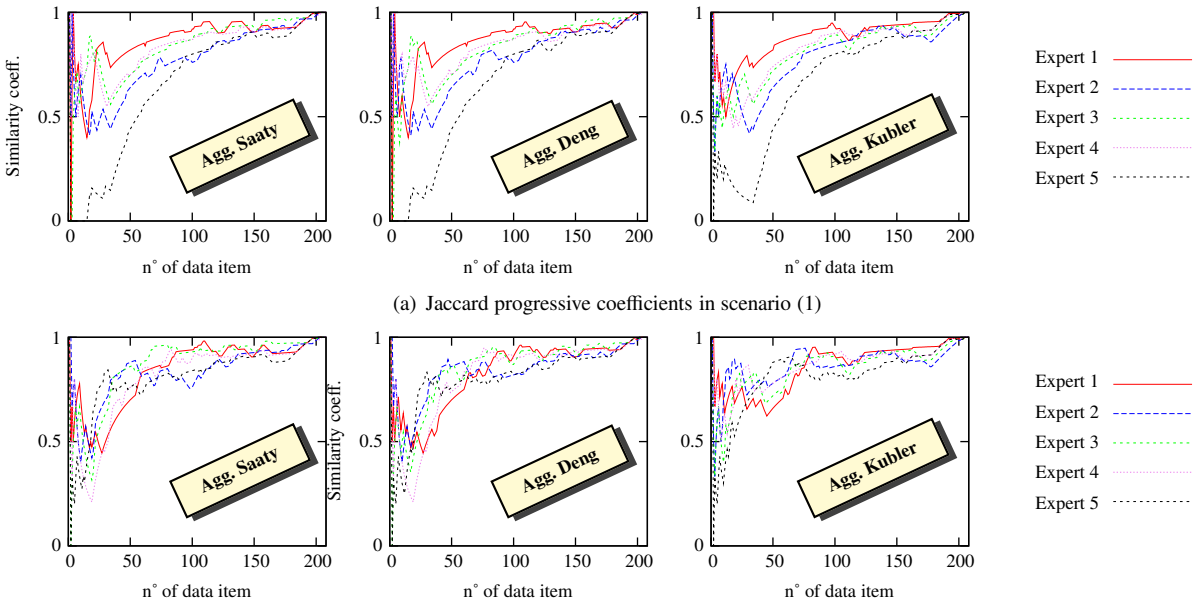
Figure 27: Comparison of the 3 aggregation operators based on the *Jaccard progressive coefficients*

Finally, because our goal is to find the best consensus among the experts, we propose to compute the *mean progressive Jaccard coefficients* for each aggregation method, as in equation 27. The second graph given in Figure 27 (*mean of similarities*) shows the evolution of the *mean progressive Jaccard coefficients* related to the aggregation method defined by Saaty, which is obtained based on the 5 curves from the graph *similarity with each expert*.

$$\begin{aligned}
J_q(\texttt{List:Saa}) &= \frac{\sum_{k=1}^{p_{\max}} J_q(\texttt{List:Saa}, \texttt{List:Saa:e}_k)}{p_{\max}} \\
J_q(\texttt{List:Den}) &= \frac{\sum_{k=1}^{p_{\max}} J_q(\texttt{List:Den}, \texttt{List:Den:e}_k)}{p_{\max}} \\
J_q(\texttt{List:Kub}) &= \frac{\sum_{k=1}^{p_{\max}} J_q(\texttt{List:Kub}, \texttt{List:Kub:e}_k)}{p_{\max}}
\end{aligned} \tag{27}$$

6.2. Comparison results

Considering the scenario of data dissemination, 5 experts $\{e_1, .., e_5\}$ have performed evaluations with regard



(a) Jaccard progressive coefficients in scenario (1)

(b) Jaccard progressive coefficients in scenario (2)

Figure 28: Computation of *Jaccard progressive coefficients* for each expert with respect to each aggregation method

to the criteria *Enumeration*, *Contextual*, and *Data size*. These evaluations are not described in detail but are commented on throughout this section. Two scenarios are defined:

(1) C_e *favored*: *Enumeration* is strongly favored over the other criteria,

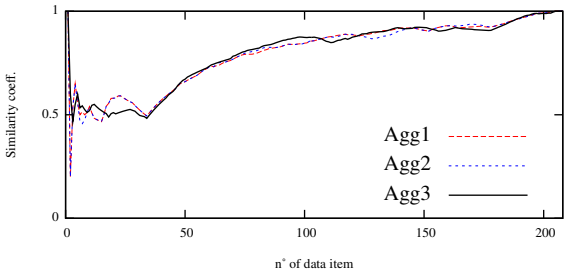
(2) *Equal-importance*: the four criteria are of equal importance,

Among the 5 experts, e_5 enumerates information that is not at all enumerated by the 4 other experts. As mentioned in section 3, this opinion is as legitimate as the others, although it is isolated. The *Jaccard progressive coefficients* between the lists resulting from each aggregation method (`List:Saa`, `List:Den`, `List:Kub`) and the lists resulting from each expert k are computed and plotted in Figure 28 for scenarios (1) and (2).

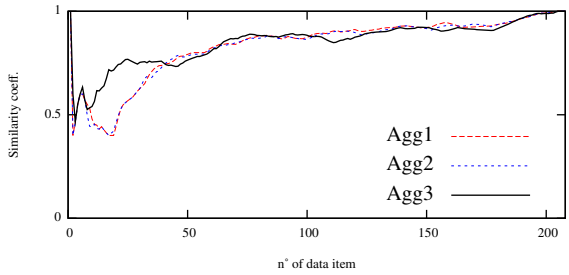
Considering scenario (1) (see Figure 28(a)), the curves show that the three aggregation methods have difficulty satisfying e_5 (the *Jaccard progressive coefficients* of e_5 always remain far below the four other curves, especially for the first 50 data items). This is explained by the fact that e_5 has an isolated point of view with respect to criterion C_e, which is strongly favored over the other. As a result, it is particularly difficult to satisfy every expert. Nonetheless, among the three aggregation methods, the method developed in this paper (i.e., `Agg. Kubler`) satisfies e_5 the most because methods `Agg. Saaty` and `Agg. Deng` have a similarity of approximately 0 between data items $n^\circ 1$ to 30, whereas our method has a similarity of approximatively 0.3. This has an impact on the satisfaction rating of the four other experts, who are less satisfied with `Agg. Kubler` than they are with `Agg. Saaty` and `Agg. Deng`, but it does not affect the final consensus because the *mean progressive Jaccard coefficients* of the three methods (see Figure 29(a)) are almost identical (the three curves overlap). This study shows, in this particular scenario, that `Agg. Kubler` better satisfies the disjunctive behavior than do the two other methods because it tries not to neglect/to leave out an opinion.

Considering scenario (2) (see Figure 28(b)), it can be concluded that no expert has been left out or treated unfairly. Indeed, unlike scenario (1), no curves are detached from the others, i.e. each aggregation method equally satisfies the experts. However, it should be noted that the final consensus is much better when using `Agg. Kubler` (see Figure 29(b)) than when using the two other methods, especially when focusing on the first 50 data items that are of major importance.

More generally, it can be concluded that the three aggregation methods globally exhibit a similar behavior in these scenarios because the *mean Jaccard progressive coefficients* are almost overlapping, whether in scenario (1) or (2) (*cf.* Figure 29).



(a) Mean Jaccard progressive coefficients in scenario (1)



(b) Mean Jaccard progressive coefficients in scenario (2)

Figure 29: Computation of the *mean Jaccard progressive coefficients* for each aggregation method

7. Conclusion

Concepts such as the Internet of Things and Ubiquitous Computing redefine how we interact with information. It is not uncommon to use intelligent/communicating products to ensure an information continuum over the PLC (e.g., for traceability purposes). Linking the product-related information to the products themselves is a formidable challenge, especially when making the information easily accessible. Over the last decades, research has been carried out to enable such a link. However, information is often deported through the network (stored in databases) and is accessed remotely. In this paper, a new kind of intelligent product referred to as "communicating material" is introduced, which provides the opportunity to embed data on all or part of the product itself. In our context, products made of "communicating material" are used to convey information between the different actors of the PLC, thus improving data interoperability, availability, and sustainability compared with standard products (e.g., a product carrying a unique RFID tag or barcode). Indeed, the same data can be copied to several parts of the material, which is useful in cases in which it is important that little or no product-related data are lost.

Although "communicating materials" provide new abilities compared with standard products, they still have low memory capacities compared with product databases which are becoming increasingly larger. Accordingly, this paper proposes an information dissemination framework to select context-sensitive information from the database (i.e., the information relevant that should be embedded in the product). This paper shows that the required information is determined by a variety of factors such as user concerns, the product environment, the company core business, and the application features. In addition, several people may be concerned about the product during the PLC and may want different types of information, leading to conflicts between groups of people.

To address this challenge, this paper develops a solution based on a MCDM method to identify data appropriate to the expected situation. To do so, an indicator of relevance is defined giving the degree to which information might be useful to have stored on the product. This method combines the AHP method with the fuzzy set theory. The AHP makes it possible to address the MCDM problem, and the fuzzy set theory makes it possible both to handle uncertain information and to aggregate the different opinions from groups of experts. Indeed, a new approach involving the aggregation of expert opinions is proposed in this paper based on the fuzzy set theory. This approach is then used in an application involving a "communicating textile". The results shows that the selected data largely meet the expectations formulated by users at a given stage of the PLC.

Further work should compare our approach to the aggregation of expert opinions with other approaches from the literature [45]. The first initial work on this topic that is presented in this paper seems to prove that our fuzzy aggregation operator is better suited to our context than classical methods. These preliminary results should further be validated by a wider study involving additional experiments. Ideally, work in this area will lead to an adaptive method selecting the best-suited aggregation method depending on the criterion importance.

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