Semantic-based collaborative decisional system integrating fuzzy reasoning in an IoT context

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Abstract

Technologies such as IoT and Big data use advanced representation models and methods to lead to coherent systems and softwares. Nevertheless, there is a substantial lack of approaches able to support uncertain data and fuzzy environment to build a bridge between physical objects, semantic real-world view and the systemic view. In this work, we propose a semantic driven approach to support a decisional system based on semantic representation and an accurate fuzzy reasoning using the Choquet Integral method. The proposed generic architecture takes into consideration the formal representation of the real world, users' needs and processes. Further, we focus on the relation between them and the dependence between different criteria. A detailed case study in the agriculture domain is also presented to showcase the interest of our proposal.
Keywords: Ontology, Fuzzy reasoning, IoT, Collaborative decisional system.

1. Introduction

The Internet of Things (IoT) is a challenging field, in which a broad range of resources (computers, devices, sensors etc.) are interconnected which provides data and events that can be filtered, combined, and aggregated to start and drive business processes. IoT applications exist in numerous sectors such as urbanization, utilities (water and energy, health, etc). Decision making in IoT has gained a lot of attention recently since decision support systems make it easier for the user to deal with the flowing input data from the different devices.

One of the most critical generated issues is the design of systems that are able to bridge the gap between user needs and the use of data. Ontologies provide a formal representation of the real world, shared by a sufficient amount of users, by defining concepts and relationships between them [13]. An ontology contains a set concepts, taxonomic relationships (that define a concept hierarchy) and non-taxonomic relationships between them, concept instances and assertions about them [11]. The focus of modern information systems is moving from "data processing" towards "concept processing", meaning that the basic unit of processing is less and less an atomic piece of data and is becoming more a semantic concept which carries an interpretation and exists in a context with other concepts.

Ontologies have proven their interest in representation models, engineering tasks and even reasoning processing [18]. They have gained much importance, not only in the field of artificial intelligence but also in the fields of information organization, information retrieval and knowledge representation. Particularly, generic ontologies that aim to integrate heterogeneous knowledge coming from different sources and allow intelligent software agents to align heterogeneous ontologies in an automatic way [17]. In real life, there are three types of uses of discerning and non-communicative ontologies (communication between people, interoperability between systems and system engineering) as well as uncertain data and information. Hence, we propose a common vision of these different types of uses integrating fuzzy logic into the process to handle vague and imprecise information. Our aim is to offer a formal semantic representation, gathering both the operational and the systemic point of view. Our contribution aims at bridging, as mentioned above, the gap between user needs and the use of IoT data. Namely, we address the following major aspects in our system by identifying and formally representing the ecosystem of work: data collection through physical components, data reasoning and decision-making.

Our proposal focuses on the building of a hierarchical model of ontologies that supports the use of distributed knowledge bases and unifies the semantic, operational and systemic views. Indeed, we present a novel and complete method which includes the integration of the Choquet Integral in the process of fuzzy reasoning for decision support. The originality of the method is distinguished by mathematical characteristics that consider the relation of dependence between criteria. We present use cases in the domain of agriculture to illustrate our proposal.

The remainder of this paper is structured as follows. The next section gives background and a related work study as well as our motivations. Section 3 presents preliminaries that will be used throughout the paper. Our proposal will be introduced in Section 4. Section 5 illustrates a case study, before we conclude the paper and give an outlook on the future work in Section 6.

2. Related work

In this section we first present a related work study on decision making in IoT technology as well as group decision making using fuzzy logic. Then, we present our motivations.

2.1. Integrating decision making in an IoT technology

The Internet of Things (IoT) is based on the idea of interconnecting different types of devices, not just computers in order to build new applications and services or extending existing ones [2]. The aim of such technology is to help users achieve a high level of cooperativeness between the different objects they interact with on a daily basis or for specific purposes and domains. In fact, the interacting devices and sensors collect information in order to be used for decision making, recommendation, predictions, personalization etc.

Decision making based on data collected from interacting objects has been increasingly used in wide range of application scenarios: smart homes [20], intelligent transportation systems [7], health care [3, 4], security [6], agriculture [14] etc. Different methods and techniques can also be found in the literature.

Al-Hamadi and Chen [3] build a knowledge base using the collected data from health IoT devices in order to help the user decide if it's safe for him/her to visit this place/environment for health reasons. This trust-based health IoT protocol relies on three dimensions for decision making: risk classification, reliability trust, and loss of health probability.

Bui et al. [7] propose a connected intersection system where different objects such as vehicles, sensors, and traffic lights are connected and share information among each other, the aim is to achieve a real-time smart and optimized traffic light control at said intersection. For decision making, two game theory models are adapted to traffic flow in order to optimize this latter.

Louis and Dunston [16] propose real-time decision-making on construction sites by implementing systems that synthesize sensor information and running the treated information on a process model. Decisions programed into the process model are then made automatically and relayed back to the entities on the construction site through the IoT infrastructure.

Khan et al. [20] focus on water management systems which monitor and control the flow and reservoir of water in a home. The authors used Recurrent Neural Network (RNN) model in order to make an automated decision support system to decide upon the appropriate state of the suction pump.

Group decision making was also investigated by several recent works [9, 19, 15]. It aims to solve decision situations where several individuals are involved and it needs to reach an acceptable decision by all the members. In particular, fuzzy methods have emerged, taking into consideration information uncertainty, vagueness and incompleteness.

Capuano et al. [8] use fuzzy ranking to collect both experts' preferences on available alternatives and trust statements on other experts. The authors then evaluate and represent interpersonal influences through a social influence network.

Banaeian et al. [5] integrate fuzzy set theory into three popular multi-criteria supplier selection methods in order to complete a green supplier evaluation and selection study for an actual company from the agri-food industry.

Renato et al. [10] classify and select the most appropriate resource for the client's request in an IoT context applying fuzzy logic based on Quality of Service attributes.

2.2. Motivations

The common problems in decision-aware systems are mainly the lack of communication between the different modules in the same system or framework. Indeed, semantic treatments, uncertainty and fuzzy contexts are not taken into consideration especially during the reasoning process. Moreover, recent works do not take into consideration the cooperation and correlation between criteria and users' preferences.

Choquet integral is richer than basic operators cited in subsection 3.2. In fact, using Choquet integral for fuzzy reasoning and multicriteria decision making has proven to be suitable for cardinal aggregation (where numbers have a real meaning) [12]. Choquet integral has also the particularity to take into consideration the interactions and dependence among criteria and not just suppose that they're independent like other aggregation operators.

One of the reasons for proposing this approach is to be able to apply it for decision making in an IoT environment. In fact, the large volume of raw data coming from a large network of connected devices is difficult to handle because it needs filtering, treating to become useful information. After that, in order to use this information for knowledge extraction and/or decision making, we need to employ semantic processing and reasoning. IoT, semantics, reasoning and data mining modules and even end users need to share information to accomplish a common purpose. This work is positioned in this scope, and the chosen application domain is agriculture. In fact, we have different types of devices interconnected in agricultural fields and our aim is to help farmers making right decisions based on the collected data (section 5 offers more details about this application).

Our proposal deals with data from its raw nature until it transforms into knowledge which can be used for reasoning, it aims to reduce the gap between users' needs and system mechanisms. The originality of our proposal consists on its rely on semantics methods and rigorous mathematical propositions.

Our motivation is to answer requirements of users in an IoT context, by integrating and aggregating user preference criteria and fuzzy reasoning in the same framework. Our framework includes both semantic technologies and integral method to provide collaborative decision-aware support between modules and intra-modules.

3. Preliminaries of Fuzzy

3.1. Fuzzy basics

Below some basic information and required definitions about fuzzy logic will be presented.

- Universe of discourse is the range of all possible values considered as fuzzy system output.
- Fuzzy set [21] is a representation of a linguistic variable that defines the possible state of output, it is a set with fuzzy boundaries. In the fuzzy theory, fuzzy set A of universe X is defined by function $\mu_A(X)$ called the membership function of set A.
- For any element x of universe X, membership function $\mu_A(X)$ equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A.

$\mu_A(X) : X \to [0, 1],$ where $\mu_A(X) = 1$ if X is totally in A;
$\mu_A(X) = 0$ if X is not in A;
$0 < \mu_A(X) < 1$ if X is partly in A;
When the universe of discourse X is discrete and finite A can be expressed as :
$\sum_i \frac{[\mu_A(x_i)]}{x_i}$

- Fuzzy rule can be defined as a conditional statement in the form of:

  IF x is A THEN y is B

  where x and y are linguistic variables ; and A and B are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively.

  Fuzzy rules are based on human experience. There are several types of outputs resulting from the rules in the decision-making systems depending on the need of the user (alert, action, decision-making considering user preference), depending on the context (fuzzy, crisp) and also depending on the user preference (precision, processing time..). All these characteristics are studied and analyzed in section 5.

3.2. Aggregation operators in a fuzzy context

To help a decision-maker choosing one or more alternatives through their criteria, we need to establish a preference relationship between these different elements. To meet this need, there are several aggregation operators shown in table 1 capable of establishing a preferential classification in a fuzzy sets context (the weight vector, the T-norm, Min-Max ..).

4. Proposed architecture

A variety of technologies have been deployed in the proposed architecture in order to enhance its robustness by means of environments that are sensitive, adaptive, and responsive to human needs.

The overall architecture as shown in Figure 1 is divided into four layers:

- Presentation layer offers end-users specific services. It deals with user interfaces such as monitoring, human-machine interface, reporting or dashboarding for visualization. It is also responsible of identifying user requirements through their queries. The presentation

Table 1. Aggregation Operators.

Operator	**Description**
	Basic operators
Median	It consists in ordering the arguments from the smallest one to the biggest one. And then taking the element in the middle. In case of even number observations, Median can't be determined exactly.
Arithmetic mean	It is the simplest and commonly used operator. It is defined as the sum of the numerical values of each observation divided by the total number of observations. Mathematically we have : $M(x_1, x_2, .., x_n) = (1/n) * \sum_{i=1}^{n} x_i$ This method Works only when all values are equally important, it has no behavioral properties.
	Fuzzy integrals
Choquet integral [12]	This method takes into account the relation of dependence between criteria. If we have μ, a fuzzy measure on X, whose elements are denoted $x_1, x_2, .., x_n$, the Choquet integral of a function $f : X \to \mathbb{R}^+$ with respect to μ is defined as : $C_\mu(f) = \sum_{i=1}^{n}(f(x_i) - f(x_{i-1})) * \mu(A_{(i)})$ where $._i$ indicates that the indices have been permuted so that $0 \leq f(x_1) \leq$ ... $\leq f(x_n) \leq 1$ and $A_{(i)} = x_i, .., x_n$ and $f(x_0) = 0$. To exploit properly this method, these steps must be executed: - An end-user configuration (attitude model). - An analysis of the criteria of objects to be recommended. - A calculation of the overall scores of the objects establishing their utility for the recommendation. - A recommendation result is provided. It takes in consideration the distance between the elements.
T- norm, T-conorm [1]	T-norm, T-conorm and negation functions are used to calculate the membership values of intersection, union and complement of fuzzy sets, respectively. T-operations have specific properties, it is commutative, associative, monotonic, and the number 1 acts as identity element, that is $T(a, 1) = a$.

layer offers the possibility for the user to choose the criteria that matter the most to him, and based on this choice, the fuzzy reasoning process (knowledge layer) allows decision making.

- Physical or IoT layer presents the IoT system. It is composed of connected devices and sensors for location, measurement, which are in contact with the real world. Information given by these devises is sent to the data layer.

- Data layer is useful to store all the raw data derived from connected objects such as sensors and the key information about users' profiles and preferences that may be needed and exploited in the future. In addition, Data layer helps to collect accurate, processed and enriched data in order to provide the knowledge module with needed inputs.

- Knowledge layer is considered as the core layer. It implements two components which will be detailed in the following subsections.

  Semantic component: establishing communication between ontology layers allows to support and organize the system processing and to guide the system designers by miming the ecosystem. The proposed ontology is conceptually organized into four ontology layers (Middle-level, domain, IoT and system ontology) and it is responsible of activating and monitoring the reasoning module in order to support reasoning tasks through its semantic and taxonomic relations.

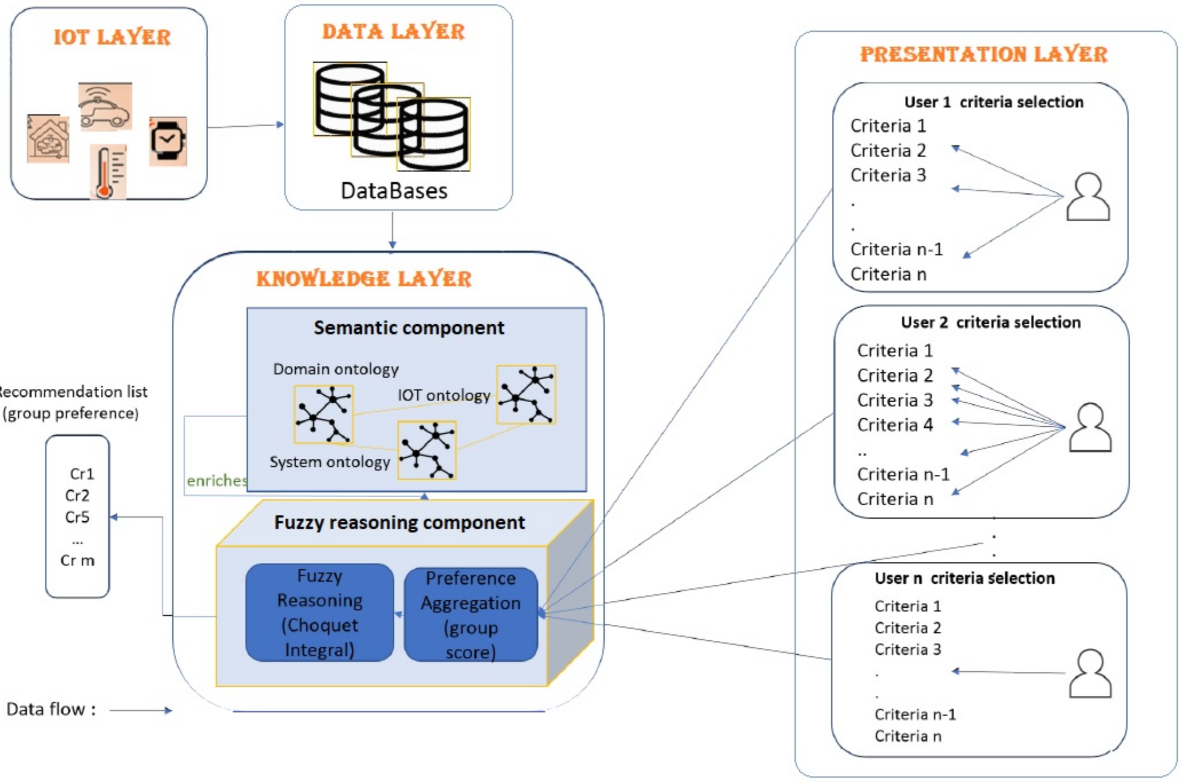

Figure 1. Semantic-based collaborative decisional system architecture.

Fuzzy reasoning component: it is designed to ensure the requested crisp and fuzzy logic reasoning in the system in order to perform an efficient decision making.

4.1. Semantic component

The use of ontologies brings several advantages in a computer system. First, ontologies offer a formal data representation collected from multiple sources through the explicit definition of terms and relations. Second, ontologies participate in correlating between users' view, domain view and system view from collected data from distributed data sources and physical devices and ontology concepts. As already stated, the idea in linking several levels of ontologies is to support distribution of knowledge, interoperability and coordinating data flows between layers.

As shown in fig 2, each of the four proposed ontology layers meets specific needs.

The used middle level ontology is common across domains to support interoperability and organize knowledge using general concepts. We propose a minimal graph with the most necessary concepts for the organization and non-functional requirements.

Domain ontology is devoted to describe domain objects (resources and processes) and define their relationships. It includes definition of general hebdomadal processes including their inputs and outputs and it is responsible of activating the processes depending on users' needs. The concepts of this ontology change depending on the domain.

IoT ontology is devoted to handle different aspects of IoT-based sensors and data collection by proposing a specific vocabulary to represent connected devices of IoT systems with no regard to the application domain described in the domain ontology.

System ontology represents an interpretation of the system processes based on the information and relationships defined in the domain ontology. It describes an information system's life cycle and needed mechanism for execution. This layer is composed of two modules. The pro-

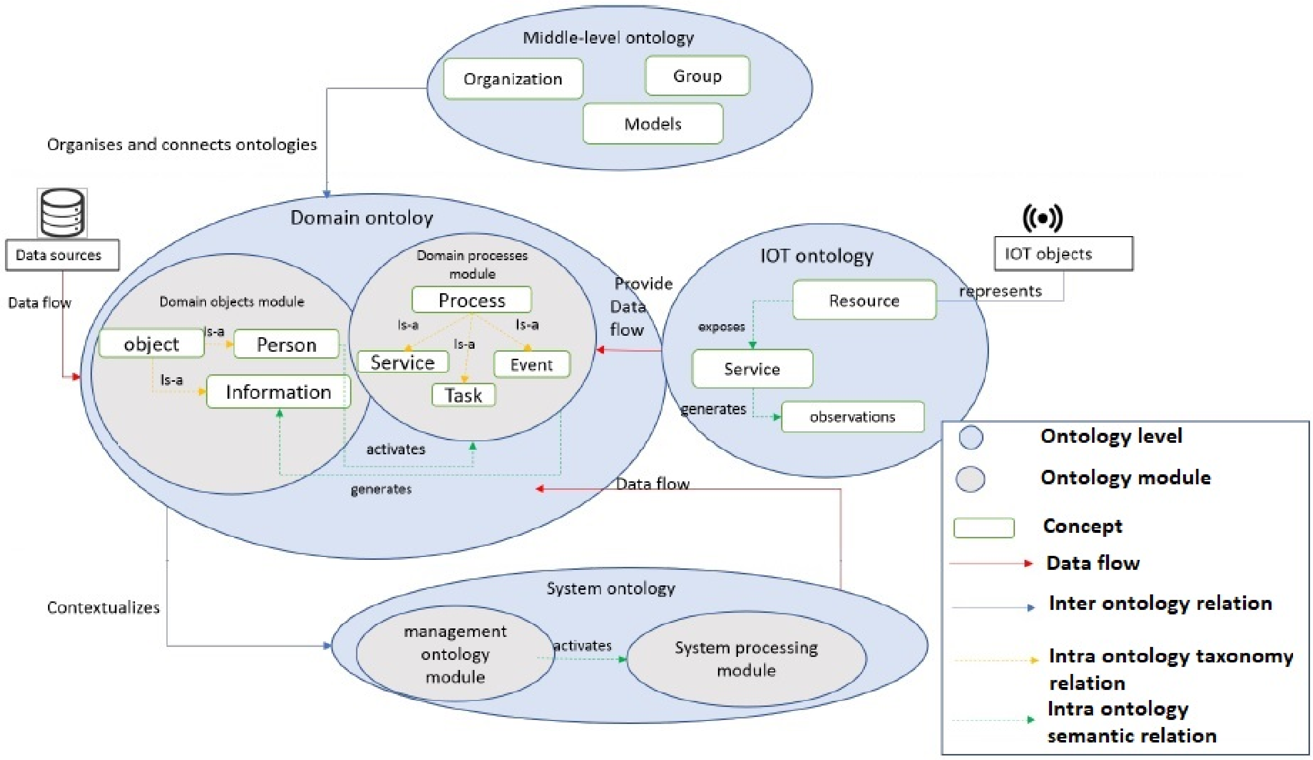

Figure 2. Ontology layers.

cessing module and the management module which monitor the mechanism by means of rules. The present relationships facilitate the integration of data and their transfer from one level to another. As we can notice that the graph can easily contain the domain ontology in the future thanks to its flexibility and adaptability.

4.2. Fuzzy reasoning component

The raw collected mass of data has no significance to end users, after being contextualized and hierarchized thanks to semantics and ontologies it becomes applicable in a specific decision-making context.

In our system, the proposed ontology and the reasoning component cooperate to produce a result. From the one hand, ontologies offer contextualized data and rules to apply and from the other hand, the fuzzy reasoning component produces an appropriate decision based on the user's choice as well as a recommendation based on group preferences.

The reasoning component is composed of two modules:

1. Preference aggregation which allows the system to provide a group preference as recommendation based on the selections and choices of other users. This module allows the user to take advantage of the previous experience of past users.

2. Fuzzy reasoning which encapsulates an enriched decision making unit with Choquet Integral to handle the uncertainty and take into consideration the interaction between criteria which is often ignored. The decision making unit is represented in figure 3. It begins by receiving one or large number of crisp criteria that will be analyzed and fuzzified. Then, it processes all received inputs according to human based, fuzzy "if-then" rules, which are expressed in the ontology layers. Finally, it averages and weights the results from all the individual rules into one single output decision which decides what to do using Choquet

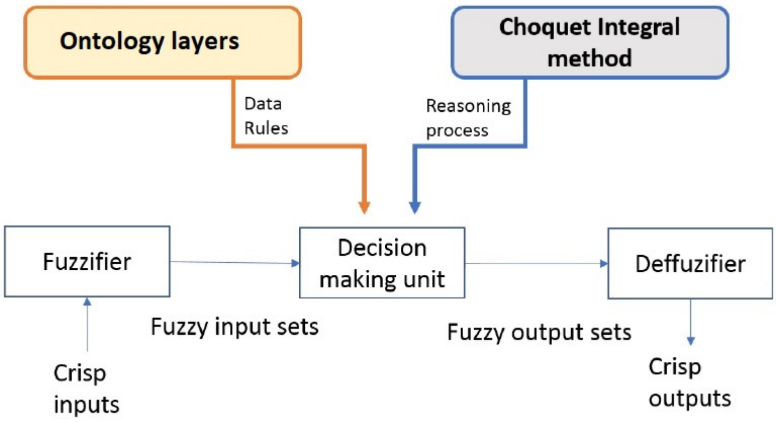

Figure 3. Ontology layers.

integral method. The result output signal is a precise defuzzified value.

5. Case study

5.1. Agriculture domain presentation

In this application, we study agricultural field, and more specifically a critical and important act for each farmer: making decisions on what seed to plant. Choosing the right seed for the field is a very important and difficult task. Each season, when a farmer decides to purchase seeds to plant in his soil, he may be confronted with countless choices to pick from. It may be difficult to choose, especially not knowing which variety the best yielding for his own soil may be. When choosing, farmers consider many references such as the records for previous years or the most recognized university studies.

In this context, new technologies such as IoT have opened up extremely productive ways to cultivate soil and planting. IoT-based smart farming is enable to enhance farmers' productivity and reduce their waste. Farmers can automate their activities (irrigation, control the weather condition..) and monitor their properties using sensors and decisional systems from anywhere.

Frequently, users hesitate to choose the right seed to plant. The proposed ontology contextualizes the user's query with semantic data and proposes the appropriate rules for the execution process. The reasoning component uses these data and rules as input, it analyzes them and executes the query with the use of Choquet Integral method. Finally, a reply is sent to the user interface.

In this case study, we will focus on Choquet integral application for individual and group decision making.

As reference for agriculture domain, we used the "Integrated Technical guide for agriculture 2016-2017" by Agriculture Chamber of the Aube, Chamber of Agriculture of the Marne, Chamber of Agriculture of Haute-Marne, Chamber of Agriculture of the Ardennes (France) to deduce the used criteria.

5.2. Individual decision making using Choquet integral

In this scenario, the user is offered three criteria which are explained in table 2.

As a first step, the user gives scores to rank the properties on scale of 1 to 9 according to his preferences and interests. These choices are depicted in table 3.

Therefore, the overall scores by individual are computed:

Table 2. Definition of evaluated criteria.

Evaluated criteria	Definition
Disease susceptibility	Several factors are responsible for many plant diseases, it can be such a significant issue on farms and need to be known and fought
Production rate	The final farms output is usually measured by weight
Soil type	The physical properties of soil directly affect the quality of sowing. For some plants, topsoil is sufficient to grow, other categories require to grow in deeper layers.

Table 3. User evaluation.

Criteria	1	2	3	4	5	6	7	8	9
Disease susceptibility			*						
Soil type				*					
Production rate		*							
Disease susceptibility and soil type								*	
Disease susceptibility and production rate					*				
Production rate and soil type					*				

μ_{sc}(Disease susceptibility) $= 0.3$
μ_{sc}(Soil type) $= 0.4$
μ_{sc}(Production rate) $= 0.2$
μ_{sc}(Disease susceptibility,soil type) $= 0.8$
μ_{sc}(Disease susceptibility, production rate) $= 0.5$
μ_{sc}(Production rate,soil type) $= 0.5$
μ_{sc}(Disease susceptibility,soil type,production rate) $= 1$

Table 4 presents an example of varieties to be planted and their characteristics according to an expert:

Table 4. Plant varieties and their characteristics according to an expert.

Variety	Properties	Membership function
Flax	D- disease susceptibility (very high)	0.9
	T- soil type	1
	P- production rate [20-50]kg	0.5
Sunflower	D- disease susceptibility (high)	0.7
	T- soil type	1
	P- production rate 40kg	0.4
Oats	D- disease susceptibility (low)	0.2
	T- soil type	0
	P- production rate [80-100]kg	0.8

If we apply Choquet integral, interaction between alternatives is considered. The results are described in table 5 and show that planting flax is the better option for this individual decision maker. The Choquet integral equation:

$C_\mu(f) = \sum_{i=1}^{n}(f(x_i) - f(x_{i-1})) * \mu(A_{(i)})$

where $._i$ indicates that the indices have been permuted so that $0 \leq f(x_1) \leq ... \leq f(x_n) \leq 1$ and $A_{(i)} = x_i, .., x_n$ and $f(x_0) = 0$.

For example, to compute $C_\mu(Flax)$:
$C_\mu(Flax) = (f(P)-0)*\mu(P,D,T)+(f(D)-f(P))*\mu(D,T)+(f(T)-f(D))*\mu(T)$
$C_\mu(Flax) = (0.5-0)*1+(0.9-0.5)*0.8+(1-0.9)*0.4$
$C_\mu(Flax) = 0.86$

Table 5. Results : Preference per individual using Choquet.

$C_\mu(Flax)$	$C_\mu(Oats)$	$C_\mu(Sunflower)$
0.86	0.12	0.76

5.3. Group decision making using Choquet integral

We tested the method on 5 experts in order to explore the feasibility of a collaborative decision between the preferences of different participants as well as to validate the coherence and integration of interactions between criteria making one decision.

The expert preferences and plant characteristics were reintroduced in table 6 where each expert expresses his views on the different plants.

Table 6. Plant varieties and their characteristics (membership values) according to 5 experts.

Variety	Properties	Expert1	Expert2	Expert3	Expert4	Expert5	Average
Flax	D- disease susceptibility	0.8	0.6	0.6	0.8	0.7	0.7
	T- soil type	1	1	1	0	1	0.8
	P- production rate [20-50]kg	0.5	0.6	0.6	0.8	0.5	0.6
Sunflower	D- disease susceptibility	0.8	0.8	0.7	0.8	0.6	0.74
	T- soil type	1	1	1	0	1	0.8
	P- production rate 40kg	0.4	0.5	1	0.4	0.4	0.36
Oats	D- disease susceptibility	0.2	0.6	0.3	0.2	0.2	0.3
	T- soil type	0	0	0	0	0	0
	P- production rate [80-100]kg	0.8	0.7	0.8	0.8	0.7	0.76

The new calculation is based on the average of overall scores forming a group preference using the following formula:

$$\mu(c) = \frac{exp_1+exp_2+exp_3+exp_4+exp_5}{nbofexperts}$$

μ(disease susceptibility) $= (0.2+0.2+0.3+0.4+0.3)/5 = 0.28$
μ(soil type) $= (0.2+0.3+0.2+0.2+0.2)/5 = 0.22$
μ(production rate) $= (0.4+0.7+0.1+0.3+0.3)/5 = 0.36$
μ(disease susceptibility,soil type) $= (0.7+0.7+0.6+0.8+0.8)/5 = 0.72$
μ(disease susceptibility,production rate) $= (0.4+0.4+0.5+0.4+0.5)/5 = 0.44$
μ(production rate,soil type) $= (0.4+0.4+0.5+0.4+0.5)/5 = 0.44$
μ(disease susceptibility,production rate,soil type) $= 1$

With aggregated data, it is possible to make a group decision using Choquet Integral (see table 7). This decision is the result of cooperation and interaction between criteria and decision makers.

Table 7. Results : Group preference using Choquet.

$C_\mu(Flax)$	$C_\mu(Oats)$	$C_\mu(Sunflower)$
0.69	0.31	0.64

Finally, with our method (users' preference cooperation and aggregation using Choquet Integral) we can deduce the following recommendation list: Flax> Sunflower> oats.

6. Conclusion

Generally, decision makers face difficulties when comparing several criteria and it's harder to achieve when dealing with fuzzy and uncertain context. The proposed system is based on several communicant layers. The different layers cooperate to create an ecosystem capable of supporting the uncertain and fuzzy context for decision making purposes. We proposed in this paper a knowledge layer which contains a semantic component and a fuzzy reasoning component. The first one participates in correlating between users, domain and system view using a multi-layer ontology. In addition, it helps to integrate collected raw data from distributed sources and physical devices and treat it to extract knowledge. The second component provides analysis and reasoning. As a conclusion, the main contributions proposed in our system are:

- The semantic representation serves to express the context and the need of the user to ensure an effective understanding of his request.
- The several layers of ontology representation allow the independence yet the correlation between the users' needs and system process.
- The reasoning component assists decision-makers by providing a method that takes into consideration the dependence between criteria.
- The proposed system offers decision making based on individual preferences as well as recommendations based on group decision.

The application experiments that have been carried out in the agricultural field show that our approach is promising and useful. Our work in progress aims to provide a complete study in order to evaluate the performance of our system. In future work, we aim to expand the fuzzy rules and decision making processes to follow the plants in different growth stages using IoT.

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