Use of the Belief Theory to formalize Agent Decision Making Processes : Application to cropping Plan Decision Making

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USE OF THE BELIEF THEORY TO FORMALIZE AGENT DECISION-MAKING PROCESSES: APPLICATION TO CROPPING PLAN DECISION-MAKING

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ABSTRACT
The agent-based simulation is a powerful tool to study complex systems. It allows to take into account different levels of granularity, as well as the heterogeneity of the entities composing the system. One of the main issues raised by these simulations concerns the design of the agent behavior. Indeed, when the agent behavior is led by many conflicting needs, desires and necessities, its definition can be very complex. In order to address this issue, we propose a new formalism to define the agent decision making process. This formalism is based on the belief theory, which is a formal theory about reasoning that allows to manage information incompleteness, uncertainty and imprecision. An application of the approach is proposed in the context of a model dedicated to cropping plan decision-making.

INTRODUCTION

Agent-based simulations are now widely used to study complex systems. It allows to take into account different levels of granularity, as well as the heterogeneity of the entities composing the system. However, the problem of the agent design is still an open issue. Indeed, designing complex agents able to act "relevantly" in the simulation is a difficult task, in particular when their behavior is led by many conflicting needs and desires.

In the agent community, numerous formalisms were proposed to model the agent decision-making process: logical formalisms, probabilistic formalisms and modal formalism (see (Das 2008)). However, most of these fromalisms are not of much use for agent-based simulations. A reason is their inadequacy to the simulation context: a formalism, to be used in simulation, has to allow thousands of agents to make a decision from many criteria in a short amount of time. Moreover, it has to be easily understable and usable by domain experts that are often not computer-scientists.

In this paper, we propose a new probabilistic formalism that is particularly well-fitted for agent-based simulations. This formalism is based on the use of utility functions. A utility function is a function that maps from a decision to a real number. The more a decision maximizes the utility function, the more it has a chance to be chosen by the agent. This type of formalisms is particularly well-fitted for agents whose decisions depend on numeric variables.

In order to compute the utility of each decision, we propose to use the belief theory. This theory allows to formalize reasoning. It can be used to make a decision between several alternatives according to a set of criteria. An advantage of this theory is that it allows to make a decision even with incompleteness, uncertainly and imprecision.

In the next section, we introduce the general context of our work.

CONTEXT: UTILITY FUNCTIONS AND AGENT DECISION-MAKING PROCESS

The use of utility functions for agent decision making is a classic approach that was used in many works (e.g. (Lang et al. 2002)). In this context, the utility of a decision is often linked to its expected outcomes: the expected utility of a decision is then computed from the resulting states of the decision's possible outcomes and from their probability of happening (Von Neuman and Morgenstern 1947).

For some applications, the decision cannot be evaluated by a unique attribute (or criterion). The decision making process of the agents will then consist in solving a multi-criteria analysis problem: an agent has to make a decision according to a set of criteria that will represent its needs and desires. In the literature, several approaches were proposed to solve this type of multi-criteria decision-making problems.

A first family of approaches, called *partial aggregation* approaches, consists in comparing the different possible decisions by pair by the mean of outranking relations (Figueira et al. 2005; Behzadian et al. 2010).

Another family of approaches, called *complete aggregation* approaches, consists in aggregating all criteria in a single criterion (utility function), which is then used to make the decision (Jacquet-Lagreze and Siskos 1982).

A last family of approaches, which is highly interactive, consists in devising a preliminary solution and comparing it

with other possible solutions to determine the best one (Ignizio 1978).

Partial aggregation approaches allow to address the problem of criterion incompatibility but lack clarity compared to *complete aggregation* approaches (Ben Mena 2000).

The approach we are interested in belongs to the *complete aggregation* approaches. It is built on the belief theory. In the next section, we describe this approach and its application for the agent decision making process.

USE OF THE BELIEF THEORY TO FORMALIZE THE AGENT DECISION MAKING PROCESS

Multi-criteria decision making using the belief theory

Generality

The belief theory, also called Dempster-Shafer theory, was proposed by Shafer in 1976 (Shafer, 1976). It is based on the Theory of Evidence introduced by Dempster (Dempster, 1967), which concerns the lower and upper probability distributions. It allows to manage incompleteness, uncertainty and imprecision of data. It has been used with success for many applications (e.g. (Olteanu-Raimond and Mustière 2008; Taillandier et al. 2009)).

The belief theory first defines a *frame of discernment*, noted Θ. It is composed of a finite set of hypotheses corresponding to the potential solutions of the considered problem.

$$\Theta = \{H_1, H_2, \ldots, H_N\}$$

From this frame of discernment, let us define the set of all possible assumptions, noted 2^{Θ}:

$$2^{\Theta} = \{\emptyset, \{H_1\}, \{H_2\}, \ldots, \{H_1, H_2\}, \ldots, \Theta\}$$

Each set $\{H_i, \ldots, H_j\}$ represents the proposition that the solution of the problem is one of the hypotheses of this set.

The belief theory is based on the basic belief assignment, i.e. a function that assigns to a proposition P, with $P \in 2^{\Theta}$, a value named the basic belief mass (*bbm*), noted $m_j(P)$. It represents how much a criterion j -called source of information- supports the proposition P. The *bbm* is ranged between 0 and 1 and has to check the following property:

$$\sum_{P \in 2^{\Theta}} m_j(P) = 1$$

Decision making approach

In our agent decision making context, each hypothesis represents the fact that a decision of the set of decisions D is the best one. For example: "$\{H_1\}$: the best decision of D is d_1", "$\{H_2\}$: the best decision of D is d_2", "$\{H_1, H_2\}$: the best decision of D can be either d_1 or d_2", etc.

The decision making process is composed of four steps.

Step 1

This first step consists in initializing the basic belief masses. For this step, we propose to use the works of Appriou (Appriou 1991). He proposed to "specialize" the criteria for one hypothesis of the discernment frame. Thus, the criteria give one's opinion only in favor of a hypothesis, in disfavor of it or do not give their opinion. For each hypothesis H_i of Θ, a subset S^i of 2^{Θ} is defined:

$$Si = \{\{H_i\}, \{\neg H_i\}, \Theta\}$$

- $\{H_i\}$: this proposition means that the hypothesis H_i is true.
- $\{\neg H_i\} = \Theta - \{H_i\}$: this proposition means that the hypothesis H_i is false.
- Θ: this proposition means the ignorance (i.e. every hypothesis can be true).
-

Thus, the initialization of the basic belief masses consists in computing, for each criterion j and for each hypothesis H_i of Θ, the basic belief masses $m_j^{H_i}(\{H_i\})$, $m_j^{H_i}(\{\neg H_i\})$ and $m_j^{H_i}(\Theta)$.

To compute all the *bbm*, belief functions have to be defined. A belief function is a function that returns a float value between 0 and 1 according to the value of a considered criterion for a given hypothesis. Let *bf* be a belief functions, j a criterion and H_i a decision of Θ. We note $V_j^{H_i}$ the value of the criterion j for the hypothesis H_i.

$$bf(V_j^{H_i}) : \Re \rightarrow [0,1]$$

Examples of belief functions are given in the application section.

Step 2

This step consists in combining criteria with each other. We propose to use the conjunctive operator introduced in (Smets and Kennes 1994) to provide a combined *bbm* synthesizing the knowledge from the different criteria. Let us consider two criteria C_1 and C_2. The conjunctive operator is defined as follows:

$$\forall H_i \in \Theta, \forall P \in \{\{H_i\}, \{\neg H_i\}, \Theta\}, m_{C_1C_2}^{H_i}(P) = \sum_{P' \cap P'' = P} m_{C_1}^{H_i}(P') \times m_{C_2}^{H_i}(P'')$$

The fusion of criteria can introduce a conflict, e.g. when one criterion assigns a *bbm* not null for the proposition $\{H_i\}$ and another criterion assigns a *bbm* not null for the proposition $\{\neg H_i\}$ (i.e. when $P' \cap P'' = \phi$). This conflict will be taken into account in the decision.

For example, let $\{C_1, C_2\}$ be a set of criteria, and H_1 an hypothesis of Θ. Let the *bbm* be defined as follows:

$$m_{C_1}^{H_1}(\{d_1\}) = 0.5,\ m_{C_1}^{H_1}(\{\neg d_1\}) = 0.3,\ m_{C_1}^{H_1}(\Theta) = 0.2$$
$$m_{C_2}^{H_1}(\{d_1\}) = 0.8,\ m_{C_2}^{H_1}(\{\neg d_1\}) = 0,\ m_{C_2}^{H_1}(\Theta) = 0.2$$

The belief masses resulting after the fusion of C_1 and C_2 are equal to:

$$m_{C_1C_2}^{H_1}(\{H_1\}) = m_{C_1}^{H_1}(\{H_1\}) \times m_{C_2}^{H_1}(\{H_1\}) + m_{C_1}^{H_1}(\{H_1\}) \times m_{C_2}^{H_1}(\Theta) + m_{C_1}^{H_1}(\Theta) \times m_{C_2}^{H_1}(\{H_1\}) = 0.66$$
$$m_{C_1C_2}^{H_1}(\{\neg H_1\}) = m_{C_1}^{H_1}(\{\neg H_1\}) \times m_{C_2}^{H_1}(\{\neg H_1\}) + m_{C_1}^{H_1}(\{\neg H_1\}) \times m_{C_2}^{H_1}(\Theta) + m_{C_1}^{H_1}(\Theta) \times m_{C_2}^{H_1}(\{\neg H_1\}) = 0.06$$
$$m_{C_1C_2}^{H_1}(\Theta) = m_{C_1}^{H_1}(\Theta) \times m_{C_2}^{H_1}(\Theta) = 0.04$$
$$m_{C_1C_2}^{H_1}(\phi) = m_{C_1}^{H_1}(\{H_1\}) \times m_{C_2}^{H_1}(\{\neg H_1\}) + m_{C_1}^{H_1}(\{\neg H_1\}) \times m_{C_2}^{H_1}(\{H_1\}) = 0.24$$

This conjunctive operator is commutative and associative. Thus, it is possible to combine the result of a previous fusion with the belief masses of another criterion.
Let C be the criterion set. At the end of this step, for each decision H_i of Θ, we obtain the combined belief masses $m_C^{H_i}(\{H_i\})$, $m_C^{H_i}(\{\neg H_i\})$, $m_C^{H_i}(\Theta)$ and $m_C^{H_i}(\phi)$.

Step 3
This step consists in combining hypotheses with each other. This combination is interesting because it allows to take into account in the final ranking, the fact that some criteria reject some hypotheses ($\neg H_i$).

We propose to use the Dempster operator (Dempster 1967) to compute the belief masses resulting from the combination of two hypotheses H_i and H_j:

$$\forall P \in 2^{\Theta}, m_C^{H_i,H_j}(P) = \frac{1}{1-m_C^{H_i,H_j}(\phi)} \sum_{P' \cap P''=P} m_C^{H_i,H_j}(P') \times m_C^{H_i,H_j}(P'')$$

The coefficient $\frac{1}{1-m_C^{H_i,H_j}(\phi)}$ is used to normalize the belief masses obtained. In the case of a total conflict ($m_C^{H_i,H_j}(\phi)=1$), no decision can be made.

For example, let Θ be composed of two hypotheses, H_1 and H_2 ($\Theta = \{H_1, H_2\}$, $\{\neg H_1\}=\{H_2\}$, $\{\neg H_2\}=\{H_1\}$). Let the belief masses be defined as follows:

$$m_C^{H_1}(\{H_1\}) = 0.66,\ m_C^{H_1}(\{\neg H_1\}) = 0.06,\ m_C^{H_1}(\Theta) = 0.04,$$
$$m_C^{H_1}(\phi) = 0.24,\ m_C^{H_2}(\{H_2\}) = 0,$$
$$m_C^{H_2}(\{\neg H_2\}) = 0.5\ m_C^{H_2}(\Theta) = 0.5,\ m_C^{H_2}(\phi) = 0$$

The belief masses resulting from the fusion of H_1 and H_2 are equal to:

$$\begin{aligned} m_C^{\Theta}(\phi) &= m_C^{H_1}(\{H_1\}) \times m_C^{H_2}(\{H_2\}) + m_C^{H_1}(\{H_1\}) \times m_C^{H_2}(\{\phi\}) \\ &+ m_C^{H_1}(\{\neg H_1\}) \times m_C^{H_2}(\{\neg H_2\}) + m_C^{H_1}(\{\neg H_1\}) \times m_C^{H_2}(\{\phi\}) \\ &+ m_C^{H_1}(\Theta) \times m_C^{H_2}(\{\phi\}) + m_C^{H_1}(\{\phi\}) \times m_C^{H_2}(\{H_2\}) + m_C^{H_1}(\{\phi\}) \times m_C^{H_2}(\{\neg H_2\}) \\ &+ m_C^{H_1}(\{\phi\}) \times m_C^{H_2}(\{\Theta\}) + m_C^{H_1}(\{\phi\}) \times m_C^{H_2}(\{\phi\}) = 0.27 \end{aligned}$$

$$\begin{aligned} m_C^{\Theta}(\{H_1\}) &= \frac{1}{1-m_C^{\Theta}(\phi)} \times [m_C^{H_1}(\{H_1\}) \times m_C^{H_2}(\{\neg H_2\}) + m_C^{H_1}(\{H_1\}) \times m_C^{H_2}(\Theta) \\ &+ m_C^{H_1}(\Theta) \times m_C^{H_2}(\{\neg H_2\})] = 0.93 \end{aligned}$$

$$\begin{aligned} m_C^{\Theta}(\{H_2\}) &= \frac{1}{1-m_C^{\Theta}(\phi)} \times [m_C^{H_1}(\{\neg H_1\}) \times m_C^{H_2}(\{H_2\}) \\ &+ m_C^{H_1}(\{\neg H_1\}) \times m_C^{H_2}(\Theta) + m_C^{H_1}(\Theta) \times m_C^{H_2}(\{H_2\})] = 0.04 \end{aligned}$$

$$m_C^{\Theta}(\Theta) = \frac{1}{1-m_C^{\Theta}(\phi)} \times [m_C^{H_1}(\Theta) \times m_C^{H_2}(\Theta)] = 0.03$$

At the end of this step, a belief mass for each proposition $m_C^{\Theta}(\{H_1\})$, $m_C^{\Theta}(\{H_2\})$,..., $m_C^{\Theta}(\{H_1, H_2\})$,..., $m_C^{\Theta}(\Theta)$ is computed.

Step 4
The last step consists in making the decision. We are only interested in the propositions that concern a unique hypothesis (one decision) and not a set of hypotheses. Thus, to evaluate each proposition we propose to use the *pignistic* probability (Smets 1990).

The *pignistic* probability of a proposition A is computed by the following formulae:

$$P(A) = \sum_{A \subseteq B} m(B) \frac{|A|}{|B|}$$

The more a proposition maximizes this probability, the more the corresponding hypothesis is true. Thus, the decision making will be based on this probability: this probability will represent the utility of the decision.

For example, let Θ be composed of two hypotheses, H_1 and H_2 and the belief masses of all the propositions be defined as follows:

$$m_C^{\Theta}(\{H_1\}) = 0.93,\ m_C^{\Theta}(\{H_2\}) = 0.04,\ m_C^{\Theta}(\Theta) = 0.03$$

The resulting *pignistic* probabilities are:

$$P(\{H_1\}) = m_C^{\Theta}(\{H_1\}) \times \frac{1}{1} + m_C^{\Theta}(\Theta) \times \frac{1}{2} = 0.945$$
$$P(\{H_2\}) = m_C^{\Theta}(\{H_2\}) \times \frac{1}{1} + m_C^{\Theta}(\Theta) \times \frac{1}{2} = 0.055$$

Thus, H_1 has more chances to be true than H_2.

Application of the belief theory to define the agent decision making process
As presented in the previous section, the belief theory allows to make a decision from a set of possible decisions according to a set of criteria.

In order to use the belief theory to formalize the decision making process of an agent, the modeler has to define several elements:

- A set of criteria that allow to evaluate the different possible decisions.
- For each criterion: a belief function for the hypotheses "this decision is the best one", "this decision is not the best one", "ignorance".

Remark that it is possible to decrease the complexity of the decision making computation by filtering the possible decisions: only decisions that are Pareto-optimal are kept.

For some agents, it will also be possible (or mandatory) to divide the decision making process into several sub-processes. This division can be used to decrease the complexity of the decision process or to use different sets of criteria that will correspond to different steps of reasoning. Indeed, for example, it is possible to divide the decision making process into two steps: the first one consisting of choosing a general objective for the agent (e.g. eating, sleeping) and a second consisting in choosing the best place to carry out this objective.

APPLICATION: CROPPING PLAN DECISION-MAKING.

The MAELIA project

The **MAELIA** (MAELIA 2011) project aims at developping an agent-based platform for the simulation of the socio-environmental impacts of norms on the water resources. In particular, this project proposes to model the impacts of norms on the behavior of the farmers that are the most important water users in many regions.

Farmer agents and culture choice

The most important behavior of farmers will consist in allocating crops and crop management into their fields. This choice will have a deep impact on the profit of the farmer and on the quantity of water used.

Using the works of (Dury et al. 2010), we defined four criteria that are taken into account during the cropping plan decision-making:

- **Expected profit**: profit that can be expected.
- **Loss at worse**: money that will be lost considering the worst scenario (no plant grown).
- **Workload**: quantity of work.
- **Similarity to last cropping plan**: influence of the last cropping plan chosen.

The next sections describe in details each of these criteria, and in particular the belief functions defined for each of them.

Expected Profit

The first criterion concerns the profit that can be expected from a given cropping plan. The profit takes into account several elements:

- Expected crop production
- Agricultural product price (current price of the market)
- Variable cost
- Workforce price
- Equipment price (tractor, irrigation systems, …)
- Aid (e.g. European Union Aid)

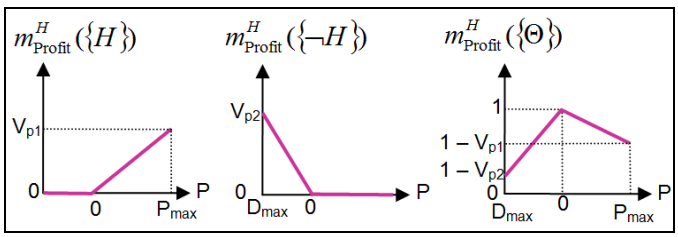

Figure 1. Belief functions for the profit criterion

The belief functions are shown in Figure 1. These functions depend on the profit made (*P*). *P* can be negative or positive. If *P* is negative, the belief mass of the proposition "this decision is not the best one" will be higher than 0. If *P* is positive, it is the belief mass of the proposition "this decision is the best one" that will be higher than 0. P_{max} is the maximal profit that can be made according to the parcel size and the market price. D_{max} is the maximal deficit that can be made considering the worst scenario (no plant grown). Two attributes have to be defined for each farmer: V_{p1} and V_{p2}. V_{p1} represents the greedy part of the farmer: the higher V_{p1} is, the more the farmer will try to make benefice at all cost. V_{p2} is the aversion of the farmer toward the deficit: the higher V_{p2} is, the more the farmer will tend to avoid deficits.

Loss at worse

This criterion concerns the loss (in terms of money) while considering the worst scenario (no plant grown). Its goal is to assess the risk taken by the farmer. The belief functions are shown in Figure 2. These functions depend on the money that can be lost (*L*). If *L* is higher than 0, the belief mass for the proposition "this decision is not the best one" will be higher than 0. L_{max} is the maximal loss that can be made according to the parcel size and the market price (variable cost). V_{l1} is computed from V_{p2} (see expected profit criterion) and from the probability that the worst outcome becomes true (it will depend on the type of culture).

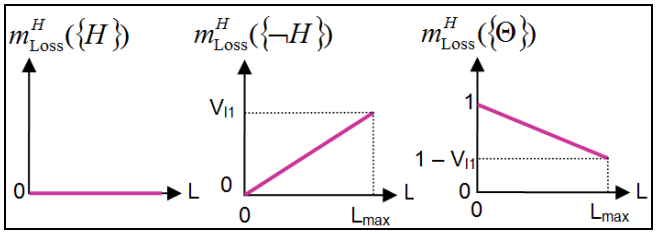

Figure 2. Belief functions for the loss criterion

Workload

This criterion concerns the workload necessary to carry out the cropping plan. Indeed, the farmers seek to minimize this workload.

The belief functions are shown in Figure 3. These functions depend on the workload value (*W*). This value takes into account the quantity of works (in terms of hours of work) necessary to carry out the cropping plan. If *W* is higher than 0, the belief masse of the proposition "this decision is not the best one" will be higher than 0. W_{max} is the maximal value that can be reach for the workload value. V_{w1} is the aversion of the farmer toward the work: the higher V_{w1} is, the more the farmer will tend to avoid working.

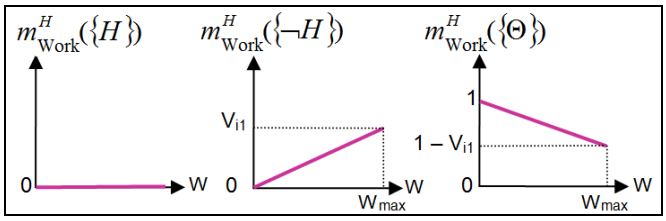

Figure 3. Belief functions for the workload criterion

Similarity to last cropping plan

This criterion concerns influence of the last cropping plan. Indeed, farmers tend to seek for stabilized cropping plan. The belief functions are shown in Figure 4. These functions depend on the similarity value compare to the last cropping plan (*S*).

The belief masse for the proposition "this decision is the best one" will be higher or equal to 0 if the similarity is higher than a given threshold S_1. If the similarity is equals or higher than a given threshold S_2, the belief masse of this proposition will be equal to V_{xp1}.

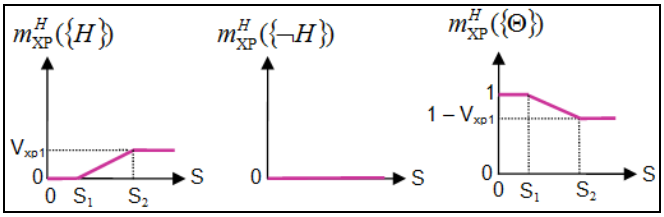

Figure 4. Belief functions for the similarity to last cropping plan criterion

S_1 and S_2 are two thresholds that allow to integrate a fuzzy aspect in the decision. One attribute has to be defined for each farmer: V_{xp1}. V_{xp1} concerns the conservative part of the farmer: the higher V_{xp1} is, the more the farmer will tend to make the same culture choices.

Conclusion

Our formalism allowed us to simply formalize the raw knowledge provided by the interviews and by the field experts. In particular, it offered us a powerful tool to aggregate the different motivations of the farmers (make profit, avoid loss …).

A first prototype of the MAELIA model is currently under development with the GAMA simulation platform (Taillandier et al. 2010). This model will take into account more than ten thousands farmers and thus will allow us to test the scalability of our formalism.

CONCLUSION

In this paper, we proposed to use the belief theory to formalize the agent decision making process in agent-based simulations. We present an application of this formalism for a simulation dedicated to cropping plan decision-making.

A key issue in the use of our formalism concerns the definition of the belief functions. In some applications, the definition can be based on expert knowledge. In other applications where knowledge is lacking, machine learning techniques can be used to build automatically these functions. In this context, we propose to develop methods to learn them directly through a participatory approach. This approach could be based on the one proposed by (Taillandier and Buard 2009).

REFERENCES

Appriou, A. 1991. "Probabilité et incertitude en fusion de données multi-senseurs". *Revue Scientifique et Technique de la Défense* 1 : 27-40

Behzadian, M.; R. Kazemzadeh; A. Albadvi and M. Aghdasi 2010. "PROMETHEE: A comprehensive literature review on methodologies and applications". *EJOR 200*(1): 198-215.

Ben Mena, S. 2000. "Introduction aux méthodes multicritères d'aide à la décision", *Biotechnol. Agro. Soc. Env.* 4(2): 83-93.

Das, S., 2008. *Foundation of Decision-Making Agents: Logic probability and modality*, World Scientific Publishing Co. Pte. Ltd.

Dempster, A. 1967. "Upper and lower probabilities induced by multivalued mapping". *An. of Math. Statistics* 38: 325-339.

Dury, J.; F. Garcia ; A. Reynaud ; O. Therond and J.E. Bergez, 2010, "Modelling the Complexity of the Cropping Plan Decision-making", *IEMS,* Ottawa, Canada

Figueira, J.; V. Mousseau, V., and B. Roy, 2005. "ELECTRE Methods". In: Figueira, J., Greco, S., and Ehrgott, M., (Eds.), Multiple Criteria Decision Analysis: State of the Art Surveys, Springer, New York, 133-162.

Geoffrion, A.; J. Dyer, and A. Feinberg, 1972. "An interactive approach for multicriterion optimisation with an application to the operation of an academic department". *Manage. Sci.*, vol. 19 (4): 357-368.

Ignizio, J. 1978. "A review of goal programming: a tool for multi objective analysis". *JORS* 29(11): 1109-1119.

Jacquet-Lagreze, E. and J. Siskos, 1982. "Assessing a set of additive utility functions for multicriteria decision making, the UTA method". *EJOR* 10(2): 151-164.

Lang, J.; L. van der Torre, and E. Weydert, 2002. "Utilitarian desires". *J. on AAMAS* 5: 329-363.

MAELIA project, 2011. http://maelia1.wordpress.com/ [Accessed 1 july 2011].

Olteanu-Raimond, A.M. and S. Mustière, 2008. "Data matching - a matter of belief", *SDH*, Montpellier, France.

Shafer, G. 1976. *A mathematical theory of evidence*. Princeton University Press.

Smets, P. and R. Kennes, 1994. "The transferable belief model". Artificial Intelligence 66(2) : 191-234.

Smets, P. 1990. "Constructing the pignistic probability function in a context of uncertainty". *Uncertainty in Artificial Intelligence* 5: 29-39

Taillandier, P.; C. Duchêne, and A. Drogoul, 2009. "Using Belief Theory to Diagnose Control Knowledge Quality. Application to cartographic generalization". *IEEE-RIVF*, Da Nang, Viet Nam

Taillandier, P. and E. Buard, 2009. "Designing Agent Behaviour in Agent-Based Simulation through participatory method". *PRIMA*, Nagoya, Japan.

Taillandier, P.; Drogoul, A.; Vo, D.A. and Amouroux, E. 2010. "GAMA: bringing GIS and multi-level capabilities to multi-agent simulation", *The 8th European Workshop on Multi-Agent Systems*, Paris, France.

Von Neumann, J. and O. Morgenstern, 1947. *Theory of games and economic behavior*, 2nd ed. Princeton, NJ: Princeton University Press.

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