

# A Proposal for Modelling Agrifood Chains as Multi Agent Systems

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**Abstract.** Viewing the modelling of agrifood chains (AFC) from a multi agent systems (MAS) point of view opens up numerous avenues for research while building upon existing advancements in the state of the art. This paper explores different aspects in MAS research areas in consensus and cooperation (argumentation, negotiation, normative systems, multi agent resource allocation and social affects) and provides insights into how viewing classical AFC problems from this perspective can bring new perspectives and research avenues.

## 1 Introduction

Understanding and controlling agri-food processes is of major importance when trying to ensure sustainability with respect to growing complexity and consumer expectation. Methodologies and tools from various sub-fields of Artificial Intelligence have showed their potential for advancing the state of the art.

Here we solely focus on the problem of dealing with the uncertain knowledge (elicitation, representation and reasoning) involved at different levels of the food chain. Such chains often model complex processes relying on numerous criteria, using various granularity of knowledge, most often inconsistent (due to the fact that complementary points of view can be expressed). The main aspect that characterises such knowledge is uncertainty that could be either regarded from a logical point of view or a provenance point of view.

Many approaches in the literature investigate the added value of a logical based representation to deal with the above mentioned problems. Such approaches [10] (mainly using ontologies and Linked Open Data) bring real added value within each step of the transformation but they have difficulty addressing overall chain transformations [23, 9, 27]. Approaches based on reasoning in presence of inconsistency (such as argumentation based approaches of [31, 34, 35, 16]) look at integrating various steps of the food chain but they do not address multi objective optimisation problems common within food chains. Furthermore, recent advances in Linked Open Data and its potential for interoperability meant that more and more ontologies are developed by various actors of the food chain. Methods for integrating these ontologies in a principled manner are still to be developed within each food chain.

This paper investigates the following research question: “*What are the salient points of addressing knowledge representation and reasoning (KRR) in Agri-Food Chain (AFC) as a consensus and cooperation problem in multi-agent systems (MAS)?*” Our claim is that viewing the problem of KRR from a multi agent system point of view opens up numerous avenues for research while building upon existing advancements in the state of the art. We will explore different aspects in MAS research areas in consensus and cooperation (argumentation, negotiation, normative systems, multi agent resource allocation and social affects) and show how viewing classical AFC problems from this perspective can bring new perspectives and research avenues. We claim that agent technology can optimise food supply chain operation by employing intelligent agent applications (as shown in supply chain management case) but also facilitate reasoning with incomplete, inconsistent and missing knowledge - a key aspect of KRR management in AFC. Agents enhance the flexibility and efficiency of supply chain management while providing an unifying framework for various key problems in AFC. The main contribution of the paper resides in this unifying aspects: by modelling AFC problems as MAS problems we benefit from a unifying setting that encompasses a plethora of related research questions.

The paper is structures as follows. After a quick introduction on multi-agent systems in Section 2 we investigate the use of argumentation (Section 3.1), multi-agent resource allocation (Section 4.1), normative systems (Section 4.2), for AFC research. Section 5 concludes the paper.

## 2 Consensus and Cooperation in Multi Agent Systems

In agrifood chains, the products traditionally go through the intermediate stages of processing, storage, transport, packaging and reach the consumer (the demand) from the producer (the supply). More recently, due to an increase in quality constraints, several parties are involved in production process, such as consumers, industrials, health and sanitary authorities, etc. expressing their requirements on the final product as different point of views which could be conflicting. Such complex systems require to be addressed both at each individual transformation level as well as in its globality (from the genome to the final product).

Autonomous agents and multi agent systems represent a way of analysing, designing and implementing complex software systems. A multi agent system can be seen as a loosely coupled network of problem solvers that work together to solve problems beyond individual capabilities of each one of them. In multi agent systems each agent has its own incomplete information, the data is decentralised and computation is asynchronous. Such systems have the advantage of distributed and concurrent problem solving with a plethora of interactions possible [25, 20]. Common types of interactions include: cooperation, coordination, negotiations, planning, norm compliance, blame assignment, etc.

When representing and reasoning about an agent’s mind, one can distinguish between:

1. Cognitive models of rational action (representing the attitudes of agents, their beliefs, intentions etc) and
2. Modelling of the strategic structure of the systems (how can agents accomplish their intentions either alone or in cooperation).

Regarding the first aspect (rational cognitive states) one can identify different attitudes such as information attitudes (beliefs), pro attitudes (desires, intentions, goals) and normative attitudes (obligations, permissions and authorisation). We will address these problems in Section 3.1 by explaining how we can model agent’s beliefs in AFC and how the different agents can “defend” and justify their beliefs in the argumentation process.

Regarding the second above mentioned aspect, in multi agent systems, cooperation can be interpreted as giving consent to provide one’s state and following a common protocol that serves the group objective [36]. We need to distinguish between unconstrained and constrained cooperation problems. Unconstrained cooperation is, for example, an alignment between two agents with the purpose of speaking the same logical language. Constrained cooperation refers, for example, to respective normative systems that impose a certain group behaviour. The strategic structure of a system has also been logically represented using coalition logic, temporal logic etc. In Section 4.1 we will explain how we can make use of multi agent resource allocation problems in order to model different cooperation problems that could arise in AFC. We will also investigate how normative reasoning can be used for AFC in Section 4.2.

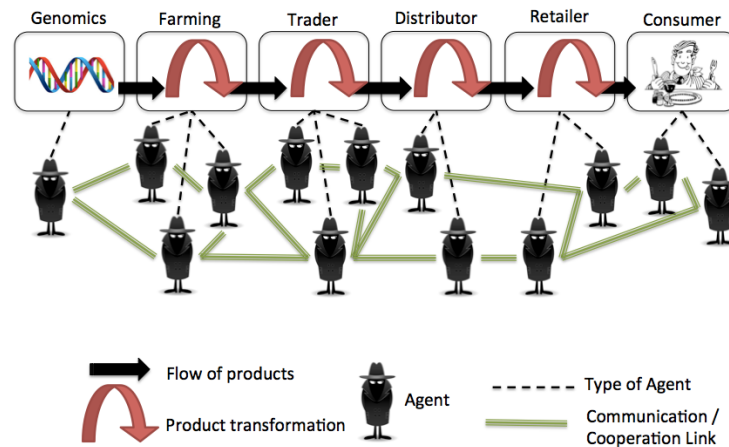
### 3 Rational Cognitive Modelling

In this section we will focus first on the modelisation of the agent knowledge.

To clarify the notions we will propose, in Figure 3.1 we show the multi agent system modelisation of agri-food chains. In the top part of the picture the agro-food chain is depicted, stemming from genomics all the way to the consumer’s plate. The food, at every step, undergoes several transformations. For instance, the grape can be selected based on genomics to have desirable farming properties (such as draught resistance, disease resistance etc.). At the next step different technological itineraries are compared in order to select the best way of growing the plant according to different criteria (yield, pesticide treatment etc.). The product may undergo several transformations at this step depending on its final form (for example, the durum wheat may be transformed in flour or in couscous etc.). At the various next steps (trader, distributor, retailer) more transformations are possible as well as important packaging issues addressed. Packaging may play an important role not only on the retail aspects but also for increasing the shelf life of aliments (modified pressure,  $CO_2$  and  $O_2$  permeability etc.) and reducing food loss.

Each step of the transformation process (from genomic studies to the consumer plate) will be modelled by one or several agents. These agents will model the knowledge (rule based systems) required at each transformation step. Ontologies dedicated to the specific domain of transformation can be employed at this step [24].

In the bottom part of the Figure 3.1 the agents from the various steps are connected via communication / cooperation links. These links along with the agents will form the multi agent system that will be used to model the agro-food chain.



**Fig. 3.1.** Multi Agent System Modelisation of Agri-Food Chains

As mentioned before, in AFC one or several agents will represent one unitary transformation. Please note that for each unitary transformation, within each individual agent, several knowledge representation challenges are to be addressed. First, the information to be represented at each step of the transformation is incomplete, imprecise and highly expressive. There are several ways of obtaining such information. For instance sensors can provide numerical information about the plant. Such information might be unreliable due to measurements errors. The numerical information has to be put in the context of symbolic information. Such symbolic information (transformation rules, ontological data) need to be represented in a logical language that allows for reasoning and for reuse. Linked Open Data can be employed for re-usability reasons. Expressive representation and reasoning languages will provide the possibility of deriving implicit information from explicitly represented knowledge.

In the next section we detail the next problem, the problem of agent to agent communication. We will focus on argumentation and negotiation. In Section 4 the multi agent interaction is studied.

### 3.1 Argumentation and Negotiation

The notion of one to one interaction among self-interested agents has been centred around argumentation and negotiation. Two conditions have to be fulfilled and namely bounded rationality and incomplete information. Let us start by addressing the last point and namely incomplete information. We will come back to bounded rationality at the end of this paper in Section 5.

Let us consider, as an illustrating example, the platform developed in the French Institute for Research in Agronomy (INRA) to link agronomy insights with socio-economic developments and behaviour of various stakeholders involved (farmers, consumers, biologists, industrial partners etc.). It aims at identifying ways and solutions to maintain the quality of production and satisfy the needs of the users, while limiting the environmental impact (see e.g. the MEANS initiative <http://www6.inra.fr/means> eng/). The long-term ambition is to homogeneously integrate information from different sources, namely the regional production practices, market organization at local, national and international levels, and along the agri-food chains. In practical applications such as the one described above, the knowledge obtained from the various actors involved is incomplete. The causes of incompleteness are numerous. First, it is difficult to obtain a complete ontology (set of rules that describe the world) from domain experts. AGROVOC [21, 30] can provide a basis for the ontology developer but the elicitation process is difficult. The basic rules used for reasoning might seem obvious for the domain expert. This calls for two important aspects to be considered:

- First, the representation language needs to be expressive enough in order for implicit knowledge to be derived from explicit knowledge. Existential rules, that allow for existential variables in the head of the rules are especially useful. The existential variables allow to represent variables that are unknown (same mechanism as value invention in tuple generating dependencies in databases) [8].
- Second, the incompleteness can be used as a way to help experts focus on the parts of the ontology that need expanding. One can use explanation facilities of query answering in presence of incompleteness [4, 6, 5, 3]. The experts, faced with the system explanation, can choose to enrich the knowledge base if the explanation (or the results) are not conform to their expectation.

When putting together the knowledge from several incomplete sources one needs to perform alignment in order to integrate the sources. Such alignment can be obtained using various methods from the literature. For instance, key discovery on the two datasets and the use of such keys as alignment candidate generators have been proven to significantly improve the state of the art [7, 26]. Reasoning can be performed on the union of the sources that share the same vocabulary. In most cases, the union of several sources is inconsistent. As false implies anything, the inconsistent knowledge bases cannot be used as such for reasoning (as any conclusion could be derived). Different inconsistency methods

have been devised in order to reason with such knowledge[22]. It is important at this step to make several observations.

In this paper we accept the idea that full specifications cannot be established in agrifood chains (thus we need to address incomplete information). On the other hand, several complementary points of view - possibly contradictory - can be expressed (nutritional, environmental, taste, etc.). We then need to assess their compatibility (or incompatibility) and identify solutions satisfying a maximum set of viewpoints. Several logical frameworks based on argumentation have been proposed in the literature where argumentation was used as a logical tool able to reason in presence of inconsistency. The reasoning process was either done using forward chaining reasoning or backwards chaining. In forward chaining reasoning all arguments and attacks were computed and extensions used in order to represent maximal consistent point of views over the argument and attack set. In backwards chaining an argument was investigated to be accepted or rejected based on the other arguments attacking it and their respective status (accepted or rejected). The two approaches come down to same semantic results, of course, but differ from a computational point of view as well as methodological [14, 33, 13, 18, 32].

Please note that argumentation theory can be used not only to deal with inconsistency but also to explain the decision made by the system to a user (as already explained above as a method to remove incompleteness). Argumentation gives the possibility of defining formal protocols of interaction between agents. This is particularly interesting when one of the agents in question is a human agent. We can design formal protocols that underpin the basis of human agent interaction. The notion of an explanatory dialogue as proposed by [3] is a way to offer an interactive explanation that takes place between the system and the user. Explanatory dialogues allow (including and not limited to) the user to ask follow-up questions, clarification questions, elaborate on previous explanations.

**Social Attitudes and Affects** When reasoning about knowledge (using classical methods or using inconsistency tolerant reasoning mechanisms) different pieces of knowledge can be of different importance for a decision maker. Existing argumentation-based systems for inconsistent ontology need to take this aspect into account and deal with such preferences on data sources (where more important knowledge is considered to be preferred to less important knowledge). Many approaches exist in literature for dealing with preferences and attacks. The state of the art considers two roles of preferences. Either preferences can inhibit attacks ([1]) or preferences can be used in a latter stage as a way of filtering out extensions. The preferences relation on the arguments can be lifted to a preference relation on sets of arguments (extensions). The latter approach has been used in agronomy and successfully validated with domain experts [17].

Another way of handling preferences is to use mental states in order to model dominant agents. As explained before, a multi-agent system is composed of multiple autonomous agents, each capable of reacting to changes in the environment. The internal workings of an agent cannot be discerned by an external ob-

server, and agents are thus treated as black boxes by other agents. One common approach to agent design involves ascribing agents with mental states based on folk psychology. Thus, for example, the family of BDI techniques [28] to agent design ascribe an agent with a set of beliefs, a set of desires, and a set of intentions which are derived from these beliefs and desires. An agent would then act in such a way so that it will attempt to fulfil its intentions. Approaches such as [2] could be used in order to refine human to human or human to agent interactions in multi agent systems.

## 4 Strategic Behavior Modelling

In this section we investigate the modelling of the strategic structure of the multi agent system (how can agents accomplish their intentions either alone or in cooperation). Cooperation means following a common protocol that serves the group objective. As already mentioned we distinguish between unconstrained and constrained cooperation problems.

Unconstrained cooperation is, for example, an alignment between two agents with the purpose of speaking the same logical language. We already discussed alignment issue in the previous section as such aspects are fundamental to ensure communication throughout several agents.

When discussing constrained cooperation we will focus on two methods. First, the strategic structure of a system can be logically represented using coalition logic in Section 4.1. Next, we explain how normative systems can impose a certain group behaviour in Section 4.2.

### 4.1 Multi Agent Resource Allocation and Coalitions

The issue of flexible allocation of tasks to multiple problem solvers received attention from the early days of Artificial Intelligence. The tasks that need to be performed are announced from a central node and other nodes subsequently place bids on the tasks they can perform. The central node collects the bid for the task and awards the task to the best bidder. This works as an abstraction of a market-based centralized distributed system for the determination of adequate allocations of heterogeneous indivisible resources. In a Multi Agent Resource Allocation (MARA) system [12], there is central node  $a$  (let's call it the auctioneer) and a set of  $n$  nodes,  $I = 1, \dots, n$  (the bidders) which concurrently demand bundles of resources from a common set of available resources,  $R = r_1, \dots, r_m$ , held by the auctioneer. The auctioneer broadcasts  $R$  to all  $n$  bidders, asking them to submit in a specified common language, the bidding language, their  $R$ -valuations over bundles of resources. Bidder  $i$   $R$ -valuation,  $v_i$ , is a non-negative real function on  $\mathcal{P}(R)$ , expressing for each bundle the individual interest of bidder  $i$  in obtaining  $S$ . No bidder  $i$  knows the valuation of any other  $n - 1$  bidders, but all the participants in the system agreed on the outcome: based on bidders  $R$ -valuations, the auctioneer will determine a resources allocation specifying for each bidder  $i$  her obtained bundle  $O_i$  (its outcome). The task of the auctioneer

finding a maximum value allocation for a given set of bidder valuations is called the Winner Determination Problem (WDP). This is a NP-hard problem, being equivalent to weighted setpacking.

An instance of the MARA problem is the problem of coalition formation (that models teamwork explicitly). A particular strength of multi-agent systems is the ability of agents to form coalitions that may achieve goals more efficiently than when agents act as individuals. Possible applications of coalition formation techniques in multi-agent systems include rescue coordination, supply chain management, e-commerce, etc. MARA in general and coalition formation in particular can be used in agrifood chains to model more general behaviour for chain organisation. Many approaches used for agrifood chains are myopic (they only refer to one transformation or one actor on the chain). Having a global view will allow certain optimisations that go beyond the individual transformations. Also a global view of the system will pave the way for seamless reverse engineering techniques where final specifications are used in order to derive (using backwards chaining) initial conditions needed for such specifications.

Three main issues studied in the context of MARA in general (that also apply in the context of MARA for agrifood chains) are [19, 29]:

1. Optimization of a coalition value. In agrifood chains this could refer to the minimising of cost of products (cost in the broad sense - depending on the resources needed). This relies however on having full knowledge on partial costs which is infeasible in certain practical cases due to incomplete knowledge (discussed in the previous section).
2. Division of a coalition value between agents (e.g. the concepts of core or Shapley value). Studying such concepts could help highlight the steps in the agrifood chain transformation with most utility (or, the inverse, steps that could be avoided).
3. Generating the optimal division of agents into exhaustive and disjoint coalitions. Such divisions are called coalition structures and the this problem is called an optimal coalition structure generation problem (CSG). Lastly, the CSG problem could be used in order to optimise the agrifood chain in its totality.

## 4.2 Normative Reasoning

Another way of organising a multi agent system is by installing a set of norms that need to be behaved by all agents. Norm aware agents make use of concepts such as obligations, permissions, and prohibitions, to represent and reason about socially imposed goals and capabilities. Such agents are able to decide whether to act in a manner consistent with norms, or whether to ignore them. Typically, norms are imposed on a set of agents in order to increase the overall utility of the system (often at the cost of individual utility), or reduce computational or communication overhead [11].

Norms, such as obligations, permissions and prohibitions, place soft constraints upon an agent. Typically, ignoring an obligation (i.e. violating it) means



that a sanction is applied to the agent, but the agent may still choose to ignore a norm in some situations. An agent is said to be norm-aware if it is able to reason about the norms that apply to it. A multi-agent system containing norm-aware agents has a number of advantages over simpler multi-agent systems. Norms allow agents to assume, by default, that other agents will behave in a certain way, reducing the complexity of their reasoning. Norms are typically declarative, and have a great deal of explanatory power. Norms thus form a good programming and understanding metaphor for both creating agents, and understanding their actions in specific situations.

A norm may be defined in terms of five components. First, a norm has a type, for example, an obligation, or a permission. Second, a norm has an activation condition, identifying the situations in which the norm affects some agents. Third, a norm imposes some normative condition on the affected agent; if this normative condition does not hold, the norm is not being followed. Fourth, norms have a termination, or expiration condition, identifying the situations after which the norm no longer affects the agent. Finally, the norm must identify the agents which it affects. These agents are referred to as the norm targets.

During its lifecycle, an abstract norm becomes instantiated. While instantiated, its normative condition may evaluate to true or false at different times. Finally, the norms expiration condition evaluates to true, after which the instantiated norm is deleted. It is possible to construct this condition as a query to the knowledge base, and from this, determine whether the norm is violated or not.

A normative environment is used to keep track of the abstract (generic norms) and instantiated norms (norms applying to one agent during a given time lapse) within the system. Since norms may be instantiated and expire as time passes, the normative environment must, at each time point, identify which norms exist in the system.

In [15] the authors proposed a rich model for tracking and determining the status norms may be represented graphically via a logical language represented as a graph. The framework presented is intended to capture the evolution of a norm over time, allowing for its instantiation and expiration, as well as recording the time periods during which a norm was complied with or violated. Since the internal structure of such a norm is somewhat complex, some technique for explaining why a norm is in a certain state is required, and a visual model for explaining norm status useful for human agent interaction.

In both cases (modelling the constrained cooperation as a multi agent resource allocation problem or as a normative system) we could impose the global view on the system that was lacking in the state of the art that only considered the localised optimisation within a transformation. Furthermore, we can also model important ethical aspects which are very important to consider but difficult to take into account in existing systems.

The main difference between the two approaches is the elicitation aspects. While in MARA one needs to rely on a complete knowledge of the utility of the various coalitions in the normative approach such requirement is no longer

imposed. One can state the different norms that the system should respect and then each individual agent will comply or not to the respective norm.

## 5 Discussion

In this paper we provided a proposal for modelling AFC problems as MAS problems. The contribution of the paper lays in the unifying framework that such modelling could bring into KRR problems in AFC. While certain approaches in KRR for AFC already employ multi agent systems techniques (such as argumentation) an unified framework where the chain can be studied in its globality could prove to be beneficial. Such claim is supported by the advantages of modelling supply chain management as multi agent system modelling proved by the state of the art. While supply chain management is a particular case of agrifood chain modelling, in general in agrifood chain modelling the incompleteness and uncertainty of the knowledge makes the problem much harder. However, this is yet another reason to benefit from the uncertainty reasoning in multi agent systems.

As mentioned before the agents we consider here are rational agents. It could be (especially in an argumentation setting) that we do not want to consider solely rational agents. Indeed, the cognitive biases should be taken into account. Detecting and highlighting such biases (which could be common in domain experts due to the narrowness of their expertise) might be able to prevent decision errors in chain management.

We conclude this paper by a quick remark about implementation aspects. As already explained the aim of the paper is to be a position paper about the benefits of modelling AFC as MAS. Of course such modelisation should be followed in practice by judicial implementations. One of the most important aspects to consider is the flexibility of the system that should be extendible in time. Another important aspect is the seamless integration with LOD ontologies (in terms of compatibility with Web Services, SPARQL endpoints and expressivity).

## References

1. L. Amgoud and S. Vesic. Two roles of preferences in argumentation frameworks. In *Symbolic and Quantitative Approaches to Reasoning with Uncertainty*, pages 86–97. Springer, 2011.
2. K. Anderson, E. André, T. Baur, S. Bernardini, M. Chollet, E. Chryssafidou, I. Damian, C. Ennis, A. Egges, P. Gebhard, et al. The tardis framework: intelligent virtual agents for social coaching in job interviews. In *Advances in Computer Entertainment*, pages 476–491. Springer, 2013.
3. A. Arioua and M. Croitoru. Formalizing explanatory dialogues. In *Scalable Uncertainty Management*, pages 282–297. Springer, 2015.
4. A. Arioua, N. Tamani, and M. Croitoru. On conceptual graphs and explanation of query answering under inconsistency. In *Graph-Based Representation and Reasoning*, pages 51–64. Springer, 2014.

5. A. Arioua, N. Tamani, and M. Croitoru. Query answering explanation in inconsistent datalog $\pm$ -knowledge bases. In *Database and Expert Systems Applications*, pages 203–219. Springer, 2015.
6. A. Arioua, N. Tamani, M. Croitoru, and P. Buche. Query failure explanation in inconsistent knowledge bases: a dialogical approach. In *Research and Development in Intelligent Systems XXXI*, pages 119–133. Springer, 2014.
7. M. Atencia, M. Chein, M. Croitoru, J. David, M. Leclere, N. Pernelle, F. Saïs, F. Scharffe, and D. Symeonidou. Defining key semantics for the rdf datasets: Experiments and evaluations. In *Graph-Based Representation and Reasoning*, pages 65–78. Springer, 2014.
8. J.-F. Baget, M.-L. Mugnier, S. Rudolph, and M. Thomazo. Walking the complexity lines for generalized guarded existential rules. In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, volume 22, page 712, 2011.
9. D. Beneventano, S. Bergamaschi, S. Sorrentino, M. Vincini, and F. Benedetti. Semantic annotation of the cerealab database by the agrovoc linked dataset. *Ecological Informatics*, 26:119–126, 2015.
10. C. Bizer, T. Heath, and T. Berners-Lee. Linked data-the story so far. *Semantic Services, Interoperability and Web Applications: Emerging Concepts*, pages 205–227, 2009.
11. W. Briggs and D. Cook. Flexible social laws. In *International Joint Conference on Artificial Intelligence*, volume 14, pages 688–693. Citeseer, 1995.
12. Y. Chevaleyre, P. E. Dunne, U. Endriss, J. Lang, N. Maudet, and J. A. Rodríguez-Aguilar. Multiagent resource allocation. *The Knowledge Engineering Review*, 20(02):143–149, 2005.
13. M. Croitoru, J. Fortin, P. Mosse, P. Buche, V. Guillard, and C. Guillaume. Bio-sourced and biodegradable packaging design using argumentation to aggregate stakeholder preferences. In *EFFoST'12 Annual Meeting*, page 1, 2012.
14. M. Croitoru, J. Fortin, and O. Nir. Arguing with preferences in ecobiocap. In *COMMA'12: Computational Models of Argument*, volume 245, pages 51–58. IOS Press, 2012.
15. M. Croitoru, N. Oren, S. Miles, and M. Luck. Graphical norms via conceptual graphs. *Knowledge-Based Systems*, 29:31–43, 2012.
16. M. Croitoru, R. Thomopoulos, and N. Tamani. A practical application of argumentation in french agrifood chains. In *Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pages 56–66. Springer, 2014.
17. M. Croitoru, R. Thomopoulos, and S. Vesic. Introducing preference-based argumentation to inconsistent ontological knowledge bases. In *PRIMA 2015: Principles and Practice of Multi-Agent Systems*, pages 594–602. Springer, 2015.
18. V. Guillard, P. Buche, S. Destercke, N. Tamani, M. Croitoru, L. Menut, C. Guillaume, and N. Gontard. A decision support system to design modified atmosphere packaging for fresh produce based on a bipolar flexible querying approach. *Computers and Electronics in Agriculture*, 111:131–139, 2015.
19. S. Jeong and Y. Shoham. Marginal contribution nets: a compact representation scheme for coalitional games. In *Proceedings of the 6th ACM conference on Electronic commerce*, pages 193–202. ACM, 2005.
20. N. R. Jennings, K. Sycara, and M. Wooldridge. A roadmap of agent research and development. *Autonomous agents and multi-agent systems*, 1(1):7–38, 1998.
21. B. Lauser, M. Sini, A. Liang, J. Keizer, and S. Katz. From agrovoc to the agricultural ontology service/concept server. an owl model for creating ontologies in the agricultural domain. In *Dublin Core Conference Proceedings*. Dublin Core DCMI, 2006.

22. D. Lembo, M. Lenzerini, R. Rosati, M. Ruzzi, and D. F. Savo. Inconsistency-tolerant semantics for description logics. In *Web Reasoning and Rule Systems*, pages 103–117. Springer, 2010.
23. D. Lukose. World-wide semantic web of agriculture knowledge. *Journal of Integrative Agriculture*, 11(5):769–774, 2012.
24. A.-R. Muljarto, J.-M. Salmon, P. Neveu, B. Charnomordic, and P. Buche. Ontology-based model for food transformation processes-application to winemaking. In *Metadata and Semantics Research*, pages 329–343. Springer, 2014.
25. R. Olfati-Saber, A. Fax, and R. M. Murray. Consensus and cooperation in networked multi-agent systems. *Proceedings of the IEEE*, 95(1):215–233, 2007.
26. N. Pernelle, F. Saïs, and D. Symeonidou. An automatic key discovery approach for data linking. *Web Semantics: Science, Services and Agents on the World Wide Web*, 23:16–30, 2013.
27. S. Pokharel, M. A. Sherif, and J. Lehmann. Ontology based data access and integration for improving the effectiveness of farming in nepal. In *Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)-Volume 02*, pages 319–326. IEEE Computer Society, 2014.
28. A. S. Rao, M. P. Georgeff, et al. Bdi agents: From theory to practice. In *ICMAS*, volume 95, pages 312–319, 1995.
29. O. Shehory and S. Kraus. Formation of overlapping coalitions for precedence-ordered task-execution among autonomous agents. In *Proc. of ICMAS-96*, pages 330–337, 1996.
30. D. Soergel, B. Lauser, A. Liang, F. Fisseha, J. Keizer, and S. Katz. Reengineering thesauri for new applications: the agrovoc example. *Journal of digital information*, 4(4), 2006.
31. N. Tamani, M. Croitoru, and P. Buche. Conflicting viewpoint relational database querying: an argumentation approach. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 1553–1554. International Foundation for Autonomous Agents and Multiagent Systems, 2014.
32. N. Tamani, P. Mosse, M. Croitoru, P. Buche, and V. Guillard. A food packaging use case for argumentation. In *Metadata and Semantics Research*, pages 344–358. Springer, 2014.
33. N. Tamani, P. Mosse, M. Croitoru, P. Buche, V. Guillard, C. Guillaume, and N. Gontard. Eco-efficient packaging material selection for fresh produce: Industrial session. In *Graph-Based Representation and Reasoning*, pages 305–310. Springer, 2014.
34. N. Tamani, P. Mosse, M. Croitoru, P. Buche, V. Guillard, C. Guillaume, and N. Gontard. An argumentation system for eco-efficient packaging material selection. *Computers and Electronics in Agriculture*, 113:174–192, 2015.
35. R. Thomopoulos, M. Croitoru, and N. Tamani. Decision support for agri-food chains: A reverse engineering argumentation-based approach. *Ecological Informatics*, 26:182–191, 2015.
36. W. Van Der Hoek and M. Wooldridge. On the logic of cooperation and propositional control. *Artificial intelligence*, 164(1):81–119, 2005.