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Francois Ledoyen, Rallou Thomopoulos, Stephane Couture, Loic Sadou, Patrick Taillandier

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François Ledoyen
UR MIAT
INRAE, University of Toulouse
Toulouse, France
francois.ledoyen@inrae.fr

Rallou Thomopoulos
UMR IATE
INRAE
Montpellier, France
rallou.thomopoulos@inrae.fr

Stephane Couture
UR MIAT
INRAE, University of Toulouse
Toulouse, France
stephane.couture@inrae.fr

Loïc Sadou
UR MIAT
INRAE, University of Toulouse
Toulouse, France
loic.sadou@inrae.fr

Patrick Taillandier
UR MIAT
INRAE, University of Toulouse
Toulouse, France
patrick.taillandier@inrae.fr
UMI UMMISCO / JEAI WARM
IRD, SU, Thuyloi
Hanoi, Vietnam

***Abstract*—An approach that is particularly well adapted to study the dynamics of adoption and diffusion of innovations is agent-based simulation. It allows modelers to take into account the complex interactions between actors as well as their heterogeneity. Numerous works have already shown the interest of this method for the study of innovation diffusion processes. However, the vast majority of these works have been limited to an abstract and simplified representation of this process. This very abstract representation does not allow users to understand and explain the reasons for the change of opinion of an agent, which is nevertheless fundamental to understanding the dynamics of innovation diffusion. In order to overcome this limitation, we propose an agent-based model of adoption and diffusion of innovations that uses a structured argumentation framework. An application of this model is proposed to study the diffusion of communicating water meters by farmers on the Louts river (South-West of France) and shows that the introduction of new arguments could impact the adoption process.**

***Index Terms*—agent-based simulation, innovation diffusion, argumentation, opinion dynamics**

I. Introduction

Rogers defines the diffusion of innovations as the process by which a new practice, idea or product spreads throughout a society [1]. Modeling has long been used to study this process. The goals are essentially to better understand the adoption process in a population, to confirm hypotheses on the causes of an observed phenomenon, or to anticipate dynamics at a micro or macroscopic level.

The Bass model [2] is the historical model of innovation diffusion, using Rogers' observations to predict the peak of new adoptions. Its descriptive power is weak because the results obtained are limited to the number of adopters at a given time; the different stages of adoption proposed by Rogers, the homogeneity of the population and the dynamics of communication are not taken into account, neither is the impact of the means of dissemination put in place by the institution. As a result, it may be ineffective in the study of certain products for which there is no data on previous adoptions.

Agent-based models can provide solutions to the shortcomings of the Bass model. Indeed, they allow modelers to describe microscopically the population and, importantly, to integrate the decision-making process proposed by Rogers as well as the description of interactions between individuals. Classical agent-based models of innovation diffusion represent the opinion of each agent on an innovation by a numerical variable that evolves during their interactions with other agents. This type of representation does not provide much information about the change of agent's opinion. Indeed, as the opinion is usually integrated in single numerical value, the reasons why the agent has changed its opinion are not known.

To overcome this limitation, a relevant framework is the argumentation model [3]. Argumentation deals with situations where information contains contradictions because it originates from several sources or corresponds to several points of view that possibly have different priorities. While several models have already proposed to explicitly represent arguments for opinion dynamics [4]–[7], to our knowledge, no agent-based model has proposed to represent arguments for the simulation of innovation diffusion.

We thus propose in this paper a model in which the knowl-

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edge of each agent is explicitly represented in the form of arguments, carrying information about the innovation. These arguments are the objects that the agents will exchange during their interactions. The advantage of this approach is to allow to retrace the state of knowledge of an agent in order to understand the evolution of its behavior in the face of an innovation. The model was implemented with the GAMA platform [8] using a plugin dedicated to argumentation.[1]

II. Related Works

Zhang & Vorobeychik [9] proposed in 2019 a critical review on innovation diffusion models. Among these models, cognitive agent models are the closest to our concerns: they aim to explicitly represent how individuals affect one another in cognitive and psychological terms. A particular popular model in this category is the relative agreement model [10]. This model, which takes its inspiration from the Rogers' observations, is centered on the notion of opinion towards an innovation. The individual's opinion and uncertainties are represented by numerical values that evolve during interpersonal interactions.

Whereas no work in diffusion innovation has used the concept of argument, in the field of opinion dynamics, several works have attempted to better specify the impact of interpersonal interactions on opinion through the use of this concept. Some of these works such as [4], [5] propose a simple formalization of the arguments in the form of a numerical value. Although these works show interesting results, they do not give information about argumentative reasoning and do not explicitly formalize the tensions between arguments.

To overcome this limitation, several works such as [6], [7], [11], [12] have proposed the use of the system introduced by Dung [13]. These works illustrate the interest of using such a formalism to represent arguments in the context of an opinion dynamics model. Among these works, [7], [14] is particularly interesting for us as it proposes a complete process of construction of opinion from the arguments and it allows us to easily integrate the heterogeneity of the agents through the notion of values.

The main idea behind our work is thus to take inspiration from the innovation modeling approach proposed in [10] and integrates the argumentation to represent the cognition of agents. Concerning the argumentation, we used a model close to the one proposed by [14] and added a notion of confidence in the arguments.

III. Model Proposed

A. Arguments

Arguments are the objects that represent the elements of information about the innovation that agents can understand and exchange. If Dung [13] considers arguments as abstract objects bearing no descriptive data, other works propose to extend this concept by adding semantics to the arguments [7], [15], [16]. In this work, we chose to use the representation proposed in [7] in which the data composing the argument play the role of support in the evaluation of knowledge.

An argument is a $(I, O, T, S, R, C, A, Ts)$ tuple:

- I: the argument identifier
- O: the option concerned by the argument
- T: the type of the argument (for: +, against: -, neutral: —)
- S: the proposition of the argument
- R: the justification of the argument
- C: the criteria linked to the argument (key-value pairs where each criterion is linked to a numerical value representing its importance)
- A: the agent that makes the argument
- Ts: the type of the source of the argument

Arguments are linked together through the notion of attack. An argument i attacks j if and only if:

$$i.T \neq j.T \wedge \exists c \in i.C, c \in j.C$$

More details about attacks can be found in [17].

B. The agents

The model is composed of *individual* agents, which represent the potential adopters of an innovation. An individual is characterized by two families of attributes: knowledge and adoption indicators.

a) Knowledge: The knowledge of an agent is represented by different variables:

- *known arguments*: list of arguments known (and used) by the agent.
- *argumentation graph*: a partial argumentation graph where the vertices are the arguments known by the agent and each weighted arc represents an attack from one argument to another with the value of the strength of the attack for the agent.
- *informed*: boolean indicating if the agent has enough arguments (n_{args}) to evaluate its individual benefit.
- *importance criterion*: Each criterion of the arguments (C of an argument) is linked to a real value between 0 (unimportant) and 1 (primordial) which represents its importance for the agent.
- *source confidence* : Each type of argument source (Ts component of an argument) is linked to a numerical value between 0 (no confidence) and 1 (full confidence), which represents the agent's confidence in the source.
- *neighbors*: all the agents with whom it is linked through the social network.

b) The variables of adoption: These attributes make it possible to quantify the opinion and to qualify the agent's state of adoption through the estimation of social value, personal benefit and their uncertainties. An uncertainty is a mixture of uncertainty and conviction about one's beliefs. This approach comes from the relative agreement model [10]. These variables are as follows:

- *social value* : real value between -1 and 1 that corresponds to an estimation of the opinion that other agents have of the innovation.

[1]The model is available here: https://forgemia.inra.fr/francois.ledoyen/argumentation_diffusion_innovation

- *social value uncertainty* : real value between 0 and 1 that represents its uncertainty about its social value. A value close to 0 means little uncertainty and vice versa.
- *personal benefit* : real value between -1 and 1 that quantifies the contribution of the innovation to the agent.
- *personal benefit uncertainty* : real value between 0 and 1 that represents its uncertainty regarding its personal profit. A value close to 0 means little uncertainty and vice versa.
- *opinion* : real value between -1 and 1 calculated from the social value and the individual benefit of the agent.
- *opinion uncertainty* : real value between between 0 and 1 calculated from the uncertainties of individual benefit and social value.
- *information state* : a boolean value indicating whether the agent has received information about the innovation.
- *decision state* : represents the adoption state of the agent (*cf. fig.* 1). This model is built from Rogers' observations.

The calculation methods for these variables are described in the section presenting the knowledge revision III-D.

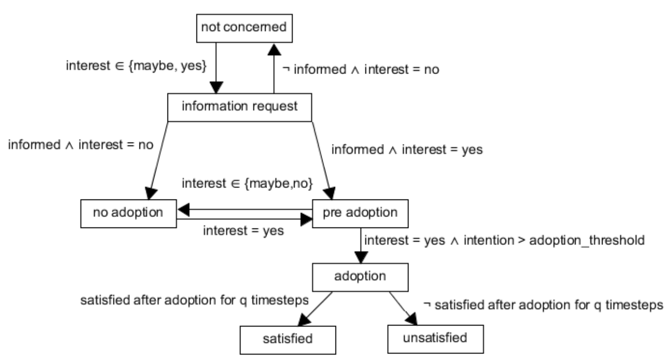

Fig. 1. State diagram of an agent's decision process

C. Model variables

The variables in the model are:

- *global argumentation graph*: complete argumentation graph in the sense that it groups together all the arguments and attacks provided by the modeler. The agent argumentation graphs are sub-graphs of this graph.
- *number of individuals*: the number of individuals.
- *p*: the time the agent needs to confirm its adoption.
- *q*: the time the agent needs to evaluate its satisfaction.
- *omega*: the probability that an agent takes into account an argument transmitted to it.
- n_{args}: the maximum number of arguments an agent can know.
- (σ_{sv}, μ_{sv}): parameters of the social value distribution.
- ($\sigma^u_{sv}, \mu^u_{sv}$): parameter of the uncertainty distribution of the social value.

D. The dynamics of the model

Concerning temporal resolution, a simulation step corresponds to a session of exchange of arguments for the agents.

At each simulations step, the processes are executed in the following order:

1) new arguments from an external source (advertisement, specialized press article...) are added to the arguments of agents searching for information *i.e.* in the state *information request*.
2) each agent having received arguments revises its beliefs according to its new internal argumentation graph to calculate its new opinion and then its adoption state.
3) each agent, according to its adoption state, can exchange one or more arguments with its neighbors.
4) the agents revise their beliefs a second time to update their decision variables.

We can distinguish three parts in this dynamic: the management of information, the revision of knowledge for decision making and interactions between agents.

Agent management of arguments

As we have seen earlier, the information is modeled as arguments in an argumentation graph (*argumentation_graph*) and integrated in a bounded size queue (*known_arguments*). An agent can become aware of an argument, mobilize it during interactions, but also forget it. Indeed, empirical research suggests that people have limited abilities to remember information [18], [19]. As in the ACTB model [20], we consider that the number of arguments with which an agent can form its opinion is limited to seven and the agent forgets the arguments it has not mobilized for a given time; its memory is thus represented as a queue.

Knowledge review and decision making

We define the notion of strength of an argument for an agent. Let us consider an agent ag, the strength of an argument arg is defined as follows:

$$strength(ag, arg) = \sum_{c \in crit} arg(c) \times ag(c) \tag{1}$$

with $crit$, the set of criteria, $arg(c)$ the value of the criterion c for the argument arg, and $ag(c)$ the importance of the c criterion for the agent.

From the notion of strength, we define the notion of value for a set of arguments. Let us consider an agent ag, the value of a set of arguments $args$ is defined as follows:

$$value(ag, args) = \frac{\sum_{arg \in args} strength(ag, arg) \times type(arg)}{\sum_{arg \in args} strength(ag, arg)} \tag{2}$$

$$\text{with: } type(arg) = \begin{cases} 1 & \text{si } arg.T = + \\ 0 & \text{si } arg.T = | \\ -1 & \text{si } arg.T = - \end{cases}$$

We define as well the notion of uncertainty for an agent concerning a set of arguments. For a set of arguments, the uncertainty is calculated according to the agent's confidence in the different sources of information:

$$uncertainty(ag, args) = 1 - \frac{\sum_{arg \in args} conf(ag, arg)}{|args|} \tag{3}$$

with: $conf(ag, arg) = ag.$*source_confidences(arg.Ts)*

Quantitative estimation of opinion

The quantitative opinion variable is representing the social value and the individual benefit.

The agents estimate their individual benefit and the associated uncertainty from their arguments. The procedure is as follows:

1) simplification of the argument graph $(\mathcal{A}, \mathcal{R})$ by removing mutual attacks of arguments with the following rule: remove each arc $(a, a') \in \mathcal{R} \wedge strength(ag, a') > strength(ag, a)$.
2) calculation of the set of preferred extensions of the simplified argument graph (using the JArgSemSAT library [21]).
3) calculation of the individual benefit and its uncertainty from the preferred extensions: evaluate each extension with the equations 2 and 3 and return the extensions for which the absolute value of the weight of the arguments is maximum.

We consider that the social value and its uncertainty do not change during the simulation: they are calculated at the initialization of the agent from Gaussian laws of parameters (σ_{sv}, μ_{sv}) and $(\sigma^u_{sv}, \mu^u_{sv})$. These parameters have to be estimated by the analysis of the collected data. Strategies for estimating these values from arguments are presented later.

The agent's overall opinion and uncertainty are computed as follows:

$$\begin{aligned} \textit{opinion} &= \frac{1}{2}(\textit{social\_value} + \textit{personal\_benefit}) \\ u_{\textit{opinion}} &= \frac{1}{2}(u_{\textit{social\_value}} + u_{\textit{personal\_benefit}}) \end{aligned}$$

Decision making process

States of interest in innovation

The state of interest concerning the innovation is calculated from the agent's opinion:

$$\textit{interest state} = \begin{cases} yes & \text{si } op - u_{op} > 0 \\ no & \text{si } op + u_{op} < 0 \\ maybe & \text{otherwise} \end{cases}$$

with :

- op: the attribute *opinion*
- u_{op}: the attribute *opinion uncertainty*

Decision statuses

The decision state of an agent is determined according to the rules presented in Figure 1. These rules take into account the states of interest and the information attribute:

1) if an agent has no information ($\neg$*informed*) its opinion is only calculated from the perceived social value and:
   - if its interest is *no*, then its decision is that it is not concerned (*not concerned*). It no longer pays attention to the information it might receive from outside potential adopters.
   - If it is interested in the information, then it starts looking for information (*information request*). The agent will have a ω probability of understanding the information. If it receives new information, it evaluates its personal benefit and uncertainty.
2) Once enough arguments have been received, the agent can add to the social value its individual benefit in the estimation of its opinion:
   - If its interest is *no* or *maybe*, it decides not to adopt the innovation (*no adoption*). This means that its individual benefit is too low, but this state is not definitive; learning an argument that challenges its knowledge can change its interest into a *yes*.
   - If it is interested, then it will pass into the pre-adoption state. This state corresponds to a period during which the agent reflects on its choice. The interactions it has with other agents can make it change its mind.
3) during the pre-adoption state the agent continues to receive information:
   - if its interest remains positive during a period of *p* time steps, the agent will adopt the innovation and put it into practice.
   - Otherwise the agent will not adopt it.
4) the adoption state is the phase during which the agent puts the innovation into practice. The use of the innovation brings the agents a certain satisfaction which is measured during q time steps:
   - if its average satisfaction during this period is positive then it defines itself as satisfied with the innovation.
   - Otherwise it is dissatisfied with the innovation.

Interactions between agents

Similarity between two agents

Like in most opinion dynamic models, we consider that in order to interact and exchange arguments, agents should not be too dissimilar in terms of opinion. The method used to calculate the similarity between two agents i and j is the one proposed in [22]. The similarity is defined by the measure of the overlap of opinions of i and j:

$$sim(i,j) = min(op_i + u^i_{op}, op_j + u^j_{op}) - max(op_i - u^i_{op}, op_j - u^j_{op})$$

. with :

- op_i: *opinion* from agent i
- u^i_{op}: *opinion uncertainty* of i

The i agent will start the chat with j only if $sim(i,j) > u^i_{op}$. This condition allows us to model the fact that agents with low uncertainty are more influential.

Link between exchange of arguments and status of decision

During a conversation an agent transmits to another agent one or more arguments from its preferred extension (the one used to calculate its individual profit). This selection is made according to its state of decision:

- an agent not concerned does not transmit arguments but may receive some.

- an agent who is dissatisfied with the innovation or does not adopt it is more likely to transmit an argument against the innovation because the arguments used to evaluate its individual benefit are mostly negative.
- an agent in *searching for information* can convey an argument for or against the innovation. The type of argument is not taken into account because the agent is at the stage where it does not yet have a stable opinion.
- an agent with a positive opinion, i.e. one who is in the process of adoption, who is adopting, or who is satisfied, is more likely to convey a positive argument.

IV. Application

A. Context

In Le Louts area (South-West of France), the mechanical meters, owned by the farmers, fail to correctly estimate water consumption because of their low accuracy. This is an advantage for the farmers as the risk of being overcharged if the allocated quota is exceeded is lower. It is for this reason that the Ministry of the Environment requires a periodic refurbishment of the metering system every 9 years. The "Compagnie d'Aménagement des Coteaux de Gascogne" (CACG), which in charge of the management of the water distribution in this area, is counting on this regulation to install its new remote-reading meters. These new meters are more accurate and allow real-time monitoring of each farmer's consumption and thus to better manage the use of water.

However, the institution has difficulties in convincing farmers to install the device because they perceive it negatively. This obstacle is closely linked to the mistrust that farmers have of the institution. A large proportion of farmers feel that the new meter does not benefit them and that it is only useful for the institution [23]. Yet, a minority, more inclined to new technologies, finds arguments in favor of innovation, such as managing equipment leaks, automatic calculation of consumption to best regulate withdrawals so as not to exceed the allocated quota and limit losses.

An analysis of various scientific documents [24] has allowed us to identified thirty-five arguments (14 (40%) against and 21 (60%) in favor) distributed according to five criteria: trust (in the institution), ecology, social, productivity, financial.

The agents represent the irrigators of Le Louts that subscribe to the CACG's pumping system (60 individuals). The attributes of the agents were initialized as follows:

- Importance of criteria: uniformly drawn between 0 and 1
- Confidence in source: uniformly drawn between 0 and 1
- Time for validation: 10
- Time for satisfaction: 15
- Social value: $\sigma_{sv} = -0.5, \mu_{sv} = 0.5$
- Uncertainty: $\sigma_{sv} = -0.5, \mu_{sv} = 0.5$
- Arguments: between 2 and 5 chosen randomly
- neighbors: between 0 and 6 chosen randomly

B. Addition of a new argument for a part of the population

The objective of this experiment is to answer the question *"What is the influence on the adoption of innovation if the institution makes a new argument in its favor to a given proportion of the population?*

A new fictitious argument in favor of innovation is added to the overall argument graph at the initialization of each simulation. This argument belongs to the category (criterion concerned) *Social* which includes 8 arguments mostly against innovation (5/8). We consider that this new argument attacks the 5 arguments against of the category *Social* and that it is not attacked by any other argument. This new argument is given respectively to 0%, 25%, 50% and 75% of the population. The choice of the agents receiving the new argument is random, which means that no social configuration is privileged.

In order to take into account the stochasticity of the model, we performed 10 replications for each proportion of agents receiving the argument. We consider that at the beginning of the simulation no agent adopted the innovation. Table IV-B shows, for each percentage of the population receiving the new argument, the average initial opinion, the average final opinion and the average innovation adoption rate for the 10 replications after 10,000 steps of interaction (with standard deviation).

TABLE I
EVOLUTION OF THE OPINION AND ADOPTION RATE WHEN A NEW ARGUMENT IS INTRODUCED

% of the pop	**mean initial opinion**	**mean final opinion**	**mean % of adopters**
0.0	-0.291 (0.055)	0.011 (0.246)	6.12 (2.016)
25.0	-0.211 (0.041)	0.034 (0.202)	6.12 (2.589)
50.0	-0.147 (0.031)	0.107 (0.07)	7.2 (2.02)
75.0	-0.101 (0.022)	0.025 (0.134)	7.02 (2.401)

A first lesson is a trend towards greater acceptance of communicating water meters even when no new argument is introduced (proportion of 0%). While it is still too early to know whether this acceptance will really be seen among farmers in Le Louts, it is worth noting that some similar phenomena were observed when mechanical water meters were introduced.

A second observation is that the average initial opinion increases with the proportion of the population to which the argument is transmitted (*cf tab.* IV-B), which is quite normal: an agent receiving the new argument will necessarily see its opinion either remain at the same level or increase, the new argument not being attacked. Thus, the higher the proportion of agents receiving the argument, the higher the average initial opinion.

Another observation is that the dynamics obtained with the addition of this new argument are close to the dynamics without any new argument (proportion of 0%). This similarity can be explained by the fact that many agents who will be brought to know this argument for a while will then replace it by another one because of the limit of arguments introduced per agent and because an agent will only exchange an argument if it is part of its preferred extension.

A final observation, which should be verified by more repetition and statistical testing, is that the average final opinion increases when the argument is given to 50% of the population, but there does not seem to be a significant difference when the argument is given to a larger proportion of the population. This can be explained by the reasons mentioned earlier on the process of argument replacement.

V. Conclusion

In this paper, we proposed an agent-based model of innovation diffusion based on the explicit modeling of information about innovation by means of arguments. The model allows modelers to take into account the heterogeneity of actors by linking the information carried by the arguments and the agent's preferences (confidence in information sources, themes of preference). We also integrated an explicit description of the states of adoption of the innovation and the dynamics of interactions that result from it.

An application of this generic model has been proposed for the issue of farmer adoption of communicating water meters. The first experiments carried out tend to show a trend towards greater acceptance of communicating water meters through argument exchanges. Moreover, for the institution that wishes to see the adoption of these new water meters, the dissemination of new arguments seems to be an efficient strategy. In order to go further in the interpretation of these results, several actions will have to be carried out. A first action concerns the increase in the number of replications of the simulations to make the results more robust. In this context, a statistical analysis on the significance of the results with statistical tests such as those of *Student* and *Wilcoxon-Mann-Whitney* will be performed.

Some of the parameters of the model used for the experiments were estimated or drawn randomly. A future objective is to set up field surveys to obtain these parameters. Similarly, it would be relevant, through questionnaires, to obtain computer data on the evolution of farmers' opinions on communicating water meters in Le Louts area, which would enable us to validate the results obtained by simulation.

In terms of model extension, we plan to couple it with the BEN agent architecture [25]. Indeed, in addition to the BDI reasoning engine, the BEN architecture introduces numerous concepts that could be interesting for our work such as the personality of agents based on the classic OCEAN model and the social relation between agents.

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