From cognitive models to multiple decision makers support systems

Frédéric Cadier, Gilles Coppin, Philippe Lenca

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Abstract.

We present in this paper a new approach for building distributed decision support systems. Multiple decision makers support systems are devoted to assist setting a consensus while taking into account all aspects related to the distributed nature of the processes. This approach is based on the integration of the individual cognitive models of the decision makers of the team and on the modeling of the dynamics of individual decisions when being interleaved. Our model allows to detect and prevent extremal group behaviors and to identify the right information transfers to be set among decision makers. This model has been tested in a realistic application framework concerning decision making in Maritime Surveillance where several operators have to converge towards a unique decision in limited time. We conclude with proposing the main elements of a design methodology for decision makers support systems based on the proposed approach.

Keywords: Distributed decision making, decision support systems, cognitive models of decision making, naturalistic decision making

1 Introduction

This paper investigates a generic approach, based upon cognitive modeling of individual and collective decision strategies, primarily dedicated to the design of distributed decision support systems, while remaining applicable to individual decision situations. This approach and related proposed design methodology are to be confronted with more "classical" ways of aiding decision and consensus among an organization, which most often do not try to take into account cognitive mechanisms of individual decision makers and the effects of organization and collectiveness on these mechanisms. We

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affirm on the contrary that, especially when considering expert decision makers, taking these elements into account allows one to change the role of the assisting system from a provider of solutions that refer to some absolute references or optimum, to a kind of *structuring mirror* that uses the analysis of decision makers' actions and strategies to extract and formalize a synthesis *meaningful for* the decision makers.

In the first step, this paper will describe the main characteristics of the distributed decision making, and the way we differ from "classical" approaches. In the second part, we will present an historical context of individual and collective modeling of decision making and decision support aid, to further extensively express our own cognitive models. In the next part, these models will be presented in agent-based simulations using the Maritime Surveillance application framework. We will then provide new directions for decision support systems that would rather support the decision makers in their daily tasks, instead of supporting the decision itself. A design methodology will be proposed for the conception of such decision makers support systems.

2 Distributed decision making

The focus in this article is distributed decision making, i.e. situations where multiple decision makers belonging to a team have to cooperate upon a unique team decision problem. As we previously discussed it in Cadier et al. [12], the distributed aspects of decision refer to spatial, temporal and/or functional characteristics.

2.1 Main characteristics

The decision making may be spatially distributed in reference to the different localisations of the decision makers, that usually lead them to different *physical* points of view upon the surrounding environment. However, this separation must not prevent cooperation that can be achieved through a network, otherwise it would be multiple separate individual decision making processes instead of a single distributed one.

Temporal characteristic of the distributed decision making may be, on the one hand, considered as "extrinsic" when referring to a dynamic and changing environment: information is only valid in a certain time frame, and the processes have to take these evolutions into account. On the other hand, this characteristic is also "intrinsic" when considering the converging dynamics of the individual decisions of the teammates into a consensus, which will constitute the unique decision of the team.

The distributed aspect of the decision making may finally be considered as functional, meaning that the decision makers may be assigned different roles, particularly depending on their competencies, leading them to different individual decisions, also called *subjective* points of view towards the team decision problem. This is especially important in our study as we are focusing on situations where decision makers are experts in their domain (cf. Section 3.2).

The three dimensions of the distributed decision making are closely associated. For example, the spatial distribution, which leads to different *physical* points of view, is linked to functional distribution which supposes that each decision maker perceives information reliable for building his own *subjective* point of view[1], while the temporal characteristic gives insight of the distributed process in terms of how these latter individual decisions will be confronted, discussed and, finally, unified.

This situation applies to our application framework, the Maritime Surveillance (cf. Section 4.1 for a complete description), where information of different kind (imagery, acoustic analysis, etc.) is necessary to fulfill the mission. A single teammate is generally not capable enough to draw a conclusion from the information coming from his specific source. The decision, i.e. the identification of the objects at sea, then requires cooperation of different decision makers having varied competencies and who can be spatially separated (e.g. a team on the ground, another one at sea, and the third one in a plane). Exchanging information between them is thus crucial within the process.

The previous situation is also characterized by the fact that individuals have a common goal and the will to work together. We can then speak of *cooperative work* and of *teams* instead of *groups* (cf. Section 3.2). This working situation does not exclude different degrees of freedom, and a hierarchical structure can be instantiated. This latter can even be useful, for example:

- when the different teammates cannot succeed to reach a consensus, whereas not to decide is worse than to make a bad decision, by allowing the leader to force the termination of the process when necessary and thus to take the more reasonable decision at the present time [2];
- or by distributing responsibilities among the different levels of the hierarchy, assigning a unique task to each one, and minimizing the risk of cognitive overload.

2.2 Positioning

Classical distributed decision support systems (DDSS) generally focus on the global structuring of the process in different stages, and usually ignore individual processes to directly work on the aggregation, or the combination, of individual results [40].

We propose to integrate individual cognitive models to the study of the distributed decision making in order to identify the articulations of the cooperation in terms of:

- information exchanged by the individuals;
- benefit to each individual, for the *subjective* point of view he constructs.

[1] Let us note that, even if these pieces of information are identical, spatial distribution might be necessary, e.g. for security reason, or simply to ensure the correct follow-up of the environment dynamic, while giving the possibility to the different decision makers to manage their own tempo.

[2] We thus try to approach an *anytime* process, i.e. being able to give a decision at any time.

Our approach is therefore resolutely *anthropocentric*. Furthermore we argue that maintaining *experts* in the loop of cooperation between individuals, via artificial systems, ensure that the complexity of the considered problems will be handled [9, 6]. This position constitutes one of our main propositions concerning design of multiple decision makers support systems (cf. Section 5).

In this article, we are thus interested in individual representations of human operators using artificial systems, when contributing to a distributed decision. We will identify elements that a DDSS should implement to support in the first place the individual processes involved in the construction of a distributed decision, and in the second place the distributed decision making itself.

3 Individual and collective modeling

In this section, we first briefly consider the different approaches of decision modeling at individual and collective levels. Then, we present our individual and collective modeling approaches by characterizing the decision maker and team under study and extensively developing our models.

3.1 Historical and scientific context

Decision making has been studied now for centuries. The historical trend for taking decision makers as pure rational actors can be considered as initialized by Bernoulli [8], as he proposed the concept of expected value for comparing decision alternatives. This first step was followed by a long list of mathematical refinements that produced concepts such as expected utility [49], subjective probability and utility or, even more recently, fuzzy notions applied to utility evaluation and aggregation [18]. An immediate criticism against this kind of approach generally points at the unrealistic capacity of computation that would be necessary for a human being, if these models happened to describe human based decision processes. Some of those models were moreover criticized after exhibiting paradoxes intrinsically attached to their principles [1]. These limitations have provided many arguments to propose other paradigms and other models of decision when human decision makers are concerned (for a brief overview of this evolution, see Barthélemy et al. [6] and Barthélemy et al. [7]).

As an alternative approach, Simon's epistemological rupture [44] proposed to consider decision under the cognitive side and to take into account – if not to adapt to – the *bounded rationality* of decision makers, that put them far from any model based upon optimized choices or even exhaustive analysis of possible alternatives, that is to say far from any "classical" utility approach as defined here above. Following this approach, we think that in order to set a proper dialog between a decision maker and his decision support system, the latter must provide some advices based upon mechanisms and structures that may be compatible with human decision making, and thus more understandable and relevant to the decision maker [15]. Moreover, studying the question of decision making from the decision maker point of view will give a proper guarantee of generality because one can assume that our models rely on mostly invariant psychological models, instead of being stuck to the problems and their possible various representations.

We thus propose to rely on cognitive approach for individual and collective decision modeling and aiding, and expand it further in the following sections.

3.2 What kind of decision maker and team do we study?

Several types of decision makers are usually considered: naive, novice, expert, and professional decision makers [5]. In this paper we shall focus on experts.

In opposition to a professional whose competencies are developed upon the problem solving *methodologies* (e.g. statisticians or operational researchers), an expert decision maker is highly familiar with the tasks he has to perform. He knows how to structure what a naive or novice would consider as amorphous. While a novice is easily overwhelmed by information, an expert is someone who "can make sense out of chaos" [42]. He is also able to convince his colleagues as well as his hierarchy, and all of them agree to acknowledge his great experience.

A main characteristic of expertise is the small amount of information processed to perform a decision: while a novice uses an overcrowded amount of information, an expert uses what is just enough. An interesting discussion about that subject can be found in Shanteau [43]. Obviously such a phenomenon is balanced by the high quality and the relevance of the information used by expert decision makers, whereas naive ones tend to use more but inappropriate information. This characteristic is confirmed by studies about memory in cognitive psychology [30]. The expert will process information in his short term working memory, but with (complex) strategies compiled in his long term memory.

We suppose the decision to be "collective", that is to say to be made by a *team*. This implies two main features.

The first one is that the decision makers gather because they have a shared task to work upon, even though they are autonomous decisional entities [46]. This task is driven by a common goal (e.g. a mission assigned to a maritime surveillance crew, cf. Section 4.1) which needs a consensual decision to be reached. This allows one to distinguish between a team and a group in which individual goals are followed by interdependent people (e.g. decisions made by stockholders in stock markets). This unique team decision constitutes the reason why teammates cooperate and interact.

The second feature is that teammates develop dependencies upon each others while working together. When speaking of a team, we suppose the decision makers to have been interacting for a long time, and that their own respective decisions to be possibly dependent of the choices and strategies of the other teammates. These dependencies imply that no teammate is able to decide alone, as he cannot obtain or process himself all the needed information, and that different competencies among the team are needed, even if those might partially overlap. Therefore, the cooperation between the decision makers is mandatory to exchange information, and deal with inherent difficulties of the decision problem.

3.3 Modeling the expert decision maker processes

In the following we'll consider that we are dealing with multi-criteria decision making. That is to say that situations faced by decision makers and alternatives among which each decision has to be made are described by values along a set of descriptive dimensions, or attributes, called *criteria*. Multi-criteria decision aid field is vast and has been the subject of numerous publications. The reader may thus refer to the following (short) list of excellent books that present the main concepts and the main central themes around multi-criteria decision aid: [38], [39], [17] and [10]. Our approach, although situated in a multi-criteria decision aid context, is different from those presented in the literature cited above [13]. It is based on a cognitive modeling of decision makers processes. By the way, we also focus mainly on two decision making tasks: choice, where the decision maker intend to select an alternative among a set of possible ones, and judgmental task, where the situation (e.g. an unknown object) is to be sorted in a given classification, and where alternatives represent the sorting possibilities identified by the decision maker [5].

3.3.1 Decision making as a search for a dominance structure

As it is classically proposed in cognitive psychology [2, 30], decision making can be viewed as an information process in which the flow of information through the cognitive system, given as a set of cognitive interwoven processes, results in a response, namely the *decision outcome*. Therefore, several kinds of processes have been studied. Among them: heuristics, like representativity or availability [21], articulation of elementary strategies [47], decision making as problem solving [20], as an identification of prototypic situations [36] and as a search for a dominance structure [31].

As one of the main features of cognitive modeling, we also need to specify what is the structure of the data such processes are working upon. In other and more cognitive words, we need to explain what could be a meaningful model of the *mental representation* a decision maker is about to build for a given decision situation, and his decision alternatives.

In particular, Montgomery and Svenson [32] have proposed that each criterion, described along an objective dimension, could induce a subjective *attractiveness scale* for each decision maker, and that the "qualitative" evaluation of that criterion on the associated scale should be called an "aspect". They also proposed that a strong relationship exists between the *strategies* of a decision maker and his mental *structuration* of a decision problem. Such a structuration depends on the structures of the attractiveness scales (numerical scales with or without thresholds, ordinal scales, etc.) and their comparability one to another, and on the potential existence of a preference order between criteria (e.g. a *lexicographic* order).

Among the possible *strategies*, one may find: the *lexicographic rule* in which ranked criteria are used to evaluate and choose between alternatives; the *dominance rule* where the chosen alternative is to be the most attractive on at least one criterion, i.e. having the highest aspect value on that criterion, and not being less attractive on the others; or the *greatest difference in attractiveness rule* which maximises the difference of the aspects over all the criteria (see Montgomery and Svenson [32] and Barthélemy and Lapébie [3] for a comprehensive study of elementary strategies).

This approach has been strongly supported by Montgomery in several papers (see for instance [31]). His basic idea is that among the many possible strategies, the dominance rule is used as a major one. Obviously it will not spontaneously apply. Hence, the decision process will reduce essentially to the *search for a representation* of the situation (in terms of considered criteria, attractiveness scales and thresholds) where one (or more) alternative dominates the others in the sense of a dominance rule.

Such a dominating alternative is called a *dominance structure*. Furthermore, a given decision maker may uses several structures according to the problem he faces, but if he is an expert, we can assume that his dominance structures are stabilized and that a given situation always elicitate the same dominance structure[3] [28].

3.3.2 Proposing a computational model of individual decision making from the observation of the decision maker choices and behaviors

Following Simon and Montgomery [31], Barthélemy and Mullet worked upon a reformulation and enhancement of the search for a dominance structure model in multi-criteria decision making setting. They proposed the Moving Basis Heuristics (MBH) [4], a meta-model of the decision maker behavior in such decision situations, devoted to the elicitation, or activation, process of *decision rules*.

Each decision rule, which thus represents one decision maker strategy, might be understood as a set of predicates that, when fulfilled, lead to a decision outcome. Each predicate is defined as a couple constituted of the aspect (recalled to be the "qualitative" evaluation of criterion) contained in the decision rule of reference and the evaluation of the corresponding attribute in the current mental representation of the situation. A predicate is then fulfilled when the mental representation is dominant over the decision rule along the associated dimension, that is to say when the decision maker estimate the current situation has reached the acceptation level on the targeted criterion.

The main difference between the dominance structure concept such as initially proposed by Montgomery and the MBH model relies in the number of considered dimensions.

Furthermore, the MBH accounts for arguments[4] that fit with cognitive hypotheses

[3]We also therefore assumed that expert's dominance structures are stored in long term memory, thanks to his experience which might be view as a learning phase. On the contrary, a novice decision maker would still have to be considered as learning, and thus have fluctuant dominance structures so that very few of them could be stored as stable in long term memory.

[4]These arguments could appear to be contradictory at a first glance but that can be combined into a coherent model of decision.

and basic models:

parsimony: due to his short-term memory capacities and limited computational abilities, the decision maker tends to manipulate only a small number of criteria;

reliability/warrantability: the sets of criteria involved in a decision rule have to be meaningful enough (in quantity and/or quality) in order to justify, individually and/or socially the decision issues. To also respect the precedent principle, the decision maker will therefore tend to use conjunctions of several criteria;

decidability/flexibility: the decision maker *has to* decide in finite and limited time. He thus has to be flexible enough to examine several possible decision rules, and never gets stuck in doubt or hesitation.

The MBH proposes two important supplementary features in order to model behaviors:

preferences: performing a decision task, the decision maker shows his preferences among the criteria. That especially means that the observable behaviors reflect the decision rules used by the decision maker, and that learning these rules from behavioral outcomes is possible;

monotonicity: expert decision makers manifest monotonicity when dealing with similar decision situations: giving a past decision situation and the decision rule that was elicited, we observe that all situations having representations where the latter decision rule apply, through the dominance rule, will lead to the same decision outcome. In other words, for all situations in which the same decision outcome is made by a decision maker, this latter manifests the use of representations that are all dominated by the same dominance structure. This property fully exploit the dominance rule and is essential when proposing *efficient* algorithms for extracting the decision rules from an experimental data space related to decision maker choices, but is not mandatory in the model [28]. However this is a main point of the model that we target and want to make explicit. Therefore a proper definition of criteria and recoding of the scale (to be used in the decision model) shall be requested to fulfil this requirement. This coding operation must at least correspond to the ordinal scaling of the preferences of the decision maker.

So, as we assume to be focussing upon an expert decision maker, we suppose that his decision strategies and behavior are stable along time[5], and, under the previous hypotheses/constraints, that we are able to compute a set of decision rules, i.e. his decision strategies at individual level[6]. This extraction might be achieved from non

[5]Note that the set of decision rules – learned from past behavior of the decision maker – might evolve during time. But this adaptation process is slow compare to the time of the decision making ones. Therefore, we can locally suppose that the set is stable, and will integrate updating functions to the foreseen system (cf.Section 6).

[6]Note that these decision rules might also be understood as prototypes in the sense of Rosch and Mervis [37].

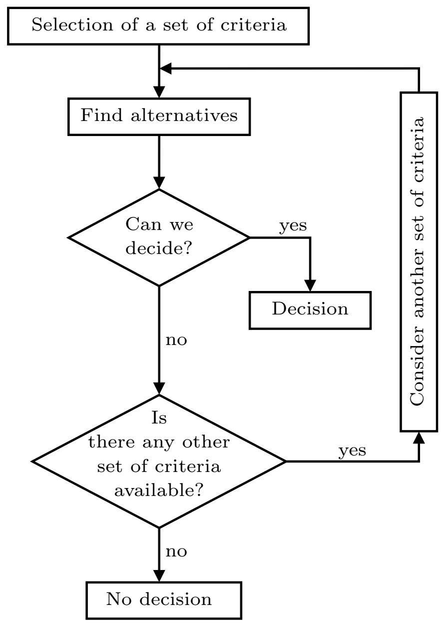


Figure 1: The Moving Basis Heuristics

intrusive observation of the expert decision maker actions [24], or from realistic stimulations that provoke adequate decisions from the decision maker [28] (cf. Section 6.1). An overview of cognitive aspects related to individual decision making and practical aspects for decision support systems may be found in Barthélemy et al. [7].

The Figure 1 represents the expert decision process according with the MBH. One can see that this process may be divided into some sequential operations that manipulate the set of criteria used by the decision maker in his search for a good decision rule:

Selection of a set criteria: depending on his preferences on the criteria, and according to the parsimony and reliability principles, a small, but relevant, set of descriptive criteria is selected by the expert decision maker to build a representation of the situation;

Find alternatives: the obtained representation activates some decision rules from the decision maker long term memory, enabling him to get a set of alternatives among all the possible decisions (cf. Section 3.3.3 for a discussion on this specific process);

Can we decide?: the question here points to whether or not one and only one of the activated decision rules is *dominated*, in the sense of the dominance rule, by the mental representation of the situation. If yes, then the related decision outcome is made, otherwise the process continues;

Is there another set of criteria available?: if some criteria have still not been considered, then according to the decidability principle, the decision maker might choose to go on within the process. Otherwise, the process ends in a "no decision" situation (also cf. Section 3.3.3 for insights into this situation);

Consider another set of criteria: this new selection also depends on the decision maker's preferences on the criteria, but also on the preceding iterations of the process that gave him insights into what are the most relevant or distinctive criteria to consider[7].

3.3.3 Partial activation and the "No decision" situation

One characteristic shared by the MBH model with the search for a dominance structure model is that the decision rules, or dominance structures, are supposed to be activated *outright* when the mental representation of the situation is built. In terms of its constituting predicates, a decision rule is thus completely or not at all activated, with no intermediary state in between.

Therefore, and since the MBH model provides extremely few details on the activation process, we propose to extend the model through a "partial activation process" of decision rules, to allow the description of an "hesitation" and the way a decision maker dispels this doubt, and also to analyze how one can be influenced by some teammates (cf. Section 3.4.1).

As illustrated in the example given in Figure 2, the activation process of decision rules and elicitation of a decision might be formalized in this way[8]:

- different decision outcomes are attached to the decision rules R_1 to R_4 stored by the decision maker in his long term memory;
- following the MBH proposal, a mental representation of the situation is built upon aspects from a selection of criteria;
- aspects constituting the decision rules R_1 to R_4 may be activated *independently of one another*, if the corresponding aspect in the mental representation of the situation is dominant;
- in our example, R_4 is totally activated, and the corresponding "Decision outcome 3" is made.

The activation process is supposed to be parallel over the decision rules. This means that the rules are not serially considered to determinate the most appropriate, or "better", one. Following the *Satisficing model* of Simon [45], the MBH only posits that a subjective threshold of "satisfaction" has to be reached to enable the decision.

[7] We here join the proposition of Klein [22], in his Recognition-Primed Decision model, that a given identification of the situation provides information about the relevant cues, and critical stimuli a decision maker must focus on to efficiently assess the situation problem and decide [11].

[8] A complete development of this process, with all the necessary algorithms details, may be found in Cadier [11].

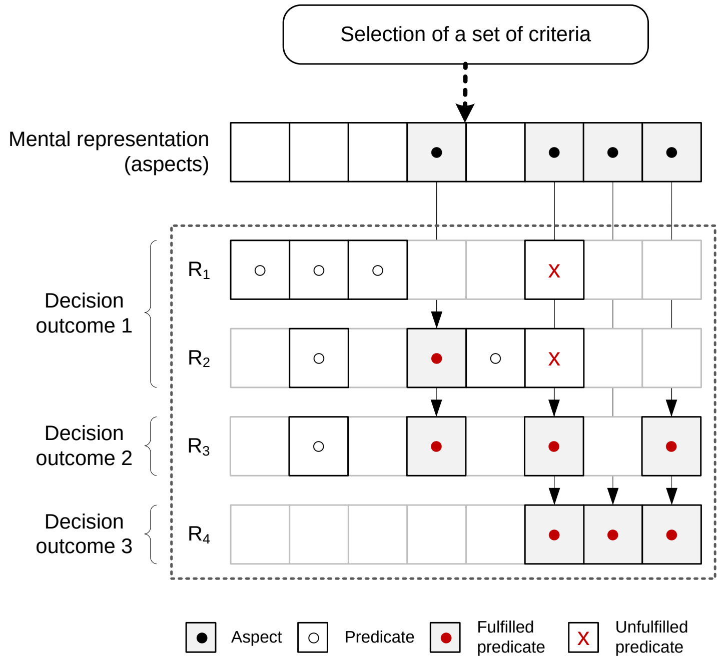


Figure 2: Activation of decision rules for a single decision maker

In our model, we then define, for each decision rule, an *activation level* that depends on the number of its fulfilled predicates, balanced by the actual preference on the rule. These preferences on decision rules are moreover supposed to be initially all equal, and to only evolve through interactions with other teammates (cf. Section 3.4.1).

The partial activations of the decision rules also allow the description of situations where the decision is impossible, illustrating the "No decision" case of the MBH. For example, it may be seen on Figure 3 that from the aspects provided by the external situation, the decision maker is unable to *completely* activate any of his possible decision rules. For a given threshold of satisfaction, we could assume that the decision maker cannot decide either because no alternative is satisfying him (all activation levels are lower than the threshold), or because more than one are conflicting (two or more even activation levels are greater than the threshold) and that he has no more time to modify his decision strategy (as it would otherwise be possible through the "Consider another set of criteria" step of the MBH). This situation will also be discussed later in this paper, when dealing with collective modeling of decision making (cf. Section 3.4).

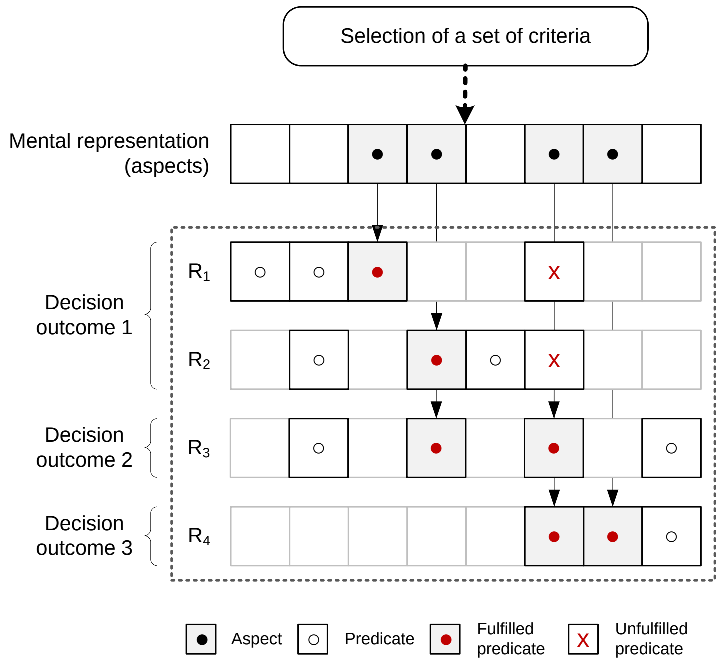


Figure 3: Partial activation of decision rules for single decision maker

3.4 Modeling the collective decision making

As presented in Ruta and Gabrys [40] in the case of classifiers fusion, most of classical approaches dealing with expert decisions aggregation and consensus work on the decision outcomes of each individual decision maker in the team. They generally try to combine and harmonize these individual results within a unique one, through an optimal process. Though this kind of approaches tend to find very solid mathematical background, they may fall under the same critics as the ones utility models are facing when considering individual decision: these approaches do not take into account cognitive processes of the individual decision makers, nor the mutual influences among these processes.

Therefore, as the first step, we would like to extend and adapt the individual cognitive models presented in the previous section to the collective setting, by considering the influences and effects of other decision makers participating in the team and working on the same problem.

Here again, we suppose decision makers under study to be experts. We suppose that they cooperate towards a common decision outcome, and that the cooperation is supported by the share of a common set of decision alternatives related to the situation to be processed, even if the decision makers' points of view may differ. Particularly, they may share only a small subset of criteria describing the situation, they may even have different measurement or interval values for a shared criterion and/or have expertise in different fields (see Section 2.1).

3.4.1 Modeling the cross-effects of individual decision processes

We suppose the decision to be "collective", that is to say to be made by a team. This means that we suppose the decision makers to be interacting, and their own respective processes to be possibly influenced by the choices and strategies of the other decision makers in the team. We present hereafter a way to model these interactions among decision processes, still using the activation of decision rules as a common background for decision making processes, but, this time, taking into account the dynamics of the decision processes underlying the decision [11].

In more concrete terms, we focus on the way decision rules could be, within the decision process, activated or inhibited, eliminated or selected while taking into account a *network of mutual influences* among the decision makers in the team. In this network, nodes stand for the decision makers of the team, and directed edges hold values coding the particular relation between the two concerned teammates in terms of mutual influence. Figure 4 thus proposes an example, a trust network, between four decision makers $DM1$, $DM2$, $DM3$ and $DM4$ where edges hold values in $[-1, 1]$. On this diagram, one can first see that the influences are not necessarily symmetrical (influence of $DM3$ on $DM1$ is 0 while the influence of $DM1$ on $DM3$ is 0.5 for instance). One can also see that some of the influences can be negative (between $DM3$ and $DM4$ for instance). In such a trust network, the influence value can be resulting from personal trust or confidence, but can also express some hierarchical and organizational constraints, or possibly a mix of these factors.

An influence network can be designed in different ways [15]. The first way consists simply in expressing *a priori* knowledge on the team through this formalism. For example, hierarchical influence could be expressed through asymmetrical values where one of the decision makers, the leader, has positive influence on all the others, and where the subordinates have only low or no influence on the leader. The second way relies on a learning phase analogous to the Hebb's rule [19]: from the observation of teammates' decisions, one can decide to reinforce the mutual influence between two decision makers DM_i and DM_j when they happen to make the same decision, and lower their mutual influence when they disagree. The influence of DM_i on DM_j would then tend towards 1 as long as the decision d_i made by DM_i appears to be a priority for DM_j, and would tend towards -1 when, on the contrary, DM_j seems to systematically inhibit d_i.

From this point, one may think about different kinds of interaction among decision makers. For a reference decision maker, picked in the team and denoted as *DMref*, we may have the following cases:

- individual decisions, either final or intermediate (in that they are only alternatives and might be revised) could be exchanged among decision makers[9]. In

[9] We do not matter for now whether decisions are exchanged willingly or not.

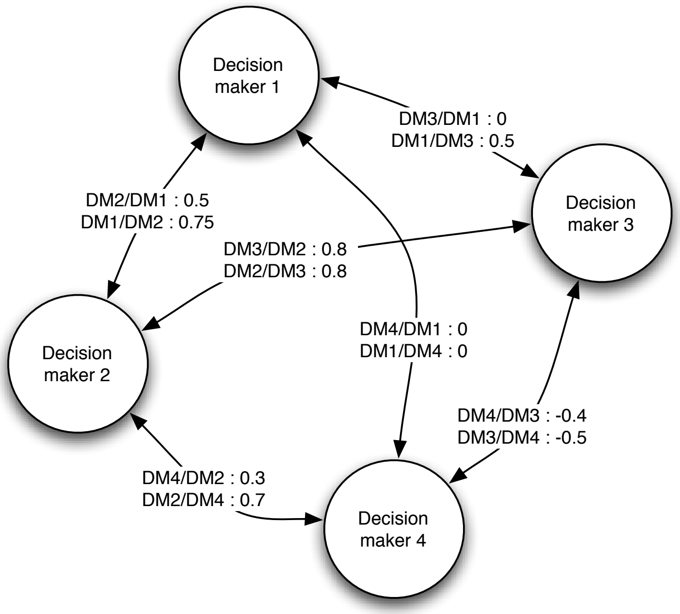


Figure 4: Simple example of social network

this case, we can imagine that the subset of decision rules of *DMref* that remain compatible with the "external" individual decision could be reinforced;

- information related to the criteria (and consequently decision rules) used by the other decision makers can be by themselves a factor of influence (even when not attached to an individual decision outcome). Here again, one may think about some reinforcement of focus around the key elements of an "external"[10] decision rule, as an effect of *DMref* imitating other decision makers in the team. In other words, if *DMref* knows that another decision maker is currently focused on specific criteria of the situation to decide about, he may adopt this specific point of view for his own decision making process.

Thus, coming back to the example illustrated in Figure 3 and expanded in Figure 5, knowing the "Decision outcome 3" proposed by a *reliable* teammate, $DMref$ may inhibit his rules R_1, R_2 and R_3 and pre-activate his rule R_4. As illustrated by the increasing and decreasing arrows in the Figure 5, we model this phenomenon by the increase or decrease of $DMref$'s preferences on his decision rules, depending on

[10]The "external" adjective here refers to the highly personal characteristic of decision rules, that are not comparable between different decision makers, even though an observer would say they work identically.

their compatibility with the "external" decision and on the value coding the influence of his teammate. Therefore, the different activation levels of the rules are directly affected by the social relation. The same would apply to influences on the criteria, by enhancing (resp. lowering) the preferences on criteria to be analyzed or used as they are compatible (resp. not) with those used by teammates, or those relevant with teammates' decisions.

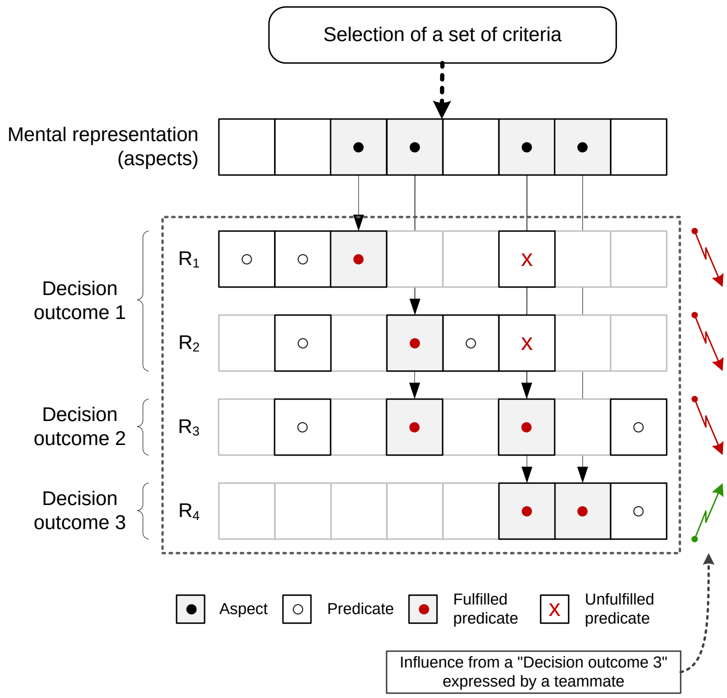


Figure 5: Activation and inhibition of decision rules for two decision makers

If the influence is strong enough, such phenomena could even outweigh some evidence from the situation that would have lead $DMref$ to finally reject "Decision outcome 3", or help him dispel a conflict between equally activated alternatives, allowing a decision he would have not been able to make alone. Results of several simulations conducted according to these principles are presented in Section 4.

3.4.2 Group dynamics and distributed decision making

If we are able to analyse and predict the effects on the decision process of a decision maker of external, final or intermediate, decision outcomes or decision rules of the other decision makers in the team, then we can give an interpretation of major group decision making phenomena resulting from the cross-effects of individual decision making processes. This kind of modeling should allow one to obtain some explanations of dynamics of collective decision making, simultaneously in terms of individual decision making processes and exchanged data. Effects such as group polarization or active minority (classically studied in social psychology [33]) may then be translated into variations and constraints upon the activation thresholds and the representation space, i.e. a set of descriptive dimensions or criteria, of the decision makers in the team:

- polarization effect may be understood as the effect of mutual influences among decision makers towards a dimensional reduction of the representation space around a common subset of criteria, associated with the reduction of the activation threshold for corresponding individual decision rules;
- active minority phenomena could be as well considered as the impact of a stable, in the sense of their decision outcomes or underlying decision rules, subgroup of decision makers onto the rest of the team where the decision makers do not exchange or communicate anymore;
- cooperation and collaboration can also be studied when considering complementary or compatible, in terms of criteria, configurations among the decision makers' respective sets of decision rules, to ensure a correct coverage of the global representation space.

If we have access to the sets of decision rules of the decision makers in the team, we may then analyse or simulate how their individual cognitive decision making processes influence one another, and dynamically converge towards a common decision outcome. These kind of simulations and some interesting results are now presented as illustrations of the presented group logic.

4 Illustration of models on agent-based simulations

4.1 A case study: decision making by the Maritime Surveillance crew

Our study uses the case of the Maritime Surveillance, which is aimed at scene analysis and situation awareness when observing ships at sea from airborne sensors.

The crew in charge of the surveillance is made up of military operators having various competencies, and different points of view corresponding to different specialized instruments they operate. The surveillance task is a process where human and software agents interact. They cooperate to achieve a common goal given by a mission they have been assigned to. There is also a hierarchy of crew members that allows one to clearly distribute roles and responsibilities, and to avoid jamming of the process, in case of dissension. They also may cooperate with teams on the sea and/or the ground.

Figure 6: Missions of Maritime Surveillance

Usually there are four operators: three sensors operators (electronic support measures – ESM –, imagery – ISAR/FLIR –, acoustic analysis – SONAR –) and a leader, the tactical coordinator – TACCO –. Additionally, there is a supplementary role, usually handled by the ISAR operator, for the observation of tracks kinematics (plan position indicator – PPI –). Operators and the tactical commander are embarked on specialized airplanes like the Atlantic2 or the Casa235, for military and civil missions ranging from surface vessel or submarine surveillance through anti-pollution fight or search and rescue at sea (see Figure 6). Civil operations might also involve non military individuals (privates, tourists, fishermen, private rescue crews, etc.) being at sea and/or at ground.

All these missions usually have a recurring task: the *track identification*. This identification involves labeling and classification of each radar echo (called a *track* since it is under processing) and determining its nature (submarine, surface vessel, commercial or pleasure, etc.), its membership (friend, foe or neutral), and its class (frigate, etc.).

In this identification task, the role of a sensor operator is to propose, assisted by his own instruments and by the set of measures that he can make, a first classification, which constitutes an intermediary decision outcome in the team decision making process. The role of the TACCO is to synthesize information provided by the sensors operators, and to establish the global track identification, which constitutes the consensus.

Regarding the nature of the crew and of the task, track identification is a distributed decision activity as we mentioned early: the goal of the identification is to provide a decision outcome, the classification of the track, and the process is distributed among the team. Let's note that the classification might be, if the mission requires it, extremely precise. Some identifications can thus provide the name of the vessel, and, consequently, all sorts of associated information, in particular via the cooperation with software agents (e.g. providing access to database).

The context of these decisions is in addition often characterized by *uncertainty conditions* and *limited time*. Moreover, error costs of misclassifying ships at sea are often asymmetrical. For example, in the military case, to mismatch a friend for a foe leads to what we are now sadly used to call a "friend shot". The opposite error does not have the same cost. In the same way, in case of a search and rescue mission, not to identify a boat being in an emergency results in providing no help, while people are in danger. The opposite error, once again, does not have the same cost. This imposes a significant level of stress on the operators being aware of the consequences of their decisions. In addition, surveillance missions can be long (up to eight hours) and tiredness might become an important source of errors, particularly if a cognitive overload appears. Two famous examples sadly illustrate these kind of situations: destruction of a civil aircraft by the North-American navy [23, chap. 6], and the strike of two civil aircrafts [35].

A good cooperation between human and software agents, in suitably distributing tasks between them, and in limiting situations of cognitive overload, can thus allow one to better process the essential data. The tasks distribution and scheduling have particularly been studied in air traffic control, e.g. in Vanderhaegen et al. [48] and in Crevits [16]. The assistance to the operators in Maritime Surveillance might thus allow to improve the quality of decisions made by the crew.

4.2 Agent-based simulations

We have conducted several simulations to mimic the individual and team behaviors of the Military Surveillance crew. We therefore have developed an agent-based framework with two kinds of agents: PPI, ISAR and FLIR operators who analyse data provided by sensors (radars) to propose classifications, and a TACCO operator who monitors the others' results to wait for their consensus, or stop them after a given time if there is no agreement. In our framework, the simulated TACCO does not have the responsibility to build the consensus, because we precisely want to simulate the effects of cooperation between the operators.

We thus developed the framework under the following constraints:

- decision agent that mimic the human operators have to be realistic, and have thus been built following the MBH meta-model. However, in the absence of experts during these experiments, the decision rules for each operator have been extracted from decision trees built from, and validated by, real experts of the domain during a preceding project [46];

- communication between the agents have to be controlled through the framework, to simulate different levels of cooperation, and observe different kinds of influences between teammates (cf. Section 3.4);

- to allow agents to reconsider a decision, when incompatibilities appear inside the team, a conflict detection have been implemented inside the operator agents. When one gets a classification, it comes into a wait-and-survey state to observe others' decision outcomes, and restarts its own process when necessary;

- the TACCO agent has thus only one major role: to stop the operators processes when conflicts can not be resolved (infinite loops detection).

As we mentioned it in Section 3.4, influences can be translated into modification of the preferences of the decision makers about their decision rules (this will modify the way these are activated) and the criteria they will use to build their mental representations of the situation.

The main ideas of the simulations were therefore to test the effects of different influence networks, together with the exploration of the MBH and partial activation algorithms' parameters space (activation thresholds, weights of influence between decision makers, etc.), in presence or not of different information exchanges. Two main results are presented.

4.2.1 Polarization effect

Two simulations have been used to correctly model this effect: the first one where no cooperation was allowed, by preventing all sort of communication between the operator agents, and the second one with all kind of communication allowed. Both simulations were launched upon the same perfect data describing a hostile patrol boat (i.e. without any perturbation from the radar equipment), and same initialization of agents' preferences.

The Figure 7 is a representation of the simulation of the process, with and without cooperation, where:

- PPI, FLIR and ISAR are operator agents working on different parts of the data describing the track;

- MHC1, FFG5 and PBF1 are possible alternatives that correspond respectively to a friendly mine warfare boat, a neutral frigate and a hostile patrol boat;

- numbered dots represent reception of messages, dashed arrows represent waiting time of agents after a decision outcome has been emitted, and plain arrows represent an agent currently working on data.

It can be seen there is no agreement when there is no cooperation: each agent manages to identify the track but there is no reconsideration because, without information about the decision outcomes of its teammates, none of them knows that there exist some conflicts. On the contrary, the cooperation enables agents to detect that their decision outcomes are conflicting with decision outcomes of the other agents (e.g. point (3) on Figure 7 where FLIR begins to reconsider its decision). By taking

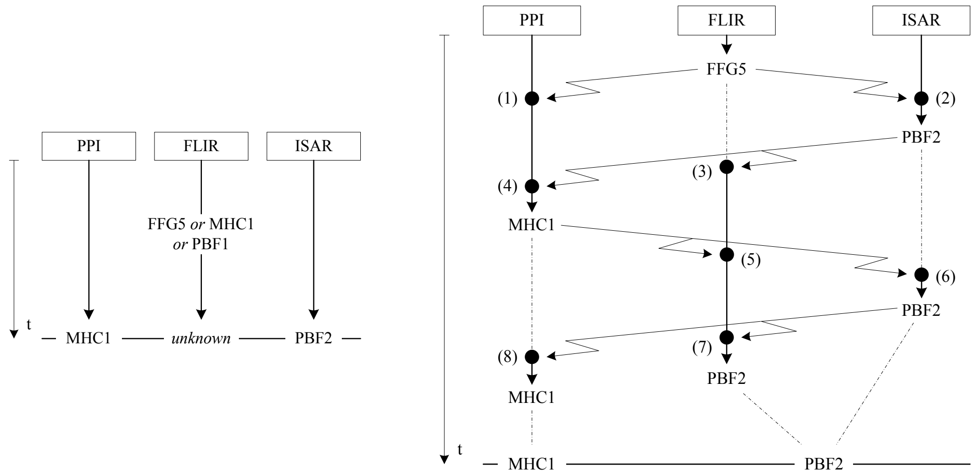


Figure 7: Simulation without (left) and with (right) cooperation: *polarization effect*.

this into account, agents modify their preferences upon alternatives and criteria they manage, and thus modify their decisions.

At the end of the allowed time, the FLIR agent that was initially incapable of choosing between its three alternatives (FFG5, MHC1 and PBF1 as can be seen of the left side of Figure 7) has been *influenced* by its teammate ISAR toward the correct PBF2 identification. The simulated team has thus been able to make decision thanks to the cooperation.

4.2.2 Towards an "extreme consensus"

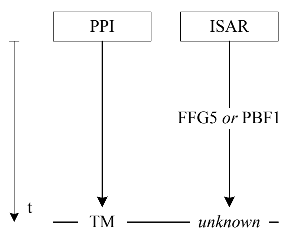
An extreme consensus is a case of polarization effect that leads to an extreme decision, in terms of risk [34]. An extreme decision is defined as a group decision that enforces and even radicalizes one of the points of view that has been proposed by one of the team members, instead of reaching an average position that is currently observed in group minds phenomena. Extreme decisions are often associated with risk taking because of their intrinsic radical nature and because of the psychological mechanisms that are supposed to underlie the processes and that do not seem to relate to any rational risk assessment.

In this example again, two simulations have been used. But here, the track data has been obtained by blurring the data of a hostile patrol boat, to see the behavior of our team when conditions of perception are bad.

Figure 8 is a representation of the simulation of the process where:

- PPI and ISAR are two operators agents working on different data representing the same track;

- TM and FFG are possible alternatives for PPI that correspond either to neutral cargos (TM1 to TM3) or to neutral frigates (FFG1 to FFG5);
- FFG5 and PBF1 are possible alternatives for ISAR that correspond respectively to a neutral frigate or to an hostile patrol boat;
- numbered dots represent reception of messages, dashed arrows represent waiting time of agents after a decision outcome has been emitted, and plain arrows represent an agent currently working on data.



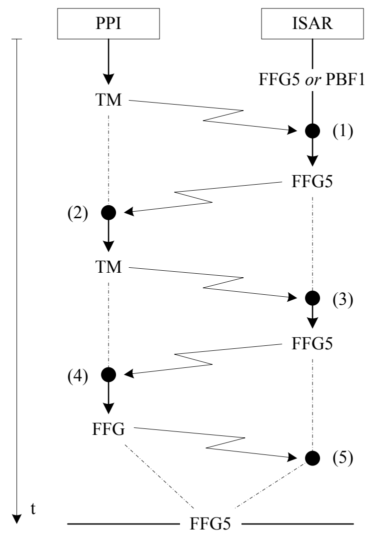


Figure 8: Simulation without (left) and with (right) cooperation: *extreme consensus*.

What can be seen is the mutual influences towards the FFG5 identification, which is far from the real nature of the boat. Firstly, after detecting a conflict in point (1) of Figure 8, initial hesitation of ISAR between FFG5 and PBF1 disappears in favor of FFG5 which is compatible with TM in terms of membership (both are neutral). Second, this modification of ISAR's decision outcome leads PPI to reconsider its outcome (points (2) and (4)) and to the final agreement on the nature of the track (frigate). Therefore, our two agents decide that the track is the neutral frigate number 5, whereas the initial data were closer to an hostile patrol boat.

4.2.3 Simulations outcomes

These two examples show up that it is possible to model many social effects, and to simulate associated group dynamics. Following this modeling, we can either anticipate conflicting situations, or incomplete treatment of data. Now we will be able to propose a number of functions that a support system should provide to prevent undesirable group behaviors and to enhance efficient ones. The situation described in Section 4.2.1 may be presented as an efficient behavior since the setting of a better communication among decision makers allows one of them to make up his mind and participate in the following steps of the identification. On the other hand, the case presented in Section 4.2.2 shows a example of bad behaviors where the mutual influences of individual decision processes lead to the non detection of an hostile target (being classified as neural instead). In both cases, the understanding of individual decision processes that contribute to the group decision making can be used to modify the way the consensus is made (e.g., enhance or inhibit the communication between decision makers, or make explicit the mutual influences and potential biases).

5 Decision makers support systems

5.1 Supporting decision makers instead of decisions

We saw in the previous sections that models of decision makers allowed to understand and to forecast decision biases or trends as soon as those models were properly learnt from sets of observations of decision outcomes resulting from stable dominance structures. We suppose moreover that the condition of stability is – by definition – achieved in the case of expert decision makers who individually or as a team rely on their own robust dominance structures to analyze the situation and to make decisions.

Following this statement, we propose to follow a new approach when providing decision aid for expert decision makers :

- instead of computing (supposed to be) optimal decision outcomes from the situation, we can focus on extracting, understanding and making explicit the existing decision rules of an expert decision maker from his history of decisions. We say in this case that we are assisting the decision maker and not the decision itself, in a human-centered approach [27, 14, 6]. We thus propose the concept of Decision Maker Support System (DMSS) instead of the classical Decision Support System (DSS);

- in the same way, when dealing with distributed and collective decision among a team of expert decision makers, we propose to extract, understand and make explicit the combinations of individual decision makers and their dynamics instead of computing a (supposed to be) optimal decision consensus that could happen to be completely out of phase for operational decision makers. This leads us to the concept of Multiple Decision Makers Support System (MDMSS) instead of the classical Distributed Decision Support System (DDSS).

In the following sections, we present some of the required functions for a DMSS or a MDMSS.

5.2 Requirements for DMSS and MDMSS

5.2.1 At individual level

As we propose to rely on existing decision human expertise – that has been identified and at least socially accepted, as explained previously – we have to change our mind about the role of an assisting system. The assisting system is no more considered as providing the decision maker with solutions that refer to some absolute reference or optimum, but on the contrary as a kind of *structuring mirror* that will use the analysis of decision maker's actions and strategies to extract and formalize a synthesis.

What can be the operational interest of this approach, if the decision maker is an expert and if the data that are initially used for extracting the most pro-eminent strategies come from him? There are at least two answers:

- first, the expert decision maker may not be able to express his own expert rules (i.e. "the expert is not expert of his expertise" [5]). Proposing to "mirror" these decision rules allow one to reach a better level of meta-cognition for the expert decision maker that may be usually drowned into daily action;
- second, this explicit expression of decision rules may be used as reminders and controls for the expert himself (an expert may be cognitively overloaded, for instance), or even as guidelines for novices.

These two kinds of practical outcomes were tested successfully in different contexts, especially in the domain of industrial process control. Here "successfully" means first that most of the extracted rules provided by the MBH model were confirmed and validated by the expert themselves. Second, the systems that were designed allowed to initialize a decision strategies management and capitalization within the companies, as a direct effect of the "structuring mirror" mentioned previously [24], and led to meaningful gains in productivity for the related processes.

In concrete terms, these former experiments showed it was possible, either from an interactive stimulation of the expert so as to cover rapidly the decision space (i.e. to generate a minimal set of rules that covers all possible alternatives, while soliciting as less as possible the expert with the use of the monotonicity principle presented in Section 3.3.2 [29]) or from a statistical non intrusive analysis of decision makers behaviors to extract most of the rules of an expert decision maker [24]. Once a set of decision rules has been provided, how can we then know the decision rule matching the situation when trying to provide the decision maker with on-line assistance? Two answers at least are possible:

- the system may rely on the past experience, and display the decision rules learnt from the user and that match the current situation. There can be an interaction with the user in order to validate one of them and therefore explicitly select the rule to be activated. This solution is clearly intrusive as the decision maker has to select himself the adequate decision rule among possible candidates displayed by the system;

- a second solution – non intrusive – consists in observing the user's interaction with the system and in deducing the current decision rule from the elements that are manipulated. As an example, one may think about analyzing the request addressed by the user to a database as composed from relevant aspects involved in decision rules.

5.2.2 At collective level

The extension of DMSS to MDMSS may be seen under the point of view of meta-cognition: as for DMSS the support system is used to re-send towards the decision maker a synthetic representation of his decision rules, the MDMSS will mostly aim at setting the same kind of communication and exchange about models of decision. The main principle of the DMSS is to mirror the expert decision maker rules, while selecting possible candidates among them when facing a decision situation. This way, the decision maker can rely on his own personal decision history and make a choice that is reinforced by the previous cases that were supposed to be similar. When consulting his own past decision cases (that describe the main contexts of application of the selected decision rules as well as possible contexts leading to decision conflicts), he may also avoid errors. This is what we call meta-cognition at the DMSS level. In the case of MDMSS, the feedback and meta-cognition must be set between teammates and not only between a decision maker and his machine, and reflect the potential group effects of the application of respective decision rules at individual level. Referring to Schmidt's typology of situations of cooperation [41], we could say that we propose the MDMSS to enhance/enrich/facilitate a confrontative mode of cooperation instead of classical augmentative or integrative one[11].

The functions introduced in MDMSS extend those of individual DMSS in order to take into account social psychology phenomena as described previously. These functions rely on the hypotheses that decision rules have been extracted from individual behavioral regularities. They are the following:

Detect group behavior: from the analysis of communication or information retrievals that are done, the system may detect some tendencies of decision makers to reduce the representation space or to align their strategies when being polarized. While doing this, the system will reduce the risk of cognitive overload, by selecting proper information;

Enhance group communication: when detecting unexplored synergies or potential conflicts, the system may advice one or several decision makers in proposing some extra dimensions to explore;

[11] It is recalled that *augmentative* cooperation represents the sharing of identical tasks or data among actors that have common characteristics, *integrative* cooperation represents the aggregation of different competencies into a unique one, and that *confrontative* cooperation means expert have the capacity and their own competencies for drawing conclusions, but that the confrontation of individual differences will finally allow one to reach a better level of performance.

Communicate/Explain/Capitalize with the group: the system may allow each decision maker to visualize and consequently better understand the decision rules of other decision makers in the team (meta-cognition). Especially a MDMSS should allow one to store and retrieve former decision situations that could indicate to a decision maker his past decisions and the related co-decisions of the rest of the team. Strong tendency to imitate or to chose willingly conflicting decision outcomes should be clearly identified and made explicit.

6 Functional description of MDMSS

The design of DMSS and MDMSS should therefore take the previously given requirement into account. This might be achieved through relying on four main kinds of functions, firstly proposed by Coppin et al. [15], and which will be more detailed hereafter:

Learning of decision making models: the integration of individual cognitive models in the system implies a learning step, where individual expressions of expert decisions and strategies will be extracted as decision rules;

Elicitation of information: the system will have to structure and present the decision rules to the expert(s). In the case of MDMSS, it does not only target the decision maker himself, but the rest of the team as well, and the elicitation may include team effects/levels of decision (mirroring usual synergies/conflicts between different decision makers for instance);

Adaptation through decision makers behaviors: as for any learning process from a limited amount of data, the results of the first phase must be considered as a biased approximation of real decision strategies. Moreover, the expert(s) is(are) supposed to evolve along time, depending on the moving context itself, as well as on their own changes. Consequently, the decision strategies and related decision rules have to be adapted and updated along time;

Exploration of the decision space: the support systems must allow the decision makers to explore the decision space that has been structured from their own decisions[12], either for their own need of comprehension of their strategies, or for the need of justification inside the team. This exploration may be done "on-line", during the operational phases of decision making, or "off-line", when the decision makers may have less constraints in analyzing their respective decision rules and the dynamics of the related group decision (e.g. during a debriefing phase).

These four phases have been applied and validated in the case of individual decision maker [25, 26], and have lead to the development of operational prototypes [24].

[12] With structuring the decision space from the decision makers strategies, we simply mean that the main references in this space will be given and localized in regard with these personal rules

They still need to be extended to the collective case, as we expect our industrial partner to design a prototype of the Maritime Surveillance framework we presented in Section 4.1.

6.1 Learning of decision making models

At the individual level, the learning phase concerns the elicitation of the individual decision rules which remains, notably in dynamic or noisy environments as we mentioned above, a difficult problem. Two approaches, at least, are possible.

The first one consist in imposing to the machine representation a format guided by considerations of cognitive realism, but also by the capacities of this format to be adapted to consensus calculation (or any reasoning trying to aggregate the different individual decisions into one unique "collective" decision). One classic methodology consists in collecting decision expertise from the expert decision makers, and in the translation of this information into the desired format, in a fixed and definitive manner. We applied this approach in the Maritime Surveillance framework context [14, 46], with an imposed format of decision trees for each individual decision process. The computed consensus proposals from these representations allowed to significantly improve the number of correctly identified tracks in a given time, and to globally decrease the time needed to the identification of the tactic situation. However, the output provided by decision trees is not fully compatible with the limited capacity of experts and our cognitive modeling approach.

The second one relies on the non-intrusive observation of the exchanges of information on the situation under analysis and individual decision outcomes, and on the adaptation (eventually continuous, cf. Section 6.3) of a generic model according to information actually observed. The format of the rules refers here to associative patterns (i.e. production rules) that are explainable for experts decision makers as they often proceed by rule association with the current situation. This direction is the one we promote, thanks to our cognitive modeling of expert strategies through the MBH meta-model devoted to the elicitation of decision rules. This approach then allows to avoid the classic bias observed during expertise verbalisations (once again, "the expert is not expert of his expertise" [5]). This solution presents the advantage to propose an adaptable model (implementation of learning techniques), along with the implementation of a more advanced man-machine dialogue that is devoted to the adapting of the learning model [26, 25].

The support system might thus integrate learning functions allowing to converge towards a stable description of the respective decision models of decision makers among the team and to the computation of a "satisfying" sets of decision rules. The definition of a "satisfying" model will be either directly bound to the predictive power of the model (comparisons of the predicted decisions with those actually made by the decision maker), or bound to the explicit acceptation of the model by the decision maker, if the system integrates adequate means of visualisation/edition (see Section 6.2 and Section 6.4 for the solutions we propose).

More precisely, given the MBH exposed in Section 3.3.2 as the individual decision model, for *each* decision maker the system has to learn the following:

- the set of criteria the decision maker's mental representations are about to be built on (by restriction of his specialized tools, or of his role and competencies), along with information on shared parts between criteria of his teammates (see Section 3.2);
- the set of decision rules defined upon the preceding set of aspects.

At a collective level, as we proposed to model influences between decision makers through networks, the learning capability of the system should allow one to either observe regularities in exchanges between decision makers, or to detect preferences in communication links, to learn specific characteristics through a sort of Hebb's rule, as proposed in Section 3.4. One may think, for example, to the case of our trust network (given on Figure 4), where the system should learn that both $DM3$ and $DM4$ are likely to reject the decision or information provided by the other one.

6.2 Elicitation of information

6.2.1 Guided by individual interests

Since the decision makers are using the system to seize data, make queries to databases, we are able to monitor what information each one is using at a given time. Knowing the set of decision rules each expert decision maker is likely to use, our agent-based simulations (cf. Section 4.2) illustrated that we are able to formulate hypotheses about what decision rule(s) he is about to activate and, therefore, about relevant information needed by, missing for or missed by the decision maker[13], and about the most probable decision he is about to make.

This elicitation could be achieved locally by the support system, for a given decision maker, or by crossing the hypotheses (either decision outcomes or criteria of interest related to the object under analysis) between teammates, and should allow notifications to the decision maker, during his search for information:

- to propose some relevant information linked to the presumedly activated decision rule(s): this information might be either unconsidered aspects, or information seized by other teammates;
- to alert the decision maker either when one of his interpretations conflicts with other decision makers' ones, or when the decision outcome he actually chose is different from, either the system's presumed one, or other decision makers' ones.

[13]Missing information is the information a decision maker would like to use but that is not available, while missed information is available but not considered by the decision maker.

6.2.2 Guided by collective behaviors

The system should also be able to analyse and act at the group behavior level (cf. Section 3.4.2). In this case, it will not try to improve each individual decision strategy, but it will propose to tune each observed strategy in a group logic in order to facilitate cooperation:

- in identifying polarization phenomena of the group that may lead each individual decision maker to adopt imitating behaviors – reinforced by facilitated access to other decision makers models – and, therefore, to collectively not correctly explore the solutions space;
- in maintaining or smoothing the effect of active minorities on the period of collective decision making: in response to the above phenomenon, it might be necessary to encourage part of the decision makers to analyse a neglected part of the decision space. On the other hand, the maintenance of an active minority may be globally judged as negative for the collective decision;
- by the synthesis and the presentation of indicators showing the current state of the consensus between individual decision makers.

6.3 Adaptation through decision makers behaviors

As stated above, the system might continually update the decision strategies represented as decision rules. This function uses the same non-intrusive observation of decision makers exchanges of information than the one exposed for the learning phase, along with the observation of behaviors with regards to the enhanced group communication provided by the system.

Such adaptation process may lead to conflicts between the existing rules and the newly observed ones [24], therefore the core of the updating function is a conflict resolution function. But once again, the monotonicity principle (cf. Section 3.3.2) ensure that the automatic update is possible, by the mean of two subprocesses:

- update of an existing rule with new information;
- removal of an obsolete rule.

For a detailed and technical review of these principles, see Le Saux [24].

At the collective level, again, the update algorithm should adapt the networks that have been constituted, either because new regularities have been observed, or because relations between agents have changed (e.g. with the confidence which can evolve between teammates).

6.4 Exploration of the decision space

One main characteristic of an expert is his incapacity to express his decision strategies and rules [42, 5]. But situations where he has to justify himself require detailed information about how and why he made a particular decision. Therefore the ability to explore his own decision space, as a feedback of past experiences, along with the ability to draw into it a passed decision path will allow the expert to be comprehensible for others. Moreover, one might be able to explore other teammates decision space to increase confidence into others' decisions.

Thus, the system should maintain an history of each decision makers decisions, by tracing each decision associated to the decision rule that lead to it.

7 Conclusion

We have presented in this paper an innovative approach to decision makers support based on cognitive models. We validated this approach on individual cases and have here extended it to the collective case, especially for a team of cooperative decision makers.

Some simulations have allowed the study of the process dynamics, at both individual and collective levels, and the formulation of propositions about a new design methodology of decision support system.

The concepts of Decision Maker Support System and Multiple Decision Makers Support System we here propose now needs real experimentations, in naturalistic condition, using a system developed with our specifications. This would likely be achieved with technical-operational scenarios validated by domain experts, and in a framework allowing non-intrusive observations of the working decision makers, namely our integrated laboratory THALES-TELECOM Bretagne, ATOL – Aeronautics Technico Operational Laboratory.

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