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Human centered processes and decision support systems

J.P. Barthélemy [a,b,*], R. Bisdorff [c], G. Coppin [a]

[a] Ecole Nationale Supérieure des Télécommunications de Bretagne, Département IASC, BP 832, 29285 Brest Cedex, France
[b] Centre d'Analyse et de Mathématiques Sociales – Ecole des Hautes Etudes en Sciences Sociales, UMR CNRS 8557, Paris, France
[c] Centre Universitaire de Luxembourg, Département Gestion & Informatique, Luxembourg, Luxembourg

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Abstract

This paper emphasizes the role of human factors in Decision Support Systems and related assisting tools that can be used in the Operational Research field. It links both historical information and real life realizations concerning the human centered processes. The historical points mentioned in the paper give only partial emphasis, according to the feeling of the authors. The aim, here, is essentially to review some tools (e.g., utility theory, cognitive modeling, etc.) that are or might be used to tackle new problems in the context of anthropocentered systems, especially when considering the recent evolution of Information Systems towards distributed ones. Several real-life problems (mostly in an industrial setting) are reviewed. They all concern applications on which the authors have worked (or are working) together.

Keywords: Human centered processes; Applied decision making; Distributed decision; Decision processes

1. Introduction

The aim of this paper is two fold:

1. To emphasize that Operational Research, as a science and a panel of techniques to aid decision makers, is highly concerned with human factors.
2. To discuss alternatives to a strict computer science approach (expert systems, knowledge based system etc.) in a complex industrial setting, in order to put human beings not only inside, but also at the center of the loop of decision making.

The first point is supported by the – less and less recent – movement of so-called Cognitive Science. The attempt at a unified approach to study natural and artificial information processes, even if sounding like an utopia nowadays, has led to some happy marriages ("d'amour ou de raison"), for instance between psychology or linguistics and computer science. The offspring of such marriages are practical devices for computing issues of human decision processes and, but more seldom, for simulating them.

* Corresponding author.
E-mail addresses: jp.barthelemy@enst-bretagne.fr (J.P. Barthélemy), bisdorff@cu.lu (R. Bisdorff), gilles.coppin@enst-bretagne.fr (G. Coppin).

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A classical approach in Operational Research for tackling decision problems is based on a *rationality principle* (cf. Section 2.1.1). In terms of parameters, data and possible decision outcomes the problems are assumed to be exhaustively described, objective functions are assumed to link data and parameters to measurements of decision outcomes. Finally, optimal solutions of these functions are assumed to correspond to the "better" decision (for those who trust in it). For over thirty years, the quest, for the *Holy Grail* of optimality has been criticized and deserted by Bernard Roy and many others (Roy, 1985; Roy and Bouyssou, 1993; Vincke, 1989) in the framework of a multicriteria decision aid. They have proposed alternative approaches in which

- Decision outcomes are viewed as a compromise between a (generally small) number of possible ones.
- The human decision maker is fully solicited in the description of the problem (possible actions, criteria; evaluations of criteria,...).
- Interactions during the decision aid process between the decision maker, the operational researcher and the software tool make it possible to guarantee both an objective description of the problem and the respect of the expectation of the decision maker.

In that respect, Cognitive Science proposed alternative new paradigms to rationality (Section 2.1.1), like Simon's bounded rationality. Our feeling is that Operational Research, as a science to support decisions, is concerned by these new paradigms as well as by the old ones. As a consequence (which will appear through the various industrial applications presented in this paper) an alternative approach to "normative" decision making is a "descriptive", but efficient and operational one.

The second point is supported by the fact that these last ten (or may be more) years have seen a more and more pronounced fading away of expectation toward automatic systems in order to tackle real and often complex decision problems. We will not further develop this argument, since, as far as we know, it no longer appears as polemical. Just some remarks to support this:

- In the case where a restrictive computer science approach leads to unreliable systems, one can observe that men and women, faced with the same problems, can solve them in a stable and secure manner.
- Companies are more and more concerned with knowledge extraction from documents and expert interviews. Adapted human centered technologies will help to prepare future expert systems.
- If experts have expertise in their domains, it is risky to imagine that they are also the expert of their expertise.

That is to say that a study of experts' know-how in a professional setting can help to model and then to insert them into an automatic device. Thus a main framing aspect for our discussion comes from the fact that we consider real-sized expert decision problems as encountered in industry, defense, finance or business administration. One of the major criticisms, generally leveled at expert systems or decision support systems proposed in these professional contexts, concerns the underestimation of specifically human expertise for solving such complex and critical problems that might exist. Our main focus is mainly on classic production control problems where the complexity of the task outweighs by far any easy automation approach, and where human operators have instead developed their own "wild", i.e., intuitive practical solving strategies. It is clear that we mainly address these decision problems where a satisfactory decision practice historically preexists. Putting the human expert operator effectively in the loop of such a decision support system represents the major guarantee of mastering efficiently the inherent complexity of the problems (Bisdorff, 1999).

There is a second reason to support point two: decision making is more and more embodied in a human machine cooperation framework.

We have to distinguish between:

- One decision maker (that can be viewed as the representative of a group (i.e., as an epistemic subject) in a singular decision situation: the decision maker is not familiar with the decision task.
- An expert decision maker, who is familiar with the decision problems he/she has to face and al-

ready has strategies compiled in his/her long-term memory.

In the first case, the decision maker needs external help and multicriteria decision aid techniques apply. In the second, software tools can be used to learn the expert decision maker strategies in order to assist him/her (possibly continuously), help him/her to improve his/her performance and to capitalize his/her know-how.

Finally a third reason to support point 2 is the new emerging concept of distributed decision. Decision making is no longer the task of one person, or one group (like decisions in organizations), but is shared by several agents (human agents and software agents) distributed (and sometimes mobile) along networks and being able to communicate only partially between each other and with their environment. In such hybrid, complex systems the more reasonable approach is surely to treat software as software and humans as humans.

This paper links both historical information and real life realizations concerning human centered processes. It is not the purpose of the authors to write a history of the human centered processes. The historical points mentioned in the paper just give partial emphasis, according to the feeling of the authors. The aim, here, is essentially to review some tools (e.g. utility theory, cognitive modeling, ...) that might be used to tackle new problems in the context of anthropocentered systems. Several real-life problems (mostly in an industrial setting) are reviewed. Three of them are more developed (Sections 2.2.1, 2.2.2 and 4.4.2). They all concern applications on which the authors have worked (or are working) together (two of them for Sections 2.2.1 and 4.4.2, three of them for Section 2.2.2).

The paper is organized along a gradient from simplicity to complexity in the description of the decision situations (to have a "simple" description of a situation does not mean that the induced problems are easy to solve, etc.). Section 2 discusses individual decision making, Section 3 group decision making and Section 4 distributed decision.

In Section 2 the notion of human centered process is introduced and discussed, first from a historical perspective (some tools inherited from behaviorism and cognitivism are reviewed), second from the – more or less recent – emergence of new industrial needs and finally from the viewpoint of practical solutions to these problems. Some practical applications using a particular cognitive modeling of the decision maker are reviewed in Section 2.2 and two of them are discussed in greater details. Section 3 is essentially intended to go "continuously" from individual decision to distributed decision. It does not by any means intend to be a comprehensive approach to group decision making. Three roots to group decision making are introduced, namely: social choice (and more generally consensus theories) game theory and social networks. Then (Section 3.2) to enlighten what could be the requirement from cognitive science, we focus on questions related to communications. Finally we briefly present some practical approaches. In Section 4.1, the notion of distributed decision is presented as well as its new requirements. In Section 4.2 we investigate the possibility of using tools and concepts inherited from both individual and group decision making. In view of the relatively negative answers we introduce in Section 4.3 a software-oriented approach as a practical solution (distributed agents). We discuss some realizations and one of them is developed further (Section 4.4.2).

A brief general discussion concludes the paper.

2. Processes involving one decision maker

The case of a unique decision maker covers:

- a single human being,
- a homogeneous group of several decision makers considered as an epistemic subject (such a context is not dedicated to group decision making, the multiplicity of the subject being necessary to smooth individual variations in the study of real decision processes).

As a consequence, we will be mainly concerned in this part with the psychology of decisions.

2.1. Human centred processes: Who? Why? How?

2.1.1. Who?

From general psychology and behavioral sciences …

We shall assume throughout this section that the decision maker involved in the process is an expert. One characteristic of expertise is the use of a fairly small quantity of information to achieve a decision (Shanteau, 1992).

From general psychology, we can follow the historical evolution of ideas and concepts that may guide our research. Starting with Hume's inquiry concerning human understanding (Hume, 1739), we see that "there appears to be only three principles of connection among ideas, namely, Resemblance, Contiguity in time and place, and Cause Effects". This associationism, continued by Hartley (Hartley, 1749), first points to the necessarily *procedural constitution* of human expertise. Indeed, Hartley distinguished two forms of association between ideas: successive and simultaneous. The first are built up when trains of ideas regularly follow one another and get bound together, whereas the second are built up between ideas that regularly come together at the same time. What remains to be considered is the effective observation of any decision expertise.

Here Watson's behaviorism comes to our rescue (Watson, 1913), in the sense that he integrates Occam's razor principle ("do not multiply entities without necessity") with Hume's associationism, but instead of considering expertise as mental capacities, he focuses on effectively observable behavior. Decision expertise is not primarily a mental capacity but rather an expert behavior.

Such an expert behavior is only conceivable in the context of a pragmatic approach towards decision problems. Here James with his attempt to construct a psychological science that will teach a person how to act is emerging (James, 1892). The meaning of ideas is only found in terms of their possible consequences and in our case here, in terms of observable satisfactory decision behavior.

But it is not a new kind of operant conditioning in the sense of Skinner (Skinner, 1938) that we are interested in: instead we rely on modern cognitive psychology where cognition is mainly studied from the information handling standpoint. Where classical behaviorism completely ignores the mind, we consider states of consciousness as one essential component of human centered processes that we are going to present later on. Indeed, the behaviorist concept of direct simple linkage between environment and behavior appears unsatisfactory. Human operators are active and intervening participants in their behavior and human memory is not a simple store of past situations, but is organized so as to efficiently assist complex adaptive behavior in real life.

Another root of behaviorism may be found among the utilitarian theorists (Bentham, Mill, … but also J. Bernouilli (Bernouilli, 1738) [1]). Utilitarianism is based upon the requirement that a human decision maker tends to choose his/her most "attractive" alternative. This approach involves the so-called "rationality principle" that can be stated in four points:

- the Decision Maker is able to exhaustively generate all the *scenarii* relative to decision situations,
- he/she is able to evaluate the attractiveness of each of them,
- he/she is able to aggregate these local evaluations into a global one,
- finally, he/she chooses alternatives with the most favorable global evaluation.

These four points are assumed, for instance, to support the classical utility theory, as axiomatised by Von Neumann & Morgenstern (Von Neumann and Morgenstern, 1944). Point 1 accounts not only for the exhaustive description of possible actions but also of the probability of occurrence of issues relative to actions. Point 2 involves the notion of utility functions attached to issues. Point 3 mixes

[1] "… le savoir conjecturer ou stochastique se définit pour nous comme savoir mesurer, le plus exactement possible, les degrés de probabilité, afin que, dans nos décisions et nos actions, nous puissions toujours choisir ou accepter ce qui nous aura paru le meilleur, plus satisfaisant, plus sûr, plus prudent: seul objet à quoi s'applique toute la sagesse du philosophe, toute la prévoyance du politique" (Bernouilli, 1738, French translation by G.Th. Guilbaud, 1952).

probabilities and utilities to compute the expected utility attached to each action. According to point 4, the decision maker will choose the action(s) maximizing the expected utility(ies).

These practices lead to various mathematical models within the behavioral sciences like utility theory, prospect theory (Tversky and Kahneman, 1981, 1992), stochastic choice and random utility models (Luce, 1969; Fishburn, 1992), and more recently media theory (Falmagne, 1996) among many others.

... to cognitive psychology

The rationality principle has been strongly attacked by Simon (Simon, 1955; Simon, 1983). [2] The principle of *bounded rationality* assumes that the decision maker is able to optimize but only within the limits of his/her representation of the decision problem. Such a requirement is fully compatible with many results in the psychology of memory: an expert uses strategies compiled in the long-term memory and solves a decision problem with the help of his/her short-term working memory.

Inheritances of bounded rationality may be listed as follows:

- decision making involves heuristics like the *satisfaction principle* (Simon, 1969), *representativeness* and *availability* (see the book edited by Kahneman et al. (Kahneman et al., 1982)). It also involves *framing effects* (Tversky and Kahneman, 1981),
- decision making appears to be close to problem solving (this point has been emphasized by Huber (1982, 1986), who has analyzed decision processes in terms of elementary operators and has studied their complexity),
- decision making involves global evaluations of alternatives that could be supported by the short-term working memory and that should be compatible with various kinds of attractiveness scales (Svenson, 1979, 1983),
- mainly, decision making can be viewed as the achievement of a more or less complex information process and anchored in the search for a *dominance structure* (Montgomery, 1983): the Decision Maker updates his/her representation of the problem with the goal of finding a case where one alternative dominates all the others (see Barthélemy and Saunier (1996) for a mathematical approach based on dynamical systems).

The Moving Basis Heuristics (Barthélemy and Mullet, 1986, 1992) instantiates these aspects under three principles:

1. Parsimony: the decision maker uses a small amount of information.
2. Reliability: the processed information is relevant enough to justify – personally or socially – decision outcomes.
3. Decidability: the processed information may change from one decision to another.

2.1.2. Why?

From expert systems to expertise managing systems

Beyond the historical features mentioned here above, practical motivations underlie the authors approach. The reasons for this is to be found in the fact that, in industrial production, human operators are faced with complex highly repetitive decision problems.

Industrial needs

Many successful and useful industrial expert systems have been realized (cf. Pomerol (1990) for instance). However a feeling of doubt about their successfulness has emerged these last 15 years. This is due to the fact that:

- The approaches are essentially local (problems with genericity and transportability).
- The user's ability is not taken positively into account.

[2] "Rationality does not determine behavior. Within the area of rationality, behavior is perfectly flexible and adaptable to abilities, goals, and knowledge. Instead, behavior is determined by the irrational and non rational elements that bound the area of rationality [...]. Administrative theory must be concerned with the limits of rationality, and the manner in which organizations affects these limits for the person making a decision" (Simon, 1983, p. 23).

Moreover, the behavior of an expert system is very far removed from a human expert's. This is not a problem *a priori*: of course a "plane does not mimic a bird" but if we have in mind to aid the expert decision maker to understand and capitalize his/her strategies, we need to understand the way he/she processes information to achieve a decision (for a discussion of the European view of this approach applied to industrial field see Wobbe (1991)).

Thus, despite their impressive performance, computerized systems often poorly adapt to changes in the environment and many computer-oriented operational models strongly compel a human expert to work like a computer. Very often, for instance, communication is implemented through dialects close to programming languages (rule-based design) compelling a human operator to simplify and abusively generalize his/her solving strategies.

Often also, expert systems do not take into account evident semantic aspects of information. As a consequence, computerized systems show a lack of reliability and adaptability and induce high costs, skills and time, for maintaining them. Such difficulties for practical use may show flexibility, hence adaptability and capacities to generalize. As an example one may consider the human processes of categorization. They do not correspond to some taxonomic knowledge; they are flexible, adaptable by local processes and use strategies involving scales of typicality, prototypes and analogy processes (Rosch, 1973, 1978). They are able to recognize atypicality and to specialize heuristics. Indeed, we observe that human categorization processes involve dynamics whose states are more topological (*Gestalt* oriented) than logical (language oriented).

In this sense we observe that tackling real-size planning and decision problems coming from industry and administration is a relevant field for applications of human centered process designs. The human operator may be seen as a user and a model, where the user accounts for ergonomic constraints and the model implies the user's cognitive abilities. Such an approach is driven by the search for stability in the sense of producing systems that show reliability, adaptability to environmental changes as well as transportability.

2.1.3. How?

Current cognitive science provides us with the insight that a cognitive system, in general, is an association of a physical working device, that is environment sensitive through perception and action, with a mind generating mental activities designed as operations, representations, categorizations and/or programs leading to efficient problem solving strategies.

Mental activities act on the environment, which itself acts again on the system by way of perceptions produced by representations. This synergy with an environment leads a cognitive system to develop autonomous abilities to auto-organization (structuring of representations, categorizing through factorization of the environment).

Designing and implementing human centered systems for planning, control, decision and reasoning therefore require studying the operational domains of a cognitive system in three dimensions:

- An environmental dimension, where first, actions performed by a cognitive system may be observed by way of changes in the environment and secondly, communication is an observable mode of exchange between different cognitive systems.
- An internal dimension where mental activities i.e., memorization and information processing generate changes in the internal states of the system. These activities are however influenced by partial factorizations through the environment (planning, deciding and reasoning change the course of the world) that appear essentially as stable cognitive constructs.
- An autonomous dimension where learning and knowledge acquisition enhance mental activities by leading to the notions of self- reflexivity and consciousness.

2.2. Practical applications

A cognitive approach in decision making within an industrial context has been developed in some depth (see for instance Laurent et al., 1994; Lenca et al., 1999), and the present special issue of EJOR). Moving Basis Heuristics and related processes have been applied in various contexts. They can be listed as follows:

Financial setting

- Banking (Lenca, 1994, 1995,b, 1996; Kant, 1996b): the goal of the study was to design saving products dedicated to a customer according to his/her own preferences relative to product characteristics.

Industrial setting

- Quality Control (Guillet, 1995; Barthélemy et al., 1995): the goal of the study was the updating of experimental designs according to the operators knowledge and strategies.
- Planning and scheduling (Laurent et al., 1994; Pichon et al., 1995; Pichon, 1996): this point will be developed below (see Section 2.2.1).
- Process Control (Le Saux et al., 1998; Le Saux et al., 1999; Lenca et al., 1999): this point will be also developed hereafter (see Section 2.2.2).

Agricultural setting

- The goal of the study was to compare various kinds of cows according to their ability to produce milk (Hubert, 1996).

Educational setting

- Counseling for educational and professional guidance (Barthélemy and Mullet, 1987, 1989; Mullet et al., 1996).

These studies are supported by several computer implementations of Moving Basis Heuristics. For instance, *Asclepius* (Guillet, 1995), and *Apache* (Lenca, 1997) are based upon optimization in posets and *CategArt* (Kant, 1995, 1996) uses connectionist principles derived from the Art network (Carpenter and Grossberg, 1988). Implementations of many other cognitive decision strategies may be found in (Lapébie, 1995; Barthélemy and Lapébie, 1995). They are based on rule learning using meta-heuristics. Practices based on constraints programming will be developed further in Section 2.2.1.

2.2.1. Solving by resolving: A production scheduling problem

This application is concerned with the problem of solving planning problems in industrial production contexts with the help of constraint logic programming tools like the finite domain solver CHIP (Bisdorff and Gabriel, 1992; Bisdorff et al., 1992; Bisdorff and Laurent, 1993; Dincbas et al., 1988; Aggoun and Beldiceanu, 1991). The study of real-size planning problems from industrial prac-

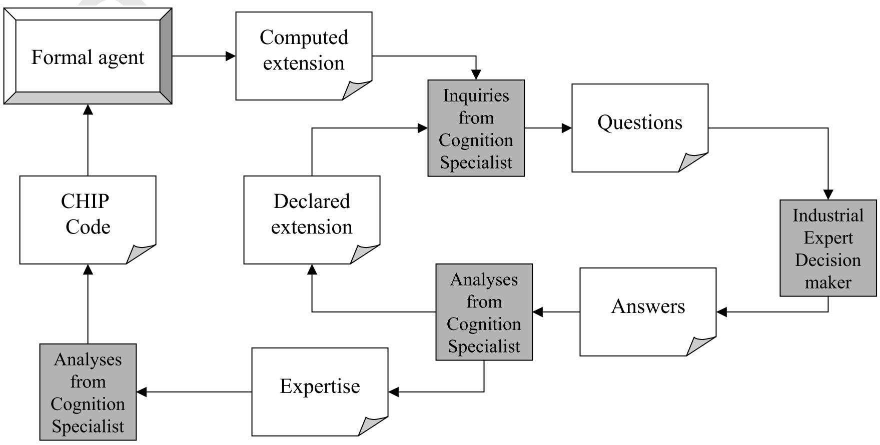

Fig. 1. Synthetic diagram of CLP cognitive-oriented decision support tool (Pichon, 1996).

tice shows that solving fairly tightly constrained planning or scheduling problems requires considerable particular industrial decision expertise in order either to introduce simplifying hypotheses limiting of pruning efficient the search space, or to start the search with a "reasonably" satisfactory initial solution.

The search for coherent sub-spaces of a decision space is inspired by moving Basis Heuristics, and leads to iterative pairs of intensions/extensions that are systematically submitted to the industrial expert decision maker and validated by him/her.

Introducing such decision expertise gives rise to a new concept of *cognitive decision support system* where a cognitive link is installed between the concrete application context and the formal description of the problem submitted to the solver. Practical implementation of such a cognitive decision aid laboratory is inspired by the work of Barthélemy and Mullet on psychological aspects of expert decision making (Barthélemy and Mullet, 1992, see Fig. 1).

The industrial experience concerns a monthly scheduling problem for wire- drawing production at the TrefilARBED Bettembourg plant part of ARBED Luxembourg steel industry. This plant produces steel-cord and horse-wire for the international tire company (Bisdorff et al., 1995).

2.2.2. Expertise acquisition

Process control methods are usually based upon either statistical or causal analysis, both tools being developed without taking into account any human operator expertise. In addition such methods prove to bed to the production process life. The promoters of this implementation (cf. Guillet and Coppin, 1994) expect human strategy to fit the process and to have interesting properties such as "noise acceptance", reliability, flexibility, genericity and intentional explanation. Therefore they propose mixing standard methods and cognitive techniques to reinforce and also to extract the strategies established by the expert operator. This mixed approach is based upon expertise acquisition methods (see Fig. 2).

Knowledge monitoring can be split up into three phases: the learning, maintenance, and re-

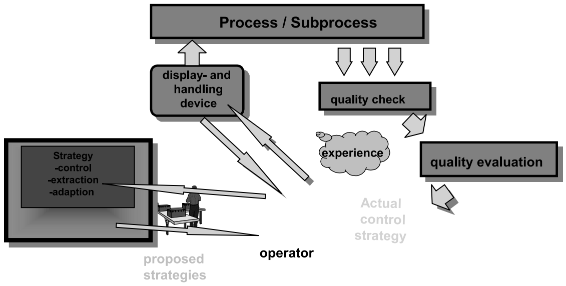

Fig. 2. Associating standard quality process control and expert strategies extraction.

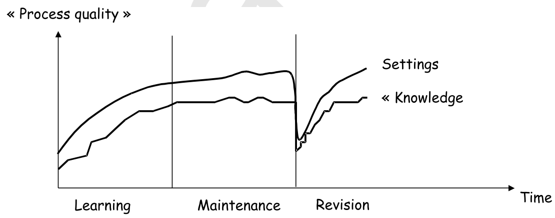

Fig. 3. Dynamics of expertise constitution and use.

considering phases. In each phase, conventional process control techniques may be associated with expert knowledge (see Fig. 3).

Knowledge acquisition is founded upon the principles involved in the Moving Basis Heuristics (Barthélemy and Mullet, 1992) discussed in Section 2.1.1. This model has mathematical implications and induces a non-trivial acquisition algorithm whose complexity is bounded (Pichon et al., 1994). Given a set of objects supporting expert knowledge, the extraction of expert classifying strategies is based on an interactive, incremental and dynamically computed questionnaire. Each question leads the expert to take a decision on an object; moreover the sequence of questions is not random like but is constructed in order to minimize the overall length of the questionnaire.

The practical study underlying this work is concerned with expert strategies acquisition on an industrial process at Thomson-CSF Detexis (now Thales Airborne Systems) in Brest. The purpose of acquisition is to improve conventional expert skill acquisition methods.

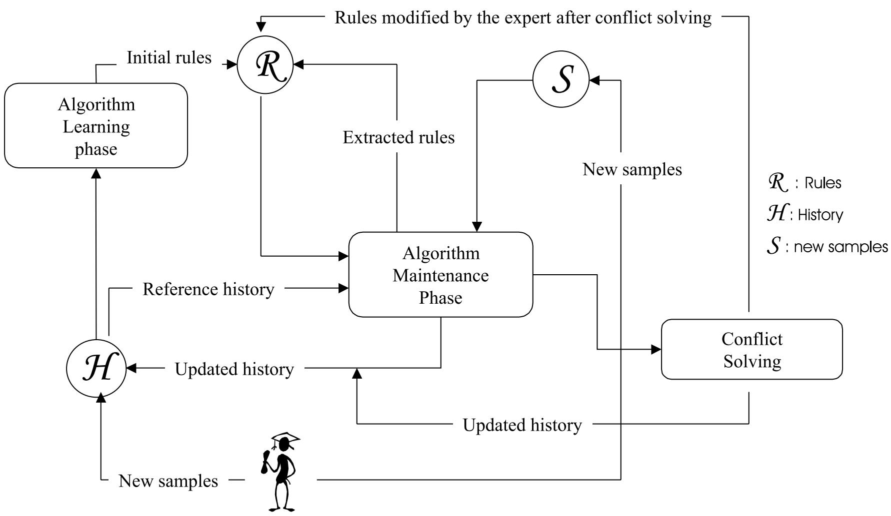

Fig. 4. General principles of COMAPS decision support tool.

These principles were applied to the design of an on-line non-intrusive expert decision maker assistance tool, that was based upon the extraction and "continuous" updating of system control strategies. The extraction and the updating of strategies were supported by the collection of the cases dealt with by the expert, and processed according to cognitive principles indicated by the Moving Basis Heuristics (limited and changing subset of attributes as a latent dominance structure for decision explanation and support) (see Fig. 4).

These works were handled in the frame of the COMAPS project[3] supported by the European Commission (for references see Section 2.2).

3. Processes involving a group of decision makers

Another main feature of human beings is their habit – will – and instinct to live, work and therefore decide together.

In fact, in many organizational or social settings, a decision does not appear as an outcome given by a "single" decision maker, but as a compromise between various divergent interests and points of views.

3.1. Group decision making theoretical settings

As associationism, utilitarianism and theories inherited from the behavioral sciences were considered as possible foundations for individual choice studies, we propose to anchor group decision making in a threefold theoretical setting: social choice, game theory and social networks.

Social choice

Social choice goes back – at least to – Condorcet & Borda voting theories (Condorcet, 1785; Borda, 1784). It was considerably renewed in the fifties by the so-called *Welfare Economics* and led to major results like Arrow's *impossibility theorem* (Arrow, 1951) and Gibbard and Satterhwhaite's *manipulability theorems* (Gibbard, 1973; Satterthwhaite, 1975).

More recently, a field called *consensus theory* has emerged. It proposes a synthetic view of social choice, preference aggregation, classification aggregation and the search for latent structures (Barthélemy and Janowitz, 1991).

[3] The COMAPS project was funded by the European Commission (Brite Euram III, BE96 3941) and involved 8 partners from Germany, Luxembourg, and France.

Games theory

On the other hand, games theory accounts for strategies of decision makers in concurrent markets. As is well known, it goes back to studies in economics in the late 19th century (e.g., Pareto and the Lausanne School (Pareto, 1909)). Popular achievements of games theory are the so-called equilibrium theorems (Pareto equilibrium, Nash equilibrium, etc.).

Games theory also appears as strongly related to utility theory (Von Neumann and Morgenstern, 1944), and social choice theory (Guilbaud, 1952).

Social networks

In the fifties, the influence of organizational networks on tasks was studied in depth within social network theory (Bavelas, 1951; Leavitt, 1951); for more recent references, see Degenne and Forsé (1994).

According to these promoters of centrality indices in graphs (see also Flament, 1963; Sabidussi, 1966), the organizational topology of the network was reduced to communication channels impacts on the tasks. Natural language processing and modern communication theories however propose an alternative approach, with the human being at the center of the communication/decision process.

3.2. Requirements from communication theory

Beyond these mathematical foundations, group decision making is greatly concerned with communicational exchanges between the various actors in the group. Studies in communication suppose three levels of structuration (see Fig. 5):

Level 0 (Digital step) is known as Shannon theory (Shannon, 1948). A source is linked to a receiver by a channel that transmits messages coded as *binary sequences*. The source has to code and the receiver has to decode. The semantic aspects in the transmitted information is ignored by the communication system. Its multiple modalities (images, texts, sounds, ...) are ignored as well. But the transmitted information cannot be assumed to be a non-structured one (not any 0/1 sequence is admissible as a message). The structuration of messages is a consequence of the need to decode without error and to guarantee inviolability during the transmission (even when the channel is a public one).

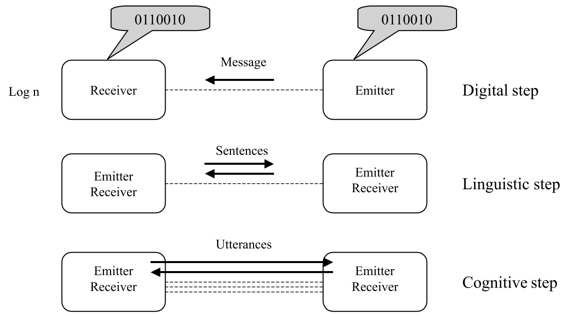

Fig. 5. Levels in communication theory.

Level 1 (Linguistic step) of communication may be referred to as a linguistic step (Chomsky, 1957). The transmitted message is a sequence of *sentences* from a natural language. Such a language-oriented approach enforces a syntactic structure on messages and makes the linguistic step fairly close to level 0. Semantics appears as being more or less governed by syntax. Despite the great success in designing, analyzing and classifying computer languages, several failures made this approach uncertain in domains like language understanding, processing and translating.

Level 2 (Cognitive step) is properly the cognitive step (see Shaumyan, 1987; Desclès, 1990), where the notion of *utterance* replaces the notion of sentences. The cognitive step tries to account for all dimensions:

- enunciative operations (linguistics),
- cognitive representations (psychology),
- goals of communication (intention & pragmatics),
- effectiveness of understanding and production (computer science and logic),
- adaptability to users,
- ergonomics of communication systems (human–machine communication and cooperation).

As suggested in Fig. 1, several modalities (dotted lines) may be involved in the communication process at the same time: images, sounds, smell, text ...

3.3. Cooperative decision making

Beyond communication processes and/or protocols, the main features of group decision making is cooperative decision making within an organization. Since March & Simon (March and Simon, 1974), this subject has been studied at length by others like Sfez (1981), Dodier (1995) etc.

However, tools coming from CSCW (Computer Supported Collaborative Work) like groupware, electronic document processing (GED), workflow and so on, have often led to operational drawbacks. These are essentially due to the fact that technical devices are far removed from business and industrial practises. Tools can be so far ill-adapted that they become rapidly inefficient. Here a reflection on the "How" is lacking. An understanding of the evolutions brought about by the introduction of decision-support tools within an organization is also lacking (Bigaret, 1999).

So, before being distributed, a decision must be cooperative. Three main non exclusive approaches are conventionally followed for this central cooperation paradigm:

- *Man–machine cooperation*: this topic concerns what is usually proposed in man–machine interfaces design and in interactive decision aid systems. Here, each man–machine association is considered as a whole and indivisible entity within the cooperation network. There must be at least one communication protocol between the two components of the cooperative entity (even if limited to information input and display), as well as a model of the assistance expected. For instance, the Personal digital assistant (PDA) model proposes automatic data retrieval depending on the situation detected and the context.
- *Machine–machine cooperation*: this means interaction between independent software "agents". Amongst these may be found specialized agents for storage, indexing, information retrieval, problem decomposition through goals and sub-goal definition, scheduling and solving related sub-problems. When independent software agents work on solving a problem, a communication and synchronization protocol must be set, and the solving process convergence must be guaranteed.
- *Man–man cooperation*: this kind of cooperation may be direct or indirect insofar it uses a machine as an intermediate communication medium. In the indirect case, communication may be completely formalized through a protocol supported by the medium machine, and formal data and information are directly available for computing. Communication may also be "informal" (natural language exchanges, for instance). In this case, some information extraction techniques are necessary, but it must be kept in mind that not all information can be digitized and that there remains a "non-translatable" part (Lyotard, 1981).

4. Distributed decision

Decision aid and decision making have greatly changed with the emergence of the ICT (Information and Communication Technology). Decision makers are now far less statically located, but, on the contrary, play their role in a distributed way. This fundamental methodological change has led to the setting of new requirements that are proposed below.

For the sake of simplicity, we focus here on symbolic systems only, and will not mention further any "action systems" that are intrinsically concerned by Distributed Decision (Coppin, 1999).

4.1. New requirements for distributed decisions

4.1.1. A distributed decision is always handled from incomplete data

Distributed decision means that several entities – human, machines – cooperate in order to reach an acceptable decision, and that these entities are distributed and possibly mobile along networks. Moreover, these entities exchange only partial information amongst each other and with their environment, due to physical and/or semantic limitations. Consequently, information to be processed by each entity proves to be *limited*.

4.1.2. A distributed decision must be robust

According to the continuous changes provoked and supported by the network, and to resulting standard questions of emergency and security, distributed decision makers must reach a robust decision. Robustness may have two different meanings here:

- the first one is related to the system's ability to support controlled changes in parameters that characterize a decision situation,
- the second one is related to the system's capacity of self adaptation to changes occurring within given limits.

In the first case, the decision remains "stable". In the second one, decision evolution rules are planned within a given domain of possible situations.

4.1.3. A distributed decision must be evolution tolerant

A distributed decision must be tolerant of evolutions and be reactive. This point may seem similar to the previous one but goes further in the sense that the evolutions are not assumed to be deterministic and planned within the decision process (even if some stochastic models could try to integrate them ...).

4.1.4. A distributed decision must be secure

A *distributed decision* also applies to "decision fields" that involve – possibly extreme – danger and great necessity for security. These kinds of applications are becoming more and more common, especially thanks to the non-localized and shared cooperative modalities of decision allowed by ICT.

4.1.5. A distributed decision must be multi-time-scaled

Some fields of application need a decision to be reached in an "any-time" mode: at any moment, it may be necessary to stop the decision process and to provide a viable decision. This constraint of course reinforces reactivity and security features. On the other hand, some decisions can be computed almost without any time constraints.

The cooperation of several heterogeneous entities in the network also brings variety to the relevant time-scales: some of them may be at machine level, while others are at decision maker level.

These features may be considered as the new requirements for a *distributed decision*. As they may sometimes lead to contradictory interests in the system, it is necessary to add to these requirements a "good-will principle": every decision maker wishes to cooperate and to contribute to a collective relevant decision. In this way, we globally follow the idea of cooperation as it is usually described from an engineer's point of view (Schmidt, 1991):

- there is a common "plan" shared by all entities,
- each entity can recognise other entities' intentions,
- each entity wish to facilitate other entities' goal reaching,
- there may be a dynamic sharing of tasks and problems to solve,
- entities try to avoid or to solve possible conflicts in the system.

Ignoring the first one of these points, we prefer to assert that the various decision makers do not necessarily follow the same objective, but that there exists in the system a meta-goal that would try, for the sake of all decision makers, to keep the system in a viable status.

One of the most important challenges maybe the most important of a *distributed decision* is to propose mathematical models that fulfill the requirements and that could be used as scientific foundations of the field. We will try to give some pointers to such mathematical approaches in the following paragraphs.

4.2. From distributed decision theoretical foundations...

Some of the technical tools presented in Sections 2 and 3 may appear as "candidates" for Distributed Decision scientific foundations, namely: consensus theory, game theory and (extended) utility theory.

Consensus theory: this theory appears to be reliable in the context of a Distributed Decision because it attempts to obtain acceptable "compromises" between conflicting and diverging opinions of different participants, in order to compute and propose collective decisions.

However, it is still assumed that the entities have access to the complete information (so that the first requirement of a Distributed Decision is not fulfilled). Moreover, the entities are not assumed to communicate, and no hypothesis is made about the information that they could possibly exchange (so the communication requirements are completely ignored in the model). For these reasons, Consensus theory may be considered irrelevant for our purpose.

Games theory: this theory has quite recently proposed some models that take into account a good number of Distributed Decision requirements: autonomy, power, cooperation and negotiation (Fudenberg and Levine, 1998).

Recent studies (Kraus et al., 1995; Kraus, 1997; Ephrati and Rosenschein, 1996) concern decision makers who do not follow their preferences or who do not want to make them public during vote procedures. This approach is quite different from conventional ones, and may be considered as a renewal of Gibbard's (Gibbard, 1973) or Satterthwaite's (Satterthwaite, 1975) proposals: practically all vote procedures may be rigged.

This result must, however, be moderated, while the "rigging" operations reveal to be NP-hard problems (Bartholdi et al., 1988; Dempster, 1967). Ephrati and Rosenschein (1996), for instance, specialise Clark tax mechanisms so that:

- participants could reveal as little as possible of their own strategies to achieve the consensus, or
- participants keep their strategies secret.

Kraus works on negotiation protocols that explicitly take time into account, and explicitly tries to work on entities that exchange and access only partial information. [4]

So Game Theory takes into account incomplete information, variability in entities strategies, as well as consensus modalities through the notion of *coalition* and evolution towards equilibrium states. But on the other hand, up to now, it has not provided any way to take care of the requirement of dynamical evolutions within the system. [5]

Utility theory and related topics: more or less recently, utility and other notions like belief functions also called degree of belief (Schaefer, 1976; Dempster, 1976) have been used in a networking framework. They allow analyses corresponding to various scales of granularity. In such networks (Bayesian networks (Jensen, 1996; Pearl, 1988), belief networks (Pearl, 1986), cognitive maps), nodes are generally attached to agents' states or intentions, and vertices to information exchanges between agents or with the environment. For instance in Bayesian networks, nodes are structured along a directed acyclic graph and represent variables (related to events or coming from measures) whose truth value is computed according to a global Bayesian probabilistic rule.

These approaches have well-known dynamic capacities that allow to take into account both robustness and evolution tolerance requirements.

But they also consist in applying a kind of "hyper-behavioristic" model that focuses on information and that excludes all human factors from the system. Even human entities in the network are considered as functional elements of the system and solely devoted to information flow control. For Bayesian networks, there is no longer account taken of the nature of variable evaluators or message emitters (human and/or machine): all of them are considered as "probabilistic automata".

Beyond these three axes, mathematical tools such as Viability Theory (Aubin, 1991) or dynamic systems (Petitot and Rosenstiehl, 1974) (with their non-linear properties and notion of attractors) could constitute foundations for a Distributed Decision theory. But practical situations do not

[4] "in most cases, the agents do not have complete information about each other. For example, an agent may hide its actions from the other agents".

[5] New and recent challenging domains related to Game Theory, such as e-business, could however make this theory completely adequate for Distributed Decision in the coming decade.

necessarily fulfill the requirements expressed above, and, more important, these approaches have not taken into account, up to now, the cognitive "white-box" modeling that we claim to be necessary. These approaches seem quite interesting to study further but do not currently provide reliable solutions to Distributed Decision theoretical modeling.

4.3. … to a practical solution: Distributed agents

When facing real situations close to the Distributed Decision requirements as previously expressed, one first needs practical solutions and realistic software technologies. So, beside any theoretical modeling, it may be useful and efficient to rely on the concept of *Distributed Agents Cooperation*.

This concept, coming from Artificial Intelligence, leads to reasonable software solution independently of any mathematical formalisation. Amongst the flourishing number of definitions of "agents", we have chosen the following basic ones coming from the Computer Science domain:

"An agent is a software entity which functions continuously and autonomously in a particular environment, often inhabited by other agents and processes" (Shoham, 1993).

"An agent is a computation system that inhabits a complex, dynamic environment. The agent can sense, and act on, its environment, and has a set of goals and motivations that it tries to achieve through actions" (Maes, 1994).

"Agency is the degree of autonomy and authority vested in the agents, and can be measured at least qualitatively by the nature of the interaction between the agent and other entities in the system. At a minimum, an agent must run asynchronously. The degree of agency is enhanced if an agent represents a user in some way [etc.] A more advanced agent can interact with data applications, services and other agents" (Gilbert and Conte, 1995).

With the recent intensive development of telecommunications, computer science has enriched the concept of agent with several specialized profiles (Nwana, 1996):

- *network management agents*: these agents continuously update communication protocols and detect failures and malfunctioning within the network (Schoonderwoerd et al., 1997; Bonabeau et al., 1998).
- *interface agents*: these assist the operator in managing large amounts of data that may for instance overload his/her personal computer. Thus, an interactive agent may filter incoming e-mail, or help in scheduling meetings. It may especially cooperate with other interface agents in data retrieval or task handling (Maes, 1994).
- *coordination agents*: these help in "connecting" distant users. They are to become major actors in the e-market, where agents may travel autonomously along the network, accessing remote databases, negotiating prices or discussing with other consumers of products and services. These agents should rapidly become a key in collaborative-design practices (Kraus, 1996, 1997; Shehory and Kraus, 1995; Sandholm and Lasser, 1997; Tsvetovaty and Gini, 1994).

Another way of categorizing agents involves distinguishing whether they are reactive or cognitive (Chaib-Draa, 1999). The simple table here below shows the variability of applications that may be covered by the distributed agent approach, jointly with the level of implication of human operators within the system (see Fig. 6).

To consider distributed cooperative systems as alternatives to centralized static ones is not a new idea. It was already proposed by cybernetics when attempting to introduce new paradigms from biology into the engineering sciences. It was again used when parallel machines were designed, and

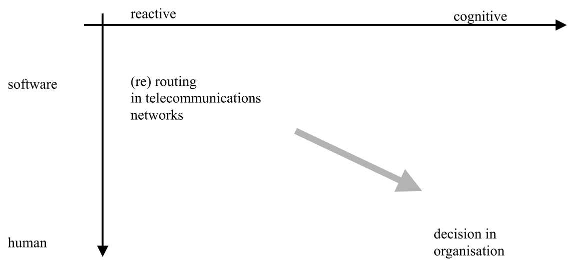

Fig. 6. Few dimensions of agent based systems and applications.

even more recently, with connectionism and neural networks.

What seems to be more innovative is that a Distributed Decision involves hybrid agents men and/or machines and that these agents have new characteristics:
- they cooperate to achieve decisions,
- they are distributed and mobile along a (physical or virtual) network,
- they communicate only partially between each other, and with their environment.

4.4.1. Multi-agent systems for distributed decisions

Agents for Distributed Decisions have already been applied in various contexts and according to various approaches. We briefly present a few of them, and another will be developed in the next section.
- Agents for decision in planning: in RETSINA multi-agents (Paolucci et al., 1999), each agent is provided with an internal planning component. Each agent, using its internal planner, formulates detailed plans and executes them in order to achieve local and global goals. Knowledge of the domain is distributed among the agents, therefore each agent has only partial knowledge of the state of the world. Furthermore, the domain changes dynamically, and part of the available knowledge may become obsolete. To deal with this issue, RETSINA agents allow interleaved planning and execution of information gathering actions. Information necessary for an agent's local plan can be acquired through cooperation with other agents.
- Agent-aided aircraft maintenance (Shehory et al., 1999): aircraft maintenance is performed by mechanics who are required to consult expert engineers for repair instruction and approval. These engineers happen to rely on external sources of information, which are often ill indexed and geographically scattered. This problem relies on distributed multi-modal information that is processed by multiple users with different preferences. A multi-agent system makes it possible to perform documents pre-analysis and to provide the users with an efficient aid tool in dealing with the information system.
- Agents for controlling a nuclear reactor (Aimar et al., 1997): the proposed approach involves a multi-agents architecture where each functional entity is represented by a cognitive agent. Agents are structured in levels in a vertically structured architecture, while dealing with different abstraction levels for the control problem. Agents of different levels cooperate to achieve common goals.
- Agents for routing in telecommunications networks: Heusse et al. (1998) present a new family of distributed algorithms for routing and load balancing in dynamic communications networks. Estimates of the current network load and link coasts are measured by sending cooperative routing agents in the network that travel with the regular packets and keep track of the delays encountered during their journey.

4.4.2. An example of an application: SMA2

As a concrete example of the proposed approach, we would like to briefly present a study in progress, applied to the field of airborne surveillance of maritime areas (SMA2 project: multi-agent system for Maritime Surveillance [6]).

The project is concerned with military missions devoted to the airborne surveillance of strategic areas on the sea, for which a multi-sensor airborne system is used. This system involves several operators, each of them being a sensor specialist, and each of them getting from his/her attached sensor a "point of view" on the on-sea tactical situation.

The decision focuses here on the identification that must be attached to a target within the global tactical situation. Depending on the locally accessible parameters, each operator is able to propose an identification class (at the higher level, a simple and common classification between "friend", "hostile", "neutral" or "unknown" categories, and at the lower level, the nature and level of threat of the analyzed ship).

[6] This project is funded by DGA/STTC Complex systems group, and involves three partners (THALES-Airborne Systems as project leader, ENST de Bretagne and CRIL Technology).

In this case, the Distributed Decision has of course to focus strongly on security and reactivity features, a bad or too delayed decision meaning possible danger for the observing aircraft. On the other hand, the system intrinsically introduces all the Distributed Decision requirements:

- The information accessed by each entity is limited (limitations are due to the sensors capacities as well as human operators cognitive constraints).
- The decision must be robust and secure,
- Different time-scales must be taken into account (depending on the sensors as well as the mission context critical, safe, ...).
- The situation is continuously evolving: so must the related decision process.

The decision support system that is proposed in SMA2 is built from a hybrid population of agents:

- organizational agents: these are devoted to the guarantee of high level social constraints (hierarchical filtering information exchanges, for instance), as well as the taking into account of the high level context (e.g. definition of the level of criticality),
- information network agents: these are dedicated to the retrieval and more generally to the management of distributed data within the system. They are not limited to "distributed database management" functions, while they integrate the management of strategic data and the computation and proposal of a consensus for identification,
- local decision aid agents: these agents are not mobile along the network, but assist the operator in focusing on the strategic items of information for identification purposes. They may involve learning processes in order to better determine this strategic part.

The global structure of the system is displayed in Fig. 7.

This structure should lead to an efficient anytime decision aid function, while involving human entities abilities and taking into account organizational features.

5. General discussion

The gradient that goes from individual Decision Making to a Distributed Decision shows a new landscape that is threefold:

Nature of the Decision Maker: Decision makers are becoming hybrid (humans and software are mixed) and do not share the same information

Nature of problems, solutions and models: in a Distributed Decision systems practical needs run ahead of software solutions and far ahead of

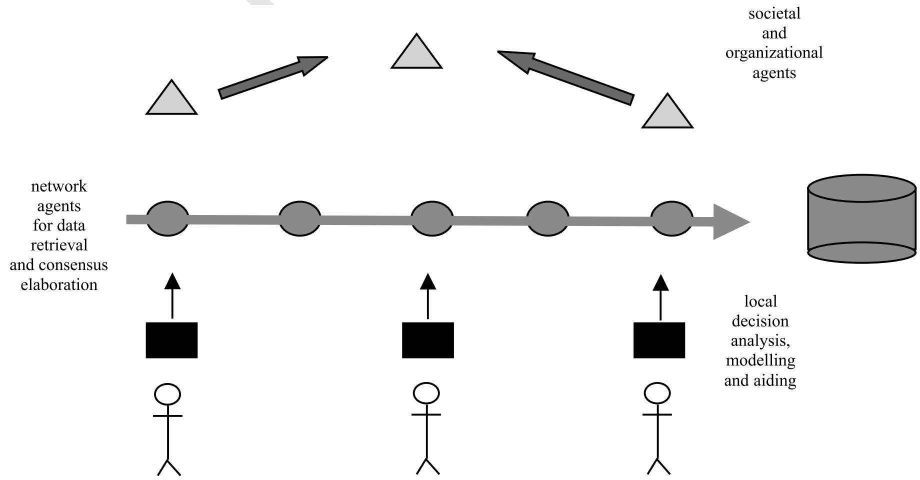

Fig. 7. SMA2 architecture synthetic diagram.

mathematical and/or cognitive modeling. This is not the case for individual decision making.

Nature of the algorithms: algorithms coming from cognitive modeling are doubly time dependent. From an internal point of view, they are sequential. From an external point of view they control the evolution in time of the Decision Maker/Process pair. Due to the flexible mobility of the agents (*l'espace, chassé par la porte du calcul, rentre par la fenêtre de la distribution*), algorithms become both time and space (again internally and externally) dependent and this situation appears as a new one (parallel computing uses a prescribed rigid architecture and full control of information exchanges; neural networks also optimise on a rigid topology with two possible exceptions: Kohonen maps (Kohonen, 1984) and ART networks (Carpenter and Grossberg, 1988)).

As this paper was oriented towards practical applications, we would like to conclude it with a more "philosophical" single question: do these new landscapes show real changes in paradigms for Decision Making within Operational Research?

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