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ACTION-ORIENTED DECISION-MAKING: T O G A METHODOLOGICAL APPROACH

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1. INTRODUCTION AND PROBLEM BACKGROUND

The design and control of very complex high-risk dynamic systems, and the need of coping with the increasing risks caused by technology to human life have led to the development of new tools for knowledge management, such as expert systems, "intelligent" tutoring, or autonomous robots.

This paper presents the autor’s point of view on the state of research in the field of "reasoning models", and gives some information on a study currently in progress at ENEA, which is oriented towards the development of "intelligent" supports for human reasoning in problem solving activities. Our interest is particularly focused on the identification and "design" of decision-making function which:

- occurs during the activity of a plant-operator, seen in the context of specification and design of knowledge-based CAO (Computerized Aid for Operator) systems [Gadomski 88], [Balducelli,89], [Businaro,88], [Gadomski,92].
- is involved in the reasoning function of intelligent autonomous robot,
- should be the basic functional element of decision-support systems,

and

- is necessary for modeling of a colaboration in multi-agent systems.

In the past, the concept of "decision-making" has been involved in many conceptual systems. Numerous brilliant observations have been made, but none of them can be onsidered sufficient for effectively implementing the human-like decision-making process" in a computer.

The first doubt which we encounter in such a problemis : does the natural language expression "human-like decision-making process" really refers to one separable abstract process or is the same expression used in the various conceptual contexts with similar but different meanings?

Many people believe that the expression "human-like decision-making process" has different meanings in different contexts of human activity, specified by the problem domain, the kind of situation and the properties of the human agent.

From such a perspective it should only be possible to individually define and analyse "domain-dependent" decision-making processes using "man-independent" formal logical tools.

From the other point of view a generalisation of human-like decision-making processes can be made which is useful for the specification of domain-dependent decision-making .

Although many computerized decision support systems have been developed, there is no general agreement about the modeling of decision-making processes/function.
Many very different decision support systems and models of decision-making are the results of explosive research and designs.

The nature of decision-making is nowadays analyzed by: mathematicians, engineers , philosophers , sociologists, psychologists and economists, each in its own professional context.

In this paper I attempt to look at a decision-making from the points of view of both the engineer and the physicist.

In such a context the old assumption of the physicists on the existence of a uniform description of the universe (description based on our measurements and observations) should be modified into an analog assumption (or work hypotesis to verify) on the existence of a uniform description of " intelligence".

At this point it may be useful to mention some engineering applications of a model of decision-making :

- to serve as a conceptual tool for the identification, specification and verification of specific decision-making processes
- to be implemented in decision support systems , or in autonomous robot reasoning systems
- to be implemented in computer aids for software design (CASE) tools for the design of "intelligent" systems.

In this paper I suggest, at the beginning, the "extraction" of decision-making from the context of human mental activity in order to analyse it in an abstract way.
This operation requires an initial specification of a decision-making which will delimit the scope of this term.
I then limit the consideration to action-oriented decision-making , where "action" is understood as being a behaviour recognised by predefined human, and which is conceptualised by him as a goal-oriented behaviour of human or another artificial agent .
I suppose that such decision-making are the only to have practical engineering sense.

2. RESEARCH CONTEXT AND BASIC PARADIGMS

Research situation in the field of "intelligent systems" is much more complicated than it is in physics. In physics, a physicists society is assumed as being an external "axiomatic" observer. In the case of reasoning processes analysis , the observers are also elements of their own research domain.
We can distinguish two main approaches to "reasoning problems".
The first is based on the ENGINEERING DESIGN PARADIGM, which is request-based design of everything software engineers are able to specify in terms of system goals and functions, and can be put into a computer.
The second is founded on the SCIENTIFIC RESEARCH PARADIGM, i.e. on the identification (=modelling) of repetitively measured or , more general, observed fenomena.

As a model of human "decision-making" which satisfies the scientific research paradigm and is also computer implementable, does not exist [Winograd,89], [Natali,83], the software engineers use some results of the scientific approach [Ullman,88], [Kusiak,88].

In practice, not all the identified properties of human reasoning are necessary in engineering models of reasoning. From the above perspective, in this paper human reasoning is reduced to human problem recognition/specification, and decision-making is treated as one component of this activity.
A mixed approach which inregrates both paradigmes, requires identification of the properties of human reasoning during top-down goal-oriented design of artificial reasoning systems.

The identification of a process of human "decision-making" can be based on the data obtained from:

a. the external observation of a human-agent behaviour by another human-agent (modeller),

b. the information given by another human-agent

and

c. the personal experience of the analyst (modeller).

In general, personal experience and mental historical records are considered an acceptable source of data for building a model of the reasoning process [Polya,57],[Newell,72].

Verification of the model is based on:

(a) IMPLICIT CONSENSUS in a predefined human community, when the individual motivations of one member are not known by the others ;

(b) EXPLICIT CONSENSUS, when an accepted theory or another conceptualisation system has been established and a proof can be/is given insite it;

(c) UTILITY CONSENSUS, when sucessful application of the model to the solution of selected practical problems has been performed;

(d) NATURAL CONSENSUS, when experimental verification of the model is performed.

In the case of the design of knowledge-based decision support systems, not only, the D-M model but also a formal structure of knowledge bases which should enable recognition of the completeness and consistency of any individually implemented knowledge system, are required.

The main problem referred to in this task is the lack of explicit consensus on such a conceptualisation system.

3. T O G A METHODOLOGY

An approach employed here to the modelling decision-making, is based on a rational consensus on the scientific and engineering paradigms, and is called TOGA (Top-down Object-based Goal-oriented Approach) [Gadomski,86,89,90,91].

TOGA is composed of three basic elements:

- the Theory of Abstract Objects (TAO), which is a domain independent conceptualization system;
- the Knowledge Conceptualization System (KNOCS), which includes the axiomatic assumptions and definitions related to: the real-world conceptualization, intelligent agent (IA), and domains of IA goal-oriented activity;
- the Methodological Rules System (MRUS) for the specification of complex problems.

The TOGA theory is partially selfreferenced and selfverified.

3.1 TAO: Theory of Abstract Objects

Any theory can be considered as a frames system which enables structuralization and operation over a certain class of sets. In the case of TAO, its domain is any numerable set called ’primitive’.

TAO is a frames system which enables the structuralization of ’primitives’ in the form of:

- Objects, specified by their names, attributes’ names, values, and value domains;
- Relational isolated networks of objects, called ’world-of-objects’ (w-o-o) which:
    * can be arbitrarily divided into ’systems’ and their ’environments’,
    * can be aggregated in ’universes’ of objects.

TAO includes the definition of the class of singular objects and the formalization of the concept of the ’point-of-view’ referred to an object.

The singular objects are particular objects which can create or modify other objects inside their world-of-objects.

The singular objects are ’goal-driven’ and are called ’abstract agents’ (AA). Certain specific subclass of AA is called ’abstract intelligent agents’ (AIA). AA can be treated as "normal" objects in another universe of objects.

The TAO theory includes operations set and rules, which enable creation and modification of TAO structures [Gadomski].

We can notice, that TAO has an algebra property.

Remark:
TAO can also be seen as a generalisation and extension of three existing approaches: entity-relationship approach object-oriented programming/design , and frame system , see for ex. [Minsky,75], [Ullman,88], [Natali,89].

TAO has the recursivity property which is still under our investigation. It is interesting to mention that the development of TAO is also driven by the rules of TOGA.

TAO can be considered as a conceptual interface between KNOCS and the AI languages. Therefore, TAO is computer implementable, and can be used as the basic ’conceptualization system’ for modeling an IA.

3.2 KNOCS: Knowledge Conceptualization System

The Knowledge Conceptualization System (KNOCS) is a system of axioms and definitions for the description and conceptualization of the real world from the perspective of a real IAs, in terms of TAO.

KNOCS assumes that every product of the human reasoning activity can be conceptualized in the frame of the Theory of Abstract Objects.

KNOCS enables the conceptualization of real world agents such as, industrial plants, robots, human operators or organizations, and it can be used as an interface between the knowledge engineer and a domain expert.

3.3 MRUS: Methodological Rules System

The Methodological Rules System (MRUS) is a methodological approach to the ’top-down’ knowledge ordering for the specification of complex problems. MRUS can be called "hyper-inference engine".

It assumes that, at the beginning of a problem specification, the knowledge of the problem solver agent is incomplete and not goal-ordered.

The problem specification activity is based on two fundamental mechanisms:

- the former is called the ’top-down’ mechanism, and indicates the specification direction: from very general statements to the details which can be the elements of the problem solution; these specification rules are based on the ’generalization hierarchy’ defined in KNOCS;

- the latter is called the ’goal-driven’ mechanism; it always controls the links between the specified/identified object and the problem ’goal’ object; this mechanism creates bottom-up rules (synthesis rules).

MURS can be a useful tool for checking the correctness of the goal-oriented activity of KEs, and for the validation/verification of their products.

3.4 Selected TOGA assumptions

Here, some basic TOGA assumptions and definitions are presented.

A1. Every product of the human reasoning activity can be conceptualised and transformed in the frames of TAO.

Def.

The ’conceptualisation system’ is an empty frames system, and an operations set which is defined on these frames.

A2. An ’Agent’ is a dynamic system which interacts with its environment in order to obtain some required/desired/preferred responses from the environment itself.

In other words, it tends to achieve some preferred states of its percepted world, i.e. it has a ’goal’.

From the point-of-view of an external observer an Agent which interacts with the Real-World is called a Real Agent (RA), and its conceptualization, in the terms of its interactions with the Real-world, is called an Abstract Agent (AA).

Let us identify the internal functional structure of an Active Agent.

A3. ’ Abstract Agent’ is the name of the trial system composed of the objects called:

’domain-of-activity’(d-o-a), ’knowledge’, ’preference’.

The ’domain-of-activity’ and the ’knowledge system’ can be structured as a set of abstract systems, and the ’preference system’ is always a single abstact system. The ’domain-of-activity’ is always considered as the ’information source’. Information can refer either to the state of the d-o-a itself or to the state of another object. In this last case, the information is structured according to the conceptualization of the d-o-a.

The d-o-a of an AA is the ’reference domain’ of its ’knowledge system’, and, from the point of view of an external agent "observer", it is called ’Knowledge Reference Domain’ (KRD).

Every ’knowledge system’ is always referred to a preselected d-o-a, and it is composed with ’passive knowledge’ and ’active knowledge’.

The ’passive knowledge’ of AA related to a d-o-a , is a set of conceptualisation systems (frames), it is used by the physical agent to transform signals from d-o-a to a form of information.
Information are the date for ’active knowledge’. In this sense, the ’knowledge system’ is the carrier of different reasoning processes, for ex. the information processing or the information choice.
Knowledge is divided into: ’domain-knowledge’, ’operational -knowledge’, and ’management-knowledge’.

Def.
’Domain-knowledge’ is a symbolic representation of the domain-of-activity in the frame of conceptualisation systems, and a set of operations available on this domain., i.e it includes too an active knowledge.

Def.
The ’operational knowledge’ of an agent X, is a set of possible interventions for X , expressed in terms of its d-o-a conceptualisation (procedure, rule, menu), and referred to a certain set of states of the d-o-a. The ’operational knowledge’ includes also ’passive’ and ’active knowledge’.

Def.
’Reference relation’ (RR) is a complex relation between a knowledge and its reference domain, for ex., between the domain knowledge and state of the d-o-a of an active agent. RR is established by AA, and is verifiable by its goal-oriented actions.

Def.
The ’Management-Knowledge’ (MK) of an active agent is a set of operations and rules available to him, and referred to the application of his/its operational- , domain-knowledge, and preference-relations system. MK includes also strategies of AA.

In TOGA, knowledge is structuralised in two hierarchies: the **generalisation** hierarchy and the

metaknowledge hierarchy.

One domain-knowledge, i.e. referred to a defined d-o-a can be divided into generalisation-levels (GL) , In this hierarchy, attributes of an object established on one GL are decomposable on the lower GL. All the definitions established on higher GLs are mandatory on all lower GLs. In the case of metaknowledge levels , they obey the following rule:

> n-th metaknowledge level is the reference domain for the (n+1)th metaknowledge, where n=0,1,2...

For ex. if in the particular situation a preselected D-M is impossible in the problem-domain then the problem conceptualisation can be shifted on a higher GL or on a meta-level of this problem.

The ’preference system’ includes relations in a form of rules between possible information and active knowledge . These relations are ordered according a priority scale.

A3. The ’Reasoning’ process is a dynamic property of the AA knowledge system.

The goal-oriented reasoning processes start from the activation of the ’knowledge system’ from some states of the ’preference system’. The results of these processes change the current state of the d-o-a of AA.
The ’preference system’ activates the knowledge system by means of the generation of a ’intervention-goal’. The ’intervention-goal’ is the conceptualization of the state of the d-o-a to be achieved.

Def.
’Intervention-goal’ is the specification of some of the attributes of the state or process in the environment of the abstract agent established by the preference system with maximal priority.

The preference system activates the knowledge only if a ’intervention-goal’ is established .

Reasoning process is composed with associations, inferences, and choices.

One d-o-a can be conceptualised from different ’points-of-view’ (p-o-v) dependending on the assumed activity goal.

A4. The Real-World (RW) is a quasi infinite source of ’information’.
Therefore, first level human domain-knowledges is also quasi infinite.

On the grounds of the above mentioned assumptions and definitions, it is possible to define that an Abstract Agent which is able to ’reason’ about its own knowledge and preference is called an ’Intelligent Agent’.

A5. AA with metaknowledge levels which enable it to operate on the knowledge, and preferences is called ’Abstract Intelligent Agent’ (AIA).

Let us define some properties of an ’Abstract Intelligent Agent’.

Def.
The functional structure of an ’Abstract Intelligent Agent’ is a tree network of AAs. The AA at the root of the tree network is called the basic-AA. Starting from this basic-AA, the ’knowledge system’ and the ’preference system’ of each AA, in any level of the tree, is the domain-of-activity of the AAs on the subsequent level.

The d-o-a of the basic-AA is called the basic-domain-of-activity (b-d-a) of the AIA.

A6. Every process A relying on a behaviour of physically realized AIA (X) in his/its physical environment, or on the change of a state of his/its knowledge or preferences is CONSCIOUS if X has such a conceptual system where the process A is describable and he/it can perform it.
In this case, we can say that process A is observable for X.

A7. A goal-oriented conscious activity of a human-agent can be conceptualised by its observer (another human-agent) as the activity of the AIA.

The first conscious d-o-a of a man, is the representation of the RW in the form of symbols obtained from the human ’sensorial perception’. For this reason, the first conscious d-o-a of the IAA is its/his first level domain-knowledge.

A8. Any arbitrarily selected artificial object from a d-o-a of a human agent, can be conceptualized by the decomposition of the interrelation between a system and its goal (GSI).
The decomposition frame is composed of a network divided into the following layers:

’**goal layer’, ’functions layer’, ’processes layer’, and ’system layer’.**

Def.
The ’System-goal’ (or design-goal) of a system X in an evironment En , is the specification of some changes or properties of the En required by the user or creator of X which should be/are obtained by the interaction between X and En.

For this reason, the system-goal must be expressed only in terms of the environment descriptions, and can only be established by the system creator or its user.

The GSI conceptual frame allows the decomposition of the relation between a designed, modified or identified system, and its goal. Of course, any "natural" object can have an infinite number of functions and goals, i.e. they depend on particular applications of an analyzed object by the human-agent.

A9. If the d-o-a of an AIA X, includes another AIA, Y, then X's domain-knowledge related to the goal-oriented activity of Y, can be conceptualised in terms of formally defined : 'intervention-goals', 'tasks' , and 'actions' referred to the Y's d-o-a .

Def.
The 'Task' is intervention-goal oriented properties of 'action', it is expressed in terms of d-o-a description, and describes what changes must be introduced in the AIA for achiving 'intervention-goal'.

Def.
The 'Action' is a specification what AIA can do for the realisation of tasks, i.e. to achieve the predefined intervention goal. Action is expressed in terms of operational and domain knowledge.

It means, an action must depend on executor possibilites.
We can mention, that one task can be performed by execution different alternative actions, and from the identification point of view, one selected action can be recognised as the carrier of different tasks.

'Tasks System' (task scenario) is executor independent but it depends on goal constrains (time, cost,..).

A10. From the p-o-v of the specified goal, an unknown ignorance does not exist, i.e. any ignorance must have attributes because they define relations for a closure of any w-o-o.

A11. Every system in the domain of activity of an AIA can either be specified (constructed) using the ENGINEERING DESIGN PARADIGM or, if it was there before, identified using the SCIENTIFIC RESEARCH PARADIGM.

One of the "interfaces" between ENGINEERING DESIGN and SCIENTIFIC RESEARCH PARADIGMS is builded on a definition of the couple: 'function' , 'carrier relation' , 'process'.

Here, I must add that 'function' is not the name of a mathematical relation but it is the name of a goal-oriented property of a pre-identified process.
From the designer perspective , when a function is defined, its 'carrier process' is a realisation of this function in an assumed context (certain 'world-of-objects').
In the situation of modeling of a human decision-making, we must assume that this unknown process/function is an element of human goal-oriented reasoning, and is identifiable by its attributes.

Remark:
The results of operations available for a AIA in the frame of an accepted conceptualization

system, can be true, false or non verifiable in a preassumed reference d-o-a.

Human reasoning referred to a certain d-o-a, is based on many conceptual systems and associative processes. A mixed, not verified in "real time" change of the conceptualisation context, frequently leads to false conclusions and intuitive convictions , i.e. to the construction of false or ’fiction domain-knowledges’ which no longer have reference to any physical or abstract d-o-a of the human agent. We can notice that the human mind is full of such types of constructions.
The above situation can be omited in the design of an artificial AIA.

4. A MODEL OF ACTION-ORIENTED DECISION-MAKING

4.1 Bulding the model

The modelling of a D-M is the modeller/designer activity in his/its d-o-a. Every D-M is based on a choice.
According to the TOGA conceptualisation, a D-M can be represented as an object in three-Dimensional Discrete Space (DDS).
The first dimension called GSI (Goal-System Interrelation), is divided into four layers: goal, function, process ,and system.
The second dimension gives the possibility of setting up the model on different generalisation levels (GL), which can be organised arbitrarily (from the initially assumed model definition up to the details level, when the model implementation will be possible).
The third dimension is used for a set up of the system description in the hierarchy of abstraction, from structures of directly measured (physical) attributes to highly abstract conceptualisations.
The TOGA methodology is a rigorously goal-oriented tool .
It is based on: ’problem’ definition, rules of definition building and is destinated for problem specification in its user d-o-a (which should be located in a computer).
Problem specification starts from the user knowledge collected in different conceptual systems and the initially specified goal which he intends to achieve.
The pyramidal , top-down problem structuralisation requires bottom-up goal-driven evaluation of user knowledge.

The requested completeness of a problem description on any GL level in DDS space, makes the IDENTIFICATION OF USER IGNORANCE (temporal BLACK OBJECTS) necessary, and indicates the knowledge which should be acquired.

The construction of an A-O D-M, requires an initial specification of the terms used. At the beginning of this task, we should construct a top definition of a ’decision-making’ for its recognition in the context of the action-oriented reasoning.

The model is constructed top-down in the generalisation hierarchy by the identification of decision-making carrier systems , neighbourhood processes, and the specification of decision-making functions necessary for the achivement of the our task goal.
The conceptualisations of the model , on every GL level, should be verified by its confronta-

tion with the existent data, and with the model attributes specified on the higher GL level.

From user points of view, these models become his conceptual subsystems for a structuralisation of his specific domain-knowledge.

4.2. Specification, Identification and Verification

In this paragraph we demonstrate only some elements of this model construction (TOGA is mainly destinated for computer as the "intelligent" support for problems specification).

The first thing we must do, is to accept an "axiomatic" top definition of an Action-Oriented Decision-Making. All model conceptualisations , constructed after, must satisfy such definition. This definition is also necessary for the identification of an abstract A-O D-M in the human reasoning process.

Omitting here, initial details, we form the following identification-definition (i-def.) of the A-O D-M process by conjoining an A-O reasoning definition and a D-M definition.

An A-O D-M process is a D-M process executed in the frame of an Action-Oriented reasoning process. For this reason, an action-oriented reasoning process is the domain of search and identification of an A-O D-M.

<u>I-Def. of Decision-Making in process conceptualisation</u>

> D-M is defined on a set of ’Alternatives’ (Al), and is a process of the CHOICE (CH) of only one of its elements (al), according to the established criterium (Cr), and relative to the decision-maker knowledge on the state of its d-o-a. The element ’al’ is called DECISION.

Of course, the definition of a D-M can be formed in a different way , but at the end , it must have the same process-based interpretation.

<u>Functional allocation of D-M</u>

According to the above definition, a D-M can be considered the process involved in all below presented meta-task (m-task) of an action-oriented reasoning system:

T1. Data acquisition (perception, conceptualisation, recognition),
T2. Situation assessment,
T3. Intervention-goal establishment,
T4. Task planning (where tasks are expressed in terms of domain-knowledge),
T5. Action planning (where actions are expressed in terms of domain- and operational-knowledge,
T6. Action initialisation.

From the designer perspective, by applying the I-Def. to the above meta-task specification, we identify A-O D-M as a m-task, which then substitute m-tasks: T3, T4, and T5.

According to the previous model of AIA , decision choice is performed in the context of :

- **knowledge,**
- **information,**
- **preferences,**

and

- **physical abilities of AIA carrier system.**

In this meaning, D-M does not depend on real situation of IA physical environment.

System allocation of D-M process

D-M is executed by abstract D-M system. Any abstract system which interacts with the RW must have its physical 'carrier system'. Fig. 1 illustrates relations between the abstract and the real world of the Decision-Maker (D-Mer).
Fig. 2 and Fig. 3 successively show , the decomposition of the external and internal worlds of the D-Mer.

We can mention that a 'decision' of an A-O D-M depends directly on the following generic attributes:

a. Conceptualised SITUATION of RW d-o-a. It is expressed in terms of domain-knowledge, and is called 'information' (inf),

b. Planned INTERVENTION-GOAL (ig). It is expressed in terms of domain-knowledge, and is an attribute of the preferences system.

c. Set of ALTERNATIVES (Al) , which are descriptions of actions executable by the D-Mer. It is an element of the D-Mer operational-knowledge, or more precisely, 0-level operational metaknowledge (An action is specified in TOGA by set of attributes, where for the D-M, the assumed initial and final state of the d-o-a are critically important).

d. STRATEGY of choice (Sc). It includes the criteria for the evaluation of the utility of the alternatives, for the achiving of the intervention-goal . A complex Sc can also include 'consequence assessment'. Sc is a 1-level operational metaknowledge.

Each one of the attributes has a value on its own GL, but is considered an object of the new 'world-of-object', on a lower GL. All of them are involved in the CHOICE operation .
Therefore, all these objects must have a 'common attributes space'.

Qualitative verification of the model

Problem structuring in TOGA, is based on the introduction on every GL level some new concepts from non structured, or structured for other goals, domain-knowledge.

Utility of such introduced terms is founded on consensus concerning their general meaning which are valide in analysed particular cases. The definitions of these concepts are necessary for their decomposition on the next GL, and they must be formed in context of attributes of the problem goal.

The GL level verification refers to the verification of properties of the problem specified on this GL.

In the case of a process modelling, qualitative dynamic properties of the process are verified.

Here, we show the mainline of qualitative verification of the model formulated on the top-GL level.

For such a demonstration , let us present our model in the form.

decision = **CHOICE** [ig, Al, Sc] **inf** ,

where CHOICE is the decision operator and which is dependent on the before defined attributes [ig, Al, Sc], which acts on a pre-specificated situation (inf).

This is a one-goal situation driven decision-making. Not correctly recognised decisional attributes values lead to false decision. For this reason, the "effectivness" of the decision (from the goal 'point-of-view') depends on the results of neighbourhood reasoning subprocesses, and is especially important for the simulation of a human IA.

The qualitative analysis of interrelations between the above attributes, enables the qualitative confrontation of assumed states with the known real situations of human decision-making.

The simplest approach to this verification, is to define two-values qualitative domains of the specified attributes values, from selected but integrated point-of-view, (for ex.,a conceptualization of the D-M attributes values from the top goal-oriented point of view) :

inf { (*sufficient, insufficient*) or (*true, false*), and (*time dependent, time independent*)},

Al {(*sufficient, insufficient*) and/or (*usefull, useless*) },

decision { (*satisfied, unsatisfied*) or (*true, false*)}.

Sc { (*unique, multiple*) and (*consequence dependent, consequence independent*)}.

The GL level model can also be verified by qualitative sensitivity analysis.

In the case of a multiagent D-M, the decision-making can be distributed according to the established competences , for ex. relatively to the possible domains of consequences, and possessed by decisional nodes, knowledge.

4.3 Problems of human A-O D-M modeling

Theoretically, an artificial IAA can have an unlimited number of metaknowledge levels, and the level of inconscius activity can be defined arbitrarily highly.

Such a situation does not exist in the case of a human IAA, he is unable to completely describe, in D-M real-time, his own first level knowledge. The access to this knowledge and the memorization of executed reasoning operations, are the main problems of any man . Therefore, for the modelling of human reasoning , a model of association network should also be attached (where , such access depends on 'importance value' of links between the elements of the knowledge system). Here we must mention that the mental conscious processes are executed sequentially but their carrier physical processes are executed in parallel.

The next difficulty lies in the lack of concepual systems for the reasoning on higher metaknowledge levels.

The human limitations referring to different general conceptualisations of D-M are analyzed in many papers, see for ex. [Masuch,89], [Winograd,87].

The other serious human problem is the stress perturbation of all reasoning processes [Kan,89]. In our conceptualisation it could be described by inconscious signal propagation from the RW to the reasoning physical system and in the end to the abstract AIA. The perturbations of fixed parameters of the abstract reasoning system, change the properties of reasoning processes and finally, their results. Such changes mainly refer to the 'importance' attribute of association links in the man knowledge base.

5. DECISION-SUPPORT SYSTEMS

5.1 Agent-oriented decision support

Here, I would like to concentrate on the plant-operator decision support systems only. The main plant accidents are caused by attributes values of perception, reasoning and execution processes specific to a man,i.e. errors of designers or operator staff. Plant behaviour unexpected by the designer, must be corrected by its users.

According to plant designer wishes, an operator should be a strictly action-oriented IA, but an operator is a human agent, sometimes irrational, with limited , and only partially controlled intelligence.

Rational A-O decisions of a human plant operator depend on his:

- current information about the plant status,
- his internal knowledge,
- preferences,

and

- externally established particular task.

The information about the plant can be considered complete, only during its normal exploitation. In the case of its abnormal behaviour, the operator's information about the plant status is sufficient for the recognition of the only foreseen types of abnormal events.

In practice, the external task and preference system specify what knowledge, and what information must be available to the operator.

In particular, intervention requested situations, the operator has either incomplete or excess knowledge/information.

Such data are evaluated by the operator preference system.

The preference system can be conceptualised as a web of potential intervention goals.

According to Lind [Lind,82], the top operator goals(in GL hierarchy) are : production, economics and safety.

The first two goals are specified by the plant designer,and knowledge support can then be established. The third creates more important conflicting situations, and the plant status management must be performed on higher GL conceptualisation levels, for ex. to stop production process.

Such activity is risk, and maximal negative-consequence driven [Gadomski,92]. If in the plant-designer perspective, the consequences of the operator actions and plant dynamics refer only to the plant status, then an artificial reasoning support seem to be very useful. In other cases, a decision support may rely on:

* fast and request-based operator access to hierachically organized information and action-oriented knowledge bases (domain, and operational),

* situation-driven risk evaluation of possible consequences i.e. so called what-if simulation,

* suggestion of risk minimalisation strategy based on the risk specification previously defined by the operator.

* current situation assessment according to the established information importance scale, and importance attributes (for ex., risks, benifits).

In complex plants, the consequences of immediately required control actions, can refer to plant staff and plant human or ecological or technological environments. In these high risk situations, a human component in the control system will alweys be necessary because the management of such incomplete and uncertain knowledge requires preferences established on thebase of intrinsically [Winograd,87] not explicity formalised [Gadomska,89], [Gadomski,90] : human axiology, social/political interests, and cultural traditions.

5.2. Multi-Agent Decision-Making

The concepts of a distributed MAD (Multi-Agent Decision-making) and DDS (Distributed Decision-making Supports) exist only in the context of the system composed of men or other "intelligent" abstract agents. Such defined decisional system implicity assumes the existence of two levels of intelligence, and two levels of decision construction: individual d-m, and common group d-m.

MAD and DDS are analyzed in different perspectives, see for ex. [GDSS, DGDSS, MAAW..].

Here, I would like to recall the basic properties of the agent which influenced d-m, i.e: **information, knowledge,** and **preferences** which are divided on individual **interests** and **axiologies**. Let‘s assume the following relative fuzzy value-domain of them: *equal, not equal.*

In this situation, we can distinguish two ideal types of MAD.

The first is based on cooperation, i.e. assumes explicity known common basic preferences.

The second is concurrent , i.e. assumes that individual preferences are hidden, and not domain of negotiation.

Both require different DDSs . The first can be called CSS (Cooperation Support System) the second NSS (Negotiation Support System), but many real human roles require DDS which support in pararel, human cooperation and negotiation activities, for ex. menagerial decison-making tasks.

6. CONCLUSIONS

The paper presents some information about the current problems in modelling of action-oriented decision-making process . A-O D-M has been presented in two perspectives.

From the first, it is viewed as one of the complex human reasoning processes, from the second as an assumption based software system. The models of the artificial IAs, can be conceptualisation tools for the identification of the A-O D-M viewed in the first perspective.

Present results of research indicate that it is practically impossible to separate human A-O D-M from his A-O reasoning context. Therefore , only an integral identification of the human dynamic reasoning system or human problem solving, should give useful results [Wang,89].

Such identification must be performed in extreme real world conditions, which enable to use the scientific research paradigm. On the other hand the modelling "in one attempt" of very complex processes requires sequential top-down models construction because the direct measurents of its internal attributes are not possible . Such modelling is based on the engineering design paradigm. For both the perspectives, development of abstract intelligent agents as conceptual or computer tools for the construction of models of human or artificial IAs seems to be indispensable.

The knowledge domain-independent conceptual system TOGA ,presented in the context of modelling of artificial A-O D-M, is also a proposal of general treatment of the goal-oriented reasoning problem.

I suppose that the following three hypotheses can be useful in the future analysis of human technological activity:

A. It is impossible to develop knowledge processing systems without a conceptualisation of its users.

B. If for the same physical process , model M1 in conceptual system X and model M2 in conceptual system Y are different but have been experimentally verified, then they are either equivalent or complementary. I.e. a conceptual system Z should exist where these models can be integrated to a model M3.

C. A man is only a non ideal physical carrier of abstract IAAs, but his preferences are always domain of social, cultural, axiological and interest negotiations which can never be explicity simulated, due to of "human nature".

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