Knowledge Management in Environmental Decision Support Systems

U. Cortés [a], M. Sànchez-Marrè [a], R. Sangüesa [a], J. Comas [b], I.R.-Roda [b], M. Poch [b] and D. Riaño [c]

[a] *Software Department, Technical University of Catalonia (UPC), Jordi Girona 1-3, E08034 Barcelona, Catalonia, Spain*
E-mail: {ia,miquel,sanguesa}@lsi.upc.es
[b] *Chemical and Environmental Engineering Lab, University of Girona, Campus de Montilivi, E17071 Girona, Catalonia, Spain*
E-mail: {ignasi,quim,poch}@lequia1.udg.es
[c] *Department of Computer Engineering & Mathematics, Universitat Rovira i Virgili, Carretera de Salou s/n, E43006 Tarragona, Spain*
E-mail: drianyo@etse.urv.es

We discuss in this paper how the results of the discipline known as Knowledge Management could improve some types of Environmental Systems. In particular we discuss Environmental Decision Support Systems (EDSS). In the last decade, EDSS emerged as a suitable software tool to support control decision-making to maximize the performance of a system and to minimize the negative impact of faults. Knowledge Management in Environmental Decision Support Systems appear as a necessity for EDSS users to place guarantees on the system's behavior but these methodologies are still under-explored. In this paper, a first approach to put forward a Knowledge Management Methodology by identifying the most relevant issues, is introduced and discussed.

Keywords: Knowledge Management, Environmental Sciences, Environmental Decision Support Systems.

1. Preamble

Complex rules govern the environment while the action of humans has an important impact upon it. For example, the increasing rhythm of industrialization, urbanization and population growth, which the earth has had during the 20th century has forced society to consider whether human beings are changing the conditions which are essential to life on earth. Often, there is a need to influence the dynamics of an environmental process and to bias its evolution into a desired direction. But environmental processes are not easy to model and our knowledge is still incomplete and uncertain. Due to these factors it is very important that every bit of knowledge about the processes, possibilities of improvement, innovation etc. be effectively revealed, pooled and distributed among all actors involved in the process of environmental management.

In recent years Knowledge Management (KM) has evolved from a desire to a full-fledged discipline that is being adopted across several activity sectors [13]. Originally it was devised as a set of methods focused on revealing the *knowledge assets* [38] of organizations in order to improve their learning ability and, in so doing, its possibilities to anticipate, innovate and secure a competitive edge, knowledge management techniques are being used in many fields to foster innovation. As some authors in the area of Environmental Systems have remarked [21], there is a pressing need to take advantage of the development of KM in Environmental Informatics. However, there are some aspects of Environmental Systems that introduce peculiarities in KM and some exploration of methodological shifts has to be done in order to benefit from the developments in KM. We present a framework for setting KM projects in Environmental systems and put forth a series of conceptualizations and methodological aspects that represent a contribution to this adaptation of KM to Environmental Informatics. More concretely, we focus on Environmental Decision Support Systems (EDSS) [7–9,28] and show how the general framework can be applied in setting KM projects in Environmental Decision Systems.

In the last decade, EDSS emerged as a suitable software tool for supporting control decision-making to maximize the performance of a system and to minimize the negative impact of faults on the environment. In many environmental processes this implies a continuous intelligent monitoring system, an increasing volume of data and, in many instances, a decreasing time horizon within which control decisions have to be

AI Communications 14 (2001) 3–12
ISSN 0921-7126 / $8.00

made. Also, the global nature of environmental problems creates the need to distribute the computation, and then again, the need for integrating and sharing the obtained partial results. Moreover, and more critically, EDSS are not only capable of generating reasonable and understandable solutions, but also they should allow to progressively extend their domain knowledge. This has been shown crucial to the acceptance of these systems in real world domains [1] and [29]. EDSS are environmental sensitive systems able to act to sustain the environment. All these aspects, in conjunction with the human expertise which is built around the operation and construction of these type of systems, give rise to interesting questions for the management of the knowledge generated by and around these systems.

Here we present a first approach to a Knowledge Management Methodology by identifying the most relevant issues and their consequences for the location, leveraging and distribution of the relevant knowledge.

The organization of this paper is as follows. In Section 2, we briefly characterize the goals of Knowledge Management in general with a special focus on its relationship with Knowledge Based technologies. In Section 3 we explore the issue of knowledge exploitation both from the point of view of Artificial Intelligence and Knowledge Management. The key idea is to present AI technolgies as a sources of knowledge. In Section 4, we address the present synergies between Knowledge Management and environmental systems, surveying some recent proposals. Then, Section 5 describes a general model for EDSS remarking the issue of the exploitation of different sources of knowledge. We present a framework based on three dimensions for devising knowledge management processes. After that, the approach is particularize for EDSS and we discuss how the quality of this management is critical for a good performance of this type of systems. In Section admp we introduce agents technology as a possible metaphor to implement EDSS using a KM approach.

Finally in Section 7, some conclusions and open questions are discussed.

2. Knowledge Management: an overview

Knowledge Management (KM) is a discipline whose main goal is to develop methods and tools for detecting, leveraging, distributing and improving the knowledge assets of an organization [26]. Its background comprises several different sources as organizational theory, information systems, general management theory, knowledge representation, human and machine learning, sociology of work, etc.

The dominant view of KM takes as starting point that knowledge originates and evolves within a community of people inside an organization with a common set of goals [42]. Knowledge is created, shared, and distributed by a given set of explicit or implicit rules which are common to all members of the organization. This knowledge takes very different forms, not all of them amenable to computerized treatment, not all of them easily converted into data. A frequent distinction is made between *explicit* and *tacit* knowledge [26]. Roughly speaking, the first one is that type of knowledge that can be verbalized easily or represented by documents, data files, rules of operation, etc. It is more of a *definitional* nature than a *tacit* knowledge. This is more closely tied with behavioral and sensorimotor aspects of knowledge. It is characterized by the difficulty of being aware of its possession and consequently, it is much more difficult to elicit and to make it explicit. This is something that should sound quite familiar to anyone in Artificial Intelligence who has been involved in knowledge elicitation from experts. In any case, it is widely recognized as a benefit for the whole organization to have instituted practices, tools and systems for turning implicit knowledge into explicit knowledge and, as a result, being able to distribute the relevant knowledge to the relevant people in the organization so as to foster organizational learning. It is a given of this conceptualization that organizational learning includes innovation and that innovative attitude improves the overall ability of the organization to compete. When adopting a knowledge management perspective several levels of ambition can be chosen:

1. *Strategic* knowledge management deals with pinpointing opportunities to find, distribute and transfer knowledge related to the long-term goals of an organization. This includes, for example, the decision to shift from one sector of activity to another one.
2. *Tactical* knowledge management is devoted to finding, distributing and transferring knowledge for the medium term goals of an organization. Usually, that implies and specialization of the strategic level initiatives to several areas of activity within the organization.
3. *Operational* knowledge management which implements the previous type of KM on the systems in charge of daily or short term operations. Typically, this may include changes in the available

data collection, in the interpretation subsystems, in the organization, and in the associated human practices.

What is common to any level of ambition is the need to find the pockets of knowledge, to devise ways to make it explicit and distribute it and to find and implement methods, tools and routines to transfer that knowledge effectively to actual people or systems. These steps can be done in several different ways. Usually KM needs to deal with how people work, how they conceptualize their work and how they turn implicit knowledge into explicit knowledge. However, it also has to deal with deciding which IT systems give support to these type of activities and how to change the human and IT dimensions as well as which are the relationship of these two dimensions with the business dimension. See [12,13,26,43] for a thorough discussion of all these aspects and a huge collection of application cases. A common criticism in all these discussions is the one that says that knowledge management methods should not be identified with the construction of Information Support systems to help in locating, eliciting, distributing and transferring knowledge. For a comprehensive discussion about this and for an illustration of actual IT systems giving support to KM projects, see [3]. Knowledge management involves, then, aspects related to people, to information systems and to business practices.

Several studies can be found which address the opportunities for cross-fertilization between KM and Environmental Informatics. See, for example, [39]. Other classical examples of KM involve an environmental aspect such as the much praised British Petroleum KM Global system which has some aspects for dealing for environmental emergencies related to the company operations [2]. We will focus the discussion on its application to EDSS.

3. EDSS: exploitation of knowledge resources

In discussing how Knowledge Management can be applied to EDSS, we have to set out by establishing what type of system an EDSS is and how it is organized. We will discuss which are the knowledge sources that any of such system should use and which are the opportunities for KM.

Our proposal for an architecture for Knowledge Management in EDSS has three levels: Data Gathering and Interpretation, Diagnosis or Prediction, and Decision Support (see Fig. 1). Those levels allow to capture the complex nature of environmental problems and to specify the interaction between the different levels of reasoning involved. It is meant to be implemented as a multi-agent system where agents respond in a rational way to their goals and events that occur in their environment. These agents have a specific set of conditions and associated goals, which indicate the events they should respond to. This architecture stresses the problem of heterogeneous information and knowledge sources. EDSS usually need to cope with very different types of data, usually ranging from huge amounts of numeric streams arriving in real time from a variety of sensors, to visual information from video cameras, to quite informal messages such as telephone calls. Incomplete, or even erroneous data may arrive.

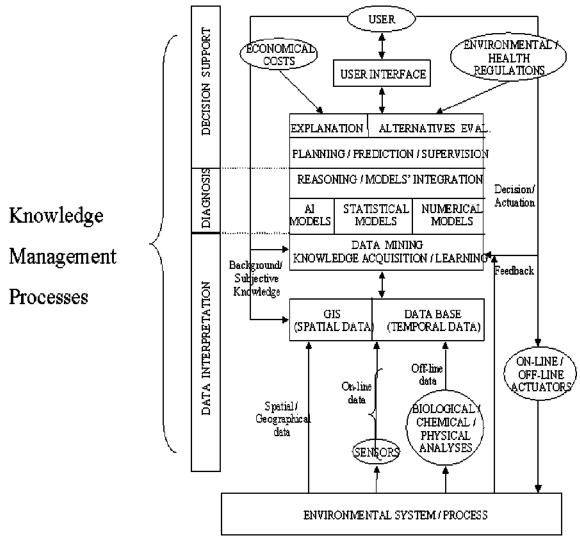

Fig. 1. EDSS architecture.

EDSS use different knowledge resources and this usually implies different ways to extract knowledge from information, that is, for making explicit the knowledge that is implicit in the data. The appropriate interpretation of this combination of several knowledge sources will result in the identification of the environmental events as:

1. Hazard identification.
2. Risk Assessment.
3. Risk Evaluation.
4. Intervention/Decision-making,

where an EDSS play an strategic role in the decision-making chain aiding to solve problems more efficiently.

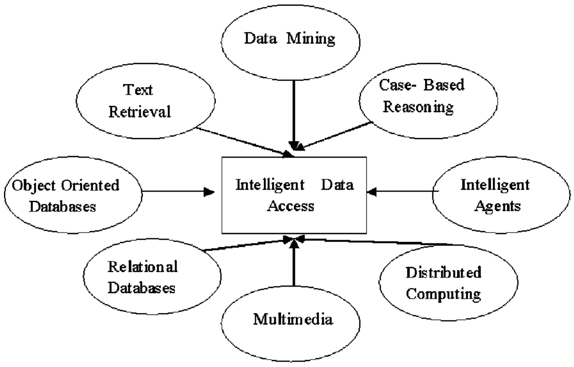

Fig. 2. Intelligent data access.

In the first step of any knowledge management cycle, that is to say, elicitation and extraction of knowledge, the intelligent access to data (see Fig. 2) provides a wide selection of helpful and powerful tools to exploit the various Knowledge resources that are available.

In environmental problems, the data space is not very easy to define, collect or interpret. In the explicit data level, there are several typical sources of knowledge. We can find conventional data bases in the form of object-oriented databases or relational databases that require, on the one hand specialized accessing languages and on the other hand, perfect matching procedures for retrieving information. Other sources of knowledge are knowledge-based systems as Expert Systems that assume a predefined knowledge structure. Depending on the system, the constraints on the accessing language and the matching procedures may also be applicable. Some other systems in this area permit a more flexible expression of knowledge queries and inexact matching procedures. For example, fuzzy logic systems show this flexibility.

More elaborated methods for knowledge exploitation such as knowledge discovery in databases or data mining are used to find hidden relationships from data reflecting past EDSS operations. So, data mining can be seen as a tool to elicit knowledge from explicit data sources.

EDSS systems have been tied to Multimedia and Geographical Information Systems (GIS). These systems provide new and very valuable sources of information. Unfortunately, the automated interpretation of the implicit knowledge is not so amenable to automated knowledge extraction methods [22]. For most of the Environmental problems there is a large amount of data about the processes themselves but the information about the causal or dependence relations among the relevant variables is usually not well-known or very rare [18].

One possible way out of this problem is to use Case-Based Reasoning (CBR) tools which usually allow fuzzy (i.e., imprecise) search. In a sense, CBR implements a sort of automatic ranking of past lessons, much in tune with the well-known method of expliciting and making available *best practice* cases and solutions that is quite widespread in many knowledge management methods. Moreover, CBR allows systems to detect impasses. This technology permit EDSS to learn by giving access to experience and expertise [32]. In some cases the use of a CBR approach includes the extensive application of ontologies to improve the use of the domain from past experiences and diminish the impasse situations. What is still lacking is clear understanding of how to build an ontologies in a systematic way [6]. Another source of knowledge that is highly relevant to EDSS and which is fundamental from a Knowledge Management perspective is human originated knowledge. One can find several profiles of people around an EDSS that may have some degree of knowledge which could be relevant to decision making. Usually this people ranks from the ones who designed the system to the those that take operational decisions based on its workings. Anyone involved in the design of EDSS or the actual environmental system operating under its control is potentially a source of information and knowledge. Several tools can be devised for serving this community, extracting the knowledge they possess and distributing it to other potentially relevant people that could learn from the accumulated knowledge. Note also, that in doing so, it is important to spot which types of this human originated knowledge could get into the EDSS knowledge system. In other words it is necessary to know which types of human knowledge can be made explicit in a form equal or at least similar to the one that is used to represent the knowledge that is used by the automated system.

4. Knowledge Management in EDSS

A Knowledge Management process usually starts by trying to answer two questions: What kind of knowledge is it necessary to integrate? and How to integrate it? The first question is usually approached as a knowledge acquisition step which is generally acknowledged to be a very slow and expensive process. Knowledge Acquisition in Environmental Problems is no exception. The availability of knowledge or even

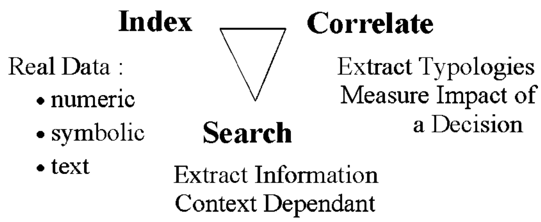

Fig. 3. Integrating technologies: What?

data sources is low given that, in many cases knowledge about an environmental process is considered strategic for the company that owns it and therefore is not to be shared.

About *what* is necessary to integrate (see Fig. 3) there seems to be a first level of integration that is made up from the incoming real data from on-line sensors and/or other sources.

Typically, the knowledge that is integrated is:

1. Data from sensors.
2. Knowledge used in decision making.
3. Knowledge from people related to the EDSS.

About the *how* aspect of its integration we distinguish several steps that we have named *classification*, *correlation* and *search*. Usually the methods in charge of this first step of acquisition and integration are some form of *classification process*. Classification aims at data complexity reduction and at increasing the level of abstraction in the description of the knowledge sources. In fact, the resulting description of a classification process implies change in the description language that evolves from a data language to a knowledge description language. Ideally this knowledge description language should adhere to the ontology of the domain.

Once a classification is obtained a second step takes place. What we call the *correlation step* boils down to the use of the indexation produced by the classification process to create abstract types of objects as classes and/or prototypes that can be used in reasoning during the decision-making process. In the correlation phase, it is important to discover the existing relationships between abstract objects and the intended decisions. This involves some type of knowledge validation. It is typical to measure how the use of an abstract object impacts on the quality of the decisions.

From the point of view of knowledge originating in people, we could see the classification-correlation processes also as a valid way of looking at what is going on in the explicitation of relevant knowledge, that is, at knowledge acquisition. The usual approach [3] is to use the interactions of people with some type of knowledge sharing system to extract new knowledge. This type of systems usually involve some utilities for messaging, document searching, expertise location, conferencing, etc. In that case the task of classification mines user-generated information in order to spot chunks of documentation that relate to the important concepts used in decision-making or that are associated with environment problems descriptions and solutions. Clustering processes for finding relevant groups of documents related to concepts, problems and process states or possible solutions are used in that classification step. Correlation here usually takes the form of relating classified documents or recommendations with the concepts and parameters that describe the current situation where decision making is taking place. The sources of this human originated knowledge are commonly unstructured and so could make the classification process harder. If, however, an organizational memory is used where the structuring concepts are the same or, at least, related to the ones used in the domain ontologies, then the process is much easier as is the corresponding *correlation* step. If all users of the system share some type of organizational memory where documents are added to and retrieved from, the correlation step has to be able to relate the documents relevant to the current decision-making situation. It is important to note that this memory is not simply a data base or a documentary data base. Instead, it tends to be a very structured knowledge base built upon documents generated as products of the day-to-day operation of the organization. Progress reports, anomaly reports, project descriptions, etc. are analyzed in order to extract the relevant knowledge and are related to organization-wide ontologies that allow very sophisticated searching.

One typical way of setting this systems is adopting the Knowledge Pump perspective [19] where interest and competence of people with reference to a given set of topics (related to the operation of the organization) are evaluated in terms of which types of documents from the organizational memory are browsed by a person (which is taken as a measure of his or her interested in the topic) and which documents are contributed by that person (which are taken as a measure of his or her competence in the main topic of the document). Of course, this idea is being extended to sources of knowledge other than documents, for example, using mail messages related to a topic or contributions to bulletin boards. The important thing is that a set of knowledge coming from humans (documents, mail, and so on) is analyzed and classified in relation to the ontology of the organization and then they can be searched in a very sophisticated way (as for example by *recommender systems* where the process of searching and its results vary according to the previous interests and competence of each single user). Usually correlation is made here in a different, not so automatic way, which usually amounts to locating the person in possession of a given knowledge and jointly deciding which course of action to take. However, there are systems that try to integrate both levels of decision making: the one that is more related to the automatic operation of the system and the one that involves negotiation between humans. The component that allows the bridging of the two systems is the common ontology used to classify knowledge at both levels.

5. Integrating technologies: the role of ontologies and tasks

In the search phase, the Knowledge Management System will select the relevant complementary information for the decision-making process. Also, in this phase, there is a task devoted to finding and organizing the context dependent information. We can identify this phase as a first step towards the construction of an ontology [20]. This methodological approach suggests that large knowledge-based systems should be organized (integrated) in order to facilitate knowledge acquisition and maintenance. This is clearly related with the notion of Knowledge-Level Model [25]. About how to integrate knowledge, the processes are more complex and most of the involved tools and methods are necessarily specialized for each domain (see Fig. 4).

The integration of raw data is usually carried out by means of a kind of data structures ranging from Data Bases to Knowledge Bases. More elaborated structures, as ontologies, are important as they include both data and knowledge. An ontology provides the means for describing explicitly the conceptualization behind the knowledge represented in a knowledge base. Ontologies are effective ways to unify terminology in a given domain. That is, they provide a means for common domain modeling. All this integration will lead the EDSS towards the extensive use of domain models in the sense of components of expertise [35]. These models should reflect both the operational and strategic knowledge embedded in the system and used by the people around it. This integration of knowledge structures and methods describes the domain's deep knowledge level.

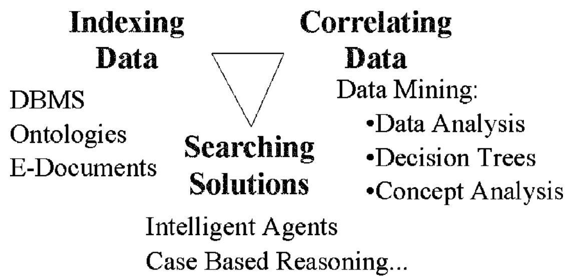

Fig. 4. Integrating technologies: How?

During the integration phase the notion of task is important. A task is an abstract description of what is needed to do in order to achieve an objective. Usually, tasks are decomposed following a top-down approach, and described by means of an and/or tree. Once tasks are decomposed they have to be distributed among agents. The general description of a task includes its name a short description, input and output, task structure, its control, preconditions and the required conditions and capabilities of the performer (an agent). In the integration phase correlation takes profit of the existing data or knowledge structures. The use of unsupervised discovery methods as for example: Data Mining, Knowledge Discovery, etc. helps to build new ways to interpret the domain. The problem-solving methods apply domain knowledge to accomplish an intended task. In general, they perform two functions: divide a task into a number of sub-tasks or directly solve a sub-task. In either case, they can consult domain models; create or change intermediary problem-solving structures; perform actions to gather more data, for example, by querying the user or performing a measurement (see Fig. 2); and expand the problem solving situation model by adding or changing facts. This integration and distributed problem solving is able to cope with the supervision of the different tasks of the system, to deal with any kind of data gathered from the process (quantitative and qualitative), and to include different types of knowledge co-existing in the domain: numerical, experiential, and predictive. The task of co-ordination among the different levels of abstraction could be performed by an agent that is responsible for detecting interdependencies between agents' activities, this assures a correct distribution of tasks in the decision-making process.

6. Agents and the decision-making process

The decision making process relies on a cycle that includes: recognition of the causes of an event (diag-

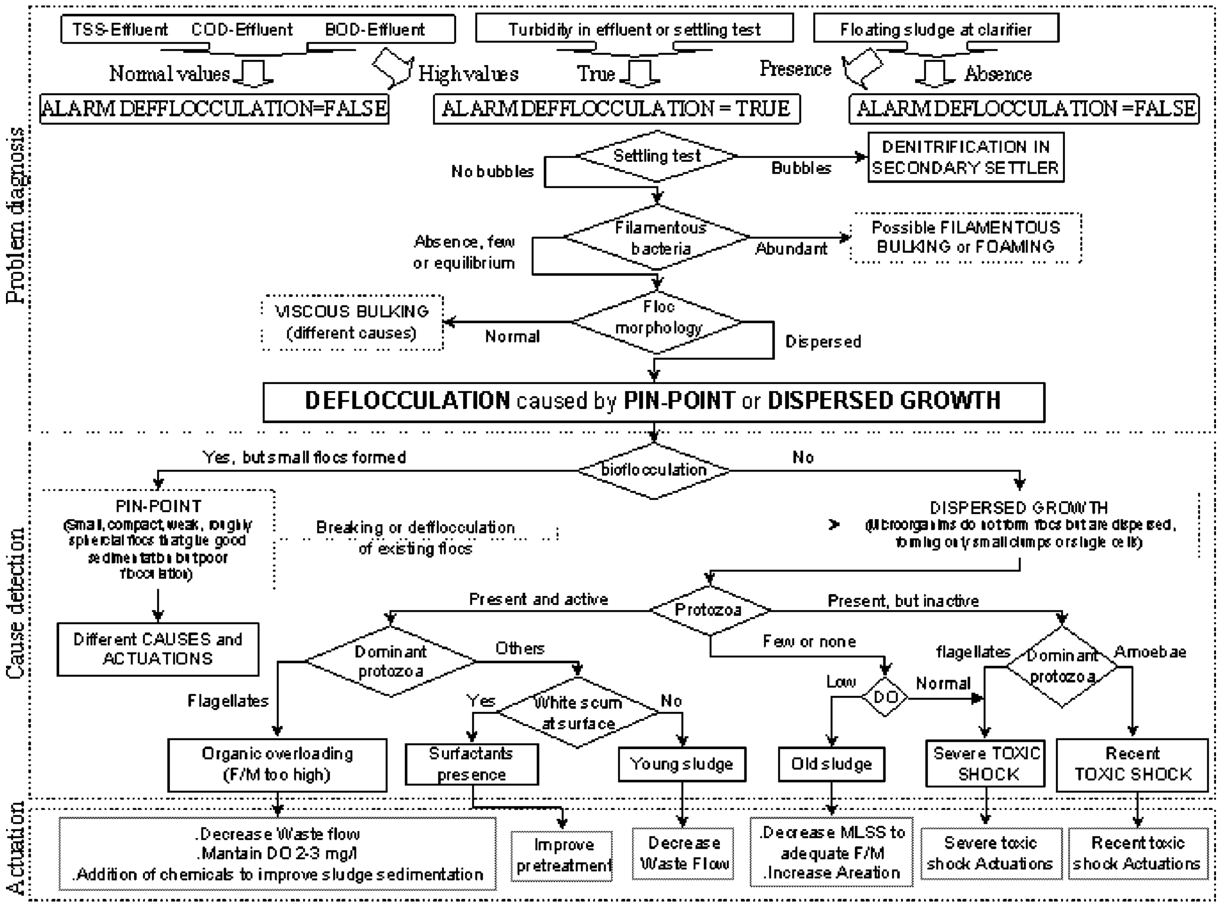

Fig. 5. Decision tree to deal with deflocculation problem in wastewater treatment plants.

nosis) or the causes for a future event (prediction), plan formation to solve the incidences and, execution of the selected actions. Any agent that performs its activities in a changing world must model that world internally. We put forth here a general framework based on agents in order to support all this cycle. The whole EDSS will be a set of cooperating agents, that is a MultiAgent System. The existence of an appropriate ontology is assumed as the completion of the task decomposition step. Several different alternatives for agent-based systems are possible to implement a decision-making system. Some agents can model aspects of the world in a explicit way and reason about them. In other multi-agent systems, these models are often distributed throughout the architecture as the model is not always needed to identify local changes or to solve local problems [16]. Figure 5 shows a decision tree that integrates part of the information that DAI-DEPUR [31] uses to take decisions. Although it refers to a very specific case in the Wastewater Treatment process, it shows the flow of information from sensors and laboratories (on the top) towards the Reasoning components. This figure shows different kinds of knowledge facilities that have to be used and coordinated using very precise communication protocols. The modeling of different kinds of knowledge or domain theories into separate levels provides the architecture with the additional modularity and independence that are required to achieve generality. The main reasons for interconnecting autonomous agents and expert systems, as shown in Fig. 6, are: to enable them to co-operate in solving problems, to share expertise, to allow parallel work, to take profit of modularity, to allow the system to be fault tolerant through redundancy, to catch and take profit from multiple viewpoint and knowledge/expertise of multiple experts, and to be reusable. Many EDSS could be analyzed as Cooperative Information Systems [40] where agents are used to cope with the different sources of information and the different tools used for problem-solving (see Fig. 6). For EDSS to be able to co-operate

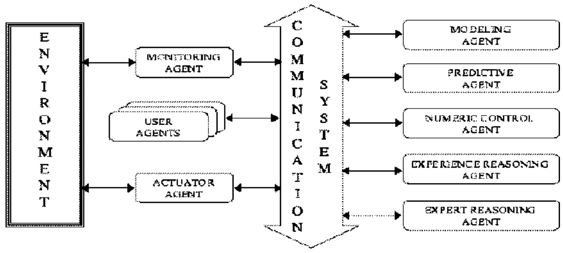

Fig. 6. Cooperation among agents.

they must have an intelligent interface that can cope with all types of requests and eventualities. Through this interface the system can communicate with other systems and reason about the information it contains. In this perspective, agents are given with meaningful units of work or tasks to be solved. Performing a task in many situations involves to initiate a communication with other agents. The design of the communication protocols among the different agents is decisive in the system's performance. A communication protocol determines how illocutions among agents are structured. Agents may simply give orders to others and expect them to be executed, in other cases negotiation or more complex exchanges can take place. The communication channels through which information moves from one agent to another can differ in many ways as for example:

- The medium (Internet or local nets).
- The form of addressing (broadcast, black-board, subject-based, personal communication, etc.).
- The locality.
- The persistence of the communication (How long?).

When something fails in this integration process then an impasse situation is produced. Failures can occur for example when an agent is unable to finish its task or to deliver the results of their task on time. As said before, the use of specific ontologies is one possibility to reduce the number of unsolved impasses. Plan formation requires co-operation between the different agents or knowledge-based systems (see Fig. 6). Agents are autonomous in the sense that they perform their tasks regardless of whether they are required or not. Moreover, we assume a hierarchical coordination where commands flow down the agent hierarchy and status information flows bottom-up. In these systems each agent usually owns an agenda containing the actions to be performed and the agent's objectives. This agenda helps the agents to build plans and to accept tasks from the manager.

The distribution of tasks can improve the system performance. Durfee [14] indicates that the combination of efforts brings:

- Confidence: Independent derived results can be used to corroborate each other, yielding a collective result that has a higher probability of being correct.
- Completeness: The union of the different subtask results can cover a greater proportion of the overall task.
- Precision: To refine its own solution, an agent needs to know more about the solutions that others have formulated.
- Timeliness: Solving subtasks in parallel can yield an overall solution faster.

For EDSS the best mechanism for task distribution are:

- Multi-agent planning: i.e., planning agents have the responsibility for task assignment.
- Agency structure: i.e., agents have fix responsibilities for particular tasks.

In this phase, the reasoning components of each agent in the system have to perform its assigned task.

7. Conclusions

Solutions for efficient Knowledge Management in Environmental Decision Support Systems have to be developed. As we have shown one has to consider the great variety of data, and the strong dependencies of environmental processes on local constraints, such as weather conditions, climatic aspects, geographical positions, environmental and/or health law regulations, etc. Methods, Models and Tasks are means to ensure desirable Knowledge-Based behavior and are crucial elements of the Knowledge-Based Systems design [35]. These represent the components of expertise needed to handle the problem. In Fig. 7, we advance a proposal to combine those components of expertise to build EDSS. Advances in the area of Model-Based Reasoning are very promising [24] and specific models are to be developed for this field. Environmental problems require models of a great generality, precision (if possible) and realism. Agent-based architectures introduce a powerful metaphor in the field of EDSS as agents integrate a collection of functionalities, achieved by the interplay about certain problem types and about the environment in which those agents

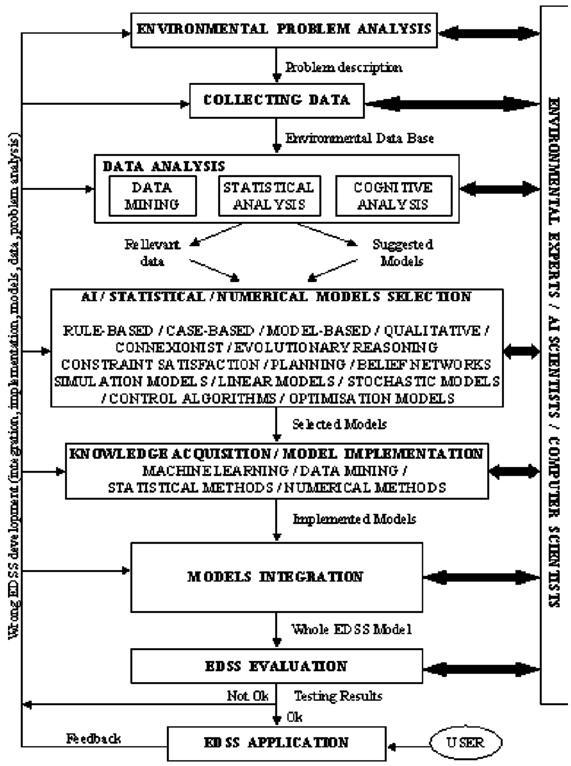

Fig. 7. EDSS development process.

operates. This allows the system to react to the changes of the environment and new situations and it is able to interact with other agents looking for an answer. The use of multi-agent systems to distribute problem solving demands both group coherence and competence. As stated the methodological use of Knowledge Management in Environmental Decision Support Systems is an open field of research in which a first attempt is the one reported by I.R.-Roda [30].

From our point of view, Knowledge Management in EDSS research has to deal with the following issues:

– Techniques for the effective integration of several data, knowledge and AI techniques.
– Improved knowledge acquisition methods.
– Ontologies or equivalent paradigms to represent better the knowledge over the Environmental system.
– Development of specific coordination models for Environmental problems.
– Intelligent sharing and reuse of knowledge.
– Reuse of EDSS generic models and tasks.
– Security issues.
– Validation procedures.
– Definition of performance metrics.
– Definition of agent performance measures.

In Fig. 7 you can see depicted an EDSS development process following the methodology proposed in [30]. The collection of data, data analysis and model selection phases clearly answer the question: what kind of technologies are needed? The rest of the model implementation, model integration and EDSS evaluation phases answer to the question: how to integrate those technologies? In our opinion this represents an easy way to transport and reuse past experiences from an environmental process to another. Also this methodology is general enough to be applied to other fields where complex processes exist. We have to keep in mind that environment is a critical domain where wrong management decisions may have disastrous economic and/or environmental consequences. EDSS are important tools to understand our environment and to design the development of our societies to be sustainable. EDSS can play a key role in the interaction of man and environment, as they have to cope with the multidisciplinary nature and high complexity of environmental problems, and so they result in a very fruitful field of work.

Acknowledgements

We acknowledge the support of and of the Spanish CICyT project AMB97-889. The European Union project IST-1999-176101. The views in this paper are not necessarily those of the A-TEAM consortium.

References

[1] N.M. Avouris, Co-operating knowledge-based systems for environmental decision-support, *Knowledge-Based Systems* **8**(1) (1995), 39–53.

[2] C. Collison, BP Amoco's knowledge repository: connecting the new organization, *Knowledge Management Review* (7) March-April (1999).

[3] U. Borghoff and R. Pareschi, *Information Technology for knowledge management*, Springer Pub. Co., Berlin, 1998.

[4] K. Branting, J.D. Hastings and J.A. Lockwood, CARMA: a pest management advisory system, *AI Applications* **11**(1) (1997), 29–48.

[5] V. Brilhante, Using formal metadata descriptions for automated ecological modeling, in: *Environmental Decision Support Systems and Artificial Intelligence, AAAI-Workshop, WS-99-07*, 1999, pp. 90–95.

[6] L. Ceccaroni, U. Cortés and M. Sànchez-Marrè, An ontology embedded into an environmentaldecision-support system for wastewater treatment plant management, in: *Workshop on Applications of Ontologies and Problem Solving Methods, ECAI '2000*, 2000.

[7] U. Cortés, M. Sànchez-Marrè, L. Ceccaroni, I.R.-Roda and M. Poch, Artificial Intelligence and Environmental Decision Support Systems, *Applied Intelligence* **13**(1) (2000), 225–239.

[8] U. Cortés, M. Sànchez-Marrè, L. Ceccaroni, I.R.-Roda and M. Poch, Artificial Intelligence and Environmental Decision Support Systems, *Applied Intelligence* **13**(1) (2000), 225–239.

[9] U. Cortés and M. Sànchez-Marrè, Binding environmental sciences and artificial intelligence in environmental modelling and software, *Environmental Modelling & Software* **14**(5) (1999), 335–337.

[10] U. Cortés, M. Sànchez-Marrè, I.R.-Roda and M. Poch, Towards Environmental Decision Support Systems, in: *Workshop on Environmental Decision Support Systems*, U. Cortés and M. Sànchez-Marrè, eds, WS-99-07, AAAI Press, 1999.

[11] J. Cuena and S. Ossowski, Distributed models for decision support, in: *Multiagent Systems*, G. Weiss, ed., MIT Press, 1999.

[12] T. Davenport and L. Prusak, *Working Knowledge*, Harvard Bussiness School Press, Boston, 1998.

[13] P.F. Drucker, *The Coming of the New Organization*, Harvard Business School Press, 1988.

[14] E. Durfee, Distributed problem solving and planning, in: *Multiagent Systems*, G. Weiss, ed., MIT Press, 1999.

[15] K. Fedra and L. Winkelbauer, A hybrid Expert System, GIS and Simulation Modelling for Environmental and Technological Risk Management, in: *Environmental Decision Support Systems and Artificial Intelligence, AAAI-Workshop, WS-99-07*, 1999, pp. 1–7.

[16] J. Ferber, *Les Systèmes Multi-Agents: Vers une Intelligence Collective*, Intereditions, France, 1995.

[17] L. Gasser, Social conceptions of knowledge and actions: DAI foundations and open systems semantics, *Artificial Intelligence* **47** (1991), 107–138.

[18] J.M. Gimeno, J. Béjar, M. Sànchez-Marrè, U. Cortés and I.R.-Roda, Modelling WWTP dynamics by means of transition networks, in: *BESAI '98*, 1998, pp. 121–135.

[19] N.S. Glance and A. Grasso, Collaborative document monitoring via a recommender system, in: *Proceedings of International Workshop on Agent-Based Recommender Systems, Fourth International Conference on Autonomous Agents*, R. Sangüesa and U. Cortés, eds, Barcelona, Spain, 2000.

[20] T. Gruber, A translation approach to portable ontology specifications, *Knowledge Acquisition* **5** (1993), 199–220.

[21] D. Heeney, L. Muprhy and L. Prusak, From waste management to knowledge management, in: *Americana 99*, Montreal, Canada, 1999.

[22] E. Jones and A. Roydhouse, Retrieving structured spatial information from large databases: a progress report, in: *Procc. of IJCAI Workshop on Artificial Intelligence and the Environment*, Montreal, 1995, pp. 49–57.

[23] Knowledge Sharing Effort, http://www.cs.umbc.edu/kqml.

[24] M.H. Lee, On models, modelling and the distinctive nature of model-based reasoning. *AI Communications* **12**(3) (1999), 127–138.

[25] A. Newell, The knowledge level, *Artificial Intelligence* **18** (1982), 87–118.

[26] I. Nonaka, *The Knowledge Creating Company*, Harvard Bussines Review Press, Boston, USA, 1998.

[27] D. Riaño, M. Sànchez-Marrè and I.R.-Roda, A wastewater treatment plant multiagent system. Practical application of agents and multiagent systems, in: *3rd World Multiconference on Systemics, Cybernetics and Informatics (SCI '99)*, 1999.

[28] A.E. Rizzoli and W.Y. Young, Delivering environmental decision support systems: software tools and techniques, *Environmental Modelling & Software* **12**(2-3) (1997), 237–249.

[29] I.R.-Roda, J. Comas, J. Colprim, J. Baeza, M. Sànchez-Marrè and U. Cortés, A multi-paradigm decision support system to improve wastewater treatment plant operation, in: *Environmental Decision Support Systems and Artificial Intelligence, AAAI-Workshop, WS-99-07*, 1999, pp. 68–73.

[30] I.R.-Roda, Desenvolupament d'un protocol per l'applicació de sistemes basats en el coneixement a la gestió d'estacions depuradores d'aigües residuals urbanes, PhD Thesis, University of Girona, 1998.

[31] M. Sànchez-Marrè, U. Cortés, I.R.-Roda and M. Poch, Sustainable case learning for continuous domains, *Environmental Modelling & Software* **14**(5) (1999), 349–357.

[32] M. Sànchez-Marrè, U. Cortés, I.R.-Roda, M. Poch and J. Lafuente, Learning and adaptation in WWTP through case-based reasoning, *Microcomputers in Civil Engineering* (Special issue: Machine Learning) **12**(4) (1997), 251–266.

[33] M. Sànchez-Marrè, U. Cortès, J. Lafuente, I.R.-Roda and M. Poch, DAI-DEPUR: a Distributed Architecture for Wastewater Treatment Plants Supervision, *Artificial Intelligence in Engineering* **10**(3) (1996), 275–285.

[34] H.A. Simon, *The Sciences of the Artificial*, 3rd edn, MIT Press, 1996.

[35] L. Steels, Components of expertise, *AI Magazine* **11**(2) (1990), 28–49.

[36] G. Stephanopoulos and C. Han, Intelligent Systems in process engineering: a review, *Comp. Chem. Enging.* **20**(6-7) (1996), 743–791.

[37] A.J. Thomson, Artificial Intelligence and environmental ethics, *AI Applications* **11**(1) (1997), 69–73.

[38] R. Tissen, F. Lekanne Deprez and D. Andriessen, *Value-Based Knowledge Management*, Addison-Wesley Publishing Company, 1998.

[39] K. Tochtermann and H. Maurer, Knowledge Management and Environmental Informatics, *Journal of Universal Computer Science* (6) (2000), 517–520.

[40] E.M. Verharen, F. Dignum and S. Bos, Implementation of a cooperative agent architecture based on the language-action perspective, in: *Intelligent Agents IV*, M.P. Singh, A. Rao and M. Wooldrige, eds, LNAI 1365, 1998, pp. 31–44.

[41] G. Weiss, ed., *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*, MIT Press, 1999.

[42] E. Wenger, *Communities of Practice: Learning, Meaning, and Identity*, Cambridge University Press, 1999.

[43] K.M. Wiig, *Knowledge Management: Practical Approaches to Managing Knowledge*, Schema Press, 1994.