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Artificial Intelligence and Environmental Decision Support Systems

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Abstract. An effective protection of our environment is largely dependent on the quality of the available information used to make an appropriate decision. Problems arise when the quantities of available information are huge and nonuniform (i.e., coming from many different disciplines or sources) and their quality could not be stated in advance. Another associated issue is the dynamical nature of the problem. Computers are central in contemporary environmental protection in tasks such as monitoring, data analysis, communication, information storage and retrieval, so it has been natural to try to integrate and enhance all these tasks with Artificial Intelligence knowledge-based techniques. This paper presents an overview of the impact of Artificial Intelligence techniques on the definition and development of Environmental Decision Support Systems (EDSS) during the last fifteen years. The review highlights the desirable features that an EDSS must show. The paper concludes with a selection of successful applications to a wide range of environmental problems.

Keywords: environmental decision support systems, artificial intelligence, problem solving

1. Introduction

The progress in human development is becoming increasingly dependent on the surrounding natural environment and may be restricted by its future deterioration. The increasing population, urbanisation and industrialisation, which our planet has faced this century, have forced society to consider whether human beings are changing the very conditions essential to life on Earth [1]. Environmental science is the interdisciplinary field concerned with man's influence on environmental processes, and, as such, it takes human activity as well as environmental processes into consideration [2]. Human beings' impact on the environment is often termed "pollution" in the broadest sense [3].

As pointed out by several authors, the environment is a complex and dynamic system where different aspects can lead to the same impact (e.g., the emission of global warming gases), while other actions might combine synergistically to create an impact which is much greater than that which would be predicted using a reductionist approach (e.g., nitrogen dioxide and hydrocarbons can react to produce tropospheric ozone). Thus, further analysis is required to assess the likely impacts that the significant aspects will have [4].

The problem of global change is complex in nature and may be represented by various interactions that operate on different spatio-temporal scales. Addressing these issues demands an integrated consideration of relevant interactions between humans and the environment [5].

Information technologies have played an increasing and central role in the planning, prediction, supervision and control of environmental processes at many different scales and within various time spans. At the same time, organisations, industries (e.g., the ISO14001, the European standard EMAS, etc.) and governments (pioneered by the 1969/70 National Environmental Policy Act (NEPA) of the United States) have started to take on a more proactive relationship with the environment by introducing appropriate legislation calling for the explicit consideration of environmental impact in the planning and decision-making process for large projects (e.g., Kyoto Summit, Agenda 21 or, the Rio do Janeiro Declaration) [6]. During the last two decades, the fast developments in information technologies and the rapid development of new and faster hardware made the establishment of interdisciplinary research links between environmental and computer scientists possible and very fruitful.

A new discipline, known as Environmental Informatics [7], which combines research fields such as Artificial Intelligence, Geographical Information Systems (GIS), Modelling and Simulation, User Interfaces, etc., is emerging. An important and difficult task for this new area is to serve as a catalyst for the integration of data, information, and knowledge from various sources in the environmental sector [8, 9]. In this paper, we will explore the Artificial Intelligence contributions to the field.

1.1. Organisation of this Paper

The goal of this paper is to show how Artificial Intelligence in particular and Information Technologies, in general have succeeded in developing adequate tools for modelling, design, simulation, prediction, planning and decision-support systems for environmental management and protection.

Many environmental problems, such as damage to the biosphere, local air pollution, the spread of harmful substances in the water, and global climatic changes, cannot be studied by experimentation. Hence, mathematical models and computer simulations are being used as the appropriate means to get more insight. In the review, we will not study the field of Environmental Modelling as very little has been developed using AI techniques and tools. A pioneering work in this field is by Robertson et al. [10] who tried to give a Eco-Logic approach to the problem. For more information about this field, the work by P. Zannetti [11] is recommended.

Another hot and important issue is that of integrating Geographical Information Systems (GIS) to address more global processes. It is recommended that the reader consult the work by K. Fedra [12, 13] and M. Goodchild [14, 15].

We will organise our review of Artificial Intelligence techniques applied to environmental problems into three broad categories:

- Data Interpretation and Data Mining techniques involve screening data to detect patterns, to identify potential problems or opportunities, or to discover similarities between current and past situations. These processes help to improve our understanding of the relevant factors and their relationships, including the possible discovery of non-obvious features in the data. From these processes it is also possible to learn new situations (see §4)
- Problem Diagnosis techniques try to recognise characteristic symptoms in order to develop and confirm hypotheses about possible causes. They can also be used to suggest strategies for repair or recovery based on the available knowledge (not always complete) and/or on past experiences. (see §5)
- Decision Support techniques involve evaluating alternatives to explore their possible consequences, to compare their relative costs and benefits, and to recommend appropriate action plans. (see §6)

Those categories are not mutually exclusive.

We will also devote a section of the paper to study some interesting and successful applications trying to cover land, air, water, weather, etc. (see §7) and give some pointers to relevant web sites (see §9). The list of references given is not intended to be exhaustive.

2. Artificial Intelligence and Environmental Issues

Artificial Intelligence has been applied to environmental management problems as, for example, in using expert systems advising emergency response teams about how to deal with industrial accidents [16], in using expert systems to assist in granting hazardous waste site

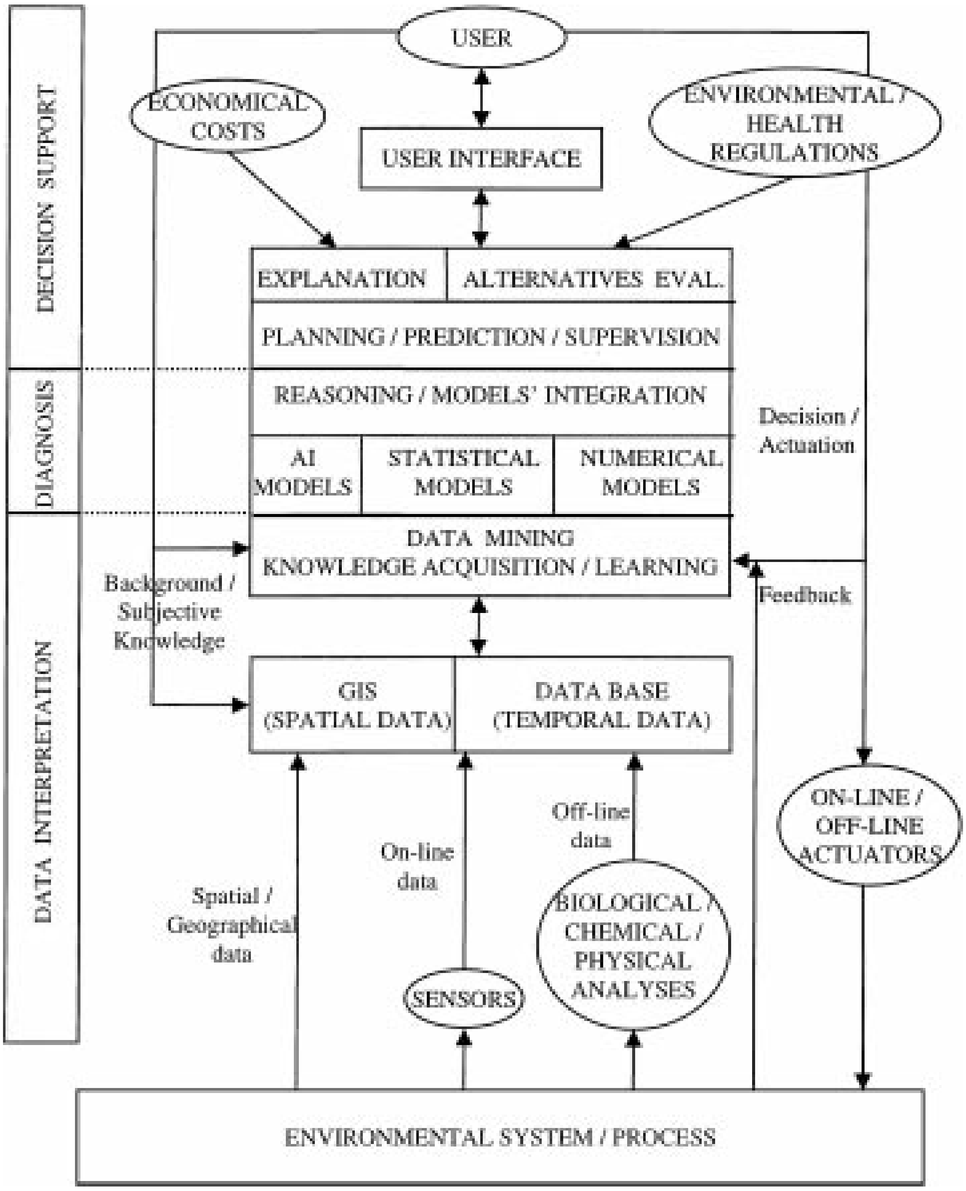

Figure 1. Environmental decision support systems.

permits [17], in modelling water quality [18], fish stock prediction [19], and many other environmental engineering applications [18, 20–22]. The first applications of Expert Systems to environmental issues appeared in the eighties. See, for example, [23–28].

More recently, Artificial Intelligence research has been oriented towards the development of Knowledge-Based Systems (KBS) [29–33]. KBS, when applied to Environmental Issues, receive different denominations such as *Decision Support Systems* (DSS) [34, 35] *Environmental Decision Support Systems* (EDSS) [36] or *Multiple Objective Decision Support Systems* (MODSS) [37] or intelligent assistants (see Fig. 1). Among those names, we chose to use Environmental Decision Support Systems. An EDSS is an intelligent information system that ameliorates the time in which decisions can be made as well as the consistency and the quality of the decisions, expressed in characteristic quantities of the field of application [34].

Ideal decision tools for valid recommendations on land, water, and environmental management must include quantitative and analytical components; must span and integrate the physical, biological, socioeconomic, and policy elements of decision making. They must also be user-friendly and directly relevant to client needs [4, 37, 38].

It is clear that the field of application is central to this point of view. An important feature of these systems is that they allow the use and capture of specialised knowledge from a wide spectrum of natural sciences, and that they can be effectively applied to a variety of environmental management and design activities [39]. This specialised knowledge may include among others: a) empirical knowledge about organisms and their environment; b) situational knowledge about local environmental conditions and their possible relationship with the global environment; c) judgemental knowledge about human beliefs, intentions, desires and priorities; and d) theoretical knowledge about biological, physical and chemical phenomena, etc.

There exists a clear understanding that an EDSS that is able to deal with all these kinds of knowledge can be useful in the environmental management process, which typically consists of four activities in the following order:

1. *Hazard identification*, which involves filtering and screening criteria and reasoning about the activity being considered. This phase may be characterised as a continuous activity of the system looking for possible adverse outcomes and includes the search for further data to enhance its own performance.
2. *Risk assessment*, which involves developing quantitative and qualitative measurements of the hazard. Environmental Decision Support Systems may include the use of numerical and/or qualitative models, which can produce estimations of the degree of potential hazard. Usually, this phase could be accomplished by a Model-based System using model-based reasoning and/or a Knowledge-based System using rule-based reasoning and/or by a Case-based System using case-based reasoning to overcome the heterogeneity of data coming from various sources and with many different levels of precision.
3. *Risk evaluation*. Once potential risks have been assessed, it is possible to introduce value judgements regarding the degree of concern about a certain hypothesis. This is possible if the system has accumulated experience solving similar situations using for exemple a Case-based Reasoning approach, whereby past experience of risk evaluation is used to assist with future judgements.
4. *Intervention decision-making*. The system needs appropriate methods for controlling or reducing risks. The system also requires knowledge about the context where the activity takes place and must be able to interpret its results and knowledge about the risk/benefit balancing methods.

Hazard identification is related mostly to data interpretation and data mining (see §4). Risk assessment and Risk evaluation are related to the problem diagnosis phase (see §5). Intervention decision-making is related to the decision support techniques (see §6).

EDSS play an important role in helping to reduce the risks resulting from the interaction of human societies and their natural environments. Some of the reasons are as follows:

- The multidisciplinary nature of environmental problems. It implies cooperation among various elements (modules) of the EDSS, each one specialised in a given topic or a certain kind of model.
- The complexity of environmental problems. In this context, it is often necessary to understand, in limited time, physical and biological processes in relation to socio-economic conditions and applicable legislative frameworks. EDSS may provide fast solutions integrating all those issues.

This interdisciplinary field has attracted the interest of researchers and an increasing number of workshops have been organised to give relevance to these efforts. For example, the AIRIES series of workshops, BESAI'98 [40], IJCAI-95 [41], AAAI'94 [42], the ENVIRONSOFT series [11]; or the events coordinated by the IFIP Working Group 5.11 `Computers and Environment` [30]. Also, there are a growing number of specialised publications and research projects (see §9) that pay greater attention to this blooming area.

3. Environmental Decision Support Systems

Following the classification proposed by Rizzoli and Young [36], Environmental Decision Support Systems can be divided into two clearly separate categories: problem specific EDSS and situation and problem specific EDSS. *Problem specific EDSS* are tailored to relatively narrow environmental problems (or domains), but they are applicable to a wide range of different locations (or situations) in the best tradition of KBS. *Situation and problem specific EDSS* are tailored both to a specific environmental problem and to a specific location. These EDSS cannot easily be applied in a new location, as many KBS can.

In addition, in the same paper, Rizzoli and Young identify a set of desirable features for an ideal EDSS that are classical in any Knowledge-Based System (KBS):

1. The ability to acquire, represent and structure the knowledge in the domain under study.
2. The ability of the knowledge base (or domain base) to separate data from models (for model re-usability and prototyping).
3. The ability to deal with spatial data (the GIS component).
4. The ability to provide expert knowledge specific to the domain of interest.
5. The ability to be used effectively for diagnosis, planning, management and optimisation.
6. The ability to assist the user during problem formulation and selecting the solution methods.

An EDSS can be described as a multi-layered system connecting the user, probably an environmental scientist, with an environmental system or process. See Fig. 1, where a chart of an EDSS is depicted. The first layer is formed of the knowledge acquisition and learning module from spatial (GIS) and temporal data base. Several AI, statistical and numerical models constitute the next layer. The next levels are the reasoning and integration modules that use several kind of models and knowledge to implement a predictive, planning or supervisory task over the environmental system. Finally, the upper level illustrates the interaction of the user with the EDSS. The user may ask it for justifications and explanations of suggested decisions and possibly validation of plausible alternatives to make a better decision.

The development of an EDSS as a complex integrated KBS relies on the idea of model refinement [43]. Every stage in the development process involves a relatively straightforward step of transformation from one model to the next. That is, from requirements to conceptual model, from conceptual model to design model, and from design model to code. In Fig. 2, a scheme of the ideal cycle of development of an EDSS is shown.

Of course, in all the cycle of an EDSS development, the cooperation among environmental experts, computer scientists and AI scientists should be needed. In the first step, the environmental problem must be analysed to get a more accurated problem description. From that description, from the environmental process itself and from environmental experts' criteria, an environmental database should be built to perform a systematic analysis. This broad analysis can include cognitive understanding, statistical and data mining techniques to obtain the relevant data, the correlation among the variables involved, and a list of possible models. The next step is to select a set of methods and models that cover all kinds of knowledge and functionalities needed for the decision-making process. Once the models are selected, they must be fully implemented by means of machine learning, data mining, statistical or numerical techniques. After that, those models must be integrated to build the final whole EDSS. The EDSS must be tested to check its performance, accuracy, usefulness and reliability, both from the user's and AI/computer scientist's point of view. If there is any wrong feature in any development stage, such as models' integration, models' implementation, selection of models, database, problem analysis, etc., the developers must come back in the flow and update the required components. When the evaluation phase is all right, the EDSS is ready to be applied to the environment.

The great contribution of Artificial Intelligence to EDSS is the integration of several methods [44–46] complementing the classical statistical models (simulation, statistical analysis, linear models, etc.) and numerical models (control algorithms, optimisation techniques, etc.). This cooperation makes the resulting systems more reliable and powerful in coping with real-world environmental systems.

Among the AI methods often used in the development of EDSS in past years, the following are worth noting:

- Rule-Based Reasoning [23, 26, 47, 48].
- Planning [44, 49–51].
- Case-Based Reasoning [20, 45, 52, 53].
- Qualitative Reasoning [54–57].
- Constraint Satisfaction [44, 58, 59].
- Model-Based Reasoning [60–63].
- Connexionist Reasoning [64–67].
- Evolutionary Computing [68–71].
- Fuzzy Logic Techniques [72–75].

4. Data Interpretation and Data Mining

Data Interpretation has been a principal area of research in AI since the very beginning. The most demanding problem in the environmental assessment context

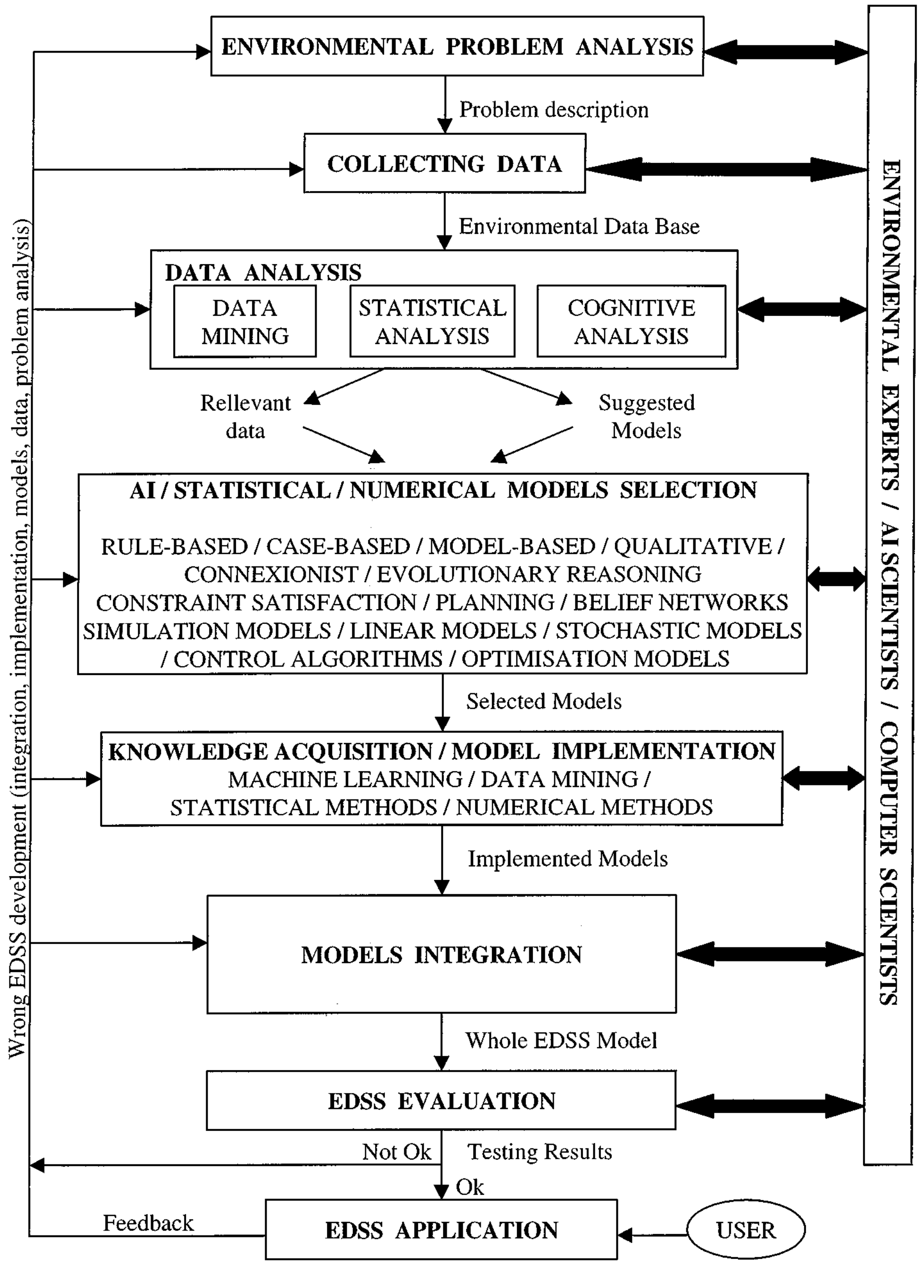

Figure 2. Development of an EDSS.

concerns the derivation of requested information from existing data (see below).

Knowledge Representation permits the definition of the different types of data that the existing methods adapt to the process. There is also a lot of work to clean, repair and transform the huge available quantities of raw data. Apart from this, the availability of meta-information or background knowledge is required to prune or guide the process.

Data mining is multi-disciplinary: it covers expert systems, database technology, statistics, data visualisation, and unsupervised machine learning. These techniques operate at the level of data and background information, where numerous and often incompatible non-commensurate pieces of information from disparate sources have to be brought together. See the lower layer in Fig. 1.

The data involved in an environmental decision problem will exhibit one or several of the following characteristics:

- Diverse data—These data will range from biophysical (climate, ecology, biology), through resource use (current and potential), economics, and policy (zoning, environmental and health regulations) to social preferences and goals.
- Variable levels of data detail, analytical detail, and data volumes—The size of the decision problem, the number of options, and the level of analytical detail required will dictate the size of the database and knowledge base.
- Unanticipated types of data—As technology and the comprehension of the problem advance, new types of data may appear (and some others may become irrelevant) and the system must support new ways to interpret them. Usually, these changes are expensive and time-consuming.
- Data redundancy—To augment the performance of certain kinds of data interpretation or inference processes, data redundancy may be suitable, but it may lead to inconsistent forms of the same data.

Usually, the transition from data to information requires an appropriate application of algorithms on data and needs to be supported by an appropriate model or theory of the application domain. Models may have to be calibrated, algorithms may have to be parameterised, etc. These tasks are very demanding and require massive knowledge processing and the availability of an appropriate model base [7, 76].

Integrating data means overcoming the heterogeneity caused by the variety of operating data systems, data formats and documentation conventions, program interfaces and software tools.

5. Problem Diagnosis

Following the schema proposed by Simon [77], any decision process can be decomposed into four basic phases: intelligence, design, choice, and implementation.

Intelligence means performing an initial exploration within the decision context (decision space). This involves looking up necessary data (see §4), isolating the raw material of the decision process –including the identification of the parties to the decision– and, most importantly, identifying the problem domain as precisely as possible. The design and choice phases are both creative processes. The first implies that different but feasible (plausible) solutions to the actual problem are created and analysed to determine the extent to which the solution solves the problem and its cost. From these alternative solutions, a plan is selected (see §6) in the choice phase —using most of the times a Case-Based Reasoning— and is executed. Its performance is monitored and stored (learned) if it gives new or relevant information (positive or negative) to the system itself or to the users [78].

The EDSS may use expert systems (simple rule-based algorithms or sophisticated fuzzy logic and uncertainty-based algorithms) [47, 79], empirical models (more or less statistically based) [33, 80], Bayesian or causal networks [60, 63, 81], or sophisticated deterministic or process-based models [55, 82–84]. See the middle layer in Fig. 1.

This progression in complexity of the methods usually corresponds to an increase in data required to support the models (see Fig. 3, adapted from [85]). The models – which are not always complete– may be used independently or as linked components of the decision process.

Expert systems have played an important role in supporting environmental decision-makers [18]. Although many applications still rely on them, the current tendency is to create agents that can employ the compiled past experience in specific areas that they can deal with, facilitating the users' tasks. In addition, expert systems provide objectivity in this highly subjective problem-solving context [86].

Another approach is that of Cooperating Knowledge-Based Systems (CKBS) [87, 88]. Given the interdisciplinary nature and decentralised management of environmental problems, the cooperation among several experts is necessary to cope with all the variables and issues both on the local and global levels. Distributed Artificial Intelligence offers a wide range of possibilities.

The typical result of this process is the choice of the level and of a formal method of description that can only be interpreted by a human or an EDSS using a general solution strategy such as: analogy or case-based reasoning to find similar, already-solved problems; redefinition of the problem (if necessary) using different

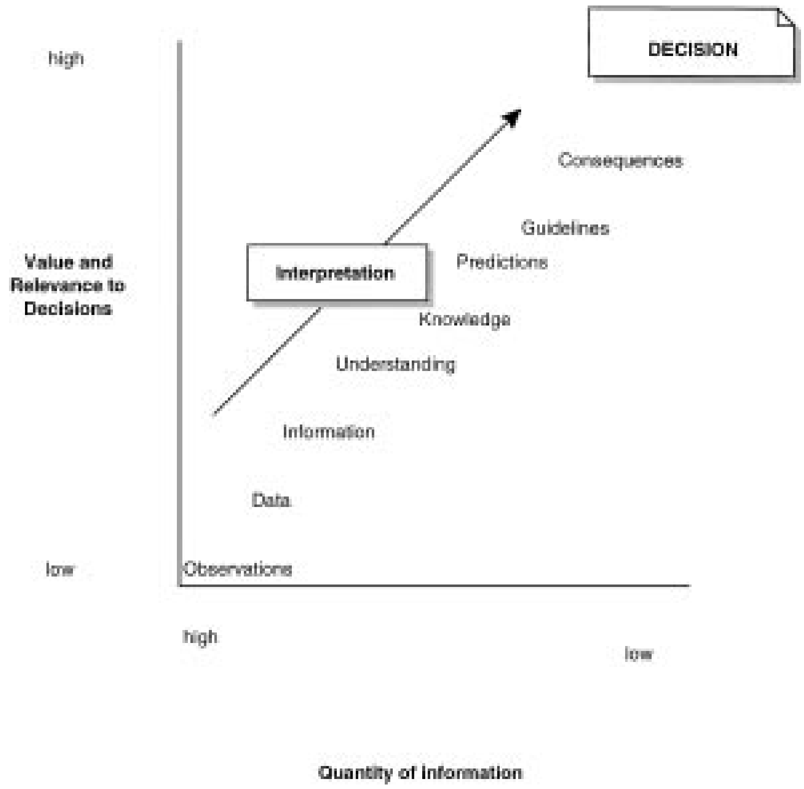

Figure 3. Information and decision.

but known terms; or deduction of a particular strategy from an existing one.

6. Decision Support Systems

Let us recall the first definition we gave of an EDSS as an intelligent information system that ameliorates the time in which decisions can be made as well as the consistency and the quality of the decisions. These systems directly support decision-makers by offering criteria for the evaluation of alternatives or for justifying decisions. The inter-operation with different partners must be interactive, user-friendly, fast and efficient. See the upper layer in Fig. 1.

With the increasing maturity of Artificial Intelligence techniques, in particular those related to Knowledge Engineering, new dimensions in assisting users in environmental decision making are available. For example, many environmental systems are characterised both by incomplete models and by limited empirical data. Accurate prediction of the behaviour of such systems requires exploitation of multiple, individually incomplete, knowledge sources. The application of multiple complementary problem solving techniques (i.e., Case-Based Reasoning and Constraint Satisfaction) [53, 59, 89], can often help to reduce this uncertainty.

In Artificial Intelligence, this situation is often referred to as having an ill-structured domain [10]. The relationships among the concepts or attributes of the domain are not well enough known and there is not much agreement among the experts. The relationships among the various phenomena that characterise the system are insufficiently understood. The multifaceted nature of the environmental problems invariably emerges when it is necessary to make a choice among different plausible solutions.

Conflict is inherent in environmental problem solving. The complexity of the fields and the multiplicity of views and interests involved call for mechanisms of reconciliation of disparate, often conflicting goals and contradictory information [37]. Sociologists, when modelling the process of environmental decision making, identify the existence of conflict and advocate the importance of negotiation and consensus making in this process [9].

Nevertheless, EDSS have an important role in these processes by deriving in a systematic, economic, and fast way the possible consequences of decisions for the environment.

7. Applications of Environmental Decision Support Systems

In this section, we will describe some Environmental Decision Support Systems. The selection includes examples ranging from Expert Systems to Distributed Environmental Decision Support Systems and applications to water, land, weather, etc. Of course, this selection is incomplete, but we understand that it will be enough to provide a good vision about the actual state of the art in EDSS.

At the level of tools, the most important characteristic is the level of integration, ranging from simple file transfer between different methods and programs to fully integrated systems. It can be expected that these kinds of systems may be designed as distributed systems.

OASIS, Operations Assistant and Simulated Intelligent System [90] was an Artificial Intelligence system designed to support the South Florida Water Management District, which operates more than 200 water structures along 3200 km of primary channels in a region of about 46,000 km^2. The system was an expert system written in LISP and developed on special hardware (a Symbolics 3640). The KB was constructed in IF-THEN fashion. It contains the company's experience acquired in more than 15 years of operation.

STORMCAST [91] is a loosely coupled distributed artificial intelligence application where typical hard real-time responses are not needed. StormCast has been built to support storm forecasting over the Scandinavian Peninsula. It may be described as a set of co-operating agents, which continuously collect and process weather data from a fixed geographical area. At each location, there is an expert module (i.e., a KBS) responsible for the prediction of severe storms. This severe storm forecasting is based on the results achieved from the monitoring agents in their own areas. This emphasises the problem solving at a local level.

MEXSES [92] is a rule-based expert system for environmental impact assessment at a screening level, implemented for the analysis of water resources development projects in the Lower Mekong Basin. The system includes diverse AI techniques such as qualitative or rule-based reasoning for the analysis of complex environmental assessment problems. The rules are in IF-THEN and WHY forms, the latter allowing the user to trace the symbolical reasoning of the system step by step. The system has an integrated geographical information system for the management of spatial environmental data. This application was the starting point for other very attractive projects such as GAIA [93].

FRAME is a Knowledge-based tool to support the choice of the right air pollution model [94]. The system is based on relational databases for supporting all the information that the system needs, and on a rule-based expert system for the explanation and help phases. The system includes a mechanism to determine users' expertise and from it give selective access to information. Both the relational database and the expert system co-operate in order to achieve an efficient knowledge management. All the information and meta-information about the models (i.e., the model base) is contained in a frame-like structure. The selection of the suitable models usually depends both on aspects connected to the physics of the actual problem to be simulated and on the available resources.

MEDEX [95] is a forecasting system designed to assist the novice Mediterranean weather forecaster by supplying the encoded knowledge and experience of a 20-year expert on Mediterranean meteorology. The system itself is an implementation of a fuzzy rule-based system for predicting the onset and cessation of seven gale-force winds. It was implemented using commercial software. Significant issues included the specification of loosely defined variables, and the treatment of system users' uncertainty and inexperience.

DCHEM, Distributed Chemical Emergencies Manager [16], is an EDSS dealing with the field of chemical accidents. It supports decision making for a specific class of environmental emergencies, the management of accidents involving electrical equipment containing toxic chemicals. It is one of the first systems that uses distributed agents technology and includes negotiation protocols in the problem-solving process.

CHARADE, Combining Human Assessment and Reasoning Aids for Decision-making in environmental Emergencies [59, 96] aims at defining a general system architecture for DSS, providing powerful facilities for situation assessment and intervention in environmental emergencies. The application selected is a control centre for wildfire fighting. The kernel of the system is based on a hybrid Case Based/Constraint-Based architecture for interactive planning. The objective is to allocate human resources and means to actions (interventions) satisfying temporal and capacity constraints.

DAI-DEPUR [86] is a distributed and integrated supervisory multi-level agent-based architecture for Wastewater Treatment Plants (WWTP) operation. It joins in a single framework several cognitive tasks and techniques such as learning, reasoning, knowledge acquisition [97] and distributed problem solving. Also, different AI techniques are combined such as rule-based reasoning, case-based reasoning and model-based reasoning. Four levels are distinguished from the domain models [43] point of view: data, knowledge, situations and plans. On the other hand, taking into account the supervision tasks, seven levels are considered: evaluation, diagnosis, supervision, prediction, validation, actuation and learning. This system was developed for the WWTP domain, but it is a general framework for complex real-world process supervision. It has been applied to several WWTP in Catalonia. Its adaptability to different plants is one of its major features as well as its CBR facilities [98].

INFORMS-R8 [99], the Integrated Forest Resource Management System Region 8 is a system in use by the U.S. Forest Service to support planning activities in two Ranger Districts. The Knowledge Base is being used to address a broad range of issues, ranging from selection of public firewood sites to assessment of wildlife habitat. The system started as a very limited application of expert systems to silvicultural treatments. Since 1990, it has become a very important decision-support system. It includes both non spatially oriented rule bases (13), such as Timber stand improvement, Single tree selection or Mast production potential; and Spatial rule bases (5), such as those for Erosion potential or Suitability for firewood.

8. Conclusions

This paper outlined how Artificial Intelligence techniques have been applied to solve Environmental Issues and how these have provided new opportunities for the design and application of Artificial Intelligence tools, namely Environmental Decision Support Systems. Many of these systems have been specially applied to Environmental Impact Assessment [30, 99–101].

The papers in this special issue of *Applied Intelligence* have reached the implementation phase in different stages of development [44, 60, 72, 102]. In a previous review by Guariso and Page [30], the situation was not the same, as there were more theoretical works than implemented applications. This is, in our opinion, a great step in the right direction. The research in EDSS is becoming an essential component in many new environmental assessment activities combining various disciplines. Its development implies versatility to work together with other scientists. Versatility to cope with the fast developments of our context.

One of the essential points of the application of AI techniques to this area relies on the knowledge-based facilities that they provide to accelerate the problem identification. Another point is the integration of several AI techniques with numerical and/or statistical models in a single system providing higher accuracy, reliability and usefulness. Today, they are already used as a basis for a better decision for action in many real applications (see §7).

The number of applications of EDSS is increasing very rapidly, and this is not only restricted to traditional hardware devices. Despite this positive impression, AI applications to environmental issues are inferior to AI systems in other fields such as medicine or manufacturing. Since the arrival of the Internet, the possibilities of connecting machines and sensors are enabling the distribution of the computation, opening new and cheap ways to effectively solve problems [103]. Using the Internet and/or intranets, accessing stored information becomes easier, allowing controlling the effects of actions and solutions in a better way; also, the time to reach and to authorise decisions will decrease [37, 104]. Moreover, the collective memory of an organisation could be better maintained and be more useful as a Case Base or a Knowledge Base [98].

As EDSS become more user-friendly, the time of learning their features is decreasing, so more people could participate – at their own level of responsibility – in the decision-making process. The importance of local decisions is increased by the use of cooperative systems [88, 93]. In addition, as local and global decisions can be reached and shared faster, the effectiveness of actions is expected to grow.

The key to useful computer-based decision support systems is integration. A basic concept of integration recognises that in any given software system for real-world applications, several sources of information, more than one problem representation or model, different problem-solving techniques, and, finally, a multifaceted and problem-oriented interface ought to be combined in a common framework to provide a realistic and useful information base.

The integrated EDSS of the next generation will be built around one or more coupled models, numerical simulation models, rule or case-driven, geographically distributed and integrated with a GIS. As Guariso and Werthner [24] already pointed out, EDSS will not and cannot do the work that remains to be done by humans. Better computer support does not automatically imply a better decision. It is still the human's responsibility to be aware of the environmental situation of our planet and to cope with all the problems connected with it.

9. Web Sites

This section details a list of web sites that happened to be especially useful during the elaboration of this document. Among them the reader will find university, research institute, government and industry addresses:

- Agenda 21.
  http://www.ess.co.at/Agenda21.html
- Artificial Intelligence Research In Environmental Sciences group (AIRIES).
  http://www.salinas.net/˜ jpeak/airies/airies.html
- Asia-Pacific Network for Global Change Research (APN).
  http://www.rim.or.jp/apn
- Binding Environmental Sciences and Artificial Intelligence.
  http://www.lsi.upc.es/˜ webia/besai/besai.html
- Biodiversity Informatuion Network (BIN21).
  http://www.bdt.org.br/bin21/
- Center for Global and Regional Environmental Research University of Iowa.
  http://www.cgrer.uiowa.edu/servers
- Environment Data News on the Web.
  http://www.uea.ac.uk/˜ e870.envdata.html
- European Environmental Agency (EEA).
  http://www.eea.eu.int
- International Environment Technology Center (IETC) of the United Nations Environment Programme. Information on Environmentally Sound Technologies (ESTs).
  http://www.unep.or.jp
- GAIA A Multi-media Tool for Natural Resources Management and Environmental Education (INCO-950809).
  http://www.ess.co.at/GAIA
- MEDEX.
  http://www.nrlmry.navy.mil/˜ medex
- Riverside Technologies Environmental Consulting/Water Resources Engineering.
  http://www.riverside.com
- The Universities Water Information Network.
  http://www2.uwin.siu/edu
- US Environmental Protection Agency (EPA) Waste Treatment Databases.
  http://www.epa.gov
- Water Environment & Technology.
  http://www.wef.org

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References

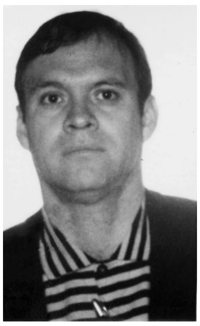
1. A.J. Thomson, "Artificial intelligence and environmental ethics," *AI Applications*, vol. 11, no. 1, pp. 69–73, 1997.
2. R. Eblen and W. Eblen (Eds.), *The Encyclopaedia of the Environment*, Houghton Mifflin Co., 1994, ISBN 0-395-55041-6.
3. S.E. Jørgensen and I. Johnsen, "Principles of environmental science and technology," in *Studies in Environmental Science*, Elsevier, vol. 33, 1989, ISBN 0-444-43024-5.
4. J. Hart, I. Hunt, and V. Shankararaman, "Environmental management systems—A role for AI?," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI'98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 1–10.
5. A. Sydow, H. Rosé, and O. Rufeger, "Sustainable development and integrated assessment," *Ercim News*, vol. 34, no. 32, 1998.
6. E. Ostrom, *Governing the Commons: The Evolution of Institutions for Collective Action*, Cambridge University Press, 1991, ISBN 0-521-37101-5.
7. F.J. Radermacher, W.F. Riekert, B. Page, and L.M. Hilty, "Trends in environmental information processing," in *Thirteenth World Computer Congress 94*, edited by K. Brunnstein and E. Raubold, 1994, vol. 2, pp. 597–604.
8. G. Stephanopoulos and C. Han, "Intelligent systems in process engineering: A review," *Computers Chem. Engng.*, vol. 20, nos. 6/7, pp. 743–791, 1996.
9. N.M. Avouris and B. Page (Eds.), *Environmental Informatics: Methodology and Applications of Environmental Information Processing*, Kluwer, 1995, ISBN 0-7923-3445-0.
10. D. Robertson, A. Bundy, R. Muetzelfeldt, M. Haggith, and M. Uschold, *Eco-Logic. Logic-based Approaches to Ecological Models*, MIT Press, 1991, ISBN 0-262-18143-6.
11. P. Zannetti (Ed.), *Environmental Systems, vol. II: Computer Techniques in Environmental Studies V*, Computational Mechanics Publications, 1994, ISBN 1-85312-272-6.

12. K. Fedra, "Decision support for natural resources management: Models, GIS and expert systems," *AI Applications*, vol. 9, no. 3, pp. 3–19, 1995.
13. K. Fedra, "GIS and environmental modelling," in *Environmental Modelling with GIS*, edited by M.F. Goodchild, B.O. Parks, and L.T. Steyaert, Oxford University Press, pp. 35–50, 1994.
14. M.F. Goodchild, L.T. Steyaert, and B.O. Parks (Eds.), "*Environmental Modelling: Progress and Research Issues*, GIS World Books, 1996, ISBN 1-882610-11-3.
15. M.F. Goodchild, B.O. Parks, and L.T. Steyaert (Eds.), *Environmental Modelling with GIS*, Oxford University Press, 1994.
16. N.M Avouris, "Co-operating knowledge-based systems for environmental decision-support," *Knowledge-Based Systems*, vol. 8, no. 1, pp. 39–53, 1995.
17. J.L Wilson, K. Mikroudis, and H.Y. Fang, "GEOTOX: A knowledge-based system for hazardous site evaluation," in *Applications of Artificial Intelligence in Engineering Problems*, edited by D. Sriram and R. Adey, pp. 661–671, 1986.
18. J. Wright, L. Wiggins, R. Jain, and T. John Kim (Eds.), *Expert Systems in Environmental Planning*, Springer-Verlag, 1993, ISBN 3-540-56063-7.
19. L. Sazonova and G. Osipov, "Intelligent system for fish stock prediction and allowable catch evaluation," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 161–176.
20. K. Branting, J.D. Hastings, and J.A. Lockwood, "Integrating cases and models for prediction in biological systems," *AI Applications*, vol. 11, no. 1, pp. 29–48, 1997.
21. C.T. Yang and J.J. Kao, "An expert-system for selecting and sequencing wastewater treatment processes," *Water Science and Technology*, vol. 34, nos. 3/4, pp. 347–353, 1996.
22. A. Shepherd and L. Ortolano, "Water-supply system operations: Critiquing expert-system approach," *Journal of Water Resources Planning and Management*, vol. 122, no. 5, pp. 348–355, 1996.
23. J. Lapointe, B. Marcos, M. Veillette, G. Laflamme, and M. Dumontier, "Bioexpert-an expert system for wastewater treatment process diagnosis," *Computers Chem. Engng.*, vol. 13, no. 6, pp. 619–630, 1989.
24. G. Guariso and H. Werthner (Eds.), *Environmental Decision Support Systems*, Ellis Horwood-Wiley, 1994, ISBN 0-77458-0255-9.
25. B. Page, "An analysis of environmental expert system applications with special emphasis on Canada and the Federal Republic of Germany," *Fachbereich Informatik*, Bericht 144/89, Hamburg, 1989.
26. J.M. Hushon, "Expert systems for environmental problems," *Environmental Science and Technology*, vol. 21, no. 9, pp. 838–841, 1987.
27. D. Sriram and R. Adey (Eds.), *Applications of Artificial Intelligence in Engineering Problems*, Springer-Verlag, 1986, ISBN 0-905451-47-3.
28. K. Maeda, "An intelligent decision support system for activated sludge wastewater treatment systems," *Instrumentation and Control of Water and Wastewater Treatment Systems*, 1985.
29. C. Gabaldón, J. Ferrer, A. Seco, and P. Marzal, "A software for the integrated design of wastewater treatment plants," *Environmental Modelling and Software*, vol. 13, no. 1, pp. 31–44, 1998.
30. G. Guariso and B. Page (Eds.), "Computers support for environmental impact assessment," in *IFIP*, North-Holland, 1994, ISBN 0-444-81838-3.
31. T. Okubo, K. Kubo, M. Hosomi, and A. Murakami, "A knowledge-based decision support system for selecting small-scale wastewater treatment processes," *Water Science Technology*, vol. 30, no. 2, pp. 175–184, 1994.
32. P. Serra, J. Lafuente, R. Moreno, C. de Prada, and M. Poch, "Development of a real-time expert system for wastewater treatment plants control," *Control. Eng. Practice*, vol. 1, no. 2, pp. 329–335, 1993.
33. R.J. Aarts, *Knowledge-based Systems for Bioprocesses*, Technical Research Centre of Finland, 1992, vol. 120.
34. I.G. Haagsma and R.D. Johanns, "Decision support systems: An integrated approach," in *Environmental Systems*, edited by P. Zannetti, vol. II, pp. 205–212, 1994.
35. M. Bender and S.P. Simonovic, "Decision support system for long-range stream-flow forecasting," *Journal of Computing in Civil Engineering*, vol. 8, no. 1, pp. 20–34, 1994.
36. A.E. Rizzoli and W.Y. Young, "Delivering environmental decision support systems: Software tools and techniques," *Environmental Modelling and Software*, vol. 12, no. 23, pp. 237–249, 1997.
37. S.A. El-Swaify and D.S. Yakowitz (Eds.), *Multiple Objective Decision Making for Land*, *Water*, *and Environmental Management*, Lewis Publishers, 1998.
38. D.E. Moon, S.C. Jeck, and C.J. Selby, "Elements of a decision support system: Information, model, and user management," in *Multiple Objective Decision Making for Land, Water, and Environmental Management*, edited by El-Swaify and Yakowitz, pp. 323–334, 1998.
39. R. Michalski and F.J. Radermacher, "Challenges for information systems: Representation, modeling, and metaknowledge," in *Recent Developments in Decision Support Systems*, edited by C.W. Holsapple and Whinston, pp. 3–22, 1993.
40. U. Cortés and M. Sànchez-Marrè (Eds.), in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI'98). European Conference on Artificial Intelligence (ECAI'98)*, Workshop Notes, 1998.
41. C. Mason (Ed.), in *Workshop on Artificial Intelligence and the Environment*. IJCAI-95 Workshop Program Working Notes, 1995.
42. *AAAI'94 Workshop on Environmental Applications of Artificial Intelligence*, Seattle, USA, 1994.
43. L. Steels, "Components of expertise," *AI Magazine*, vol. 11, no. 2, pp. 28–49, 1990.
44. P. Avesani, A. Perini, and F. Ricci, "Interactive case-based planning for forest fire management," *Applied Intelligence*, vol. 13, 2000.
45. 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*, vol. 12, no. 4, pp. 251–266, 1997. Special issue on Machine Learning.
46. S. Krovviddy, W.G. Wee, R.S. Summers, and J.J. Coleman, "An AI approach for wastewater treatment systems," *Applied Intelligence*, vol. 1, no. 1, pp. 247–261, 1991.
47. P. Serra, M. Sànchez-Marrè, J. Lafuente, U. Cortés, and M.

Poch, "DEPUR: A knowledge based tool for wastewater treatment plants," *Engineering Applications of Artificial Intelligence*, vol. 7, no. 1, pp. 23–30, 1994.

48. D. Chapman and G.G. Patry (Eds.), *Dynamic Modeling and Expert Systems in Wastewater Engineering*, Lewis Publishers: Chelsea, 1989.
49. D. Charlebois, S. Matwin, and D.G. Goodenough, "Planning with agents in intelligent data management for forestry," in *IJCAI-95 Workshop on Artificial Intelligence and the Environment*, edited by C. Mason, 1995, pp. 69–70.
50. S. Krovviddy, W.G. Wee, M. Suidan, R.S. Summers, J.J. Coleman, and L. Rossman, "Intelligent sequence planning for wastewater treatment systems," *IEEE Expert*, pp. 15–20, December 1994.
51. R. Kangari and S. Rouhani, "Reservoir management and planning expert system," in *Knowledge-Based Expert Systems in Water Utility Operations and Management*, edited by S.J. Nix, A.G. Collind, and T.-K. Tsay, American Water Works Association (AWWA) Research Foundation, December 1989.
52. E.K. Jones and A. Roydhouse, "Retrieving structured spatial information from large databases: A progress report," in *IJCAI-95 Workshop on Artificial Intelligence and the Environment*, 1995, pp. 49–57.
53. S. Krovvidy and W.G. Wee, "Wastewater treatment system from case-based reasoning," *Machine Learning*, vol. 10, no. 3, pp. 341–363, 1993.
54. Ll. Mora-López and R. Conejo, "Qualitative reasoning model for the prediction of climatic data," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 55–67.
55. M. Lundell, "Qualitative modelling and simulation of spatially distributed parameter systems," Ph.D. Thesis, École Polytecnique Fédérale de Lausanne, 1996.
56. U. Heller, P. Struss, F. Guerrin, and W. Roque, "A qualitative modelling approach to algal bloom prediction," in *IJCAI-95 Workshop on Artificial Intelligence and the Environment*, edited by C. Mason, 1995, pp. 21–26.
57. B. Kompare, "Qualitative modelling of environmental processes," in *Environmental Systems*, vol. II: *Computer Techniques in Environmental Studies V*, edited by P. Zannetti, Computational Mechanics Publications, 1994.
58. R. Paggio, G. Agre, C. Dichev, D. Dochev, G. Umann, and T. Rozman, "TRACE—A development platform for environmental decision support systems," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 145–160.
59. CHARADE Report, Istituto per la Ricerca Scientifica e Tecnologica, 1995.
60. R. Sangüesa and P. Burrell, "Application of Bayesian network learning methods to wastewater treatment plants," *Applied Intelligence*, vol. 13, 2000.
61. J.D. Englehart, "Bayesian-risk analysis for sustainable process design," *Journal of Environmental Engineering*, vol. 123, no. 1, pp. 71–79, 1997.
62. O. Varis, "Bayesian decision analysis for environmental and resource management," *Environmental Modelling and Software*, vol. 12, nos. 2/3, pp. 177–185, 1997.
63. H.G. Chong and W.J. Walley, "Rule-base versus probabilistic approaches to the diagnosis of faults in wastewater treatment processes," *Artificial Intelligence in Engineering*, vol. 10, no. 3, pp. 265–273, 1996.
64. J. Zhu, J. Zurcher, M. Rao, and M.Q.-H. Meng, "An on-line wastewater quality predication system based on a time-delay neural network," *Engineering Applications of Artificial Intelligence*, vol. 11, pp. 747–758, 1998.
65. C.-H. Wen and C.A. Vassiliadis, "Applying hybrid artificial intelligence in wastewater treatment," in *Engineering Applications of Artificial Intelligence*, vol. 11, pp. 685–705, 1998.
66. H. Raman and V. Chandramouli, "Deriving a general operating policy for reservoirs using neural network," *Journal of Water Resources Planning and Management*, vol. 122, no. 5, pp. 341–347, 1996.
67. S.S. Tan and F.E. Smeins, "Predicting grassland community changes with an artificial neural-network model," *Ecological Modelling*, vol. 84, nos. 1/3, pp. 91–97, 1996.
68. A.E. Mulligan and L.C. Brown, "Genetic algorithms for calibrating water quality models," *Journal of Environmental Engineering*, vol. 124, no. 3, pp. 202–211, 1998.
69. D. Halhal, G.A. Walters, D. Ouazar, and D.A. Savic,"Water network rehabilitation with structured messy genetic algorithm," *Journal of Water Resources Planning and Management*, vol. 123, no. 3, pp. 137–146, 1997.
70. D.A. Savic and G.A. Walters, "Genetic algorithms for least-cost design of water distribution networks," *Journal of Water Resources Planning and Management*, vol. 123, no. 2, pp. 67–77, 1997.
71. B.-T. Zhang, P. Ohm, and H. Mhlenbein, "Water pollution with evolutionary neural trees," in *IJCAI-95 Workshop on Artificial Intelligence and the Environment*, edited by Mason, C., 1995, pp. 32–40.
72. A. Genovesi, J. Harmand, and J.-P. Steyer, "Integrated fault detection and isolation: Application to a Winery's wastewater treatment plant," *Applied Intelligence*, vol. 13, pp. 207–224, 1999.
73. S.A. Manesis, D.J. Sapidis, and R.E. King, "Intelligent control of wastewater treatment plants," *Artificial Intelligence in Engineering*, vol. 12, no. 1998, pp. 275–281, 1998.
74. K. Sasikumar and P.P. Mujumdar, "Fuzzy optimization model for water quality management of river system," *Journal of Water Resources Planning and Management*, vol. 124, no. 2, pp. 79–84, 1998.
75. N.B. Chang, Y.L. Chen, and H.W. Chen, "A fuzzy regression analysis for the construction cost estimation of wastewater treatment plants," *Journal of Environmental Science and Health*. Part A-Environmental Science and Engineering and Toxic and Hazardous Substance Control, vol. 32, no. 4, pp. 885–899, 1997.
76. S. Džeroski, J. Grbović, and W.J. Walley, "Machine learning applications in biological classification of river water quality," in *Machine Learning and Data Mining: Methods and Applications*, edited by Michalski et al., 1997.
77. H.A. Simon, *The Sciences of the Artificial*, MIT Press, 3rd edn. 1996, ISBN 0-262-69191-4.
78. M. Minsky, "Negative expertise," in *Expertise in Context*, The MIT Press, edited by Feltovich et al., pp. 515–521, 1997.
79. P. Feltovich, K. Ford, and R. Hoffman (Eds.), *Expertise in Context*, AAAI Press/The MIT Press, 1997, ISBN 0-262-56110-7.
80. J.M. Gimeno, J. Béjar, M. Sànchez-Marrè, U. Cortés, and I.

R.-Roda, "Discovering and modeling process change: An application to industrial processes," in *Proceedings of the Second Int. Conference on the Practical Application of Knowledge Discovery and Data Mining (PADD 98)*, London, U.K., March 1998, pp. 143–153.
81. O. Varis and S. Kuikka, "BeNe-EIA: A Bayesian approach to expert judgement elicitation with case studies on climate change impacts on surface waters," *Climatic Change*, vol. 37, no. 3, pp. 539–563, 1997.
82. F. Verdenius and J. Broeze, "Generalised and instance-specific modelling for biological systems," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 117–132.
83. J. Rickel and B. Porter, "Automated modeling of complex biological and ecological systems," in *IJCAI-95 Workshop on Artificial Intelligence and the Environment*, edited by C. Mason, 1995, pp. 21–26.
84. A.J. Jakeman, D.A. Post, S.Y. Schreider, and W. Ye, "Modelling environmental systems: Partitioning the water balance at different catchment scales," in *Environmental Systems*, edited by P. Zannetti, vol. II, pp. 157–170, 1994.
85. A.D. Wittaker, "Decision support systems and expert systems for range science," in *Decision Support Systems for the Management of Grazing Lands: Emerging Lands*, edited by J.W. Stuth and B.G. Lyons, pp. 69–81, 1993.
86. M. Sànchez-Marrè, U. Cortés, J. Lafuente, J. R.-Roda, and M. Poch, "DAI-DEPUR: An integrated and distributed architecture for wastewater treatment plants supervision," *Artificial Intelligence in Engineering*, vol. 10, no. 3, pp. 275–285, 1996.
87. T. Ohtsuki, T. Kawazoe, and T. Masui, "Intelligent control system based on blackboard concept for wastewater treatment processes," *Water Science and Technology*, vol. 37, no. 12, pp. 77–85, 1998.
88. N.M. Avouris, "Cooperating expert systems for environmental applications," in *Environmental Informatics: Methodology and Applications of Environmental Information Processing*, edited by N.M. Avouris and B. Page, pp. 111–125, 1995.
89. J. Hastings, K. Branting, and J. Lockwood, "A multi-paradigm reasoning system for rangeland management," *Computers and Electronics in Agriculture*, vol. 16, no. 1, pp. 47–67, 1996.
90. SFWMG (South Florida Water Management District) OASIS: The South Florida Water Management District's Operation Artificial Intelligence Program, 1987.
91. G. Hartvigsen and D. Johansen, "Cooperation in a distributed artificial intelligence environment—The StormCast application," *Engineering Application of Artificial Intelligence*, vol. 3, pp. 229–237, 1990.
92. K. Fedra, L. Winkelbauer, and V.R. Pantulu, *Expert Systems for Environmental Screening: An Application in the Lower Mekong Basin*, International Institute for Applied System Analysis, 1991.
93. K. Fedra, "GAIA A multi-media tool for natural resources management and environmental education," (INCO-950809), 1998.
94. G. Calori, F. Colombo, and G. Finzi, "Frame: A knowledge-base tool to support the choice of the right air pollution model," in *Computer Support for Environmental Impact Assessment*, edited by G. Guariso and B. Page, pp. 211–222, 1994.
95. M. Hadjimichael, P. Arunas, L. Kuciauskas, and R. Brody, "MEDEX: A fuzzy system for forecasting mediterranean gale force winds," in *Proceedings FUZZ-IEEE96. IEEE Int. Conf. On Fuzzy Systems*, New Orleans, 1996, pp. 529–534.
96. P. Avesani, A. Perini, and F. Ricci, "Combining CBR and constraint reasoning in planning forest fire fighting," in *Proceedings of the First European Workshop on Case-Based Reasoning*, 1993, pp. 235–239.
97. M. Sànchez-Marrè, U. Cortés, J. Béjar, J. de Gràcia, J. Lafuente, and M. Poch, "Concept formation in WWTP by means of classification techniques: A compared study," *Applied Intelligence*, vol. 7, no. 2, pp. 147–166, 1997.
98. M. Sànchez-Marrè, U. Cortés, I. R.-Roda, and M. Poch, "Sustainable case learning for continuous domains," *Environmental Modelling and Software*, vol. 14, pp. 349–357.
99. S.B. Williams and D.R. Holtfrerich, "A knowledge-based reasoning toolkit for forest resource management," in *Multiple Objective Decision Making for Land, Water, and Environmental Management*, pp. 251–268, 1998.
100. K.Q. Luo and Y.L. Huang, "Intelligent decision support for waste minimization in electroplating plants," *Engineering Applications of Artificial Intelligence*, vol. 10, no. 4, pp. 321–333, 1997.
101. F. Stagnitti, "A decision support tool for aquaculture," *Environmental Modelling and Software*, vol. 12, nos. 2/3, pp. 229–236, 1997.
102. S. Džeroski, D. Demšar, and J. Grbović, "Predicting chemical parameters of river water quality from bioindicator data," *Applied Intelligence*, vol. 13, pp. 7–17, 2000.
103. J. Baeza, D. Gabriel, and J. Lafuente, "An expert supervisory system for a pilot WWTP," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 25–35.
104. R. Balstad, "Information technology for public policy," in *Environmental Modelling: Progress and Research Issues*, edited by M.F. Goodchild, L.T. Steyaert, and B.O. Parks, pp. 7–10, 1996.
105. J.P.M. King, R. Baares-Alcántara, and Z. Manan, "Minimising environmental impact using CBR: An azeotropic distillation case study," in *Workshop Binding Environmental Sciences and Artificial Intelligence (BESAI 98)*, edited by U. Cortés and M. Sànchez-Marrè, 1998, pp. 95–108.



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