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Intelligent Decision Support Systems in Environmental Management Proplems

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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. Recently, a new discipline called "Intelligent Environmental Informatics" is emerging. This new discipline integrates environmental science with artificial intelligence (AI) and computer science Using AI concepts and techniques new forms of intelligent decision support systems can be created that allow the computer to act as an intelligent assistant. Such systems focus on strategic decisions and not operational ones. This paper discusses the technical aspects of the intelligent decision support systems in environmental management problems. In addition, the paper identifies the main characteristics of the intelligent environmental decision support systems (IEDSSs).

Keywords: Intelligent decision support systems, Knowledge-Based systems, Artificial intelligence, Knowledge management.

1. INTRODUCTION

"Environmental Informatics" integrates environmental science with computer science [1]. This discipline combined many research fields such as Artificial Intelligence (AI), Geographical Information Systems, Modeling and Simulation, User Interface, etc. An important and difficult task for this new area is to serve as a catalyst for the integration of data, information, and knowledge from different sources in the environmental sector.

AI research has been oriented towards the development of knowledge-based systems (KBSs) for environmental management problems [2,3]. The first applications of expert systems (ESs) to environmental issues appeared in the eighties [4,5]. For example, in using ESs advising emergency response teams about how to deal with industrial accidents [6], in using ESs to assist in granting hazardous waste site permits [7], in modeling water quality [8], fish stock prediction [9], and many other environmental engineering applications [10,11,12].

KBS, when applied to environmental issues, receive different denominations such as Decision Support Systems (DSS) [13, 14], Environmental Decision Support Systems (EDSS) [15] or Multiple Objective Decision Support Systems (MODSS) [16] or Intelligent Environmental Decision Support Systems (IEDSS)[17,18,19,20]. Among those names, we chose to use IEDSS. An IEDSS 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. 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.

The objective of this paper is three-fold. First, to explore the technical aspects of developing IEDSSs from the artificial intelligence point of view. Second, to investigate the main features and characteristics of such systems. Third, to discuss the difficulties and challenges which are facing the designing process?

2. TECHNICAL ASPECTS OF THE INTELLIGENT ENVIRONMENTAL DECISION SUPPORT SYSTEMS

From our point of view, and based on the published studies during the last years, Intelligent Environmental decision support systems (IEDSSs) are AI-based decision support systems . IEDSS is a consultation knowledge-based system that contains the knowledge and experience of one or more experts in a specific domain that anyone can tap as an aid in solving problems. It consists of a knowledge base that stores the expertise, inference engine that thinks and reasons, and interface that communicates with the user. Expert knowledge is the key component of the success of the IEDSS for any application. The knowledge consists of facts, concepts, theories, procedures and analyzed to make it understandable and applicable to problem solving or decision making. This section is dealing with a brief discussion of the two main technical aspects in the developing pf IEDSS, namely ;(a) knowledge representation techniques and (b) the reasoning methodologies.

2.1 Knowledge Representation Techniques

Knowledge is the main key for developing IEDSS for any application. Although, a computer cannot have experiences and learn as the human mind can, it can acquire knowledge given to it by human experts. A variety of knowledge representation schemes are used including; *lists, trees, semantic networks, frames, scripts and production rules* [21]. *Lists* are used to represent hierarchical knowledge. Hierarchical knowledge can also be represented visually with graphs called *trees*. *Semantic networks* use circles called nodes that represent objects or events. The nodes are interconnected with lines called arcs that show relationships. *Frames and scripts* are two types of schemes dealing with stereotyped knowledge. Frames are used represent facts about objects and events. And details are given in sub-elements called slots. Scripts describe knowledge that is a sequence of events or procedures. Frames and scripts permit a system to infer details of specific common objects and events. *Production rules* are the most commonly used knowledge representation methods. The rules are two part statements with a premise and a conclusion and are written in the form of an *if-then* statement. They also may state a situation and corresponding action.

2.2 Reasoning Methodolgies

The field of reasoning is very important for the development of knowledge-based systems. The research area in this field covers a variety of topics, e.g.; automated reasoning, case-based reasoning, commonsense reasoning, fuzzy reasoning, geometric reasoning, non-monotonic reasoning, model-based reasoning, probabilistic reasoning, causal reasoning, qualitative reasoning, spatial reasoning and temporal reasoning [21]. In fact these methodologies receive increasing attention within the AI in environmental informatics community [17].

2.2.1 Reasoning with Production Rules

Rules are easily manipulated by reasoning systems. Forward chaining can be used to produce new facts (hence the term “production” rules), and backward chaining can deduce whether statements are true or not. Rule-based systems were one of the first large-scale commercial successes of artificial intelligence research. An expert system or knowledge-based system is the common term used to describe a rule-based processing system. It consists of three major elements, a knowledge base (the set of if-then rules and known facts), a working memory or database of derived facts and data, and an inference engine, which contains the reasoning logic used to process the rules and data.

Rule-based systems solve problems by taking an input specification and then “chaining” together the appropriate set of rules from the rule base to arrive at a solution. Given the same exact problem situation, the system will go through exactly the same amount of work to come up with the solution. In other words rule-based systems don’t inherently learn. In addition, given a problem that is outside the system’s original scope, the system often can’t render any assistance. Finally, rule-based systems are very time-consuming to build and maintain because rule extraction from experts is labor-intensive and rules are inherently dependent on other rules, making the addition of new knowledge to the system a complex debugging task.

Forward chaining is a data-driven reasoning process where a set of rules is used to drive new facts from an initial set of data. It does not use the resolution algorithm used in predicate logic. The forward-chaining algorithm generates new data by the simple and straightforward application or firing of the rules. As an inference procedure, forward chaining is very fast. Forward chaining is also used in real-time monitoring and diagnostic systems where quick identification and response to problems are required.

Backward chaining is often called goal-directed inference, because a particular consequence or goal clause is evaluated first, and then we go backward through the rules. Unlike forward chaining, which uses-rules to produce new information, backward chaining uses rules to answer questions about whether a goal clause is true or not. Backward chaining is more focused than forward chaining, because it only processes rules that are relevant to the question. It is similar to how resolution is used in predicate logic. However, it does not use contradiction. It simply traverses the rule base trying to prove that clauses are true in a systematic manner. Backward chaining is used for advisory systems, where users ask questions and get asked leading questions to find an answer. One advantage of backward chaining is that, because the inference is directed, information can be requested from the user when it is needed. Some reasoning systems also provide a trace capability which allows the user to ask the inference engine why it asking for some piece of information, or why it came to some conclusion.

2.2.2 Reasoning with Fuzzy Rules

In the rich history of rule-based reasoning in AI, the inference engines almost without exception were based on Boolean or binary logic. However, in the same way that neural networks have enriched the AI landscape by providing an alternative to symbol processing techniques, fuzzy logic has provided an alternative to Boolean logic-based systems. Unlike Boolean logic, which has only two states, true or false, fuzzy logic deals with truth values which range continuously from 0 to 1. Thus something could be ***half true* 0.5 or *very likely true* 0.9 or *probably not true* 0.1.** The use of fuzzy logic in reasoning systems impacts not only the inference engine but the knowledge representation itself. For, instead of making arbitrary distinctions between variables and states, as is required with Boolean logic systems, fuzzy logic allows one to express knowledge in a rule format that is close to a natural language expression. For example, we could say *If **temperature is hot and humidity is sticky then fan speed is high.***
The difference between this fuzzy rule and the Boolean-logic rules we used in our forward- and backward-chaining examples is that the clauses **"temperature is hot"** and **"humidity is sticky"** are not strictly true or false. Clauses in fuzzy rules are real-valued functions called membership functions that map the fuzzy set "hot" onto the domain of the fuzzy variable "temperature" and produce a truth-value that ranges from 0.0 to 1.0 (a continuous output value, much like neural networks).
Reasoning with fuzzy rule systems is a forward-chaining procedure. The initial numeric data values are ***fuzzified***, that is, turned into fuzzy values using the membership functions. Instead of a match and conflict resolution phase where we select a triggered rule to fire, in fuzzy systems, all rules are evaluated, because all fuzzy rules can be true to some degree (ranging from 0.0 to 1.0). The antecedent clause truth values are combined using fuzzy logic operators (a fuzzy conjunction or and operation takes the minimum value of the two fuzzy clauses). Next, the fuzzy sets specified in the consequent clauses of all rules are combined; **using** the rule truth values as scaling factors. The result is a single fuzzy set, which is then ***defuzzified*** to return a crisp output value.

2.2.3 Reasoning with Cases

The case is a list of features that lead to a particular outcome. (*E.g. The information on a patient history and the associated diagnosis*). The complex case is a connected set of subcases that form the problem solving task's structure (*e.g. the design of an airplane*). Determining the appropriate case features is the main knowledge engineering task in case-based AI software. This task involves defining the terminology of the domain and gathering representative cases of problem solving by the expert Representation of cased can be in any of several forms (*predicate, frames).*
The idea of case-based reasoning is becoming popular in developing knowledge-based systems because it automates applications that are based on precedent or that contain incomplete causal models. In rule-based systems an incomplete mode or an environment which does not take into account all variables could result in either an answer built on incomplete data or simply no answer at all. Case-based methodology attempt to get around this shortcoming by inputting and analyzing problem data. For more technical information, see [22].

3. THE GENERAL FEATURES OF THE INTELLIGENT ENVIRONMENTAL DECISION SUPPORT SYSTEMS (IEDSSS)

An important feature of IEDSSs is that they allow the use and capture of specialized knowledge from a wide spectrum of natural sciences, and that they can be effectively applied to a variety of environmental management and design activities. This specialized 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) judgmental knowledge about human beliefs, intentions, desires and priorities; and d) theoretical knowledge about biological, physical and chemical phenomena [23, 24].

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 characterized 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 judgments regarding the degree of concern about a certain hypothesis. This is possible if the system has accumulated experience solving similar situations using for example a Case-based Reasoning approach, whereby past experience of risk evaluation is used to assist with future judgments.
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 section 4). *Risk assessment and Risk evaluation* are related to the problem diagnosis phase. *Intervention decision-making* is related to the decision support techniques.

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:

(a) The multidisciplinary nature of environmental problems. It implies cooperation among various elements (modules) of the EDSS; each one specialized in a given topic or a certain kind of model.

(b) 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 organized to give relevance to these efforts. For example, (a) the Artificial Intelligence Research in Environmental Sciences group series of workshops, Binding Environmental Sciences and Artificial Intelligence. , IJCAI, AAAI and (b) the ENVIRONSOFT series or the events coordinated by the IFIP Working Group 5.11 Computers and Environment.

During the last ten years, there are a growing number of specialized publications and research projects that pay greater attention to the environmental area. Based on the analysis of the published results during the last ten years, table 1 shows the different roles of the expert systems technology in environmental management tasks.

Table 1. Some examples of the roles of expert systems in enviromental domain

Task	**Description**	**Example**
Interpretation	Inferring a situation from it's description	Determination of a crop growth stage
Prescription or debugging	Solution finding to a known problem	Prescription of nutrients to correct a deficit which is causing a reduction in a plant's growth rate
Prediction	Inferring like consequences of given situations	Prediction of a crop pest number in the future
Design and configuration	Selection of actions and components and there interconnection to achieve a pre-determent specification	Selection of chemical mix, from stock available, to control pets, diseases or combination of both
Planning	Determine an entire cause of actions before initiation and their implementation	Planning the development of a site after mineral extraction
Mentoring and control	Continuous interpretation signals with expected values and governing of overall behaviour system	Controlling a greenhouse environment

Diagnoses and repair	Fault detection with a repair or remedy suggestion	Identification of a crop growth rate problem and subsequent corrective actions
Instruction	Education about a subject field or domain area	Education of manger about a new subject area

4. THE INTERDISCIPLINARY FIELD OF INTELLIGENT ENVIRONMENTAL DECISION SUPPORT SYSTEMS

Following the classification proposed by Rizzoli and Young, 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 Artificial Intelligence and Environmental Decision Support Systems 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 optimization.
6. The ability to assist the user during problem formulation and selecting the solution methods.

An IEDSS can be described as a multi-layered system connecting the user, probably an environmental scientist, with an environmental system or process. The development of an IEDSS as a complex integrated KBS relies on the idea of model refinement. 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 [25, 26].

The IEDSS 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 IEDSS is ready to be applied to the environment.

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

- Rule-Based Reasoning
- Planning
- Case-Based Reasoning
- Qualitative Reasoning
- Constraint Satisfaction
- Model-Based Reasoning
- Connexionist Reasoning
- Evolutionary Computing
- Fuzzy Logic Techniques.
- Artificial Neural Networks.
- Data Mining.
- Fuzzy Systems.
- Generic Algorithms and Genetic Programming.
- Intelligent call Support Systems.

- Knowledge-based Systems.
- Machine Learning.
- Multiagent and distributed systems.
- Ontologies.

Moreover, application areas is also associated with any environmental field such as:

- Biodiversity
- Ecological system modelling and simulation
- Emergency management
- Environmental-crime detection
- Environmental impact assessment
- Environmental method oversight
- Forest and land management
- Global climatical amendment

- Marine pollution
- Meterological prediction
- Natural resource management
- Remote sensing
- System ecology
- Waste management
- Wastewater treatment management
- Water resource management.

5. Conclusions

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

AI methodologies and techniques offer potentially powerful tools for the development of intelligent environmental decision support systems. The variety of knowledge representation and reasoning techniques enabling the design of a robust IEDSS. The key to the success of such systems is the appropriate selection of the knowledge representation scheme that best fits the domain knowledge and the problem to be solved. That choice is depends on the experience of the knowledge engineer.

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