The Role of Artificial Intelligence in Environmental Decision Support Systems

Hisham S Katoua
Management Information Systems Dep
Faculty of Economics & Administration
King Abdulaziz University, Jeddah, Kingdom of Saudi Arabia
Email: dr_ hisham_sa {at} hotmail.com

Abstract: **Artificial intelligence (AI)technology has the potential to further improve the performance of the environmental decision support systems .This produces a new generation of such systems called,intelligent environmental decision support systems (IEDSSs) and yielding a new interdisciplinary field of research.This field includes;artificial intelligence, knowledge management and computing,machine learning ,management and environmental sciences. This paper invistigates and discusses the role of the AI concepts and methodologies in developing the IEDSSs .The focus in this paper is to discuss the following aspects: (a) knowledge management and engineering, (b) reasoning methodologies ,and (c) expert systems. Results suggest that, the choice of the appropriate intelligent technique increases the robustness and efficiency of the environmental decision support systems.**

I. Introduction

The IEDSS consists of a knowledge base that stores the expertise, inference engine that thinks and reasons, and interface that communicates with the user. 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. Expert knowledge is the key component of the success of the IEDSS for any application. During the last ten years, there are a growing number of specialized publications ,workshops , conferences and research projects that pay greater attention to the environmental area. 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.

On the other side,the reasoning mechanism(inference engine) is the main component in the development of IEDSSs.This field receives increasing attention within the enviromental informatics community [17]. This field covers a variety of reasoning techniques, 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].

The objective of this paper are three-fold. First, to explores the technical aspects of developing IEDSSs from the artificial intelligence point of view.Second, to investigates the main features and characteristics of such systems.Third, to discusses the difficultes and challenges which are facing the designing process.

II. THE ROLE OF KNOWLEDGE ENGINEERING IN IEDSSs

The IEDSS is knowledge-based system to perform a specific environmental task .This system allows the use and capture of specialized knowledge from a wide spectrum of natural sciences. 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.

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.

From the knowledge engineering and computing point of view, there is a variety of knowledge representation techniques and schemes.These schemes include ; cases,ontology,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.

III. THE ROLE OF REASONING TECHNIQUES IN IEDSSS

A. *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. 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 inferencing 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 inferencing, 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 inferencing 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.

B. *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. 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.

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.

C. Case-Based Reasoning

The idea of case-based reasoning (CBR) is becoming popular in developing the new generation of the environmental knowledge-based systems because it automates applications that are based on precedent or that contain incomplete causal models . 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).

In a 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].

IV. The Role of Expert Systems Tecnology in Environmental Management Tasks

Based on the analysis of the published results during the last ten years, we can summarize the different roles of the expert systems technology in the following enviromental management tasks.

- Determination of an entire cause of actions before initiation and their implementation, e.g. Planning the development of a site after mineral extraction
- Fault detection with a repair or remedy suggestion, e.g. Identification of a crop growth rate problem and subsequent corrective actions.
- Education about a subject field or domain area, e.g. Education of manger about a new subject area
- Selection of actions and components and there interconnection to achieve a pre-determent specification, e.g. Design and configuration of chemical mix, from stock available, to control pets, diseases or combination of both.
- Solution finding to a known problem, e.g. Debugging and prescription of nutrients to correct a deficit which is causing a reduction in a plant's growth rate.
- Inferring like consequences of given situations, e.g. Prediction of a crop pest number in the future.
- Inferring a situation from it's description, e.g. Interpretation and determination of a crop growth stage.
- Continuous interpretation signals with expected values and governing of overall behavior system, e.g. Mentoring and controlling a greenhouse environment.

In addition, it can be reported the following features of the IDSSs;

The ability to be used effectively for diagnosis, planning, management and design.

The ability to acquire, represent ,structure and manage the knowledge in the domain under study.

The ability of the knowledge base of static and dynamic knoeledge of the specific task.

The ability to assist the user during problem formulation and selecting the solution methods.

The ability to deal with spatial data .

The ability to provide expert knowledge specific to the domain of interest.

V. Conclusions

Artificial intelligence technology offers potentially powerful methodologies,techniques and tools for the development of intelligent environmental desion 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 technique and the reasoning approach that fits the domain knowledge and the problem to be solved. Such selection is a very difficult knowledge engineering process.

References

[1] K. Maeda, "An intelligent decision support system for activated sludge wastewater treatment systems," Instrumentation and Control of Water and Wastewater Treatment Systems, 1985

[2] N.M Avouris, "Co-operating knowledge-based systems for environmental decision-support," Knowledge-Based Systems, vol. 8, no. 1, pp. 39–53, 1995

[3] 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

[4] J. Wright, L.Wiggins, R. Jain, and T. John Kim (Eds.), Expert Systems in Environmental Planning, Springer-Verlag, 1993

[5] 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. Cort´es and M. S`anchez-Marr`e, pp. 161– 176,1998

[6] 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

[7] 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
[8] 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
[9] 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
[10] E. Rizzoli andW.Y. Young, "Delivering environmental decision support systems: Software tools and techniques," Environmental Modelling and Software, vol. 12, no. 23, pp. 237–249, 1997
[11] CORT´ ES, M. S ` ANCHEZ-MARR`E AND L. CECCARONI, "Artificial Intelligence and Environmental Decision Support Systems", Applied Intelligence 13, 77–91, 2000, Kluwer Academic Publishers. Manufactured in The Netherland
[12] Cortés, U., Sànchez-Marrè, M., Sangüesa, R., Comas, J., R-Roda, I., Poch, M. and Riaño, D., Knowledge Management in Environmental Decision Support Systems AI Communications. 14(1), 3-12 , 2001
[13] Cortés, U., M. Sànchez-Marrè, L. Cecaronni, I. R.-Roda, and M. Poch, Artificial Intelligence and Environmental Decision Support Systems, Applied Intelligence, 13(1), 77–91, 2000
[14] Poch M., Comas J., Rodríguez-Roda I., Sànchez-Marrè M. and Cortés U., Designing and building real environmental decision support systems, Environmental Modelling and Software, 19(9), pp. 857-873 ,2004
[15] J. Klodoner, "Case Based Reasoning", Morgan Kaufmann Publishers Inc, 1993
[16] Sànchez-Marrè, M., J. Comas, I. Rodríguez-Roda, M. Poch and U. Cortés,.Towards A Framework for the Development of Intelligent Environmental Decision Support Systems, 4th International Congress on Environmental Modelling and Software (iEMSs'2008). iEMSs'2008 Procceeding Vol. 1, pp 398-406,2008
[17] Sànchez-Marrè M., Gibert K., Sojda R. S., Steyer J. P., Struss P., Rodríguez-Roda I., Comas J., Brilhante V. and Roehl E. A., Intelligent Environmental Decision Support Systems. Chapter 8 in the book edited by Jakeman, A.J., Rizzoli, A., Voinov, A. and Chen, S.,Environmental Modelling, Software and Decision Support. State of the Art and New Perspectives, pp. 119-144. In the series: Developments in Integrated Environmental Assessment, vol. 3. Elsevie Science, Amsterdam, 2008
[18] Crossman, N.D., Perry, L.M., Bryan, B.A., Ostendorf, B., CREDOS: A Conservation Reserve Evaluation and Design Optimisation System. Environmental Modelling and Software 22,449-463,2007
[19] Dorner, S., Shi,J., Swayne, D., Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model. Environmental Modelling and Software 22, 211-222, 2007