Expert systems and simulation

Brian R. Gaines* & Mildred L. G. Shaw

Department of Computer Science, York University
4700 Keele Street, Downsview, Ontario, Canada M3J 1P3
&
*Department of Computer Science, University of Calgary

Simulation and expert systems are contrasted as computer-based technologies for the support of human knowledge processes. An overview is given of ES developments emphasizing that an ES is not just a static encoding of expertise but rather a dynamic process promoting the acquisition of knowledge. Applications of ESs to industrial control problems are discussed where the links to classical control and simulation can be most readily seen. Simulation and ESs are shown to be complementary technologies distinguished in supporting decision and action, in either providing access to simulated experience of the world, or providing access to discussion about the world. The combination of simulation and ES technologies is examined and shown to form a basis for very powerful system designs.

INTRODUCTION

Simulation has been one of the most significant applications of computing systems since the early development of the digital computer. Is is particularly important in control, decision support, and in aiding human knowledge processes by allowing theories and ideas to be tested in operational form. In recent years there has been an explosion of interest in another type of aid to human knowledge processes, with applications in control and decision support, **expert systems** (ESs) which provide one person with interactive access to another person's skills encoded in a computer in some way.

At first sight this new technology seems quite remote from that of simulation. ESs encode the processes of the human mind, knowledge representation and inference. Most simulation applications are concerned with physical variables that seem far more concrete, and certainly better understood, that the concepts of "knowledge" and "reasoning". There also appears to be a confrontation of paradigms involved:

(a) the classical approach to designing a system solving some problem is to identify the problem in detail, model it mathematically, and then develop an algorithm for its solution either analytically or through simulation;
(b) the ES approach is to assume that the problem is not identifiable in detail but that heuristic solutions to it exist and are exemplified in the skills of experts who are known to be able to solve it, and to model the behavior of the expert in order to develop an algorithm.

This is a substantial shift in problem solving techniques that represents a fundamental change in scientific paradigms. The success of ES technology in solving previously intractable problems in industrial control, medicine, geology, and so on, has created widespread interest in the technology and acceptance of the new paradigm. It has many significant immediate applications. However, there are many links between the technologies of simulation and those of ESs, and possibilities for even more significant applications if the two can be blended effectively together.

This paper considers two significant relationships between simulation and ESs:

(i) that an ES can be considered as the simulation of the mind of a person whereas most simulation is that of the physical world - these can be seen as complementary developments of computing to provide new **media** to support the knowledge, decision and control processes of people;
(ii) that ESs and simulations can be combined in decision support systems and the varied interplay possible between people, simulated experts, simulations and the real world can be used to design new forms of system with enhanced capabilities;

The paper commences with an overview of ES developments emphasizing, in particular, that an ES is not just a static encoding of expertise but rather a dynamic process promoting the acquisition of knowledge. It illustrates some applications of ESs to industrial control problems where the links to classical control and simulation can be most readily seen. It goes on to show that simulation and ESs may be viewed as complementary technologies and that the distinction between them is one that already exists in human experience and its support through artificial media. Finally, the combination of simulation and ES technologies is examined and it is concluded that this will form a basis for very powerful system designs.

EXPERT SYSTEMS: AN OVERVIEW

The computer simulation of people in the roles of experts on some topic has become an important application of interactive computer systems. It has generated a new industry based on creating expert systems to make the practical working knowledge of a human expert in a specific subject area such as medicine or geology widely available to those without direct access to the original expert (Reitman 1984). Programs now exist that have made practical achievements in medical diagnosis, interpretation of mass spectroscopy results, analysis of geological survey data, and other problems where one would normally go to a human expert for advice.

One of the first ES developments was the **fuzzy logic** control system developed in 1974 by Mamdani and Assilian. The system accepted human knowledge of control strategies expressed verbally and encoded it directly as computer programs which acted on the environment (Mamdani & Assilian 1981). This work was undertaken as part of a study of machine learning in process control and the system controlled was a small steam engine. The verbal rules were of the form:

If the pressure error is positive and big and
the change in pressure error is not negative
medium or big
Then make the heat change negative and big.

Fig. 1 Rule from fuzzy logic controller

Priming the learning machine by such rules was first introduced because learning took too long. It was expected that the rules would act like verbal instructions to a human operator and aid the machine in setting up an initial approximate control strategy. However, it was found that rules such as this may be interpreted algorithmically to produce computer control programs that are more effective than those derived from classical control theory. Additionally, the learning machine then proceeded only to "learn" less effective strategies. Hence interest switched to the process whereby human expression of verbal rules that appear vague can lead to highly effective control strategies, that is to the development of ESs.

The rules on which a particular ES is based may be seen as ways of representing knowledge. This is not a new concept as such rules have been used in the past quite independently of computer systems. Figure 2 is an excerpt from a training manual for lime kiln operators (Peray & Waddell 1972). It seems that the encoding of expertise into a set of fairly vague but highly applicable rules is a standard way of making it available to others.

1. When the burning zone temperature is
drastically low:
(a) reduce kiln speed;
(b) reduce fuel.
2. When the burning zone temperature is
slightly low:
(a) increase I.D. fan speed;
(b) increase fuel rate.

Fig. 2 Rules from a lime kiln operator's manual

In parallel with the controller development, other ESs were being developed for completely different domains. MYCIN is a well-known medical diagnosis ES which aids a clinician to act as a consultant on infectious diseases (Shortliffe 1976). It uses rules of the form:

RULE 50
If 1) the infection is primary-bacteremia, and
2) the site of the culture is one of the
sterile sites, and
3) the suspected portal of entry of the
organism is the gastro-intestinal tract,
Then there is suggestive evidence (.7) that the
identity of the organism is bacteroides.

Fig. 3 A MYCIN rule

These rules are obtained from specialists in microbial infections and their application to particular data is fairly simple data processing. The rules are validated through their application to many cases and revised when they fail to give the correct diagnosis.

MYCIN is designed to interact with a clinician in order to make a diagnosis and suggest therapy for a particular patient with a suspected microbial infections. It first gathers data about the patient and then uses this to make inferences about the infections and their treatment. Fig. 4 shows part of a dialog between MYCIN and a clinician responsible for testing and treating a patient.

--------PATIENT-1--------
(1) Patient's name: (first-last)
**FRED SMITH
(2) Sex:
**MALE
(3) Age:
**55
(4) Have you been able to obtain positive
cultures from a site at which
Fred Smith has an infection?
**YES
--------INFECTION-1--------
(5) What is the infection?
**PRIMARY-BACTEREMIA
(6) Please give the date and approximate time
when signs or symptoms of the primary-
bacteremia (INFECTION-1) first appeared.
(mo/da/yr)
**MAY 5, 1975
The most recent culture associated with the
primary-bacteremia (INFECTION-1) will be
referred to as:
--------CULTURE-1--------
(7) From what site was the specimen for
CULTURE-1 taken?
**BLOOD
(8) Please give the date and time when this
blood culture (CULTURE-1) was obtained.
(mo/da/yr)
**MAY 9, 1975
The first significant organism from this
blood culture (CULTURE-1) will be referred to
as:
--------ORGANISM-1--------
(9) Enter the identity of ORGANISM-1:
**UNKNOWN
(10) Is ORGANISM-1 a rod or coccus (etc.):
**ROD
(11) The gram stain of ORGANISM-1:
**GRAMNEG
(12) Have there been POSITIVE cultures from
sites which are NOT associated with
infections about which you are seeking
advice?
**NO
(13) Did ORGANISM-1 grow aerobically?
**YES (8)
(14) Did ORGANISM-1 grow anaerobically?
**YES
(15) What is the suspected portal of entry
of ORGANISM-1 into the sterile site?
**GI (6)

Fig. 4 Some interaction with MYCIN

The Spread of Expert System Technology

Since the initial success with MYCIN a very wide range of ESs have been developed. Fig. 5 is a brief summary of some well-known expert systems and their applications.

DENDRAL	structure of chemical compounds from mass-spectral data and knowledge of mass spectrometry
META-DENDRAL	inferring rules of mass spectrometry
MYCIN	diagnosis of blood infections and recommendations for treatment
TEIRESIAS	knowledge acquisition and debugging
EMYCIN	empty (essential) MYCIN expert system shell
PUFF	EMYCIN with knowledge base for pulmonary function disorders
MOLGEN	scientist's assistant for planning experiments in molecular genetics
PROSPECTOR	assisting evaluation of geological prospects
CASNET	diagnosis of glaucoma (eye disease)
XCON	(or R1) system for configuring VAXs
INTERNIST	advisors for general internal medicine (can deal with symptoms and diagnose 500 diseases)
AM	automated mathematician discovers interesting conjectures in mathematics
CRYSALIS	infers protein structure from electron density maps

Fig. 5 Some well-known expert systems

Fig. 6 is a brief summary of the areas of application and numbers of ESs in use in 1983 (Gevarter 1983). The numbers and domains have both increased greatly since these tables were prepared as research and applications of ES have developed world-wide. It is now impossible to make any accurate count since most universities have some activity and many industrial expert systems are regarded as highly proprietary. The initial problems of **knowledge engineering**, of extracting knowledge from experts and encoding it for computers are beginning to be overcome and ESs can now be prototyped very rapidly for some applications (Shaw 1984, Boose 1984).

FUNCTION	NUMBER	DOMAINS
Diagnosis	9	medicine, computer faults, nuclear reactor accidents
Data analysis	8	geology, chemistry, protein crystallography, medicine, oil-well logs
Analysis	5	electrical circuits, naval threat, mechanics, digital circuits, earthquake damage assessment
Design	3	computer system configuration circuit, chemical synthesis
Planning	10	chemical synthesis, robotics, molecular genetics, medical diagnosis, scheduling
Learning	2	chemistry, heuristics
Concept formation	1	mathematics
Monitoring	1	patient respiration
Computer-aided instruction	9	electronics, mathematics, medical diagnosis, coaching, plant operation
Knowledge acquisition	2	medical diagnosis, geology
Expert system construction	10	medical diagnosis/consulting, electronic diagnosis
Intelligent assistant	7	weapons assignment, medicine, radiology, computer sales, nuclear plant configuration
Management	2	project, automated factory
Automatic programming	7	modelling of oil-well logs
Image analysis analysis	2	understanding images

Fig. 6 Applications of expert systems

The Importance of Meta-Knowledge

MYCIN works well when the rules are complete and correct, but it was difficult to set up the rules initially. It was also difficult to trace the rules causing errors in the deductions of MYCIN if the clinician feels that something has gone wrong. To overcome these problems TEIRESIAS (Davis & Lenat 1982) was added as an auxiliary ES with expertise about MYCIN as shown in Fig. 7. It has the facility to explain MYCIN's decisions, and help the clinician amend the rules when they lead to incorrect conclusions.

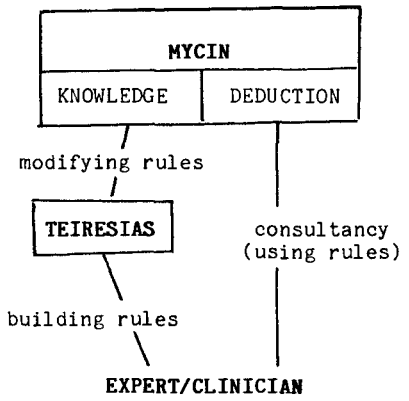


Fig. 7 MYCIN and TEIRESIAS, an advanced ES

TEIRESIAS uses a similar rule-based approach to reasoning as does MYCIN but the rules are now rules about the forms of rules and the use of rules. The rules of Figs. 1 through 3 are expressions of inferences from data about the world to conclusions about it, a basic level of knowledge processing. Davis discovered that similar rules could express inferences at a higher level about relations between these basic patterns of inference. A typical one of these **metarules** has the form:

```
METARULE003:
If 1) there are rules which do not mention the
      current goal in their premise
   2) there are rules which mention the current
      goal in their premise
   Then it is definite that the former should be
      done before the latter.
```

Fig. 8 A TEIRESIAS metarule

The effect of the metarules on the dialog is that the clinician and MYCIN/TEIRESIAS are now able to discuss the rules and inferences made as well as the patient, organisms and infection. Figure 9 shows a debugging sequence in which MYCIN has made an incorrect diagnosis and TEIRESIAS aids the clinician in correcting it.

```
My therapy recommendations will be based on the
  following probable infection(s) and potential
  causative organism(s):
INFECTION-1 is PRIMARY-BACTEREMIA
    <Item 1>  E.COLI [ORGANISM-1]
    <Item 2>  PSEUDOMONAS-AERUGINOSA [ORGANISM-1]
Are all these identities correct?
++** N
Are there any identities missing?
++** Y
Which one(s)?
++** KLEBSIELLA-PNEUMONIAE PROTEUS-NON-MIRABILIS
Are there any identities that shouldn't have
  appeared?
++** Y
Which one(s)?
++** PSEUDOMONAS-AERUGINOSA
Do you want to
  1] track down the problem yourself, or
  2] allow me to guide the debugging, or
  3] ignore it for now and fix it another time?
Type 1, 2 or 3
++** 2
We'll start with the PSEUDOMONAS-AERUGINOSA
  first. The following rules were used in
  deducing that the identity of ORGANISM-1 is
  pseudomonas-aeruginosa
RULE184
Since [1.1] the category of ORGANISM-1 is not
    known
  [1.2] the gram strain of ORGANISM-1 is gramneg
  [1.3] the morphology of ORGANISM-1 is rod
  [1.4] the aerobicity of ORGANISM-1 is
    facultative
  There is weakly suggestive evidence (.3) that
    the identity of ORGANISM-1 is pseudomonas-
    aeruginosa
Is this rule correct?
++** Y
Should its premise have failed for this case?
++** Y
Which clause of the premise should have been
  false? [give #]
++** 1
No conclusions were reached concerning the
  category of ORGANISM-1. Should it have been
  possible to conclude a category?
++** Y
Which one?
++** ENTEROBACTERIACEAE
There were no rules successfully invoked in the
  attempt to deduce that the category of
  ORGANISM-1 is enterobacteriaceae.
The following (potentially applicable) rules were
  NOT executed because the starred [**] clause
  failed:
RULE116
If  1) the identity of ORGANISM-1 is not known
 ** 2) the gram strain of ORGANISM-1 is not known
    3) the morphology of ORGANISM-1 is not known
    4) the site of CULTURE-1 is csf
    5) the infection is meningitis
    6) the age (in years) of Albert Hall is less
       than or equal to .17
  then there is weakly suggestive evidence (.33)
    that the category of ORGANISM-1 is
    enterobacteriaceae
RULE050
If  1) the morphology of ORGANISM-1 is rod
    2) the gram strain of ORGANISM-1 is gramneg
    3) the aerobicity of ORGANISM-1 is facultative
 ** 4) the infection with ORGANISM-1 was acquired
       while the patient was hospitalized **
  then there is suggestive evidence (.7) that the
    category of ORGANISM-1 is enterobacteriaceae
Are all these rules correct?
++** Y
Should any of them have been successfully invoked?
++** N
Is there a rule missing?
++** Y
Ok, then I need a rule that would allow me to
deduce that the category of ORGANISM-1 is
enterobacteriaceae.
Would you like to give me such a rule now?
++** Y
```

Fig. 9 Changing MYCIN's knowledge base by interaction with TEIRESIAS

In this dialog the clinician noticed an identity was missing in those deduced by MYCIN. He chose to allow TEIRESIAS to guide the debugging, and it used the metarule of starting with the identity which appeared incorrectly. The program then reconstructed the deductive process, asking the clinician to confirm its actions at each stage,

or comment on anything incorrect. It confirmed the facts about the particular case in hand and checked that the rules were correct. Before very long the issue has become sharply focused for the clinician and the system.

The main guideline in debugging MYCIN is that a rule must be found which is relevant to this particular patient, but true in general, and enhancing the set of rules of knowledge. The new rule is added to the set of knowledge rules, with a tag explaining who added it and in what circumstances. This allows the ultimate level of explanation to be given in terms of who added the rule and the reasons given. Whereas MYCIN's rules are specific to microbial infections, those of TEIRESIAS are more general and can be used in other domains. Davis (1983), for example, shows TEIRESIAS being used as an investment decision system for clients of a stockbroker.

Inductive Acquisition of Knowledge

The interaction with TEIRESIAS demonstrates the dynamic nature of ESs. They have often been presented in the literature as means of capturing expert knowledge as if that knowledge was a static, finished product, universal in nature and owned by one person. In practice knowledge is fluid, situational and generally distributed across groups of people. The initial priming of an ES with the knowledge of one or more experts is a way of getting started. Metarules cannot be effective unless the basic vocabulary and patterns of inference have been at least approximately established. However, an ES then becomes an entity that grows with the knowledge and experience of its users. It is a support tool for their knowledge acquisition and refinement as well as a way of making it more accessible to themselves and others.

The use of metarules allows ES to be programmed interactively by their users. From one perspective TEIRESIAS can be seen as an important development in automatic programming. From another it can be seen as a way in which a machine acquires knowledge through interaction with a person. Metarules may also be used to implement knowledge acquisition procedures in which machines acquire knowledge directly through their interaction with the environment, i.e. a process of **machine learning** (Michalski & Carbonnel 1983).

Mamdani, Procyk and Baaklini (1976) found that learning could be introduced effectively in the steam engine controller through metarules that expressed the way in which the basic rules should be changed as a result of performance feedback. The learning level of their controller operator on rules of the form:

If time is small and error is negative big
  Then desired change is big.
If time is big and error is positive zero
  Then desired change is zero.

Fig. 10 Rules from fuzzy learning controller

The use of a very high level of metarules for knowledge acquisition is illustrated by AM (Davis & Lenat 1982) which searches for "interesting" conjectures in mathematics. What is remarkable about AM is the very notion of what it is doing. This is the highest level of scientific creation, looking for the patterns underlying knowledge. The concept of something being interesting seems peculiarly human and certainly too vague to form the basis of a computer program. However, AM is not only able to generate profound conjectures in mathematics but also meaningful ways of arriving at them. It is judged by the quality of its musings as it considers what it is doing.

Figure 11 shows two of the few hundred rules used by AM. Most of them are sufficiently general to apply to other situations. In an organizational context, for example, Rule 19 indicates that a committee which has decision-making powers that do not apply to its sub-committees below a certain size has an interesting property (that of requiring a quorum). Its sub-committees also have an interesting property (that of being quorate).

19. If concept C possesses some very interesting property lacked by one of its specializations S,
Then both C and S become slightly more interesting.

38. If there are no known examples for the interesting concept X,
Then consider spending some time looking for such examples.

Fig. 11 Two rules of high generality from AM

AM has been criticized for some of the short-cuts taken in its implementation which cast doubts on the conclusions that may be drawn about the power and generality of the mechanisms used (Ritchie & Hanna 1984). Lenat and Brown (1984) have analysed its success in mathematics and failure elsewhere and suggest that AM had easy access to much of what it appeared to discover through the natural expression of certain mathematical conjectures in Lisp. However, inductive inference without presupposition is impossible (Gaines 1977) and AM provides an interesting example of Kant's (1781) notion of **synthetic a priori** knowledge. AM's knowledge of mathematics is synthetic, not analytic, because it could not infer it from existing premises. However, it is also **a priori** because it was available to it, but only through its exploratory experience (Gaines & Shaw 1984a).

Inductive inference of knowledge through machine learning procedures is a significant alternative to direct access to the verbal knowledge of experts, and comes closer to capturing the knowledge of main interest. We want to know the basis for what the experts **do** rather than what they **say** they do. Michalski & Chilausky (1980) have reported an interesting comparison of two ESs for plant disease diagnosis, one constructed directly from the expert's stated rules, and the other constructed automatically by an algorithm for logical induction of structure from behavior. The ES with induced rules had a better performance in diagnosis and the expert agreed that its rules, although not obvious at first, were better than his own.

Summary

Expert systems have developed in the past decade from experiments in artificial intelligence to a

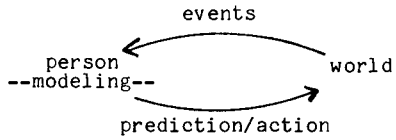
major commercial industry. They allow human expertise in knowledge representation and inference to be encoded for computers and used for problem-solving. They provide not only a static recording of expertise but also the capability to develop and extend that expertise and tailor it to local situations. Successful applications include not only high-level human cognitive skills such as medical diagnosis, but also important industrial control skills where people carry out tasks that could not be automated using previously available techniques. The most recent developments of ES include knowledge acquisition not only through interaction with experts but also through inductive inference from experience.

EXPERT SYSTEMS AS A NEW MEDIUM FOR COMMUNICATION

We commenced by noting the differences between the classical use of simulation to support human knowledge processes by making available operational models of the world, and the recent development of expert systems to support human knowledge processes by encoding them directly for the computer. There is one obvious link between ES and simulation if we view ES as simulating the knowledge processes of the person. However, this is a terminological link generated by taking simulation in its most general context rather than in the specific context of activities which have been termed simulation in the past in the computing imdustry.

A more subtle link is to analyse simulation and ES as providing **complementary** approaches to providing aids to the person in coping with the world. Simulation provides models of the world which can be used to test ideas before they are tried in the real world. ESs provide models of people which can be used to discuss ideas before they are tried in the real world. This distinction is one that predates computers and occurs in human knowledge acquisition and the media to support it. We may gain knowledge of the world by direct action or by conversation with others as shown in Fig. 12.

DIRECT EXPERIENCE - TWO-WAY



CONVERSATION - TWO-WAY

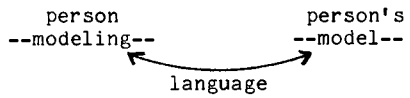
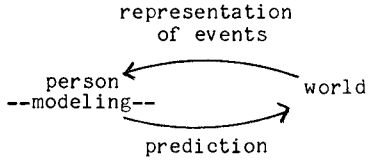


Fig. 12 Two modes of human knowledge acquisition

As shown in Fig. 13, representational media such as photographs and television provide an alternative channel for experience of the world. Symbolic media such as letters and books provide an alternative channel for conversation about the world.

MEDIA (REPRESENTATIONAL) - RADIO, TV - ONE-WAY



MEDIA (SYMBOLIC) - BOOKS, JOURNALS - ONE-WAY

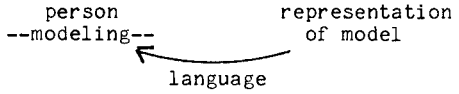
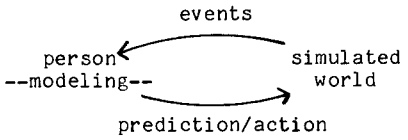


Fig. 13 Two modes of operation of media

A major disadvantage of past media has been that they are one-way. We can experience remote events through television but cannot interact with them. We can access the thoughts of an absent person through his writing but cannot discuss them with him. As shown in Fig. 14, computing can be regarded as a providing a new medium which is two-way and hence interactive (Gaines & Shaw 1984). Simulation corresponds to mediating direct experience of the world. Expert systems correspond to mediating conversations with people.

COMPUTER SIMULATION OF DIRECT EXPERIENCE- TWO-WAY



COMPUTER SIMULATION OF CONVERSATION - TWO-WAY

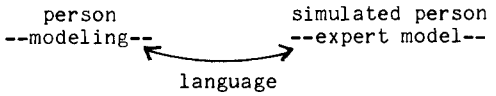


Fig. 14 Computing in the evolution of media: an interactive medium for encoding simulated worlds and people

However, once we view simulation and ES in this way, and when we realize the capability of ES to acquire knowledge both from people and through experience, it is apparent that the two complementary uses of computers shown in Fig. 14 may be combined in a variety of ways. Figure 15 shows a system in which simulation and ES provide mutually supportive capabilities to a person in a decision support system that might well be termed a computer-based **prosthetic brain.**

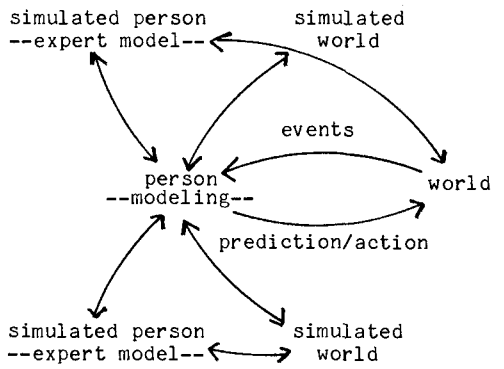


Fig. 15 Combination of simulation of the world and simulation of the expertise of people in a decision support system

In this example, the person interacts with the world. He may test predictions and actions in simulated worlds. He may ask advice from simulated experts. He may turn control over to simulated experts. The simulated experts may use the simulated worlds as part of their knowledge processing. The simulated experts may have access to real-world experience for knowledge acquisition. The simulated worlds may be updated from real-world experience, by the person or by simulated experts.

This example shows that many combinations of simulation and ES technologies are possible. We may expect future system designs to draw on both and that the power gained through the optimal combination of these technologies will be much greater than the sum of each used separately.

CONCLUSIONS

Simulation and expert systems are complementary techniques for using computers to support human knowledge processing. Attention is focused on ES currently because they are a recent development involving a change in paradigm that has proved effective in industrial applications. There are many benefits to be gained from the application of ESs to problems where the classical approach of modeling the problem and computing an optimum solution is not possible and where, instead, it is possible to generate a solution by modeling a person solving the problem. This allows the automation of tasks that were previously beyond computer implementation because of our lack of in-depth understanding of the processes involved. However, there are even greater benefits to be agined through combination of simulation and ES techniques in integrated systems, and we may expect the focus of attention to shift to such possibilities as ES technology becomes better understood and more readily available.

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