TRANSFERRING KNOWLEDGE

A Parallel Between Teaching Chemical Engineering and Developing Expert Systems

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Since the coining of the phrase "artificial intelligence" (AI), in 1955, to describe codes imitating various aspects of the human intelligence, numerous books, reviews, and research papers have been published which deal with the socio-economic aspects of introducing such technology into the human environment. According to John McCarthy [1] (inventor of the AI phrase), too few people are working, a quarter of a century later, in AI research and too many on its applications. This imbalance in the present effort is mainly due to the considerable market developed during the last ten years for one of the most visible and successful applications of AI, *i.e.*, expert systems (ES) tools and services. The latest Ovum report [2], for example, estimated that sales of ES products and development services in the US and Europe were over $400 million in 1988, with an annual increase of approximately thirty percent.

While it is true that better tools originating from computer science laboratories will make AI products more closely mimic the best of human intelligence and will eventually render machines more flexible in their learning process, the real debates around widespread implementation of AI products are still to come.

From a philosophical point of view, the advent of AI is a true sign of an imminent grand inter-disciplinary marriage. According to Haugeland [3], AI has little to do with computer technology and much more to do with abstract principles of mental organization. From the same philosophical point of view, the successful ES technology belongs to a micro-world strategy that is really not made for exploring the underlying principles of general intelligence and common sense.

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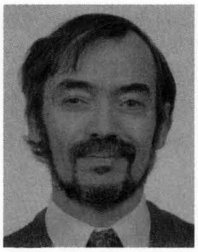

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ES DEVELOPMENT AND TEACHING

Two Information Processing Disciplines

For a specialist or a real expert, developing an expert system prototype is a challenge in knowledge engineering and information processing which is both difficult to define and fascinating because of its inter-disciplinary nature. On the other hand, the development of professional competence in teaching can be seen as an increased ability to play various assigned roles more effectively, even if such a statement may not seem obvious to someone starting a teaching career.

Different roles require different teaching strategies which can be based on defendable theories about how people learn, grow, and develop. Some of these theory-based models of teaching are more appropriate to some objectives than to others. At the higher education level, the most relevant models pertain to the mastery of subject matter and deal mainly with information processing goals, although not necessarily excluding other social and personal development goals.

The information processing models of teaching

In a general article on the influence ES technology will have on how chemical engineers do their job in the future, Barnwell, et al., predicted that it could have a major impact and dramatically change the role practising chemical engineers play in their respective industries. Major chemical processing companies have already established groups to explore and exploit ES technology

focus mostly on the development of the information processing capability of students and on the systems that can improve their information processing capability [4]. In general terms, information processing refers to the ways people handle stimuli from the environment, organize data, sense problems, and generate concepts and solutions to problems. Some information processing models are concerned with the ability of the learner to solve problems and with the productive thinking process, while others are more concerned with general intellectual ability and/or strategies derived from research and development disciplines.

A broad overview of the entire expert system development and implementation process is warranted in order to define the specific skills required to develop expert systems. According to Harmon, *et al.* [5], there are seven phases which can summarize the effort of many people who have fielded commercial expert system applications. This division into seven phases would apply mainly to mid-size or large efforts since the phases of a smaller effort tend to blur together. These seven phases are briefly described in Table 1 in relation to the various skills required to perform the goals characteristic of each phase.

The skill analysis presented in Table 1 indicates that in order to develop expert systems, one needs primarily to be proficient in the art or science of information processing. Although not all teachers and professors excel at information processing, by the very nature of their profession all have to work regularly at transferring information from notes, textbooks, and personal expertise to students avid for useful knowledge.

TABLE 1
Seven Phases of Expert System Development as a Function of Their Goals and the Skills Required

Phase	Goals	Skills Required* M	IP	PR	C
Front End Analysis (1)	• Identify problem		X	X	
	• Evaluate cost/effectiveness	X			
	• Find management support	X		X	
Task Analysis (2)	• Circumscribe task		X	X	
	• Set development schedule	X			
	• Identify knowledge required	X	X		
Prototype Development (3)	• Set information gathering strategy		X		X
	• Develop proof of concept prototype		X		X
System Development (4)	• Arrange overall structure		X		X
	• Build knowledge system		X		X
Field Testing (5)	• Test system with users		X	X	
	• Iterative validation		X	X	X
Implementation (6)	• Prototype system				X
	• Train users		X	X	
Maintenance (7)	• Arrange means to update	X	X		
	• Update system		X	X	X
	TOTAL	5	12	7	7

* *M Skills required in management*
IP Information processing
PR Public relations
C Computing

REPRESENTATION AND PROCESSING OF KNOWLEDGE

The branch of psychology that studies human cognition is called cognitive psychology. Cognitive in this broad sense refers to the acquisition, processing, and utilization of knowledge [6]. While behavioural psychology provided the initial research base for the development of instructional technology, the emergence of cognitive approaches to the analysis of behaviour has led to a new emphasis on the nature, development, and representation of knowledge.

A central design issue pertaining to the instructional planning of learning experiences is how much and what kinds of knowledge transfer can be expected from the specific content of textbooks, lectures, or homework problems to the tasks that students will be expected to handle in subsequent courses or in professional life [7].

There are many possible changes that can take place in students as a result of learning experiences, but since the time and resources are fundamentally limited, only a few of the possibilities can be realized.

In an attempt to develop a taxonomy of educational objectives, a committee of college and university examiners concluded that the most common educational objective in American education is the acquisition of knowledge or information [8]. Knowledge or information may be justified as an important objective or outcome of learning in many ways. Perhaps the most common justification is that with increase in knowledge or information there is a development of one's acquaintance with reality. Such reality may represent what is known by convention or definition, what are known as the findings or outcome of inquiry in the various fields, what are known as the more fruitful ways of attacking problems in the field, or what are known as the more useful ways of organizing a field [8]. This list of goals, which was made to characterize the development of knowledge by education, is almost identical to the central tenet of most methodologies for building ES. In fact, the explication of knowledge domain strategies and knowledge structure has to be accomplished much more meticulously if the knowledge is to be transferred into an unforgivingly logical computerized format.

KNOWLEDGE REPRESENTATION IN CHE

The need to formalize and quantify knowledge structures for AI products has created new trends in knowledge representation that will transform not only how things are perceived but also how engineers think about them. These trends have also started to be visible in recent literature dealing with applications of AI in chemical engineering.

Qualitative reasoning, for example, is a well-defined method for dealing with qualitative models. Some of the proposed process engineering applications include fault simulation [9,10], generation and testing of failure modes [11], and explanation of process behaviour [12]. The shortcomings of qualitative reasoning have stimulated researchers into looking for a more quantitative approach to knowledge representation such as the order-of-magnitude reasoning approach [13]. Reasoning with order-of-magnitude approximate relations makes possible the quantification of some engineering common sense and offers a vocabulary for formalizing concepts and handling diverse forms of knowledge.

A novel approach that exploits symbolic processing and knowledge representation to mimic the adaptive distributed architecture in the human brain was also recently applied to chemical engineering problems. Artificial neural networks are claimed to be particularly suitable for chemical process engineering tasks requiring pattern recognition or continuous input-output control in process with uncertain models or data [14].

Knowledge-based approaches for handling experimental knowledge as well as quantitative and model-based knowledge have emerged as the most appropriate approach for automated process diagnosis. But in order to overcome some of the drawbacks associated with the use of KBES in this context (such as poor efficiency and lack of generality), the focus was put on creating architectures which could explicitly recognize the structured nature of problem-solving activities [15,16]. Integrating compiled knowledge with deep-knowledge is a methodology that is at the same time more efficient at problem solving and also a more accurate representation of the mental models of process operators and engineers [17].

For design activities, KBES will also require hybrid approaches combining the symbolic and numerical domains. The inherent dualism present in such coupled architectures is very much in correspondence with reality. Various approaches have been proposed to incorporate the different types of knowledge and problem-solving strategies which are applied during the design process [18,20]. When the notions necessary to link the knowledge segments are amalgamated into the database design, the spirit of knowledge engineering is also infused into the database. The resultant DBS preserves not only the data but also the knowledge of a certain domain. It is then more ready to interact intelligently with a process designer.

EXPERT SYSTEMS IN CHE

Several review papers on ES or KBS applications in process engineering have been published during the past five years [21-24]. Most of these publications outline the opportunities offered by the evolving AI technology in terms of new conceptual developments and new facilities provided by flexible and friendly computing environments.

In a general article on the influence ES technology will have on how chemical engineers do their job in the future, Barnwell, *et al.* [25], predicted that it could have a major impact and drastically change the role practising chemical engineers play in their respective industries. Major chemical processing companies have already established groups to explore and exploit ES technology. A survey [26] reporting ES applications activities in the industrial sector showed that most of the companies which had demonstrated some interest in the technology had also formed some kind of AI group or task force to foster the successful development of ES within the operating units of the company. Most respondents of this survey predicted that eventually ES technology would become part of computing's mainstream, following a similar pattern established during the recent implementation of the database technology. It was also felt that by reaching a mainstream status the technology would have a significant impact on the chemical engineering profession and could become a primary vehicle for technology and expertise transfer and accumulation.

Universities have also begun to respond to the new needs created by the introduction of ES technology in industry by creating centers such as the Laboratory for Intelligent Systems for Process Engineering (LISPE) established at MIT in 1986 [27]. The original focus of LISPE was to move the use of computing into the earlier stages of the chemical product life cycles and expand it in real-time operations as well as in all other aspects of process operations.

Courses in AI, once the sole domain of computer science and research-oriented projects, are now being made available in chemical engineering curricula as technical electives to graduate and undergraduate students. The re-emergence of artificial intelligence in the early part of the 80*s* was a sufficient stimulus for the Computer Aids for Chemical Engineering Committee (CACHE) to create a special task force with the mission of addressing the role of AI and its derivative environments in the education of chemical engineers [28]. An initial objective of the task force was to generate a compilation of current AI research projects in chemical engineering. Fifteen papers representing the breadth of then-current research and development in progress collected by the task force committee were published as a special issue of an international journal [29].

In the first of two articles on instructional computing in the chemical engineering curriculum, Seider [30] notes that although there is some evidence of computer-oriented problems in courses other than design and control, the level of utilization of computers lags far behind that in the design and control courses. On the topic of expert systems, Seider concluded his paper by stating that in spite of the flurry of activity to develop logic-based systems principally in the fields of design and control, there was, at the time (1988), no evidence of the use of expert systems in chemical engineering coursework.

In a slightly more recent article, Douglas and Kirkwood [31] described an approach to teaching the conceptual design of chemical processes to undergraduates which is based on a very structured approach to inventing petrochemical processes and which would be used as the basis for a hybrid expert system. In another article, Venkatasubramanian [32] described the experiences at Columbia University a few years ago in incorporating a graduate course, specifically designed for chemical engineers, on the applications of knowledge-based ES (KBES) methodology in process engineering. One of the conclusions of these experiences in teaching the interdisciplinary area of AI and process engineering was that student understanding was significantly facilitated through teaching with the aid of examples from chemical engineering and of exercises involving typical process engineering problems. Such a treatment was felt to be missing from courses previously provided by the computer science department.

CONCLUSION

From domain experts and accumulated expertise through a computing machine and back to train and support domain experts, the development of ES requires many of the skills common to those required to teach engineering courses. Trying to make machines simulate the human thought process has forced psychologists and programmers to sit together and develop better models to explain some of the human thinking process. Similarly, the development of KBES for the transfer of expertise and deep knowledge will require that professional communicators of knowledge sit with programmers to draft out adequate strategies and elaborate operational models.

The lessons learned today by organizing domain knowledge and optimizing the generality and efficiency of its transfer into KBES will show the way to new means of knowledge representation. The results of such efforts will then surely benefit educators who are themselves in the business of transferring concepts and knowledge. The articulation of some aspects of tacit knowledge as well as the creation of adequate interfaces between qualitative and quantitative reasoning are two specific examples of grey areas where progress could drastically change how chemical engineering courses are taught in the future.

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REVIEW: THERMODYNAMICS

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as liquid crystals, rubbers, biological systems, and non-equilibrium thermodynamics, Professor Astarita makes it easier for the student to appreciate the relevance of thermodynamics to diverse systems that he or she will encounter later as a researcher.

The author consistently adheres to a high standard of logical and mathematical rigor. A number of intellectually challenging examples and problems are included at the end of each chapter. Extensive literature for further study is also provided. Even small details, such as the usually interesting (but not always obviously relevant) quotations at many points in the text and the attractive typographical layout of the book, help retain the attention of the reader.

It is clear that the intention of this book is to give a broad, somewhat philosophical treatment of classical thermodynamics. Because of this, the book is sometimes limited in the depth of coverage of some of its many topics. I found the omission of certain key concepts, such as Legendre transforms or stability in general thermodynamic systems, to be the most significant potential weakness of the book. Also, no attempt is made to provide the student with the computational skills required to handle complex real-life problems. A minor complaint that I have is that a different notation is used in each chapter; this might lead to some confusion.

Overall, this book is a welcome addition to the thermodynamics literature and is worthy of consideration as a textbook for all or part of an advanced thermodynamics course. The last chapters of the book might provide a useful starting point to researchers interested in applications of classical thermodynamic theory to polymers, electrochemical, and electromagnetic systems. ❐