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Expert Systems in Document Delivery: The Feasibility of Learning Capabilities

ABSTRACT

To solve the problem of document delivery in Mexico, the authors developed SEADO (Expert System for Document Supply). SEADO consists of three main components: a knowledge base, an expert system shell, and the database. The knowledge base was built through fault tree analysis and through structured flowcharts. The shell was developed with EXSYS, a generalized expert system development package. The database was based on information sources of various kinds: printed material, local databases, public databases, etc. To evaluate the impact of different learning capabilities, the authors decided to test alternative ways of achieving a predictor for the system to perform in a dynamic and adaptive way. Learning by a weighted-based scheme was compared with a probability-based scheme.

INTRODUCTION

Today, to be able to get a surrogate from a foreign database is almost trivial, but getting one's hands on a document can be more or less cumbersome at different latitudes. The problems involved in document delivery do not seem to be of great concern to the builders of expert systems (ES). A recent search on the literature of this subject reported only two efforts in this direction (Bianchi & Giorgi, 1986; Waldstein, 1986). The authors have good reasons to believe that this application is the first of its kind in Mexico as well as in all of Latin America.

The first part of this paper explores the conditions where SEADO (Expert System for Document Supply) was conceptualized; the second is devoted to the architecture of SEADO. After some background, the last part deals with the control sketch topic: learning capabilities.

EXPERT SYSTEM FOR DOCUMENT SUPPLY (SEADO)

SEADO has been under consideration for some time as a way of achieving several goals that have remained unfulfilled due mainly to lack of human resources in the area of librarianship in Mexico. Briefly, this paper will explain the reasons behind trying an ES as an alternative way to solve some problems. Table 1 sketches the current environment where the expert system is designed.

TABLE 1
THE WORKING ENVIRONMENT AT THE TECHNOLOGICAL INFORMATION NETWORK FOR MEXICAN UTILITIES

Population served:	690 Researchers
	4,000 Engineers
Means:	Network of 13 special libraries in electric utilities and industry's R & D labs
Acquisitions:	5,000 requests unfilled annually
Types:	30% Journal articles
	25% Conference proceedings and books
	15% Conference papers
	13% Technical reports
	9% Patents
	8% Standards
Constraints:	Incomplete collections (locally and nationally)
	Lack of funds for acquisitions
	Lack of trained staff
	Pressure for expediting
	Poor telecommunications network
	Lack of understanding of the importance of library

Why Should We Start an Expert System?

Apart from the long list of problem criteria given by Liebowitz and DeSalvo (1989, pp. 6-8) which for the most part holds, the authors wished to pursue the following goals:

1. capture the experience from the experts available;
2. make better distribution of human resources;
3. help in making better decisions (thus saving time and money);

4. free the experts from routine tasks;
5. ensure continuous operation in the absence of the experts; and
6. improve the quality of library operations.

The expected results in terms of day-to-day operations should be:

- The expedition of pre-ordering searching
- The evaluation of the best supplier
- The expert's support in decision making
- The expert's knowledge upgrade

SEADO Architecture

Liebowitz and DeSalvo (1989) have defined the process of expert systems construction as follows:

> Building an expert system is an incremental activity which involves the development, critiquing, and subsequent refinement of a succession of prototypes. The successive approximation of the final expert system depends on the results of user trials with the prototypes. (p. 38)

An important aspect in the development of the expert system is the design of its structure or architecture. As Hayes-Roth et al. (1983) have established, the term *architecture* refers to the science and method of design that determine the structure of the expert system. The emergent principles reflect current understanding of the best way to design structures that support intelligent problem-solving. In this context, the architecture of the SEADO consists of the following main components: A knowledge base (KB), an expert system shell (ES), and the database (DB). These components are described briefly below.

The Knowledge Base (KB)

The real power of an expert system is the knowledge base, since it contains the available knowledge of the human experts which is generally developed by the interaction of a knowledge engineer and the knowledge expert in the domain of expertise.

Various methods have been proposed to acquire and formalize knowledge concerning a special universe of discourse (Chachko & Stakbovaya, 1972; Eick & Lockemann, 1985; Weiss & Kulikowski, 1984; Yung-Choa Pan, 1984). Tools from conventional systems analysis can improve the knowledge engineering process through formalization and standardization of expert systems building methods. One of the major advantages of this approach is that it produces a set of specifications, explicative and graphic, for the empirical performance of the system. Knowledge engineering is, after all, a creative science wherein can be developed systems that imitate the behavior of a human expert even though the underlying computer system is vastly different from the human mind in its form, functions, and capabilities (Liebowitz & DeSalvo, 1989, p. 64).

At Instituto de Investigaciones Electricas (IIE), the authors have been using successfully two methods for knowledge acquisition: Fault Tree Analysis (FTA) and Structured Flow Charts (SFC) (Rodriguez & Rivera, 1986).

The FTA approach to building KBs is especially suitable when knowledge is presented in the form of engineering drawings, operational guidelines, maintenance procedures, and heuristic rules. The SFC approach is more adequate when knowledge is procedural and is obtained directly from human experts or from a manual or handbook.

Thus, when the SFC approach is used to build KBs, the charts explain how the human expert makes decisions and arrives at conclusions. If the flowcharts come unstructured from the expert, they should be structured by using only the basic building figures of structured flowcharting: the sequence, the decision, and the loop or cycle (McGowan & Kelly, 1976).

The knowledge base consists of representing human expert knowledge in the form of an SFC which is easily converted to production rules. Figure 1 shows how rules are obtained for each one of three basic structured figures. These rules are condition-action pairs which specify that IF some condition is true, THEN some action is performed.

Production rules, like a knowledge representation technique, have the following advantages:

1. They are easy to express, to understand, and to work with.
2. Every rule expresses a decision procedure.

The rules obtained to select the appropriate supplier using the SFC approach have been divided into seven groups, one for each type of document request: books, conference papers, conference proceedings, journal articles, technical reports, and standards and patents.

In the case of books, there are six possibilities for the assignment of a supplier when the place of publication is Mexico. The place of publication is established via the breakdown of information in the ISBN table. The information about this table that is used by the system will be described later. Figure 2 shows the SFC for the latter case.

Some of the rules obtained from the flowchart follow:

IF publisher from Mexico and book at Gonzalez Libros Tecnicos (GLT)
THEN order to GLT.

IF publisher from Mexico and book not at GLT and is found in Table A-1 and book at American Bookstore (AB)
THEN order to AB.

IF publisher from Mexico and book not at GLT, not at AB and is found in Table A-2 and Book at Delti

THEN order to Delti.

IF publisher from Mexico and book not at GLT, not at AB, not at Delti and is found at LL

THEN order to Local Libraries (LL).

IF publisher from Mexico and book not found at GLT, AB, Delti and LL

THEN order to publisher.

These rules have been captured and stored in a generalized expert system development package which is described below.

Inference Machine (Shell EXSYS)

At the beginning of SEADO's development, several expert systems' programming languages were considered in the design of the KB and the Inference Machine (IM). Recently, the shell EXSYS was selected because it seems to have advantages over other programming languages. Some of these advantages are shortened ES development time, more facilities such as an input processor, and explanation mechanism, and a rule tracer which debugs the KB. Furthermore, the shell EXSYS is more suitable to the authors' needs since the expert's knowledge is easily represented as in production rules.

EXSYS is a generalized expert system development package which asks the user questions relevant to a subject, and has the user answer by selecting one or more answers from a list or by entering data. The computer continues to ask questions until it reaches a conclusion. This conclusion may be the selection of a single solution or a list of possible solutions arranged in order of likelihood. The ES can explain how it arrived at its conclusion and why.

The development of the ES with EXSYS can be applied to any problem that involves a selection among a definable group of choices where the decision is based on logical rules. Furthermore, the rules can involve relative probabilities or weights (certainty factor) of a choice being correct.

EXSYS can communicate with external programs for data acquisition, calculation or result display, and data can be passed back to EXSYS for analysis. Furthermore, EXSYS can receive data directly from databases and spreadsheets.

The Database (DB)

The database which provides the necessary data that the expert system uses to execute some of the rules associated with it contains tables (dictionaries) based on information sources of various natures, i.e., printed repertories, local databases, public databases, etc.

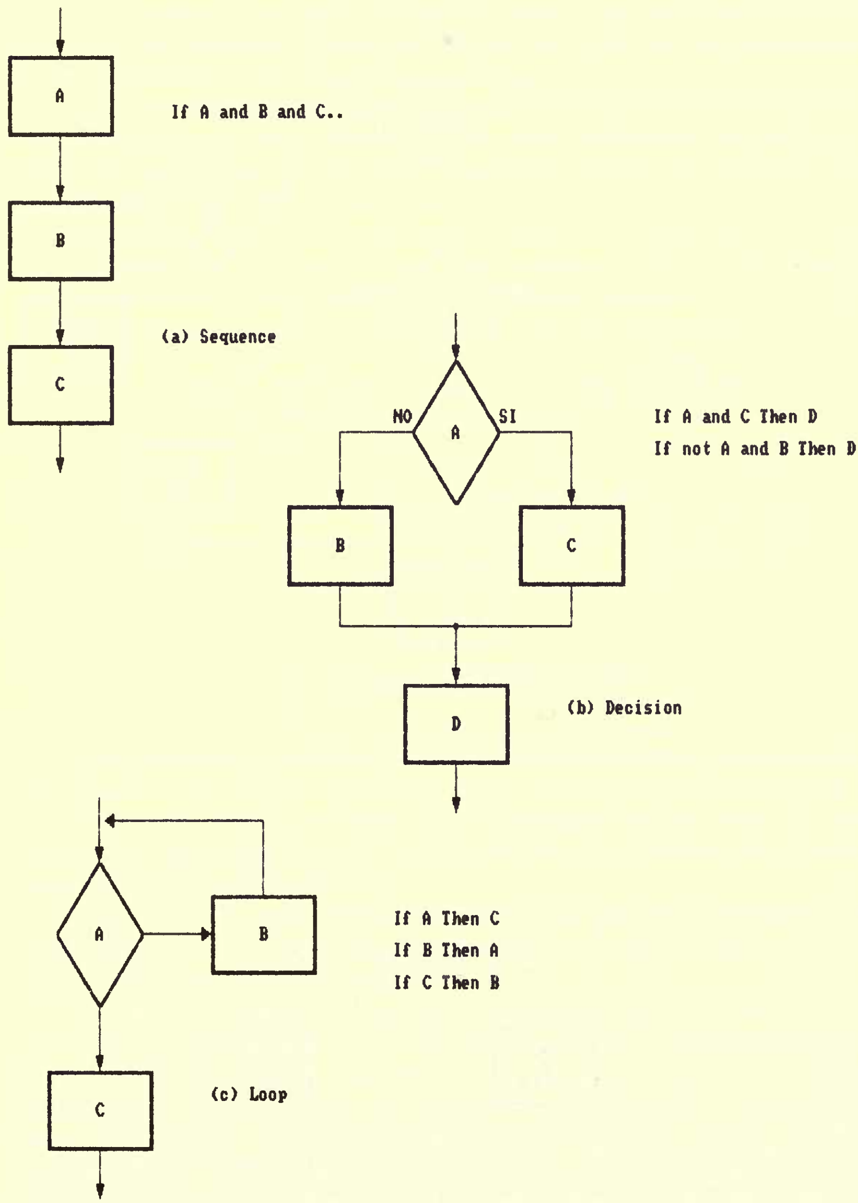

Figure 1. Conversion to production rules of the three basic building blocks of structured flowcharts

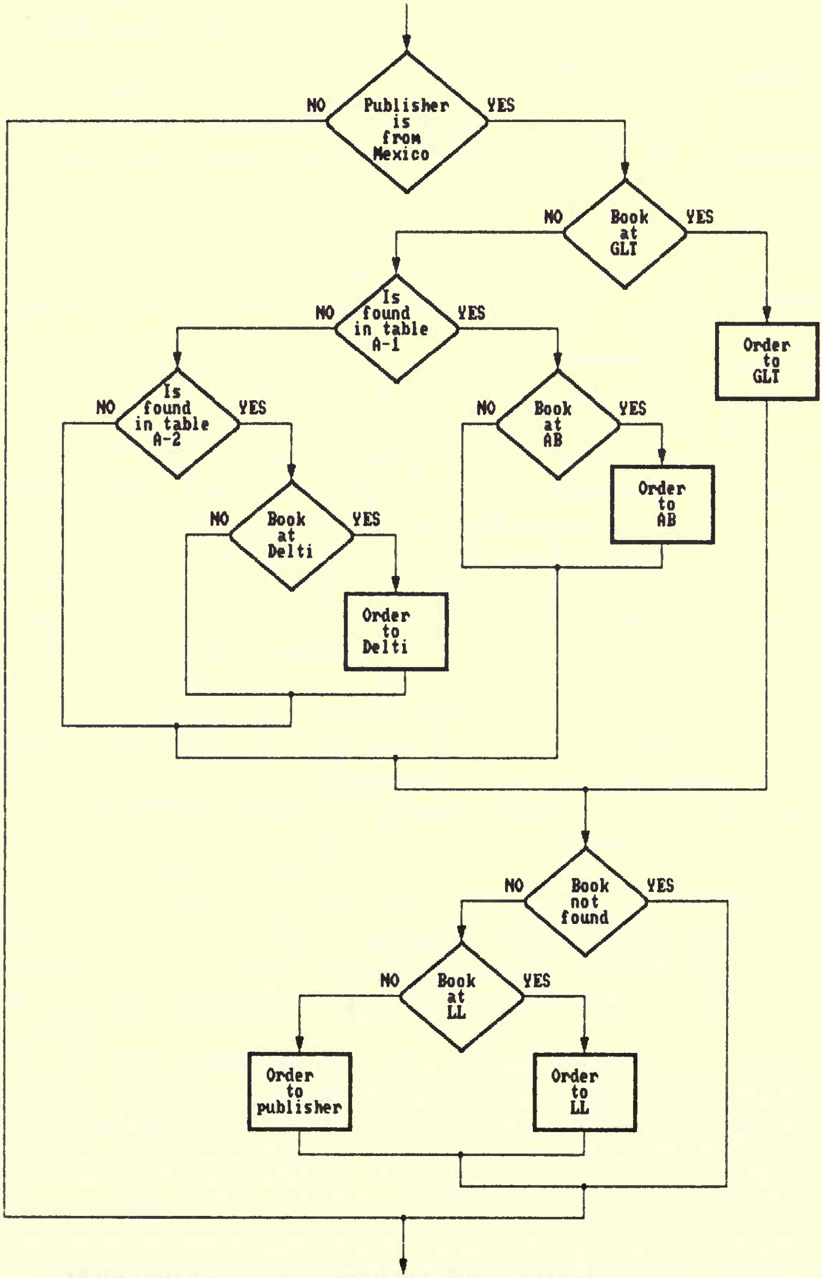

Figure 2. Flowchart for suppliers when the publishers are from Mexico

For each type of bibliographic material, there exists a set of tables that the expert system uses to identify certain parameters which allow the ES to select the supplier. Here only one of the tables and its main function are described. Details on the tables built for this purpose are given in Pontigo et al. (in press).

In cases where the bibliographic material contains the ISBN number as a data element—for example, books and conference proceedings—Table 2 includes a list of ISBN numbers, places of printing, and publishers.

By means of this table, the expert system finds and identifies data (such as publisher) that some of the rules request to be fired. The database can be enriched at any moment with relevant information which will be evaluated periodically to ascertain its value for the system.

TABLE 2
LIST OF PUBLISHERS (EXAMPLE)

ISBN	*Place*	*Publisher*
0-387-10771-1	New York, NY	Springer-Verlag
0-12-685480-7	Orlando, FL	Academic Press
0-07-023655-0	New York, NY	McGraw-Hill

LEARNING CAPABILITIES

The reasons for exploring these attributes have been given elsewhere in regard to the expert system at large. In this case, the number of occurrences is not big enough to be considered in any way the only reason for this endeavor, but it is sufficient to illustrate the benefits obtained on a larger scale.

The learning capabilities of SEADO are geared to maintain size control and, at the same time, to streamline the system and allow for a more efficient overall operation.

Previously mentioned was the broad problem to be solved with the expert system—namely, to make the operation of document delivery more efficient through the use of prior experience and ordering information. The problem may be stated more precisely as follows: *We need to design an expert system for document delivery that is dynamic and adaptive.* Adaptivity and dynamism are attributes which were not simple to achieve mainly because of the amount of information that has to be dealt with in traditional systems. No doubt, many others have come across these problems, but there are no direct references to them in the literature.

The authors have raised the following questions related to learning capabilities in regard to the design of ES, both in dynamic and adaptive behaviors:

1. How can we design in order to guarantee the best use of information used in the process?
2. There have to be changes in the system with the acquisition of a particular type of material. What changes? How much change?
3. What number of cases processed yearly is significant for depletion rules to hold without degrading the quality of decisions?

The Experiment

In order to evaluate the impact of different learning capabilities, the authors decided to test alternative ways of achieving a predictor for the system to perform in a dynamic and adaptive way. Learning via a weighted-based scheme was compared with a probability-based approach.

The design of the ES incorporated a criterion for depletion rules based on Pareto's Law of Diminishing Returns, also known as the 80/20 rule. According to Pareto, 80 percent of the orders should be delivered by 20 percent of the suppliers. The expectation is that the databases used as sources for the experts' decisions be streamlined with the same rule at least once a year. The idea was to compare one of the weighted criteria with another, based on the probability of acquiring something given prior acquisitions history.

The best data available for the first comparison used the criterion "Potential use in research projects" as expressed by the population of the originating sources as represented in the shelflist, to be compared with data available on acquisitions from 1985 to 1989 (see Table 3).

Using information about the suppliers from each group described, data were ranked and compared using the Spearman Correlation Coefficient (rs) with results of $rs = 0.607$ when all suppliers were included and $rs = 0.19$ when the two biggest suppliers were excluded. This shows the poor correlation of the two criteria used. Figures 3 and 4 show the cumulative distribution in both cases.

In the comparison of probabilities, the probability of the report's producer being a contributor was rank-correlated both to the acquisitions from 1985-86 and to 1986-89. The Spearman Correlation Coefficient (rs) finding was $rs = 0.922$, with very little distortion when the two big suppliers' data were pulled off: $r = 0.858$.

The technical reports purchased come mainly from two suppliers; however, thirty-six sources have been used from 1985 to 1989. Table 3 shows the participation of the suppliers.

It is sound to suppose that, for the expert system, it is simple to discriminate the data supplied regardless of the degree of participation of the supplier. In fact, the identical data source used for the selection of suppliers allows for alternative ways of becoming more efficient. The procedure would be to branch before the 20 percent of suppliers is defined. With two big suppliers, namely, NTIS and EPRI (6 percent) providing 86 percent of the reports, those two can be channeled before looking at the table for other suppliers, thus providing the opportunity to apply the 80/20 rule over the 14 percent left. In this way, the selection can be achieved over 85 percent, plus 80 percent of the 14 percent, for a total of 97.2 percent.

TABLE 3
DEALER'S ORDERS, TECHNICAL REPORTS (1985-1989)

	Code	*'85-'86*	*'87-'89*	*Total*	*Prob. (%)*
1	AAP		1	1	0.09
2	ABH		1	1	0.09
3	AO	1		1	0.09
4	BAE		1	1	0.09
5	BAI	5	4	9	0.88
6	CAW		1	1	0.09
7	CAZ	2	5	7	0.68
8	CBK	1		1	0.09
9	CBX	4		4	0.39
10	CBY	3	1	4	0.39
11	CCA	5	2	7	0.68
12	CCM	4	4	8	0.78
13	DBA		5	5	0.48
14	EAO	124	156	280	27.31
15	EAQ	9	11	20	1.95
16	EBF		5	5	0.48
17	EBP	4		4	0.39
18	ECE		2	2	0.19
19	ECG		1	1	0.09
20	ECI		1	1	0.09
21	GAC		7	7	0.68
22	GAE		1	1	0.09
23	GAY	2		2	0.19
24	IAQ	2	1	3	0.29
25	IBP		2	2	0.19
26	ICM		1	1	0.09
27	JAA		1	1	0.09
28	LAY		2	2	0.19
29	MAJ		2	2	0.19
30	NAG	1		1	0.09
31	NAI	268	341	609	59.41
32	NAS	2	1	3	0.29
33	QAO		1	1	0.09
34	TAN	2		2	0.19
35	UAZ	6	18	24	2.34
36	UBA	1		1	0.09
37					
38					

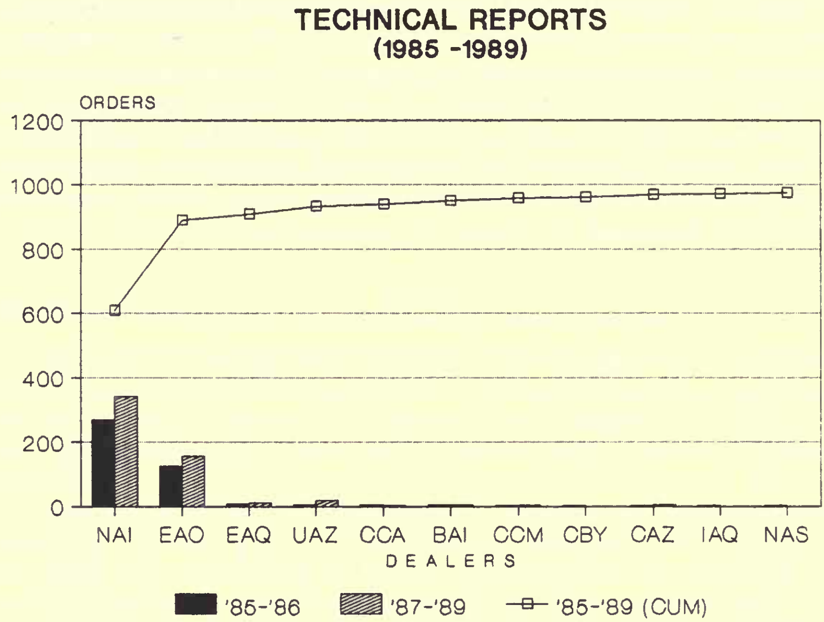

Figure 3. Cumulative distribution (all suppliers)

Obviously, in the case of a search for the 80 percent of all reports, the data disregarded after depletion would have left only data from the big suppliers. This degrades the quality of the decisions based on such data because the 80/20 rule was imposed on high frequencies that account for the major part of the universe. The large concentration of those report producers as represented in the authors' holdings also comply with the so-called "Matthew Effect" (Merton, 1968).

Some useful weighted criteria are:

- Similarity in subject field of the producer
- Potential use in research projects
- Quality and credibility of the source
- History of use
- Bibliographical accessibility
- Availability
- Visibility of originating institution

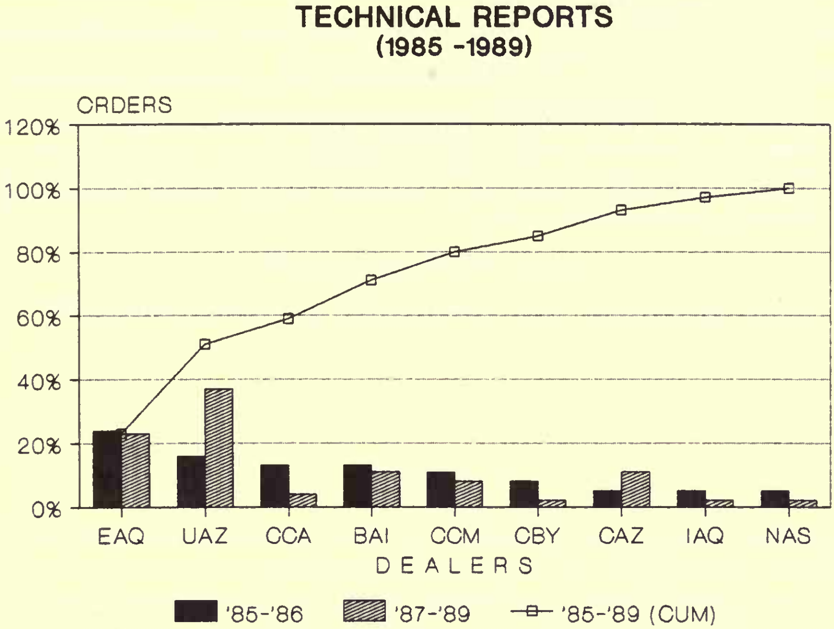

Figure 4. Cumulative distribution (without two big suppliers)

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