A Conceptual Model For An Intelligent Fuzzy Decision Support System

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Abstract

This paper reports on the conceptual development of an architecture for building intelligent fuzzy decision support systems (IFDSS). The changing nature of decision making in today's fast paced environment calls for new techniques for dealing with both quantitative and qualitative components of decision making. Soft computing tools like fuzzy reasoning offer much promise in this area. After reviewing the components of traditional decision support systems architecture, the paper describes the components of a new, more robust type of decision support system based on expert systems and fuzzy reasoning methodologies. The paper concludes with the application of this IFDSS methodology to the domain of educational assessment.

Introduction

Research on decision making has been conducted by three broad (but not necessarily, mutually exclusive) groups (Bell, et al, 1988). Decision theorists are interested in developing rational procedures for decision making - how people should make decisions if they wish to obey certain fundamental laws of behavior. Psychologists are interested in how people do make decisions (whether or not rational) and in determining the extent to which their behavior is compatible with any rational model. They are also interested in learning the cognitive capacities and limitations of ordinary people to process the information required of them if they do not naturally behave rationally, but wish to.

A third group, the methodologists, are concerned with the bottom line: how do you improve the quality of decisions in practice? It is one thing to talk of axioms and proofs and cognitive limitations - but how can you really help? The methodologists want to build systems that will support managers in making the types of decisions they are faced with in the real world. Solving problems in the real world is challenging for two primary reasons: an overabundance of data and a complex and dynamic decision making environment (Gupta, 1996). Though advances in computer hardware and software have made instantaneous access to large volumes of data a reality, the overabundance of data can be overwhelming to the decision maker. Obtaining useful and timely information from this data is a challenge.

Another problem solving challenge is today's highly competitive decision making environment, in which conditions and situations change rapidly, making unexpected and challenging problems an everyday occurrence in the lives of decision makers. This dynamic environment often forces the decision makers to make quick decisions even though they lack the necessary hard data.

The methodologists have been at the forefront of the struggle to develop decision systems that will support decision makers faced with the uncertainty present in a fast-paced environment. While statistical probability has been the most popular technique for dealing with uncertainty, new techniques are needed in order to more correctly reflect the true nature of uncertainty in real world decision making. This paper proposes the integration of fuzzy logic and fuzzy reasoning tools with a decision support system as a way to more effectively represent the pervasive imprecision faced by decision makers in the real world.

The next section gives a brief history of decision support systems. A description of the architecture of traditional decision support systems follows. The conceptual architecture of an intelligent fuzzy decision support system (IFDSS) and the application of this design to the domain of assessment will be introduced next. Discussion and an outline of tasks for the future will conclude the paper.

Background

Computer systems for problem solving and decision making have been around since the end of World War II, when computers became available for non-military tasks. They have been the target of research and application from many disciplines. Over time, systems have been built on different principles and with different aims. Three concepts regarding problem solving and decision making are important to this discussion: decision support systems, expert systems, and fuzzy reasoning.

The concept of decision support systems is built on the paradigm of *support*. That is, a computer system is placed at the disposal of the decision maker, who may use data or models to recognize, understand, and formulate a problem, and make use of analytical aids to evaluate alternatives. The term "decision support systems" (DSS) was coined at the beginning of the 1970's to denote a computer program that could support a manager in making semi-structured or unstructured decisions (Klein and Methlie. 1990). Semistructured decisions can be defined as those decisions dealing with problems which have both routine and non-routine components. Some parts of the problem are routine and can be approached with standard problem-solving procedures; others require intuition and judgment. Unstructured decisions involve nonroutine situations where there is no known problem solving heuristics. These decisions depend a lot upon judgment.

This DSS concept is the result of research in two areas: studies of human problem solving in the 1950's and 1960's and the work on interactive computer systems in the 1960's. As time sharing systems became available, several business schools in the US and Europe started to work on computer systems for decision support (Klein and Methlie, 1990). At first, this area was dominated by demonstrating the applicability of this new concept to managerial decision making. This was then followed by a great interest in software development. New tools, DSS generators, for easier building of such systems were created. With the introduction of microcomputers, developments in DSS speeded up. For instance, software for supporting decision making is available today for almost any financial problem.

A second important concept to add to our body of knowledge of computer systems for problem solving and decision making is the concept of expert systems. This concept was created at almost the same time as the DSS concept, with the DENDRAL project at Stanford University in the late 1960's (Feigenbaum et al, 1971). During the 1970's, several research projects were launched in artificial intelligence laboratories. The commercial use of expert systems started at the beginning of the 1980's, but widespread commercial use came with the more powerful microcomputers and cheaper software. Two fundamental results were derived from research on expert systems: that it is possible to simulate expert problem solving; and that this problem solving can be explained by the system.

A third concept related to the area of problem solving in decision making situations is the concept of fuzzy logic and fuzzy reasoning (Zadeh, 1992; Zimmermann, 1991; Negoita, 1985). Decision makers face uncertainty every day and manage to make decisions. Many times, this uncertainty is accompanied by imprecision. Sometimes they may not make the best decisions, but they have found ways to cope with the main issues. One common method of coping is our ability to use subjective and incomplete descriptions. For example, when a manager learns that morale is low, they are able to reason with that information.

When expert systems technology was first applied to decision making problems, it fell short in several respects. The main problem was that this technology was not capable of handling the classical DSS functions which are more computational than logical. Also problem solving in decision making domains is not solely symbolic reasoning, which was the predominant problem-solving method of expert systems. It is not due to just data retrieval and numeric calculations either, which are the functions found in a traditional DSS. What is needed is a system which can process quantitative and qualitative data of varying levels of precision and, by reasoning, transform this data into opinions, judgments, evaluations and advice. These new intelligent systems must be able to expect a tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality (Zadeh,1997).

Obtaining the benefits of the three concepts cited above is not just a matter of interconnecting the existing software tools from the DSS, expert system, and fuzzy reasoning areas. A new framework must be developed which is based on the paradigm of decision support, but also enables us to incorporate specialized knowledge and expertise into the system and at the same time deal with subjective and imprecise information. This will add the capability of reasoning to the functionality of DSS and will enable it to give advice on classes of problems that have been difficult for DSS systems to handle until now.

DATABASE **MODEL BASE**

DBMS

DSS GENERATOR

ACCESS TO OTHER COMPUTER SYSTEMS **EXTERNAL DATABASE ACCESS**

USER INTERFACE

Figure 1: A conceptual model of a traditional DSS

Traditional DSS architecture

The traditional DSS architecture is composed of a database, a model base, a DSS generator, and a user interface (Stair, 1996). Some DSS systems also include a connection to external databases and access to other computer-based systems (see Figure 1). The user interface of a DSS allows decision makers to easily access and manipulate the DSS and allows the use of common decision domain terms and phrases. It assists with all aspects of communication between the user and the hardware and software that comprises the DSS. The DSS dialogue requires tradeoffs between simplicity and flexibility.

The DSS generator acts as a buffer between the user and the other DSS components, interacting with the database, the model base, and the user interface, enabling the user to build a system that will assist them in making a particular type of decision. External database access allows the DSS to tap into vast stores of information contained in the organization database, while connections to other computer-based systems provides access to information external to the organization, e.g., world wide web. Natural language search engines may be used to make it easier for the user to find the information they need.

The purpose of a model base in a DSS is to give decision makers access to a variety of models and to assist them in the decision making process. The model base can include model management software that coordinates the use of models in a DSS. Depending on the needs of the decision maker, one or more models can be used. Examples of classes of models are financial, statistical, graphical, and project management.

The traditional DSS architecture was designed to help decision makers handle problems which could be modeled on a computer. Most of these models were developed for use in manipulating preprocessed quantitative data. The models do not do very well if there is missing data or if the data is imprecise. In addition, they do not employ the use of reasoning patterns used by experts in the domain. It is this situation that has led to research and development of decision support systems based on soft computing concepts such as fuzzy reasoning.

Architecture of an intelligent Fuzzy DSS

Fuzzy Reasoning

The goal of an intelligent fuzzy DSS (IFDSS) is to integrate, with the capabilities of a traditional DSS: data management, modeling language, decision methodology, symbolic reasoning and explanation facilities. and qualitative reasoning. However, we want to stay within the paradigm of DSS, that is, to support decision making. As we perform the decision making tasks, we may have to solve very specialized problems requiring expertise for their solution. We want to be able to provide the expertise in the form of quantitative and qualitative knowledge bases along with qualitative reasoning capabilities.

People usually organize their knowledge by causal relationships, and in reasoning they apply rules in the language they are most familiar with, i.e. the human language (Ebert, 1996). Many of the facts and rules that belong to human expertise contain fuzzy predicates and thus are fuzzy propositions. This is particularly true of heuristic rules which are often used in decision matching situations. However, the application of rules of classical logic implies the meaning of propositions is unambiguous (Zimmer, 1983). Because many of the factors in real world decision matching are necessarily vague and imprecise due to time constraints, an alternative method must be used, permitting approximate reasoning from vague inputs. The method selected here is based on fuzzy reasoning (Zadeh, 1992, Zimmermann, 1991; Negoita, 1985). As stated by Zadeh, fuzzy reasoning refers to a process by which an imprecise conclusion is deduced from a collection of imprecise observations or antecedents. and such reasoning is qualitative rather than quantitative in nature.

An important consideration for the use of fuzzy reasoning is the importance of retaining the semantic richness of the descriptions of decision making situations. Often, a probability distribution is used in order to compensate for the fact that a nominal value of a parameter. even if explicitly defined, is rarely known with absolute precision (Ebert, 1996). In these cases, uncertainty due to imprecision associated with the complexity of the situation as well as vagueness of human thought and perception processes is equated with randomness only. The distinction between probability and linguistic imprecision is not made due to the problem that the statistical methods to be applied need precise numbers or degrees of probability. In other words, the probability of a rule may be ill-defined, and instead of specifying a pseudoprecise numerical value which is expected by such a statistical tool, the decision maker would simply say that the consequence is *more* or *less likely*, where the terms "*likely*" and "*more or less*" are vague and imprecise descriptors. The application of such vague judgments introduces uncertainty which is the result of imprecision or fuzziness, not randomness.

Since much knowledge possessed by effective decision makers consists of qualitative information and reasoning patterns, it is natural to think of building decision support systems with fuzzy reasoning embedded in them. If we take the traditional framework of DSS, we can extend this framework in four different directions as follows (Klein and Methlie. 1990; Hajek and Ivanek, 1982):

1. **Intelligent assistance to support the decision making methodology and expert advice on a specific problem domain** - intelligent assistance in the form of decision analysis is a powerful aid in helping individuals to face difficult decisions. This "dialog" between the system and the user should employ as much natural language and qualitative response data as possible. Expert advice means going beyond the usual capacity of a DSS to ask for an expert opinion. This capability requires a knowledge-base containing domain knowledge consisting of reasoning patterns for the decision making situations to be encountered. An example would be a financial analysis knowledge-base for a DSS to support company credit decisions. One fundamental aspect of expert advising is that it very often requires a significant amount of fuzzy reasoning.

2. **Explanation of the conclusion** - a good DSS should improve the learning process of the user. Users tend to have more faith in the result and more confidence in the system if they can see the reasoning that was applied to the problem. Also, system development is faster because the system is easier to debug. The explanation should lake advantage of the ability to convey both quantitative and qualitative reasoning.

3. **Assistance when using statistical, optimizing, or other quantitative operations research techniques** - it is well known that many decision makers do not use such techniques properly because they do not have the requisite expertise in their use. For example, many decision makers do not remember the underlying assumptions for appropriate application of control charts to product quality. The use of intelligent assistant can guide a novice user in using the tools properly and help the user learn good strategies for using the tools.

4. **Guidance in using the DSS resources: developing intelligent user interfaces** - an intelligent user interface should enable the user to select and use the resources of the DSS properly and effectively. A simple knowledge base can be designed for use in asking questions of the user concerning his or her problem, so as to help him or her to select the right model.

Conceptual Framework for an Intelligent Fuzzy DSS

The structure of any DSS is defined by the subsystems which comprise it, the integration between subsystems (communication and control) as well as the hierarchical structure of the system (Klein and Methlie, 1990). The components of the proposed IFDSS are listed below and shown in Figure 2:

1. **An intelligent user interface and IFDSS generator**- similar to the traditional DSS architecture, the user interface should allow thc decision maker to easily access and manipulate the IFDSS by assisting with all aspects of communication between the user and the hardware and software that comprises the IFDSS. The big difference lies in the language of communication. The IFDSS user interface should allow communication to take place using natural language with heavy emphasis on the use of linguistic categories and hedges. For example, the decision maker should be able to describe an assessment decision situation using categories like *promise, effort, collegiality, competence, etc.*

2. **Quantitative model base** - many problems still involve some manipulation of numeric data. Models designed to manipulate numerical data for classification, pattern recognition, forecasting, and project management are examples of numeric manipulation useful in the decision making environment.

3. **Soft computing model base** - in order to permit approximate reasoning based on imprecise input data or vague knowledge about the underlying process, it is necessary to provide the decision maker with soft computing methodologies such as fuzzy decision support models. Examples of these models would be fuzzy classification, pattern recognition, control, and forecasting.

4. **Dynamic knowledge base** - this is a repository of both generic reasoning-related knowledge and specialized knowledge and expert reasoning. A key aspect of this module is that new knowledge is constantly being assimilated through information being derived from user transactions and information interchange with the IFDBA interface.

5. **IFDBA interface** - this module provides front-end support (intelligent assistance) to the user when interacting with the dynamic knowledge-base. In addition, it allows the user to get an explanation of the model results including any reasoning employed. It should have a natural language interface.

6. **DBMS** - provides support for organizing data and allows access to procedures for searching and selecting data.

7. **Inference engine** - determines which reasoning rules apply to a problem and executes them in order to "infer" new knowledge. This component should be domain independent so that it can be used in several different decision areas.

8. **IFDSS generator** - as with the traditional DSS architecture, the DSS generator acts as a buffer between the user and the other IFDSS components, interacting with the database, knowledge base, model bases, and the user interface.

The main objective of this new IFDSS framework is to achieve synergies by integrating soft computing and expert systems technologies into the DSS framework. To illustrate the application of this framework to a real world decision making situation, the design and development of a system for educational assessment will be described.

DYNAMIC KNOWLEDGE | QUANTITATIVE MODEL | SOFT COMPUTING

DBMS

IFDSS GENERATOR

ACCESS TO OTHER COMPUTER SYSTEMS | EXTERNAL DATABASE ACCESS

IFDBA INTERFACE

INTELLIGENT USER INTERFACE

Figure 2: A conceptual design model of an intelligent fuzzy DSS (IFDSS)

Design and development of an Intelligent fuzzy DSS for educational assessment

Assessment is one of the fundamental decision making tasks. Forms of assessment include evaluating employees and assessing the prospects of alternative investment options. Decision makers strive to base their assessment decisions on as much knowledge as possible. Sometimes they have enough valid numeric data to use in a quantitative model. At other times, they are forced to make a decision based on imprecise or vague information. The specific example of an IFDSS for assessment described here was developed for use by teachers who must make assessments of individual students' writing abilities.

Writing Assessment

The task of writing assessment in an educational environment is labor intensive and fraught with imprecision. The grader needs to spend a considerable amount of time reading the writing sample, evaluating it for all factors related to measures of style, content, and writing effectiveness. and then assigning a grade. The grader must not show any bias when scoring the writing sample; they must be consistent, using the same set of scoring rules every time.

A very popular scoring system used by many school districts is the holistic scoring method. This method involves evaluating the writing sample for the various components of good writing, e.g., clarity, organization, support, mechanics, etc., then combining these evaluations into an overall rating. When evaluating the components of good writing, the grader must frequently resort to reasoning with linguistic categories such as *mostly clear, confused, etc.* The reason for this is that the rating categories for writing are vague and imprecise. The grader then combines these "linguistic" ratings into an overall score.

A significant problem with human grading of student writing samples is that there is no guarantee that the human graders will apply the same rules in the same manner every time. It is unlikely that there will be a high level of consistency in grading among a group of graders. This makes comparisons of writing evaluations difficult.

Prototype Intelligent Fuzzy DSS

The prototype IFDSS developed here is a PC-resident, knowledge-based system that assists teachers who need to make assessment decisions about student writing samples. The system's primary purpose is to help the teacher to produce an evaluation of a student's writing in the most efficient and effective way possible and to greatly increase the consistency of the teacher's application of scoring rules. A secondary purpose is to provide less experienced teachers with a tool for further developing their writing sample assessment skills.

The holistic scoring knowledge base for the scoring system consists of information about holistic scoring of writing samples and the domain knowledge of several expert teacher graders. The holistic scoring method involves assessing the writing sample for the various components of good writing, e.g., clarity, organization, support, mechanics, etc., and then combining these assessments into an overall assessment score. Since the decision maker (the one who is making the assessment) must resort to reasoning with vague and imprecise linguistic categories such as *mostly clear, confused*, etc., this dynamic knowledge base supports fuzzy reasoning.

The model base of the IFDSS consists of two parts. The holistic scoring model base contains a fuzzy reasoning module which enables the user to build assessment decision models using fuzzy logic and holistic scoring principles. The statistical model base contains statistical models for use in classification, pattern recognition, and project management. The main use of these models is for classification and management of the writing assessment results.

The inference engine is used to "fire" or process appropriate rules for the application in order to determine the final assessment. The DBMS provides user support for storing, organizing, and retrieving student assessments.

The IFDSS generator acts a buffer between the user and the other IFDSS components. Front-end support in the form of intelligent assistance to the user when interacting with the assessment knowledge base is given by the

IFDBA interface. Finally, the intelligent user interface assists with all aspects of the natural language communication between the grader and the IFDSS.

Figure 3 displays the components of the IFDSS.

HOLISTIC SCORING KNOWLEDGE BASE	STATISTICAL MODEL BASE	HOLISTIC SCORING MODEL BASE

DBMS

IFDSS GENERATOR

INFERENCE ENGINE

IFDBA INTERFACE

INTELLIGENT USER INTERFACE

Figure 3: Components of the IFDSS for assessing student writing

Testing and validation

Proper testing and validation of any DSS system is important for determining the accuracy, completeness, and performance of the system (O'Leary et al, 1990). Over a one month period, 255 student writing samples were assessed by teachers using the IFDSS. At the end of this one month testing period, the expert teacher graders reviewed the assessments and agreed the system was very effective in helping the teachers assess the quality of student writing samples. The teachers using the IFDSS remarked about the speed with which they were able to make assessments. They felt using the system enabled them to concentrate on evaluating the factors that are important in the holistic scoring method without having to worry about the actual manipulation of scoring categories.

A controlled experiment was set up to determine just how effective teachers performing writing assessments with the IFDSS were compared to teacher assessments made without the system. The three expert teacher graders reviewed each of 200 writing samples and assessed the quality of each one. The same 200 cases were independently reviewed and assessed by three different teachers using the IFDSS. The results indicated that the teachers using the IFDSS agreed with the three domain experts in 194 of the 200 cases for an agreement rate of 97%. There also was a significant difference in the time each group took to make the assessments. The teachers using the IFDSS assessment tool took one-third less time to do the assessments (see Table 1).

GRADERS	AVERAGE TIME (min.)
Expert Teacher	15
Grader 1(with IFDSS)	11
Grader 2(with IFDSS)	9
Grader 3(with IFDSS)	9

Table 1: Average assessment time

Discussion

The impact of the IFDSS student writing assessment system on the time it takes a teacher to do an assessment of a writing sample, as well as the accuracy of the assessment, is important. One of the problems with using writing sample assessments is that they are time-consuming. This means that some teachers are not using this form of assessment as often as they or the school district would like. By reducing the time for doing an assessment by approximately one third, the writing sample evaluation process becomes more efficient and hopefully, more utilized. With better decisions on the assessment of a student's writing, more relevant instruction can be given to that student.

This increase in efficiency would not be valuable if the accuracy of the assessment suffered. The test results show that the accuracy of the teachers using the system is equal to that of the expert teacher graders. This means the system assisted the average teacher in making decisions as accurate as the best teacher decision makers when it comes to assessing student writing samples.

Another significant impact the IFDSS writing sample assessment system has had is in teacher development. Using the explanation and help facilities built into the system has enabled teachers to refine their knowledge on how to assess student writing. This has been noted particularly by the newer teachers using the system. These results indicate that it is desirable to include an explanation facility when building an intelligent fuzzy decision support system.

The above related approach to student writing assessment can be generalized to other areas of assessment. As a first step, important factors that influence the assessment results must be identified. Rating categories for each of these factors would then be developed using the domain experts. Encoding the rules and models used by the domain experts would complete the process. Since most assessment decisions are based on categorization into fuzzy values such as *strong, weak,* etc., the fuzzy reasoning and classification scheme provides a model for encapsulating this knowledge and reasoning with it. The process of incorporating important factors and heuristic knowledge from the domain enables the development of decision support systems which are able to achieve the goals of effective assessment.

The most important result of this work has been the validation of a new architecture for decision support systems capable of performing expert reasoning using imprecise information. This architecture can be used as a guide for building intelligent decision support systems that are robust enough to tolerate the imprecision present in many real world decision making tasks.

Summary

This paper presents ideas on the development of a conceptual model for an intelligent fuzzy decision support system (IFDSS) architecture. The proposed architecture provides the decision maker with the benefits of both quantitative and qualitative reasoning models. It has been demonstrated that using the decision support paradigm and the goal of improving the quality of decisions allows one to integrate new soft computing models of reasoning such as fuzzy reasoning.

The IFDSS system for supporting teachers in assessing student writing samples can be generalized to support other assessment problems that organizations face. Further research will include refinement of the IFDSS model to allow for more robust application to many different decision making areas.

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