Fuzzy Logic: Intellectual Knowledge Management

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ABSTRACT: This paper discusses the process through which knowledge acquisition, technical tools and organization actors can contribute to an organization development in developing knowledge as a systemic competitive weapon. It examines the relationships between the technology and human value, because they are vital instruments of the knowledge management (KM) process. KM is related to intelligent agents, information technology (IT), and strategic decision-support systems (SDSS) such as Fuzzy Logic controller. It attempts to provide useful insights on KM efficiency. A conceptual model of KM efficiency in the organizations supported by the combination of intelligent agent’s role and intelligent systems resources is presented.  
Key word:- Knowledge Mgmt, fuzzy Logic, IT, DSS, technical tool.

I. INTRODUCTION:

Knowledge management is an emerging field that has commanded attention and support from much of the industrial community. Many organizations are now engaging in KM in order to leverage knowledge both within their organization and externally to their shareholders and customers. KM deals with the process of reading value from an organization’s intangible assets. These assets, or knowledge, can be classified as either tacit or explicit. Explicit knowledge is that which has been codified and expressed in formal language (4). It can be represented, stored, shared and effectively applied. Tacit knowledge is knowledge that is difficult to express, represent and communicate (4). The distinction between types of knowledge is relevant because each type must be managed differently. Knowledge is a true asset of an organization, and its integration across departments and disciplines should be emphasized. Dealing with several technical tools and human values, knowledge management (KM) shows how learning

organizations, intelligent organizations and enterprise management can re-engineer their processes using an applied knowledge-based approach. Intelligent agents (human value) and technical tools can provide the basis for long-term organizational effectiveness of firms that wish to institutionalize KM. The relationships among KM efficiency, intelligent agents and technological tools are highlighted. The purpose of this paper is to reinforce the roles of intelligent agents and technical tools in the building of KM efficiency. This paper discusses a conceptual model for KM efficiency and a framework for the roles of intelligent agents and technical tools. A form of knowledge representation suitable for notions that cannot be defined precisely, but which depend upon their contexts.

II. STRATEGIC DECISION-SUPPORT SYSTEMS

An organization should have the capacity to exploit its knowledge and learning capabilities better than its competitors if it decides to assume a given competitive strategy. This capacity depends on its intelligent agents. In fact, they should believe that it is possible explicitly to link strategy, knowledge and performance in order to increase the probability of adding value. Some firms are able to define the needed links between the strategy and what their intelligent agents need to know, share and learn to operate during the strategy implementation.

Knowledge may be of several types, each of which may be made explicit. When the explicit causal knowledge is shared, often in the form of environment, competitors and situation analysis, it enables managers to co-ordinate the formulation of strategies and tactics for achieving objectives. Since the early 1970s, a growing number of studies in the area of DSS decades have been reported (1), and they reflect the need to
establish a substantive and coherent field of management information systems.

An effective DSS design may consider a common set of DSS elements, including DSS environment, task characteristics, access pattern, DSS roles and function and DSS components (2). Moreover, managers have to make decisions within complex scenarios and to consider several strategic alternatives. This means that management activities need the contribution of SDSS, that is, a set of adequate combination of specialized software and hardware (6). SDSS may be included in an efficient KM in a co-operative and integrated way, for example in order to deal with sales strategy and new technology choices. The design of such SDSS should be developed according to management needs and intelligent agents' skills. SDSS can be useful even for planning in small business management.

III. FUZZY LOGIC: INTELLECTUAL KNOWLEDGE MANAGEMENT

Rule based logic has been used to capture human expertise in classification, assessment, diagnostic and planning tasks. Probability has traditionally been used to capture decision making under uncertain conditions. For example, consider the rule: IF Symptom-A is present THEN diagnosis is illness-X. There will be situations in which we are uncertain about the presence of Symptom-A. In such cases we can enter the probability of Symptom-A being present which will result in a confidence factor in our diagnosis of illness-X. A number of methods have been used to propagate probabilities during rule based inference. Many of these techniques are based on the probabilistic inference techniques used in Mycin and Prospector. The weakness of such techniques is that they do not reflect the way human expert’s reason under uncertainty. Expert Rule knowledge builder allows an alternative methodology to the probabilistic reasoning approach. This involves defining Symptom-A and illness-X as logical attribute with values likely, unsure, unlikely. This allows the expert to dictate the relationship between the symptoms and diagnosis, instead of relying on the mathematical propagation of probabilities.

Many people confuse the above example of uncertain reasoning with fuzzy reasoning. Probabilistic reasoning is concerned with the uncertain reasoning about well-defined events or concepts such as Symptom-A and Illness-X. On the other hand, Fuzzy Logic is concerned with the reasoning about ‘Fuzzy’ events or concepts. Examples of fuzzy concepts are ‘temperature is high’ and ‘person is tall’. When is a person tall, at 170 cm, 180 cm or 190 cm? If we define the threshold of tallness at 180 cm, then the implication is that a person of 179.9 cm is not tall. When humans reason with terms such as 'tall' they do not normally have a fixed threshold in mind, but a smooth fuzzy definition. Humans can reason very effectively with such fuzzy definitions, therefore, in order to capture human fuzzy reasoning we need fuzzy logic. An example of a fuzzy rule, which involves a fuzzy condition and a fuzzy conclusion, is:

**IF wages is high THEN credit risk is low**

Fuzzy reasoning involves three steps: Fuzzification of the terms that appear in the conditions of rules. Inference from fuzzy rules. Defuzzification of the fuzzy terms that appear in the conclusions of rules. Fuzzification:-

Lotfi Zadeh pioneered a method of modeling human imprecise reasoning using fuzzy sets. Using this technique, the concept 'tall' is related to the underlying objective term which it is attempting to describe; namely the actual height in centimeters. The transformation of an objective term into a fuzzy concept is called fuzzification. As an example, the term 'tall' can be represented in figure 1.

![Fig. 1 Concept of fuzzification](image_url)

It shows the degree of membership with which a person belongs to the category (set) 'tall'. Full membership of the class 'tall' is represented by a value of 1, while no membership is represented by a value of 0. At 150 cm and below, a person does not belong to the class 'tall'. At 210 cm and above, a person fully belongs to the class 'tall'. Between 150 cm and 210 cm the membership increases linearly between 0 and 1. The degree of belonging to the set 'tall' is called the confidence factor or the membership value. The shape of the membership function curve can be non-linear.
The purpose of the fuzzification process is to allow a fuzzy condition in a rule to be interpreted. For example, the condition 'person = tall' in a rule can be true for all values of 'height', however, the confidence factor or membership value of this condition can be derived from the above graph. A person who is 180 cm in height is 'tall' with a confidence factor of 0.5 (membership value of the club 'tall'). It is the gradual change of the membership value of the condition 'tall' with height that gives fuzzy logic its strength.

Normally fuzzy concepts have a number of values to describe the various ranges of values of the objective term which they describe. For example, the fuzzy concept 'tallness' may have the values 'Tall', 'Medium height' and 'Short'. Typically, the membership functions of these values are as shown in figure 2.

![Membership function for fuzzy system](image)

Typically, fuzzy concepts have an odd number of values; 3, 5 or 7. We can extend the above values by adding very short and very tall. The real power of fuzzy logic systems, compared to crisp logic systems, lies in the ability to represent a concept using a small number of fuzzy values. This therefore reduces the number of rules required to capture the knowledge relating to that concept. To achieve the same accuracy with crisp logic, a large number of logical values would be required resulting in a large rule base.

### IV. FUZZY INFERENCE

Inference from a set of fuzzy rules involves fuzzification of the conditions of the rules, then propagating the confidence factors (membership values) of the conditions to the conclusions (outcomes) of the rules. Consider the following rule:

**IF (applicant is young) AND (income is low) THEN credit limit is low**

Inference from this above rule involves (using fuzzification) looking up the membership value of the condition 'applicant is young' given the applicant's age, and the MV of 'income is low' given the applicant's wages. The method proposed by Lotfi Zadeh is to take the minimum MV of all the conditions and to assign it to the outcome 'credit limit is low'. An enhancement of this method involves having a weight for each rule between 0 and 1 which multiplies the MV assigned to the outcome of the rule. This weight can be edited on the Pattern rules view, or assigned at run time. By default each rule weight is set to 1.0. In a fuzzy rule base a number of rules with the outcome 'credit limit is low' will be fired. The inference engine will assign the outcome 'credit limit is low', the maximum MV from all the fired rules.

In summary fuzzy inference involves:

- Defuzzification of the conditions of each rule and assigning the outcome of each rule the minimum MV of its conditions multiplied by the rule weight.
- Assigning each outcome the maximum MV from its fired rules.
- Fuzzy inference will result in confidence factors (MVs) assigned to each outcome in the rule base.

### V. DEFUZZIFICATION

If the conclusion of the fuzzy rule set involves fuzzy concepts, then these concepts will have to be translated back into objective terms before they can be used in practice. For a rules set including the credit limit rule described in the previous section, fuzzy inference will result in the terms 'credit limit is low', 'credit limit is medium' and 'credit limit is high' being assigned membership values. However, in practice, to use the conclusions from such a rule base we need to defuzzify the conclusions into a crisp credit limit figure. To do this we need to define the membership functions for the credit limit outcomes as shown in this diagram:

![Membership function for fuzzy system](image)

The defuzzified value of credit limit is calculated as the centre of gravity of the three Mvs (viewed) as weights placed at 500, 1000, and 1500.
While the main principles of fuzzy logic are broadly agreed on, there are a number of various methods of fuzzy inference and defuzzification. The methods described above are the most widely used and are the ones implemented in expert rule knowledge builder.

VI. KNOWLEDGE OBTAINED BY INTELLIGENT AGENTS

In a management environment, agents are conceptually defined as entities that are able to understand the sense of a given situation and to act according to some orientations (Russell and Norvig, 1995). Other definitions refer to an environment where other agents exist and interaction takes place (Shoham, 1997; Wooldridge and Jennings, 1995). These interacting agents are owners of a great amount of knowledge, professional experiences and beliefs that they can share and constitute a ground, which may account for the achievement of useful co-ordination levels during interactions. Meaningful interactions in dynamic environments cannot be accomplished on the sole basis of message exchanging due to turbulence and uncertainty. In order to obtain better results, the communication among intelligent agents should assume a co-operative form and be supported by IT resources.

The study of intelligent agents has become one of the most important fields in understanding organizations’ performance. Organizations depend on people for sustaining their knowledge levels. Since knowledge systems increase the professional performance of individuals, the individuals become prepared to create and embed knowledge in the organization. Intelligent agents are playing a vital role in bringing about the rise of new advantages and participating actively in consistent innovation, because this is the key to an organization’s development (Pearson, 1991). They may be used as a promising solution for assisting the updating of knowledge in a timely manner (Rasmus, 1999; O’Leary, 1998).

The concept of the human intelligent agent is based on individual competence, that is, personal capacity to act in various situations according to rules, beliefs and professional procedures. It also includes education, experience, values and social skills. The success of organisations is supported by an organised and integrated set of competencies. The acquisition of new knowledge leads the intelligent agents to participate in a number of various knowledge relationships, creating multiple perspectives of the same situation. These perspectives may contribute to enlarge the number of possible solutions, which improves the quality of the decision-making process. The existing knowledge may be the point of departure to creative efforts, thereby creating links to new knowledge areas. If intelligent agents can access various databases for solving a problem, they may get a deeper understanding about the situation and they will be able to contribute more adequately to the decision-making process.

Moreover, intelligent agents use their unique competencies to deal with problems and opportunities. In fact, they can be prepared to convert data and information into meaningful knowledge, which is shared and focused on competitive strategies. Research on intelligent agents and co-ordination of multi-agents has drawn tremendous interest from business communities.

According to this perspective, an organization can be better understood using intelligent multi-agent architecture. The development and the analysis of co-ordination and interactions among multiple intelligent agents allow understanding better the process of KM.

Team creativity depends on creative individual agents and is receiving considerable attention from some researchers.
involved in unstructured problems (Amabile et al., 1996). In fact, teams can bring together the right mix of intelligent agents who have the appropriate set of knowledge, skills, information and abilities to suggest solutions in what concerns difficult and unpredictable problems. The quality of their results depends on how well individual knowledge can be communicated among intelligent agents.

VII. MANAGEMENT PERFORMANCE

Organizational analysis often starts with a performance determine whether a strategy should be reviewed or changed, and to identify areas of organizational strength. Analysis guided by objectives. Performance levels can help managers to Performance measurement is related with the organization’s key areas, such as expansion, innovation and productivity, which are critical to the development and prosperity of the organization. Obtaining, creating and managing knowledge to support strategic decisions making and implementation is a practical problem that organizations should solve. A formal strategic KM system can enhance the organizational effectiveness and preserve data, ideas, operational solutions and acquired knowledge within the organization. There is growing interest in building complex systems by co-coordinating and integrating intelligent systems. Nowadays, intelligent systems are used to measure performance levels and intense efforts are being made to improve their features in order to obtain adequate conclusions and better decision-making activities. For example, DSS applications include:

- strategic planning;
- requirements analysis;
- business process re-engineering;
- business planning and control;
- project management; and
- Performance measurement.

The objectives of a strategy of an organization may be stated in terms of expansion, differentiation, sales, market share or profitability, top managers have to monitor the performance measures as indicators of objectives' achievement. By examining performance according to an evaluation procedure, management will be better able to understand the reasons for the strategic results. If the evaluation procedure is sufficiently detailed, it will be possible to understand the reasons for differences in performance and to decide some corrective actions.

VIII. CONCEPTUAL MODEL

The model is divided in two areas: the area of technical tools for specification of intelligent systems resources and the area of intelligent agents destined to focus their roles on organizations performance. The major factors are discussed and directions for future research are suggested. It emphasizes that problem-solving strategies, strategic decisions, organizational effectiveness and management performance can be the logical results obtained from KM efficiency based on intelligent agents and technical tools, namely IT and DSS. This model takes into account various determinants of the relationships among various fields. The top portion of the model shows the main sources where knowledge can be acquired. KM has to deal with two domains:

1. Technical tools such as fuzzy logic controller and
2. Intelligent agents.

Technical tools include IT and SDSS because they contribute intensively to the formulation of competitive strategies. The factors that affect drastically the technical tools are development, differentiation and integration. As explained previously, intelligent agents are person whose functions imply learning efforts, creativity and decision capacities at different levels in the organization. Intelligent agents make knowledge progresses based on each individual's efforts and skills. Nevertheless, the behavior of each intelligent agent depends also on the motivation methodology adopted by the organization and on the actions that management takes. Within this architecture, technical tools and intelligent agents can contribute to knowledge-development decisions based on certain predictive modeling methods.

The adequate combination of IT, SDSS, and intelligent agents' activities can lead the organization to a particularly strong competitive set. In its architecture, the KM efficiency model uses intelligent agents to acquire and develop knowledge units, DSS for managing decision-making processes and IT to support those processes. Thus, the organization could obtain a solid basis for its strategic decisions, achieve higher levels of organizational effectiveness and provide impressive qualitative results of management performance.
Until now, this model has only been conceptualized according to literature review and our personal perspective. Further work will be required in order to validate this model. In the near future, it will be confirmed, using the validation of several hypotheses based on the analysis of empirical research (data collected from technical experts and managers).

IX. CONCLUSION

This paper intends to provide insights to a better understanding of KM in what concerns the possibility of enabling organizations to attain higher performance levels and to experience several solutions to competitiveness problems. Its considerations provide considerable support for the importance of intelligent agents, IT and SDSS as a decisive contribution to KM efficiency. Consequently, these considerations intend to represent an important step forward in presenting KM efficiency as decisive support for the competitive development of organizations.

The architecture of the model proposed here should be improved in order to include new actors and the consideration of a wider set of technical tools, which could offer significant contributions to achieve better KM efficiency levels. A major short-term goal is to enhance and validate this model with real data suitable to dealing with the evolution of manager’s comprehension of the strategic value of KM:

![Figure 5 Efficient model of Knowledge Management](image)

References