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A fuzzy expert system for business management

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ABSTRACT

Nowadays firms are required to reach high levels of specialisation in order to increase their competitiveness in complex markets. Knowledge management plays a fundamental role in this process as the correct implementation of strategies is determined by the information transfer and dissemination within the organisation. In this paper, a fuzzy expert system focused on increasing accuracy and quality of the knowledge for decision making is designed. A model based on fuzzy rules to simulate the behavior of the firms, is presented under the assumption of determined input parameters previously detected and an algorithm is developed to achieve the minimal structure of the model. The result is a fuzzy expert system tool, called ESROM, which gives valuable information to help managers to improve the achievement of the strategic objectives of the company. A main contribution of this work it that the system is general and can be adapted to different scenarios.

1. Introduction

Nowadays, firm managers are becoming aware of the need for information analysis tools in order to support business decisions in the current complex and turbulent business environment (Handfield & Melnyk, 1998). Competition in changing environments due to fast progression of technical advances turns competition on information into the main competitive parameter in order to prevent and anticipate changes in customer needs, technology, industry trends and other competition parameters (Wacker, 1998). Therefore, the evolution of business computing networking and client/server architectures are impelling utilization of shared information in a decision support context.

In this context, the use of Decision Support Systems (DSS) is increasing and becoming generalized (Hasuike & Ishii, 2009; Inaad, 2009; Sharma, Iyer, Mehrotra, & Krishnan, 2010; Vigier & Terceño, 2008). Even though, the development of new algorithms involves a fast progression in accuracy of DSS (Demoulin, 2007; Wen, Chen, & Pao, 2008), the use of new DSS techniques has been scarcely applied in the field of Operations Management (OM) (Garbolino & Taroni, 2002; Lotfi & Pegels, 1996). In fact, even though management information systems literature has broadly dealt with tools to assist in managerial decisions, the wide utility these systems generate for specific Operations Management (OM) decisions is not still generalized (Stenforsa et al., 2007).

However, the use of surveys based on questionnaires in OM research is widely extended for academics and practitioners in order to define constructs, dimensions and variables to enhance understanding of OM issues (Wacker, 1998). Statistical multivariable techniques have been intensively applied in empirical studies with different levels of reliability and validity (O'Leary-Kelly & Vokurka, 1998).

Different studies have analyzed the relationship between operations strategy and performance through the use of statistical analysis, as we can see in Arias-Aranda (2002, 2003), Arias-Aranda, Minguela, and Rodríguez (2001). These studies analyze the relationship between operations strategy and performance through flexibility as a moderating variable within the service setting of engineering consulting firms in Spain. Artificial Intelligence (AI) techniques are also used in this field, like Bayesian classifiers (Abad-Grau & Arias-Aranda, 2006), expert systems (Miah, Kerr, & Gammack, 2009; Shiue, Li, & Chen, 2008), case-base reasoning (Li & Ho, 2009; Lin et al., 2007) and so on.

Under these conditions, the aim of this research is to combine two different approaches: the use of surveys based on questionnaires in OM research with current techniques of AI. In this paper we develop a fuzzy modelling mechanism which is capable of implementing four objectives: (i) representing the knowledge obtained in terms of natural language, (ii) expressing the results obtained from the questionnaires analysis in a way that can be easily understood by non-experts users through fuzzy logic, (iii) generating a rule base automatically from numeric and linguistic data, (iv) acting as simulator of output results according to different input conditions controlled by the user. In order to achieve these objectives, this paper proposes a fuzzy expert systems, called ESROM,

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which will help to manager to make decisions about the company by means of simulating actual situations.

The rest of the paper is organized as follows: Section 2 provides some preliminaries on the fundamental theoretical aspects underlying this paper: Operations Management and Expert Systems. In Section 3, the case study is presented. In Section 4, an automatic learning algorithm applied to a determined relationship of OM variables will be suggested. In Section 5, an algorithm to obtain the minimal sets of rules to make more understandable and efficient the system will be presented. In Section 6, the expert system tool (ESROM) will be described and a simulation of the previously generated based system fuzzy rules will be done. Finally, in Section 7 presents the conclusions and future research.

2. Background

This section provides some basic background about the topics covered in the paper: Section 2.1 presents a quickly overviews about OM and Section 2.2 refreshes the basic ideas in Expert Systems.

2.1. Operations management

The maintenance, control and improvement of the organizational activities that are required to produce goods or services for customer is the business definition for Operations Management. It has been studied in literature according to its different types and dimensions. Operations strategy, operational flexibility and performance are the dimensions studied in this research.

The structural and infrastructural decisions that constitute the operations strategy are process, service or customer-oriented driven (Berry & Parasuraman, 1997; Tersinea & Harvey, 1998). The categories of decisions identified by literature regarding the operations strategy are layout, push vs. pull orientation of the service delivery process, degree of standardization of the process, number of different services offered, information technology focus (cost saving vs. service upgrading), relation between back and front office activities, human resource management, degree of customer participation and new services design and development (Arias-Aranda, 2002). These configure the basis of the operations strategy construct analyzed in the present study.

Operational flexibility measures the capability of the firm to adapt to environmental changes in a fast way without incurring in increasing costs (Brill & Mandelbaum, 1989). Different dimensions and flexibility types have been identified in operations management literature (Gupta & Goyal, 1992; Ramasesh & Jayakumar, 1991). General dimensions of flexibility are expansion, distribution of information, routing, labor and equipment, market flexibility, services and servuction, process, programming and volume.

Finally, performance measures configure the third party of this analysis. According to the (Abe & Lan, 1995) classification, measures were presented as financial/efficiency and customer oriented.

2.2. Expert systems

A knowledge-based expert system is a collection of facts representing the knowledge of Subject Matter Experts (SME) (Dym & Levitt, 1991; Kandel, 1992). Usually, their knowledge is expressed as a set of inference rules in the form *if* antecedent *then* consequent. The antecedent clause is a test, and may take the form of an expression formed of logical conjunctions and disjunctions of (variable, value) pairs, or other logical expressions which evaluate to True or False. Typically, antecedent clauses are written as conjunctive expressions. A rule whose antecedent is in any other form can be re-written as a set of rules with only conjunctive form antecedent clauses (Andrews, 1986). If the antecedent clause evaluates to True, then we say that the clause is satisfied and the rule "fires", or is activated. As a forward-chaining process, facts asserted by the rule consequent may trigger additional rules to fire. In a fuzzy expert system, the variables in the antecedent and consequent may be linguistic. This means that their values are expressed in natural language terms which easily represent the knowledge of the subject matter experts (Kandel, 1992; Zadeh, 1965). Fuzzy set theory specifies a method for the mathematical specification and interpretation of such values, and for performing logical inference using these values. A fuzzy expert system is an ideal method for the representation and application of knowledge in a domain such as OM. It presents some advantages: (i) describing the knowledge using linguistic terms such as "high" instead of crisp terms and (ii) acting as simulator the actual situations.

3. The case study

In this section we describe the case study in detail. The expert gave us collected data about the operations strategy, level of flexibility and performance from a sample of 71 engineering consulting firms in Spain. Three firm types (Civil, Industrial and Environmental) were considered covering most activities of Engineering Consulting Firms. A questionnaire was the technique used to obtain data for the study. Initially, a copy of the questionnaire was sent to 10 firms representing every turnover and activity group as a pre-test. They were asked not to answer the questionnaire but to remark all doubts or possible mistakes detected. Only small syntactic changes were made but none of the firms remarked difficulties for concept understanding or misuse. The questionnaire has 122 questions in three main groups divided in blocks of questions each one. The first one related to operations management divided in nine blocks. A second block formed by the flexibility questions divided in seven blocks. And the third group for the results in two blocks for turnover and customer satisfaction. See the complete questionnaire in *Questionnaire raised to companies involved in the study (English)* (http://ic2.ugr.es/~jmsa/).

The flexibility dimensions of Ramasesh and Jayakumar (1991) were used as the main framework for the analysis of flexibility in services. According to the specific nature of service industries, some adaptations were included in the model in order to ensure validation of the study. Some of these adaptations were suggested by the operations managers during the pre-test stage. A factor analysis was performed in order to test whether the items used to measure the different flexibility dimensions grouped consistently. Finally, seven flexibility dimensions were identified through this analysis. Items configuring each flexibility dimension were also measured through a five-points Likert scale. In this case agreement with each of the statements defining every flexibility dimension configured all items relating system flexibility.

Performance measures used in this study were classified according to Abernethy and Lillis (1995). Respondents were asked to indicate of a five-point Likert scale the importance of each measure in the range "little or no importance" to "outmost importance". Operational measures were categorized as financial/efficiency and customer satisfaction measures. Slights adaptations were made according to the pre-test in order to adapt the measures to engineering consulting firms standards. Respondents were asked to assign a level of relevance to each measure in a Likert scale (1–5).

Tables 1–3 show the variables used in the study and the items of the questionnaire with respect to. Under the column *Variable* we have the variables names used in this study. The column *Block* indicates the questionnaire blocks where these variables appear.