Expert Systems with Applications 40 (2013) 6412–6426

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A fuzzy-decision-tree approach for manufacturing technology selection exploiting experience-based information

Liam Evans [a,*], Niels Lohse [a], Mark Summers [b]

[a] University of Nottingham, University Park, Nottingham, UK
[b] Airbus Operations Limited, Filton, Bristol, UK

ARTICLE INFO

Keywords:
Experience-based decision support
Manufacturing technology selection
Fuzzy decision tree
Data mining

ABSTRACT

Manufacturing technology selection is traditionally a human-driven approach where the trade-off of alternative manufacturing investments is steered by a group of experts. The problem is a semi-structured and subjective-based decision practice influenced by the experience and intuitive feeling of the decision-makers involved. This paper presents a distinct experience-based decision support system that uses factual information of historical decisions to calculate confidence factors for the successful adoption of potential technologies for a given set of requirements. A fuzzy-decision-tree algorithm is applied to provide a more objective approach given the evidence of previous manufacturing technology implementation cases. The model uses the information relationship of key technology decision variables, project requirements of an implemented technology case and the success outcome of a project to support decision problems. An empirical study was conducted at an aircraft manufacturer to support their technology decision for a typical medium complexity assembly investment project. The experimental analysis demonstrated encouraging results and practical viability of the approach.

1. Introduction

Manufacturing technology selection is a complex decision activity that when not managed correctly can lead to the rapid decline in an organisations wellbeing (Garcia & Alvarado, 2012). It is commonly based on the subjective judgment of the decision makers involved. The experience and knowledge of the individual decision team members support each phase from evaluation to selection. The task is multifaceted, consisting of the wide evaluation of alternative options against a set of conflicting criteria and process requirements. The span of information and narrow expertise results in a challenging activity of justifying a technology that may not yet be fully understood. Much of the information is also immature and technologies are often selected based on expected performance attributes rather than proven results. It is not always clear why a technology is or will be successful until after it has been implemented and the choice is often supported by anecdotal evidence from similar implemented cases and past experiences of decision makers.

The manufacturing technology selection literature is particularly attentive to decision models that rely on the input of expert opinion, where a trade-off based on weighted criteria determines a relative ranking. These approaches, such as the analytic hierarchy process (AHP) (Chang, Wu, Lin, & Chen, 2007; Cimren, Catay, & Budak, 2007) and quality function deployment (QFD) (Almannai, Greenough, & Kay, 2008; Lowe, Ridgway, & Atkinson, 2000), are good for organising and analysing complex decisions, however, they are based on the judgement of experts and lack in reuse of lessons learned. Upon a decision and a new technology being implemented, the lessons stored by the expert are mentally recalled to support other decision problems. Subjective-based approaches such as the AHP do not include such information and are reliant upon the opinion of the decision team to rank alternative options. The methods within the literature lack in applying evidence that is a form of decision experience, and lessons are not recorded and reused over time. The difficulty of representing the exact decision activity is that decision makers use their subjective judgment and experience to select an appropriate technology.

Multi-criteria decision-making (MCDM) tools do not retain and reuse knowledge, and managers are unable to make effective use of knowledge and experience of previously completed projects to help with the prioritisation of future cases (Tan, Lim, Platts, & Koay, 2006). Several authors have attempted to capture and reuse knowledge to support similar selection processes (Chtourou, Masmoudi, & Maalej, 2005; Fonseca, Uppal, & Greene, 2004; Yang, 2002). They include case and rule-based reasoning where structured information and knowledge is acquired from an expert. Although knowledge-based approaches provide much better support for decision-making compared with traditional MCDM methods, they appear to have a number of limitations. Rule-based systems collect information directly from an expert or through

* Corresponding author.
E-mail address: liam.evans@atkearney.com (L. Evans).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.05.047

questionnaires and represent the knowledge through an IF-THEN type production rules. This type of acquisition requires constant maintenance and updating to ensure the information is kept up-to-date (Er & Dias, 2000; Masood & Soo, 2002). Conversely, case-based reasoning (CBR) systems work extremely well by retrieving and adapting old solutions to solve new problems (Kraslawski, Koiranen, & Nyström, 1995; Tan et al., 2006; Toussaint & Cheng, 2008), however inference will locate the nearest single match to provide a solution rather than use multiple rules to justify a decision. The knowledge acquisition processes for both approaches are time and cost intensive.

The knowledge acquisition process is subjective where the opinion of the expert and their interpretation of best practices can be biased. Knowledge can easily be influenced and may not reflect reality compared with factual historical information, which can lead to further discrepancies within the justification. The transformation of data, information and knowledge will also vary depending upon the definition of the problem and solution (Evans, Lohse, & Summers, 2012). Much of the literature has attempted to solve the problem by analysing a technology as a single entity. Existing process practices are based on historical information of previously completed decision-making tasks. Therefore, the relationship between a historical decision and future decision-making activity requires further investigation.

The methodology in this paper is an information-driven approach that uses a form of pattern recognition on factual historical decision-making data to rank technologies against a set of project requirements. The experience-based approach is reliant upon structured data of historical cases to support new manufacturing technology decision problems. Experience is a representation of a historical decision case that includes the original project requirements, selected technical attributes of a technology and the overall agreed case performance. Instead of relying solely on expert knowledge of a problem domain, the approach is able to utilise the specific knowledge of previously experienced situations to solve new problems.

Data mining appears to be well suited to the problem by providing an objective-based approach. It is able to determine underlying patterns among historical cases and deliver knowledge to support decision-making. The case-based approach uses previously implemented cases as evidence to support new case classification. The advantage of using such an approach is the ability to extract knowledge from a dataset in a human-understandable form. This semi-automatic approach of using knowledge to support new cases discovers explicit rules from a set of cases.

This research contributes to the field of manufacturing technology selection by supporting the decision process through experience decision case information rather than the technical performance properties of a technology alone. Context information can be considered for different decision problems, and the system updates and learns over time. The knowledge and output provides a good explanation of results and allows ranking of various alternatives.

The proposed approach to manufacturing technology selection adopts the fuzzy decision tree (FDT) data mining algorithm. It is suited to the problem as historical manufacturing decision cases would be represented by both fuzzy and nominal attributes. The difficulty of defining parameters where no definitive boundary exists between its evaluations is best resolved using fuzzy logic. Whilst the financial performance of a technology may be easy to define in quantitative terms, for parameters where a definitive performance is not obvious, fuzzy logic would resolve through the judgement of multiple experts. Where the opinion of several experts may vary, the logic is able to accurately combine the judgement. This approach is more objective than a subjective technique such as the AHP that relies on personal judgement to form a recommendation.

The approach possesses a number of advantages compared with existing methodologies in the literature to support manufacturing technology selection: (1) by representing the support decision information as historical decision cases, a technology is considered based on its performance in decision case; (2) the model is flexible and can handle a variety of decision variables for both project requirements and technical properties of a technology; (3) the model is not reliant upon an expert to enter and formalise their knowledge of the logic of the decision process; and (4) the approach is not so mathematically elaborate that decision makers will have difficulty using them in practice.

The rest of the paper is organised as follows: Section 2 presents background information on manufacturing technology selection, data mining and FDTs. Section 3 presents the problem definition of the decision practice within industry and from the literature. Section 4 presents the experience-based technology selection methodology and introduces each phase of the proposed model. Section 5 provides an industrial case study to demonstrate the applicability and conducts a results analysis. Section 6 concludes the findings the research.

2. Background

2.1. Manufacturing technology selection

The term *technology* is defined by Steele (1989) as "knowledge of how to do things". Within manufacturing, technology is the provider of the capabilities to enable organisations to provide its customers with goods and services, both now and in the future. This leads to an aim of technology selection that is to obtain a new know-how, components, and systems in general technological capabilities, which are important building blocks for core competences that will help a company make more competitive products and services, more effective processes, and/ or create completely new solutions (Torkkeli & Tuominen, 2002).

Technology selection and justification involves decision-making that is critical to the profitability and growth of a company in an increasingly competitive global scenario. However, these selection and justification processes require the analysis of a large number of economic (tangible) and analytical (intangible) factors (Chan, Chan, & Tang, 2000). A number of researchers have summarised the selection and justification of manufacturing technology in recent years. Raafat (2002) provided a comprehensive bibliography on the justification of advanced manufacturing technologies (AMTs), whilst Khouja and Offodile (1994) reviews commonly used AMT justification approaches and their advantages and disadvantages. In general terms, most authors agree on three groups of investment appraisal techniques (Badiru, Foote, & Chetupuzha, 1991; Chan, Chan, Lau, & Ip, 2001; Small, 2006; Small & Chen, 1997): the economic approach, the analytical approach, and the strategic approach. Recent studies have adopted hybrid approaches based on a combination of economic, analytic and strategic appraisal techniques. Traditional economic techniques alone are not capable of handling intangible factors in the evaluation process (Ordoobadi, 2011). This creates a challenging problem in that the quantification of such factors combined can be conflicting. The majority of these techniques are formed under two groups: MCDM and intelligent/ knowledge-based decision-making.

The MCDM approaches range widely from original techniques reported in the literature and a combination of hybrid methods. A number of authors investigated applying the AHP to a variety of manufacturing selection problems (Arbel & Shapira, 1986; Bayazit, 2005; Chang et al., 2007; Datta, Sambasivarao, Kodali, & Deshmukh, 1992; Goh, 1997; Jaganathan, Erinjeri, & Ker, 2007; Yang, Chuang, & Huang, 2009). The AHP provides a methodological