

AN INTELLIGENT TECHNOLOGY SELECTION ALGORITHM FOR COMPLEX DECISION ENVIRONMENTS – A UNIQUE KNOWLEDGE BASED APPROACH

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This paper investigates the role of an intelligent technology selection algorithm for complex decision environments. The elicitation and formulization of expert decision thinking is presented in support of a unique approach to the subject. The problem definition is defined and an overview of the current state of the art provides a background into the subject area. The notion utilizes a knowledge base in prior selection of criteria ratings in a fuzzy ruled base system for analytic factors. The approach aims to optimize investment portfolios at manufacturing organizations by providing an efficient and quality decision-making process.

Keywords: knowledge based decision-making, manufacturing technology selection, decision support

1. Introduction

Industrial managers are faced with the dilemma of selecting a single most appropriate technology from a range of competing options. The rapid development of technologies, together with the increasing complexity and variety has made the task of technology selection difficult. Current approaches to the technology selection have narrowly focused on assessment of the financial viability of technology options, or conventional investment justification factors. In many cases, the support tools are not fully adapted for technology selection (Shehabuddeen *et al.* 2006).

State of the art manufacturing technologies improve operational efficiency and can be attractive to companies wishing to attain higher profitability margins from existing products and processes. As organizations focus on developing advanced technologies, the market becomes saturated with capable solutions. This leads to a progressively more difficult process of identifying the optimal manufacturing process due to the number of complex technologies that exist.

Technology selection and justification require the analysis of a large number of economic (tangible) and analytical (intangible) factors in a decision support environment (Chan *et al.* 2000). Economic evaluation tools are traditionally net present value (NPV), payback period (PB) and return on investment (ROI). These provide financial understanding of how an investment will perform.

Intangible analytical factors are generally more difficult to be quantified. Elements such as productivity, flexibility and operator skill level tend to rely upon decision-makers assessments based on knowledge, past experience and subjective judgments. Decision-makers express their opinion on comparative importance of various factors in linguistic terms rather than exact numerical values.

The level of complexity in a decision-making process can vary by factors such as product, process, industry, *etc.* Aircraft manufacture is particularly unique in that products are large scale, manufactured in relatively low volumes and have a typical lifespan of twenty-five years. In terms of technology selection, decision quality is important as technologies are expected to mature throughout a product lifecycle. Cost of change is high and can have a detrimental effect on an organizations product flow. Aircraft assembly processes are also built around complex systems that require high analytical evaluation based on conflicting social/technical elements.

Decision makers are often faced with this level of uncertainty in an unpredictable business environment. The decision process is relied upon by experience, knowledge and intuition, and can vary dependent upon the personnel conducting the process.

This report presents a unique approach to quantifying analytical elements in manufacturing technology assessment. The application of knowledge elicitation techniques and such formulization is applied in a fuzzy ruled based system. Although this research focuses on the analytical elements of assessment, the final reasoning would combine economic, strategic and analytic elements based on captured information in a decision support environment. This report provides an overview of the literature review and detailed discussion of the approach to knowledge based decision-making in technology selection.

2. Literature Review

Technology selection is one of the most challenging decision-making areas the management of an organization encounters. It is difficult to clarify the right technology alternatives because the number of technologies is increasing and becoming more and more complex. However, the right technology could create a significant competitive advantage for a company in a challenging business environment. The aim of technology selection is to obtain a new know-how, components, and systems which will help a company to make more competitive products and services, and more effective processes, or create completely new solutions (Saen, 2007).

The term 'technology' is defined by Steele (1989) as 'knowledge of how to do things', or 'capabilities that an enterprise needs in order to provide its customers with the goods and services it proposes to offer, both now and in the future'. Currie (1989) discusses the topic of justifying new technology to senior management as an important reason for implementing any process of technology selection. Previous work on the selection and implementation of new technology has proven that traditional cost accounting methods to justify technology are outdated. Houseman (2003) explains that this is evident in the situation where senior management require detailed cost-benefit information to demonstrate the short and long term returns from new technology.

Badiru *et al.* (1991) discusses the general literature on technology selection justification methodologies. A reliable methodology for evaluating a manufacturing technology for specific operations is essential to the exploitation of the recent advances in technology. The authors present some prevailing justification methodologies based on three decision models: *Economic*, *Analytic* and *Strategic*.

It is clear that the analytical evaluation and justification of manufacturing technologies is a complex and difficult task. Some research has been published in this area using a variety of tools and techniques. Lowe *et al.* (2000) developed a decision model using techniques from the quality function deployment (QFD) tool. The multi-attribute matrix analysis had been applied to the evaluation of potential products for an innovative metal forming process. The evaluation tool does not substitute a comprehensive economic analysis, but allows the necessary subjective allocating characteristic settings, importance weighting and interrelationship score to be determined. The tool develops a knowledgeable relationship chart based on the subjective views entered by the decision-making team. Although no specific accuracy can be achieved in each case compared with economic value, the approach provided a well defined methodology to production technology evaluation.

Chan *et al.* (2000) presented a technology selection algorithm to quantify both tangible and intangible benefits in a fuzzy environment. The research developed an application of the theory of fuzzy sets to hierarchical structural analysis and economic evaluation. From an analytical point of view, decision-makers expressed their opinions on comparative importance of various factors in linguistic terms rather than exact numerical values. By aggregating the hierarchy, the preferential weight of each alternative was found and called fuzzy appropriate index. The approach provided a methodology for determining the criteria importance of subjective criteria in linguistic terms such as 'high', 'equal', 'low'. The approach addresses the concern of making a decision from using vague and uncertain information when it is difficult to obtain an exact or precise assessment.

Almannai *et al.* (2008) developed a decision support tool based on QFD and the failure mode and effect analysis (FMEA) toolset for manufacturing automation technologies. The research describes an integrated approach developed for supporting management in addressing technology, organization and people at the earliest stages of manufacturing automation decision-making. The approach initially uses QFD to select an automation option by answering questions "Why are we automating, and what is the best alternative", which then leads to the assessment of associated risk using the FMEA toolset. The importance of evaluation elements are firstly cross referenced to the investment drivers to determine an importance list of elements using a 1–9 scale. The elements are rated against each option and relating to the importance ranking of each, a final score is summed. Using a simplified FMEA template, associated risks with the best alternative are identified.

Lee *et al.* (2009) applied the analytic network process (ANP) to deal with the selection of technology acquisition modes. The study identified twenty-one influential

factors from empirical studies grouped into five criteria: *capability*, *strategy*, *technology*, *market*, and *environment*. The final decision was based on the resulting priorities of the alternative acquisition modes. The approach intends to effectively aid decision-making which mode is adopted for acquisition of required technologies. Almannai *et al.* (2008) and Lee *et al.* (2009) discuss how decision makers must select a precise number using the scale chart. These approaches do not provide information on what number to choose and rely on the expert judgment of the decision-maker; the lack of tuition leads to aloofness among the chosen number.

The author has recognized a common decision-making domain discussed in the literature. The domain consists of three supporting entities which are considered in a 'technology selection model'. The decision-making problem involves a tradeoff between requirements, and capabilities of an organization and technology in the ultimate selection of the optimal alternative. In a multi-stakeholder environment, decision-makers from different levels, departments and backgrounds select a solution. A form of requirements will often be determined and presented in the form of a hierarchy. Requirements such as technical capability, quality, process time, cost, *etc* will be agreed by the stakeholders. These factors evaluate each alternative identified in the tendering process. In order to compute data within the decision model, rules and knowledge are applied by experts involved. It is at this stage in the process where the accuracy of the decision can vary as different decision-makers are involved. The obtained data is combined in the technology selection model and economic / analytic decision models will seek the optimal solution.

Challenges in the existing approaches are the lack of assistance from experts and previous cases. It is apparent that there is a wealth of knowledge in experts within organizations and literature, but very little is applied in technology selection.

Baines (2004) has recognized that a manufacturing technology is typically acquired through some form of explicit or implicit decision process. The process is typically complex with a wide range of potential characteristics. It can be largely based around the judgment of a few senior personnel or be documented as an organizational procedure, or only exist in the form of company practice and know-how.

It is clear that there is a lack of intelligent approaches applied in the evaluation of manufacturing technologies for complex analytical elements. The existing decision-making methods and frameworks provide an amorphous approach that relies upon subjective judgments. Knowledge based selection tools provide artificial intelligent tools working in narrow domains to provide intelligent decisions with justification. Knowledge is acquired and represented using various knowledge representation techniques such as rules, frames and scripts, and applied to the decision model.

In recent years, the exploration of intelligent systems has been researched in decision scenarios where knowledge is retained and reused to support future decision making. Masood and So (2002) explored the application of rules in an expert system for rapid prototype (RP) system selection. Intelligent rules were captured through

questionnaires and a review of literature. The system recommended an RP system together with full specifications on the basis of interactive question-answer sessions with the user.

Shaskikumar and Kamarani (1995) developed a knowledge-based expert system for the selection of industrial robots. The system used a knowledge base and rules to determine the optimum robot for a process. Rules and parameters determined from literature and discussions with experts formed the knowledge base. Based upon the user response; the system scans all rules and eliminates those that do not contain a response. The expert system then asks the questions related to the next parameter. The process terminates once all of the '*if-then-else*' conditions for the specific problem have been satisfied and displays the recommend robot to the user.

Tan *et al.* (2006) developed an intelligent decision support system for manufacturing technology investments. A hybrid intelligent system integrating case-based reasoning (CBR) and a fuzzy neural network model was proposed to support managers in making timely and optimal manufacturing technology investment decisions. The system comprised a case library that holds the details of past technology investment projects. Similar cases are retrieved and adapted, and information on these cases can be utilized as an input in the prioritization of new projects.

In terms of intelligent technology selection, little has been done in capturing manufacturing knowledge and formulating it such that it can assist in a decision support system for complex aerospace decision environments. Houseman (2003) explored technology selection in the aerospace industry and presented a methodology to quantify both tangible and intangible benefits of certain technology alternatives within a fuzzy environment. Mountney (2009) investigated the identification, acquisition and sharing of innovation manufacturing knowledge for the preliminary design of complex mechanic components for an aircraft engine manufacturer. The capture of tacit and explicit knowledge in the early stages of design was conducted through semi-structured interviews and analyzed using a grounded theory approach to reveal the meaning behind the occurrence of situations. The research provided a knowledge base in the design of aircraft engine blisks as a reference platform.

Current state of the art in terms of literature review for technology selection has focused on justifying economic and analytical elements in the evaluation of alternative solutions. Most approaches rely on proven tools such as QFD, ANP, decision matrices and AHP, providing optimum selection guidance. These tools however rely on reliable and accurate scoring using numeric scales. It is clear the lack of intelligent methods used in the analytical justification is diminishing the quality of the chosen solution.

Knowledge based decision-making has the ability to increase the quality and swiftness of the decision-making process, and provide a system that can benefit the organization. This research will now present the conceptual framework of a

knowledge-based decision support system for the justification and evaluation of alternative manufacturing technologies for analytical evaluation factors.

3. Knowledge-based Decision Approach

The research to date has proposed a unique intelligence approach to analytic evaluation of alternative manufacturing technologies. The conception of a three stage decision analysis process tends to deal with complex analytical evaluation in a conflicting criteria environment. Figure 1 presents the methodology and sequence of three key elements: *knowledge base*, *decision model* and *appraisal*. This report focuses on the analytic algorithm within the decision model element.

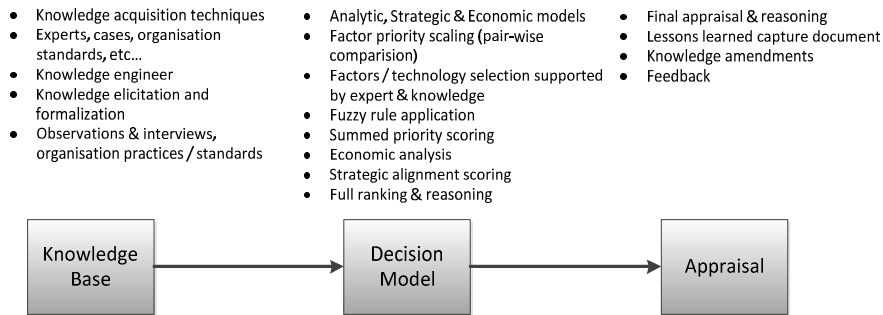


Fig. 1. Decision Analysis Process

The formulation of the knowledge base will be conducted through techniques described in the literature for knowledge elicitation and acquisition. The knowledge base intends to provide expert rules and facts supporting elements in the decision model. The model will comprise pair-wise comparison techniques, a detailed knowledge assisted technology / criteria selection platform (using linguistic and numeric terms), and a fuzzy rule based algorithm for each criteria element. The concluding appraisal stage presents the reasoning of ranked solutions and provides techniques for lessons learned and knowledge refinements.

Research by Cooke (1994) discusses the process of eliciting knowledge from a human source that is thought to be relevant to the information required. Knowledge acquisition not only involves the elicitation of knowledge, but also the explication and formalization of that knowledge that can be understood by the decision model. The author discusses the varieties of elicitation techniques and organizes them on the basis of methodological similarity and recommended applications. The research explains the circumstances around when particular techniques are used and how observation and interviews acquire knowledge rules and facts.

Knowledge acquisition is capturing data which is further formed to information and knowledge. Common forms of knowledge acquisition include semi-structured interviews. A knowledge engineer will interview an expert, transcript the session and analyze such data to formulate rules and facts. The analysis of documentation, such as organization standards and policies, can also append a knowledge base. It is

important to verify such information with an expert before scripting in a knowledge base.

This research proposes to develop a dynamic and active knowledge base through semi-structured interviews and the analysis of documentation. The following provides an example of a knowledge rule from a review of previous cases:

Technology: Laser Scanner x3
IF criteria **IS** supplementary operator access
AND process is general stage 03 assembly
THEN criteria rating: “*Wing unusable during actual process operation*”

The knowledge base will assist in the evaluation of alternative manufacturing technologies by providing knowledgeable rules and facts to individual decision elements. The decision model consists of two critical stages, formulation and evaluation. Formulation is the development of a formal model for a given decision. This is unique and designed aligned to the decision objective. The evaluation stage is algorithm intensive using formal decision methods. The objective is to produce a formal recommendation based on information, data or knowledge processed by the decision model.

The analytic decision model proposed in this research consists of five stages, each presented in a schematic model in figure 2:

- 1) *Identification of criteria factors & description*
- 2) *Criteria importance*
- 3) *Technology / criteria selection platform*
- 4) *Fuzzy rule algorithm*
- 5) *Sum priority scoring*

It is apparent that the lack of methodology for technology selection has caused decision-makers to consider technologies to criteria they believe appropriate. This can often lead to diverse factors being considered by different decision-making teams. It has therefore been identified to provide an adequate list of considered criteria for the applied context in addition to definition and ratings. For example, a decision-maker considering the criteria ‘supplementary operator access’ may not be fully aware of its precise meaning and how to evaluate such factors, information may be documented in the knowledge base as follows:

Criteria Name: Supplementary operator access
Definition: An element of a technology that may affect further manufacturing processes in the existing set up
Ratings:

- a. No inconvenience caused to other operations
- b. Flexible, stop start process, little effect caused
- c. Affects other processes during process

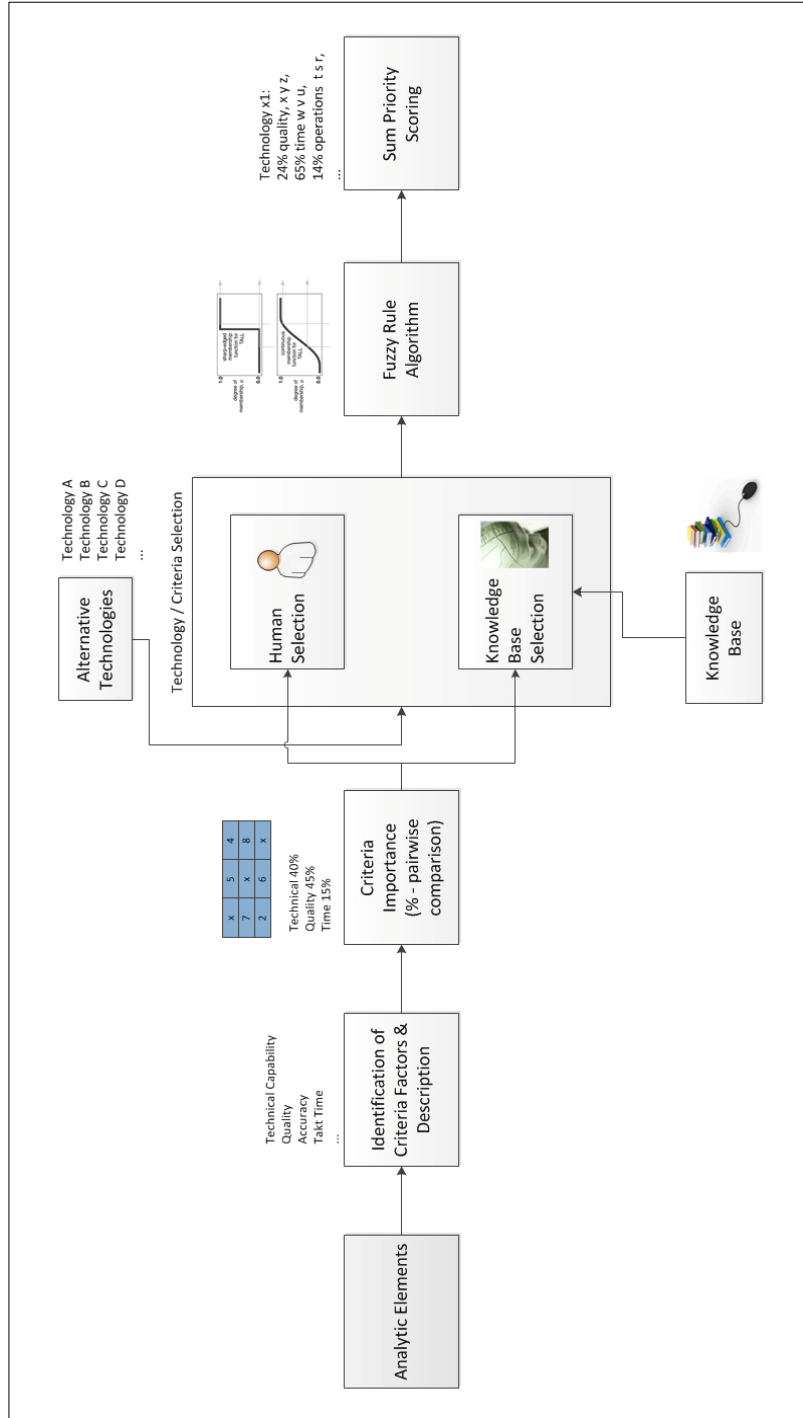


Fig. 2. Analytic Evaluation Model

Upon selection of criteria, the project will be presented in the form of a hierarchy. The top level of the hierarchy will consist of the overall project aim, *e.g. select optimum technology*, followed by the criteria in level two and sub-criteria in level three. The final level will outline the alternatives.

Once the hierarchy has been finalized and all criteria selected, the importance of each criteria will be determined. Using the pair-wise comparison technique, each criterion will be evaluated against one another to form an overall importance value. It is a process of comparing factors within the same criteria element to determine which has greater quantitative property. The intention is to have access to previous cases providing information and clarity of elements and how they have been previously rated, the same process is applied to the sub-criteria.

The two most algorithmic calculations occur in stages three and four of the proposed methodology. The technology / criteria selection stage intends to accurately and effectively evaluate each alternative against the criteria list by selecting the most appropriate rating for that particular criteria / technology, in linguistic terms.

The knowledge base will contain rules from previous cases or interviews with experts from prior technology evaluations. The initial search of the knowledge base will select ratings for criteria / technology decision elements. If a technology has been evaluated on a past project, it is likely that when evaluated again, the resulting rating will remain the same, if the elements and context remains.

This provides detail to select the same rating in the active project and for the decision-making team to continue evaluating other technologies / elements. Once the knowledge base has been fully searched and the criteria ratings selected, the decision-makers manually complete the remaining decision elements. As this stage relies heavily on subjective judgment, the detailed criteria information in linguistic terms will provide reasonable information for personnel to make judgment.

The subsequent stage in the decision methodology will be to apply the fuzzy rule algorithm. This entails a series of fuzzification, rule evaluation, aggregation of rules and defuzzification exercises. Fuzzy rules developed by an expert will provide accurate scoring for criteria that has a number of dependencies. Depending upon a rating selected for sub-criteria, the final criteria scoring will rely on the ratings of the sub-criteria. For example, if two sub-criteria have received low ratings but a third received a high rating, the final accurate criteria rating is unclear as the sub-criteria receiving the high rating may have more importance over the two criteria receiving low ratings. An expert in this area will develop knowledge rules and validate them throughout the research project.

The most commonly used fuzzy inference technique is Mandani-style fuzzy inference method. This requires a crisp input and relies upon the linguistic fuzzy membership sets to provide a crisp output value. Fuzzy membership sets for individual linguistic terms are spread between values 0 and 1. A particular linguistic term fuzzy rating may only be applied across a small region, for example, between 0.4 – 0.7. This approach therefore proposes the decision-maker to select a figure that

best suits a technology. If the decision-maker believes a technology highly satisfies the criteria, they can select a higher value related to the linguistic term.

To provide an illustrated example, a criterion with two sub-criteria elements, ‘supplementary operator access’ (A) and ‘sequence flexibility’ (B) are dependences of ‘operations’ (C). Figure 3 provides the basic structure using the Mamdani-style fuzzy inference method.

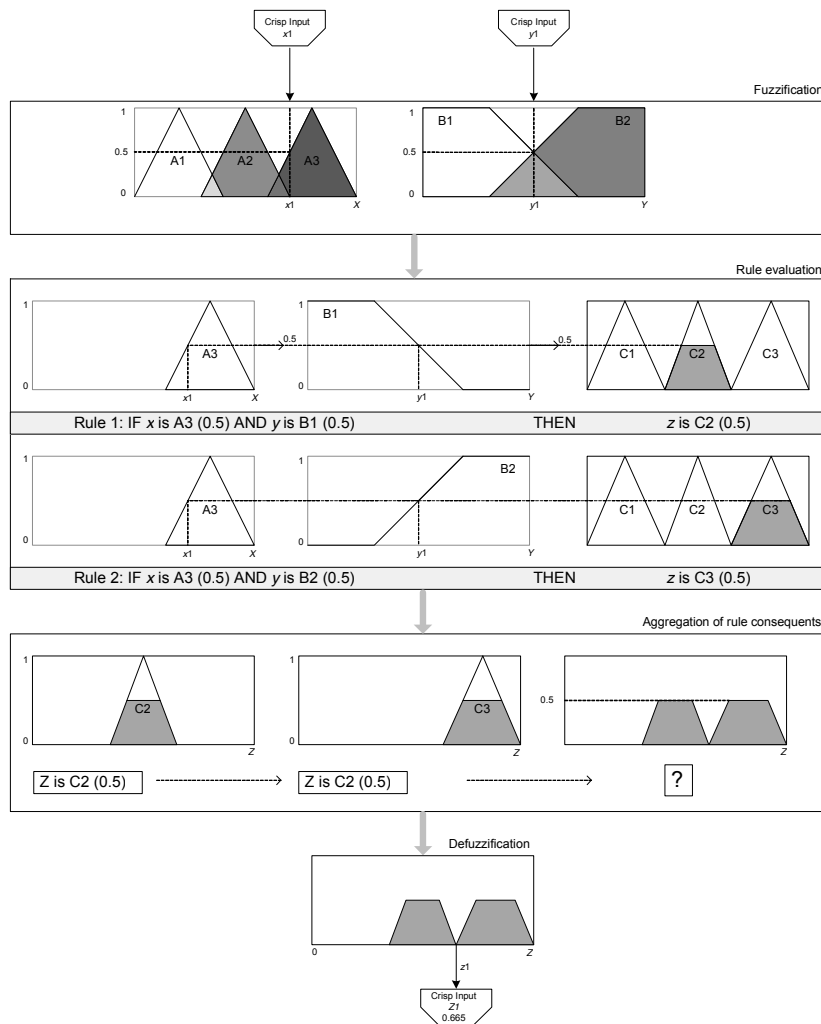


Fig. 3. Mamdani-style fuzzy inference example

The example illustrates how the decision maker chooses two crisp input values for A (xI) and B (yI). Crisp input value xI was selected as 0.7, the linguistic term chosen in the prior stage was $A3$, which lies between 0.6 and 1.0 on the scale. The decision-maker chose 0.7 as they believed this is where the technology lay between the 0.6 and 1.0 values. A crisp input value of 0.5 was chosen for B which lay within the $B1$ linguistic term. As previously discussed, a series of fuzzy rules have been determined by experts.

The following stage involves rule evaluation, this step takes the fuzzified inputs and applies them to the antecedents of the fuzzy rules. If a fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) obtains a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function. Using the centroid defuzzification technique, a crisp output value is determined. This crisp output generates a final numeric scoring for criteria against an alternative. In the example provided, the output value for operations criteria is 0.665; this is based on the two input crisp values of 0.7 and 0.5 for two particular criteria that have fuzzy rule relationships. This process is completed for all criteria / sub-criteria / technology decision elements.

The final stage of the decision model is to complete a summed priority scoring. Once each of the criteria has received a crisp scoring, it is multiplied by the importance value generated using the pair-wise comparison and summed for each technology. Each technology will therefore be given a final numeric value.

The final stage of the decision analysis process shown in figure 1 is the appraisal. It is important for a knowledge engineer to review all decision elements in order to document lessons learned and compose refinements to the knowledge base. Additional knowledge will be verified and new rules and facts added to the system.

4. Conclusion

This study has proposed an intelligent approach to the analytic evaluation of complex manufacturing technologies. The literature review has directed the authors to propose an environment capable of handling complex and conflicting analytic factors in an evaluation process, based on linguistic terms using fuzzy rules. A detailed study of literature and corporate practices in the aerospace, automotive, pharmaceutical and defense industries, has developed an approach that aims to provide an accurate and valid approach to technology selection.

This paper contributes to the field by proposing a method which applies intelligent thinking to technology selection. Previous studies were limited using static analytical techniques such as AHP, QFD, and did not deal with the complexity and lack of expert knowledge and tools available. They were limited in the use of knowledge and previous cases, and relied heavily on the subjective view of the decision-maker.

The development of this tool drew upon a pool of expertise in technology selection by understanding current practices. The proposal applies widely known artificial intelligent techniques in a context that has received little attention from AI practitioners.

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