A KNOWLEDGE BASED APPROACH TO ACTIVE DECISION SUPPORT

XIA YAN

(B.Sc., Fudan University)

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SUMMARY

In recent years, more and more attention has been put on supporting high-level cognitive tasks, such as framing of problems, alternative generation, making tradeoffs involved in preferences, and handling incomplete information, misinformation, and uncertainty. However, traditional decision supports tend to play a passive role in decision-making process, which seems not efficient enough for such tasks. As an advanced variation and refinement of the traditional passive decision support philosophy, active decision support tools are capable of actively participating in the decision-making process so that a more fruitful collaboration between the decision makers and decision tools can be achieved.

The main purpose of this thesis is to propose a knowledge-based active decision support method. The method is a new concept of intellectual support to decision makers, which challenges the traditional way of solving a decision problem. When looking for a final solution to a decision problem, we used to only search the feasible alternatives satisfying the constraints of a problem. However, the new method enables the decision maker to have higher utility solution by considering the “infeasible” solutions as well. It is different from other intellectual approaches in its attempt at providing decision makers decisional guidance, which overcomes decision makers’ fixation of considering only the feasible alternatives, suggests more alternatives and stimulates the discovery of opportunities lie in the alternatives overlooked by decision makers. Another active decision support idea based on statistical techniques is also included. The idea is to automatically refine the domain knowledge available for making efficient multi-criteria decisions through a serious of multivariate analysis tools.

To illustrate these notions, the new methods and ideas are integrated in to a conceptual Knowledge-Based System (KBS) framework in the later part of the thesis. The provision of these active supports can enhance KBS' capabilities for achieving decision objectives; extend the limits of 'bounded' rationality by promoting improved understanding, better insights, and more extensive analysis.

Then, as an application of enhanced KBS architecture, an Expert System (ES) is conceptually designed for R&D model management. The general architecture is designed and illustrated clearly with domain dependent knowledge. Then, the R&D ES is applied to a practical model selection problem. The results of the application show that the guidance for judgmental inputs can actually improves decision quality, user learning, and user satisfaction. Furthermore, the knowledge base constructed in this thesis is helpful in making R&D model selection decisions and can be imported as standard knowledge storage to a commercial ES software.

The designed methods are flexible enough to enhance other decision-support or decision-making tools. In the final part of the thesis, possibilities of applying the methods to other complex decision situations are discussed.

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LIST OF NOTATIONS

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANOVA	Analysis of Variance
Ch	Checklist models
DSS	Decision Support Systems
DT	Decision Tree
Ec	Economic Analysis models
ES	Expert Systems
GA	Genetic Algorithms
KBS	Knowledge Based Systems
R&D	Research and Development
MAUT	Multi-attribute utility theory
RO	Real Options analysis
Pr	Programming models
SA	Simulated Annealing

CHAPTER 1 INTRODUCTION

1.1 Background

Management is a process by which organizational goals are achieved using resources. The success of management depends on the performance of managerial functions, such as planning, organizing, directing, and controlling. To perform their functions, managers are engaged in a continuous process of making decisions. All managerial activities revolve around decision-making. The manager is primarily a decision-maker. Organizations are filled with decision-makers at various levels.

For years, managers considered decision-making purely an art that is a talent acquired over a long period through experience. This is because a variety of individual styles could be used in approaching and successfully solving the same types of managerial problems. These styles were often based on creativity, judgment, intuition, and experience rather than on systematic methods grounded in a scientific approach.

The impact of computer technology on organizations and society is increasing as new technologies evolve and current technologies expand. When the 21^{st} century begins, major changes have been observed in how managers use computerized support in making decisions. As an increasing number of decision-makers become computer literate, more and more aspects of organizational activities are characterized by interaction and cooperation between people and machines. From traditional uses in transaction processing and monitoring activities, computer applications have moved to problem analysis and solution applications.

Decision-support systems (DSS), defined as ‘interactive computer-based systems, which help decision-makers utilize data and models to solve unstructured problems’ (Gorry and Scott Morton 1971), is evolving from its beginnings as primarily a personal-support tool, and is quickly becoming a shared commodity across the organization. With computer-based capabilities, DSS enhance the overall effectiveness (e.g., by increasing reliability, accuracy and efficiency of obtaining relevant information) of decision makers, especially in their unstructured and semi-structured tasks.

1.2 Motivation

However, these decision supports tend to play a passive role in decision-making process. Interactions among decision supports, decision makers, and reality are illustrated in Figure 1.1 in a form of information exchange cycle. At the beginning of the decision-making process, decision makers collect problem related information from the reality environment, make assumptions to simplify the problem and input information to decision support tools. Decision makers then require alternatives and predicted outcomes from the tools. They set criteria for choice of the alternatives and send this information to the tools. Then the tools induce a solution according to decision makers’ requirements and send it back to decision makers. After a decision is made, the solution of the problem is implemented to the reality. The implementation results are collected by the decision makers and sent to the tools to improve next-time performance so that a better solution and a better decision can be made in the future.

From such an information exchange point, the interaction between a decision support tool and a human user is often initiated by the user who requests a result or a response from the tool. Thus, what all the traditional decision-support tools and decision models trying to do is to facilitate good decisions by providing decision-makers the information they need. The information flows among tools, human decision makers and the environment is changed by the reality or the decision-maker while the tools just passively respond to these changes. These decision supports do not promote use in a forward-looking mode. They only provide information to decision makers within which decision makers themselves have to search and find new opportunities for development. Therefore, these tools play a relatively supportive but passive role in decision-making processes.

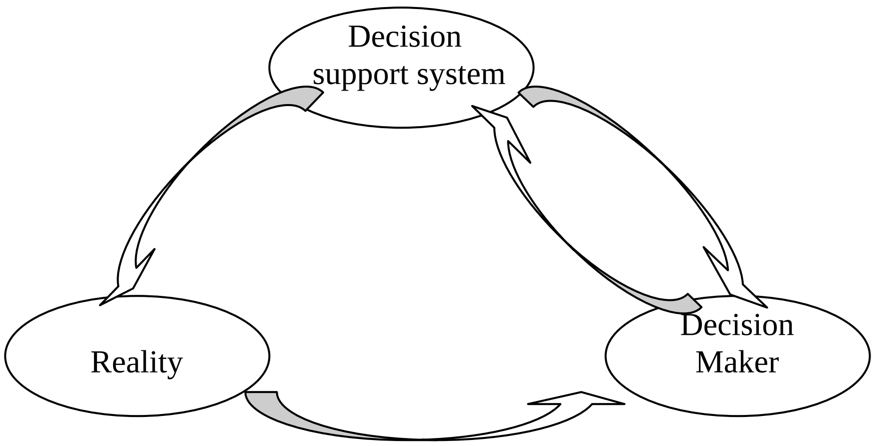


Figure 1.1 Information exchange cycle

Due to the passive role in decision processes, the supports offered by conventional DSS to decision-makers are still at a relatively superficial level and do not make much difference from their traditional processing and monitoring responsibilities. In other words, the traditional DSS provide only a weak form of support that does not exploit the full power and potential of computer-based systems' capabilities to provoke decision makers' new understanding of the problem.

On the other hand, more and more attention has been put, in recent years, on providing support for the high-level cognitive tasks, such as framing of problems, alternative generation, making tradeoffs involved in preferences, and handling incomplete information, misinformation, and uncertainty.

The support required by these high-level cognitive tasks is analogous to referring the decision-making tasks to human staff assistants and staff advisors. Normally, a staff assistant makes efforts to understand the changing requirements of the task, the needs of the decision maker, and the best way to support the particular decision maker. For this, the staff assistant constantly monitors the current status of the task, provides interim reports, and is sensitive to the needs and the peculiarities of the decision maker and the context in which the decision is made. This means support for high-level cognitive tasks must involve a form of reasoning, learning, and idea generation based on judgmental inputs, just like real human mental activities.

Therefore, advances are needed in developing more effective decision supports by providing more active, forward-looking contributions to high-level cognitive tasks and to the achievement of decision objectives.

Till 1990's, the evolution had been in the direction of building a DSS to provide more effective support for the low-level cognitive tasks, such as data storage and retrieval, data drilling, manipulation, and consistency checking (Radermacher 1994).

However, with advances in software and hardware technology, the data, model and interface components of DSS are now much more sophisticated and powerful than they were decades ago. The databases are larger, more current and easier to query and search, the models are more complex reflecting reality, and the interfaces are much more user-friendly. The environment for developing more positive supports to high-level cognitive tasks is much more mature and accordingly research in such field is largely motivated.

1.3 Contribution

As an advanced variation and refinement of the traditional passive decision support philosophy, active decision support tools are capable of actively participating in the decision-making process so that a more fruitful collaboration between the human and the decision support tools can be achieved.

The purpose of this thesis is to propose new methods providing active decision support for high-level cognitive tasks. The major focus has been put on a method which is a new concept of intellectual support to decision makers. It challenges the traditional way of solving a decision problem. When looking for a final solution to a decision problem, we tend to only search the feasible alternatives satisfying the constraints of a problem. However, the new method enables the decision maker to have higher utility solution by considering the “infeasible” solutions as well. It is different from other intellectual approaches in its attempt at providing decision makers decisional guidance, which overcomes decision makers’ fixation of considering only the feasible alternatives, suggests more alternatives and stimulates the discovery of opportunities lie in the alternatives overlooked by human decision makers.

Another method is to provide new resource support for multi-criteria decision-making. The method is to refine the domain knowledge available for making decisions through a series of multivariate analysis tools. Utilizing statistical tools in the process is a novel way to realize the knowledge refining purpose, although it does not refine the knowledge based on the system's experiences of solving problems like a human expert.

To illustrate these notions, the proposed decision support tools are applied and integrated as intelligent components into a generic knowledge-based system (KBS) framework, which is then applied to develop a specific Expert System (ES) for R&D model guidance. The provision of these supports can strengthen KBS' capabilities for achieving the decision objective; extend the limits of 'bounded' rationality by promoting improved understanding, better insights, and more extensive analysis; and add to the functionality of other Decision Support System (DSS) frameworks. They are also flexible enough to enhance other decision-support or decision-making tools especially for situations with complex problems and expert decision makers.

1.4 Organization of the Thesis

The thesis is organized into seven chapters as follows:

Chapter 2 reviews past research in the area of active decision support and highlights four major ideas to provide such support for complex decision-making situations. Chapter 3 describes a new method, combing the relevant prior works, for providing intelligent decision support. The statistical based knowledge refining methods providing resource support is also included. Not only the components and the workflow, but also the contributions and the basic idea of these methods are established in this chapter. Chapter 4 proposes an advanced KBS architecture incorporating the proposed active support methods. Key components for designing such architectures are identified as well. The system is described in detail in terms of its goals, functional features and information flow. Chapter 5 illustrates the architecture through building an Expert System in R&D

model guidance domain. The construction of a domain dependent knowledge base for the system is also included. While in Chapter 6, the designed Expert System is applied to a practical model-choosing problem. Finally, Chapter 7 provides a summary of emerged research problems and attained conclusions in this study as well as observations and recommendations for future directions of research in providing advanced forms of decision support.

CHAPTER 2 LITERATURE REVIEW

2.1 Active Decision Support Introduction

Active decision support, advocated by Manheim (1988) and Mili (1988), is an advanced variation and refinement of the traditional decision support philosophy. Traditional decision support philosophy merely calls for support tools that can enhance human decision-making. They are largely passive partners in decision-making, since they are not capable of taking initiatives and can only respond to users' requests. While the active decision support is concerned with developing advanced forms of decision support where the support tools are capable of actively participating in the decision-making process, and decisions are made by fruitful collaboration between the human and the tool such as machine.

The notion of active participation in decision making can represent a broad range of ideas such as: monitoring the decision making process of the user and detecting inconsistencies and problems; understanding and inferring users context, goals and intentions and automatically scheduling and carrying out the required activities; alerting the decision maker to the aspects of the problem and problem-solving process that are not getting enough attention; criticizing decision maker's actions and decisions from various perspectives; stimulating creative ideas; serving as a sounding board for ideas; and carrying on insightful conversations with decision maker that can lead to creative formulation and solutions of decision problems (Raghavan 1991).

Manheim and Isenberg (1987) suggested active decision supports having few features that can provide the high-level cognitive support. These features include: (a) maintaining an explicit representation of the decision maker's conceptual problem-solving model and using it to guide support activities; (b) providing tools for supporting the 'natural heuristics', such as 'do the easy things right away' as well as tools for rational model-type such as linear programming and break-even analysis model; and (c) providing tools to enhance the user's ability to balance strategic (global and long-term) and opportunistic (local and short term) thinking.

The active decision supports aim at improving the decision-making effectiveness through ‘active participation’ ideas mentioned above such as stimulating creative ideas, criticizing choices, and guiding decision structuring. These decision supports operate almost independent of explicit directions from the users and provide support in a number of forms such as suggesting alternative actions and indicating issues that the users may have overlooked. They also use alternative models of the problem-solving processes, ask the users to make choices at the intermediate stages allowing the users to determine the problem-solving paths, and maintain updated models of the user problem-solving processes. Thus, the active decision supports are capable of active participation in the decision-making processes. They complement users' problem-solving abilities in the application domain (Rao et al. 1994).

In recent years, some of the emerging technologies have been used in providing active supports. Keen and Scott Morton as far back as in 1978 foresaw that decision support may be achieved by exploitation of many technologies (Keen 1978). Modem database technology, graphical user interface, hypermedia, multimedia, expert systems, neural networks, fuzzy logic, genetic algorithms, distributed systems, client-server, object-oriented approach are examples of recent technologies that can carry out decision supports that were not feasible in 1978.

Research concerning active decision supports is carried out under a variety of labels such as intelligent decision supports and symbiotic decision supports. Currently there are four broad threads of ideas in the active decision support area: idea stimulation, autonomous processes, expert systems, and active elicitation and structuring.

2.2 Idea Stimulation

Idea stimulation is widely recognized as an important form of active decision support (Young 1982, Krcmar et al. 1987, Nierenberg 1987). There are at least two systems that illustrate this approach (Krcmar 1987, Nierenberg 1987).

Krcmar et al. (1987) developed a DSS that can help users identify new ways to exploit information technology as a competitive weapon. They used questions as triggers for stimulating new ideas. Trigger questions are developed using a theoretical model that is widely used for studying information technology and its impacts.

The underlying model provides primitive variables for characterizing information technology, impacts, and their inter-relationships. Each relationship in this model represents a potentially new idea for exploiting information technology as a competitive weapon. This provides a basis for stimulating new ideas - facilitating the user to think about the potential relationships between the variables in the model. The system accomplishes this by systematically instantiating the model variables, and posing questions about the possible relationships. Since the number of questions at any point in time can be combinatorially explosive, the system uses contextual information for pruning down the irrelevant ones. However, the authors did not provide any system performance measures.

Whereas Krcmar used a problem-specific model for idea stimulation, Nierenberg (1987) employed a set of domain independent modules for stimulating ideas. Their system, named Idea Generator, is essentially a decision-structuring tool. The underlying structuring technique uses primitives such as problem, goal, actions, and strengths of relationships for structuring a decision problem. The system uses several idea generation modules for helping the user identify novel actions.

Each idea generation module in the system is based on a specific scheme for provoking novel thoughts. Some of the schemes used by the modules are: Think of similar situations; Think of metaphors for the situation**;** Think from other perspectives ,that is think of how other people may solve the problem; Focus on goals one at a time and then collectively; Reverse your goals and actions; Focus on the people who will be affected by your actions.

The user can collect the ideas they generate into a temporary workspace. The system provides facilities for grouping, pruning, and synthesizing these ideas. Authors claimed that the system has been used in several simple business problems and has proved to be quite effective.

2.3 Autonomous Processes

Active supports can also be implemented as a set of agents that watch over the decision making process of the user and trigger appropriate responses autonomously. Several ideas in this direction include observing decision maker's activities and scheduling the necessary related tasks; keeping track of the pending tasks and ensuring that they are completed; eliciting and enforcing constraints; forcing a divergent process if the user is judged to be prematurely converging; and forcing a convergent process if user appears to be disorganized with too many tasks and thoughts.

Manheim (1988) proposed a general architecture for active decision supports based on autonomous processes. The key aspect of his architecture is the existence of two kinds of processes in the system: user directed, and system directed. User directed processes correspond to tasks in conventional passive decision supports, such as retrieving data and requesting analysis. The system directed processes, on the other hand, are processes that are autonomously initiated by the system while playing its role as an independent and active agent in the decision making process. For example, the system initiating processes for consistency checking and critiquing at periodic intervals.

The ability of the system to play active roles in this architecture rests on the following critical factors: understanding the decision making processes of the user; having criteria for judging the quality of the decision making process; and having strategies for improving the process. Once these requirements are met, the system can closely monitor the decision making process of the user, and intervene as and when necessary to criticize and offer suggestions. The system can raise pointed questions and extract rationale and justifications for users' actions, and force him to think of additional alternatives and contingencies. It can also anticipate users needs, schedule processes and perform useful analyses in advance.

One application of such autonomous process in recent years is Provider Order Entry system for drug dosing. The automated alerts suggest dose amounts to the clinician in real time. Many advanced ordering systems offer decision support facilities to determine optimal dosing by automatically calculating adjustments based on patient weight or renal function stored in the medical record, and check for interactions with other concurrently prescribed drugs, known allergies and diseases. Some may also prompt the user to enter required corollary (consequent) orders. Applications that allow direct entry of medication orders are among the most difficult clinical computing applications to develop, yet they have been demonstrated to dramatically reduce serious medication errors (Sittig and Stead 1994).

Bindels et al. (2000) developed a test ordering system, named GRIF, with automated reminders for primary care. GRIF system can provide automated feedback on test ordering in general practice. It reads the patient data and checks whether any of the rules fires and which feedback has to be provided. If a request is not according the guidelines, the reminder system generates and displays a reminder that overlays the normal user interface of the order entry form. Through such autonomous process, the system generates the actual recommendations and supports the user’s decision making in an active way.

2.4 Active Problem Elicitation and Structuring

Here active decision supports are based on a problem structuring technique that is suitable for problems of interest. Some examples of such structuring techniques are goal-oriented structuring, analytical hierarchy structuring, constraint satisfaction paradigm, etc. Since structuring techniques are normative models of decision making, they immediately provide: a basis for active problem elicitation, a basis for making recommendations, criteria for judging the decision making process, and a framework for incorporating idea stimulation and other machine-based personalities.

The key objective of active decision supports based on this approach is helping the users to effectively organize and structure their own knowledge and expertise for solving problems. The GODESS system (Pearl et al.1982) is an excellent example of such a system.

The acronym GODESS stands for goal-oriented decision structuring system. Goal-oriented structuring is an adaptation of the means-ends analysis technique that is widely used in Artificial Intelligence (AI) planning systems. Here a problem is structured in terms of goals, actions, preconditions, states, factors, and strengths of relationship between these components.

GODESS can play both support and decision-making roles. In the support role, the system carries on an active dialog with the user and formulates the decision problem in terms of the primitives of the goal-oriented structuring technique. The system is domain-independent and its only knowledge is that of the structuring technique. Therefore, it relies on the decision maker to be knowledgeable about the problem, and supply the problem-specific knowledge.

GODESS uses an And-Or tree to structure the details of the problem as they unfold during the elicitation process. The tree is used throughout the dialog process for meaningfully communicating with the user, making decisions about how the focus should shift between various parts of the problem, and determining what aspects of the problem need further elaboration. At the end of problem information gathering, the system processes the information accumulated in the And-Or tree to make recommendations.

The GODESS work adds several key ideas for developing active decision supports: active problem elicitation and decision structuring; domain independent decision support; exploiting users' knowledge of the decision problem; and adapting AI problem-solving techniques for decision structuring.

2.5 Expert Systems as Active Decision Supports

In recent years, researchers have focused on tandem architectures that synthesize expert systems and decision support systems to provide active decision supports. Expert systems (ES) attempt to mimic human experts' problem-solving abilities. When an organization has a complex decision to make or a problem to solve, it often turns to experts for advice. The experts it selects have specific knowledge about and experience in the problem area. They are aware of the alternatives, the chances of success, and the benefits and costs the business may incur. Companies engage experts for advice on such matters as what equipment to buy, mergers and acquisitions, major problem diagnostics in the field, and advertising strategy.

A traditional ES is typically a decision-making or problem-solving software package that can reach a level of performance comparable to - or even exceeding- that of a human expert in some specialized and usually narrow problem area. The basic idea behind an ES, an applied AI technology, is simple. Expertise is transferred form the expert to a computer. This knowledge is then stored in the computer, and users run the computer of specific advice as needed. The ES asks for facts and can make inferences and arrive at a specific conclusion. Then, like a human consultant, it advises non-experts and explains the logic behind the advice. Expert systems are used to support many tasks today in thousands of organizations. The more unstructured the situation, the more specialized and expensive the advice is, which is the value of support from ES.

An ES must have the following features: Firstly, ES must possess the expertise that will enable the system to make expert-level decisions and must exhibit expert performance and adequate robustness; Secondly, the basic rational of artificial intelligence is to use symbolic reasoning rather that mathematical calculation. This is also true for ES. That is, knowledge must be represented symbolically, and the primary reasoning mechanism must also be symbolic. Typical symbolic reasoning mechanisms include backward chaining and forward chaining; Thirdly, the level of expertise in the knowledge base of ES must be high. That is the knowledge base must contain complex knowledge not easily found among non-experts; Finally, ES must be able examine their own reasoning and explain why a particular conclusion was reached.

Classic expert systems (ES) having the features mentioned above may also be regarded as active DSS because they can be used merely for advice rather than for decisions. But the supports offered by these systems are poor, since they only act like an agent to provide advice according to decision makers' requirement. However, it is possible to develop expert systems to function effectively as active decision support. The key is to develop them as critiquing agents (Miller 1984, Mili 1988) rather than as expert decision-making agents.

Miller (1984) provided a comprehensive description of the ATTENDING system, a critiquing expert system from the medical domain. The system becomes operative only after the user has a tentative decision. The system interacts with the user and gathers the details of the problem, users' decision, rationale and justifications. This dialog process itself can be very insightful to the decision maker as he is forced to communicate and justify his decision to the system. After the details are collected, the system reconstructs a plausible decision-making process using its knowledge base and internal models, and identifies potential problems and possible improvements.

In the 1992, Franz Edelman DSS prize-winning paper, Angehrn (1993) introduced the conversational framework for decision support. The conversational framework is the basis of a new generation active and intelligent decision support systems and executive information systems. The active DSS will be equipped with the tools that will act as experts or mentors to decide when and how to provide advice and criticism to the user, while the user formulates and inquires about its problems under the continuous stimulus. This kind of active DSS promotes use, creativity, exploratory learning, and adaptability.

De Clercq et al. (1999) constructed a real-time critiquing system CritICIS used in critical care environments such as Intensive Care Units (ICU). The DSS reads in the necessary patient data and compares the data with the guidelines. Whenever a guideline is not followed, the system sends a warning to the ICU care providers. The system has access to two sources of data: 1) a Patient Data Management System (PDMS) that holds clinical data such as prescribed drugs and established diagnoses, and 2) a patient monitoring system that broadcasts physiological data such as a patient’s blood pressure or heart rate. A strategy using automated knowledge acquisition techniques for development of guidelines for the ICU is also proposed.

In addition to the current critiquing approach CritICIS adopted, the author suggested a more pro-active approach. This approach would enable physicians to ask the system for advice regarding certain complications, treatments or differential diagnoses instead of just being warned by CritICIS when a guideline is not followed.

A closely related approach is to endow the expert system with reasoning processes of different problem-solving perspectives and use them for critiquing.

For example, a decision maker can greatly benefit by getting his business decision analyzed from the marketing perspective, finance perspective, legal perspective and so on. AI systems such as PARRY and POLITICS have demonstrated the feasibilities of these approaches. It may be possible to extend this approach for playing other kinds of generic roles such as devil's advocate, adversarial, optimistic, pessimistic, conservative, aggressive personalities and so on.

Another popular approach for active support is to use embedded intelligent agents in the decision support system for purposes such as: automatic selection and construction of models, explaining the results of model runs, recognizing patterns in data, and making complex retrievals and inferences. Though these are valid active support ideas, they are less interesting from our perspective and therefore are not discussed further.

2.6 Summary

Four broad themes of ideas for developing active decision support: idea stimulation, autonomous processes, expert critiquing systems, and active elicitation and structuring techniques. Though they are described as disjoint ideas, these four threads of ideas are closely related to each other and will be combined together to provide more effective decision support in this thesis.

In the following chapters, new methods for intelligent decision support and resource support will be described and then be incorporated into a KBS framework to perform advanced functions.

CHAPTER 3 ACTIVE DECISION SUPPORT DESIGN

3.1 Introduction

Resource support approach and Intellectual support approach are two general decision support strategies and are here used to develop active decision support for high-level cognitive tasks. New ideas of resource support and Intellectual support are proposed in this chapter, standing in striking contrast to the approaches underlying the conventional decision support philosophy, and methods to realize these ideas are designed according to the operational terms of the two general support approaches.

3.2 General Decision Support Strategies

For developing decision support, there are three major strategies: resource support, process support, and intellectual support. In the resource support approach, the focus is on providing the information and the analytical resources that are necessary for decision-making. Examples of the resources needed for decision-making are: Data bases; Models, which include statistical models, OR/MS, optimization models, other quantitative models, qualitative and symbolic models and causal models; knowledge bases, which include domain specific bases, general heuristics and expert system modules.

In the process support approach the emphasis is on addressing the generic needs of decision-making processes. Some of the operational levels goals of this approach are: supporting the planning, organizing, and the execution of complex and inter-related tasks that constitute decision-making; supporting flexible process sequences during decision making; supporting interruption and resumption; simulating decisions and studying their potential consequence; supporting multiple worlds/contexts for exploring potential scenarios; providing various schemes for choice reduction; maintaining details about intermediate decisions and their inter-relationships.

In the intellectual support, the focus is on higher level cognitive activities of decision making including innovation and creativity. In operational terms, it translates into the following kinds of support: active elicitation and structuring of problems, surfacing the assumptions, justifications and contingencies, stimulating creative ideas, learning, and discovery; suggesting alternatives and improvements; critiquing decision makers' processes, judgments, and decisions; overcoming decision makers tunnel vision, fixations, and biases; promoting convergent and divergent thinking; employing machine-based personalities for analyzing problems from diverse perspectives; the machine playing various kinds of sounding board roles. For example: playing a devil's advocate role.

This thesis concentrates on the resource support and intellectual support approaches. The major goal is to resolve the design and implementation problems underlying these approaches. The active support will not be addressed as an explicit goal, as it is a constant theme throughout this research.

3.3 Active Intellectual Support

3.3.1 Basic Idea

The underlying idea of the new intellectual support is to overcome decision makers’ fixation of considering only the feasible alternatives, suggest more alternatives and stimulate the discovery of opportunities lie in the alternatives overlooked by decision makers.

It is different from other intellectual approaches in its attempt at providing decision makers with decisional guidance. This means the approach will serve as a guide for decision makers seeking new information that is critical to reach a better solution or decision. Through such guidance, a more positive support will be offered during the whole decision-making process so that some opportunities overlooked by human decision makers can be identified.

Generally, to ensure a good decision, decision-makers tend to examine all the possible alternative solutions for a decision problem and choose the best one of them. Such course of action often requires decision-makers to consider the impact of each alternative on the entire organization from a systems point of view, because a decision made in one area may have significant effects in other areas. Since the uncertainties usually make a decision problem more complex, the common way for such systems consideration is to settle down the resources available for solving the problem at the beginning of a decision process. Therefore, the inputs of traditional decision support models, like the Simon's model and operations research models, are often fixed, based on which solutions are selected and decisions are made.

However, when inputs of a decision process (i.e. resources) are confirmed, focuses will usually be put on the alternatives that will not violate the fixed level of these resources (i.e. constraints) if they are selected. These alternatives are defined as feasible solutions. By simply respond to the input information offered by decision makers, conventional decision supports only help to search the feasible solutions for an optimal output (i.e. solution). Such kind of search is a bounded and ineffective one, since relatively fewer alternatives are examined and opportunities in infeasible solutions are ignored.

The basic idea of this approach is shown in Figure 3.1. A solution's desirability is measured on two dimensions, namely, decision makers' preference and solutions' feasibility.

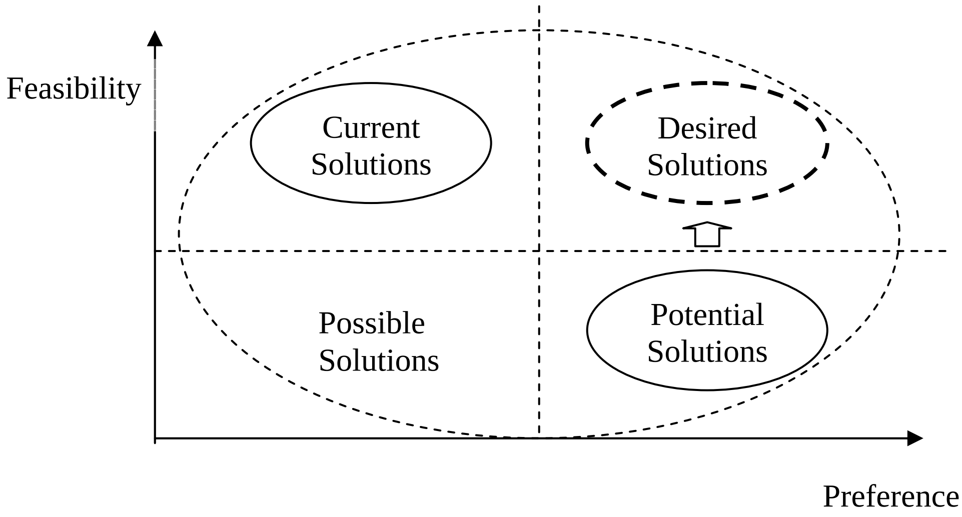


Figure 3.1 Idea of intellectual support

With the help of conventional decision support tools, the solution obtained by decision makers is defined as a current solution. Since the current solution is selected based on original inputs in a principle of not violating all the input constraints, it has advantage in feasibility. Nevertheless, current solutions may make little sense (i.e. low utility level) according to a particular preference on time, risk and other factors, that is a feasible solution is not necessarily a good decision to a certain decision maker.

Opportunities for better decisions lie in those solutions that are of high-level preference but poor feasibility according to original inputs (i.e. resources level). Such solutions are defined as potential solutions. If potential solutions can be moved from the preferred but infeasible position up to the preferred and feasible position where the solutions there are defined as desired solutions, the decision problem can be solved in a better way satisfying both the resource requirements and human preferences. Such shifts become possible as long as some key inputs are changed or constraints of resources are loosen from original level. In this case, guidance in how to determined new information in what area is needed to be seek for to facilitate such shifts is probably of great help, especially to those decision makers without sufficient domain knowledge. The method to be proposed is exactly designed to provide such supports.

In essence, the idea of active intellectual support here is not only support decision makers in identifying opportunities previously neglected by them, but also help them to actually improve decision-quality through these opportunities. To realize this idea, a novel method is proposed and described in detail in the following section.

3.3.2 Support Method

The method to realize the idea described in the previous section is in a form of feedback loops. Feedback is a flow of information, appearing as a closed loop, from the output component to the decision-maker concerning the system's output or performance. Traditional decision supports also utilize feedback loops between systems and decision-makers. There is a continuous flow of activity from intelligence, design to choice, and furthermore at any phase there may be a return to a previous phase (feedback). The seemingly chaotic nature of following a haphazard path from problem discovery to solution by decision-making are explained by these feedback loops, which are generally from the selected alternatives' performances in the implementation phase. This means the feedback loop only starts to work after a course of action has been taken and can only benefits the systems in providing better performance in the next decision process.

However, in the proposed approach, the feedback loop is initiated before the final act is taken, thus opportunities for implementing a better solution can be offered. Through this loop, certain information is sent to decision-makers to help them identify crucial areas to seek new opportunities and the new information from decision-makers is the basis for another run of the inference engine and will probably lead to a better solution.

But what is the information offered by the system to stimulate decision makers' discovery and how they can help to identify important issues for a better solution. To answer these questions, besides the loop structure, two more elements need to be designed. One is the searcher for identifying the opportunities and the other is a trigger to initiates and terminates the searching work. Figure 3.2 shows the work process of the proposed method and demonstrates clearly the relationships between different parts.

Triggers are certain prescribed conditions which, when true, invoke the use of rule sets. They have already been used in conceptual database modeling, in office automation, in Artificial Intelligence and even briefly in the DSS literature (Sprague 1982, Clemons 1981). Examples of use are to monitor the state of a system, to serve as prompts or reminders, and to detect exceptional circumstances. A tremendous application for triggers in DSS includes invoking appropriate subsystems into action when the 'state of the system' permits. (How and when the system's state is evaluated will be readdressed later in this section.)

However, there has been little movement in the DSS field about triggers to promote seeking for desirable solutions. That is to say, while the current position of the firm is not necessarily unfavorable with respect to decision objectives, gaps in existing alternatives might be identified. Thus, triggers can provide decision makers with such opportunities of stimulus-response and live action: they identify problems and opportunities as they emerge. These could, if successfully exploited, improve the decision quality.

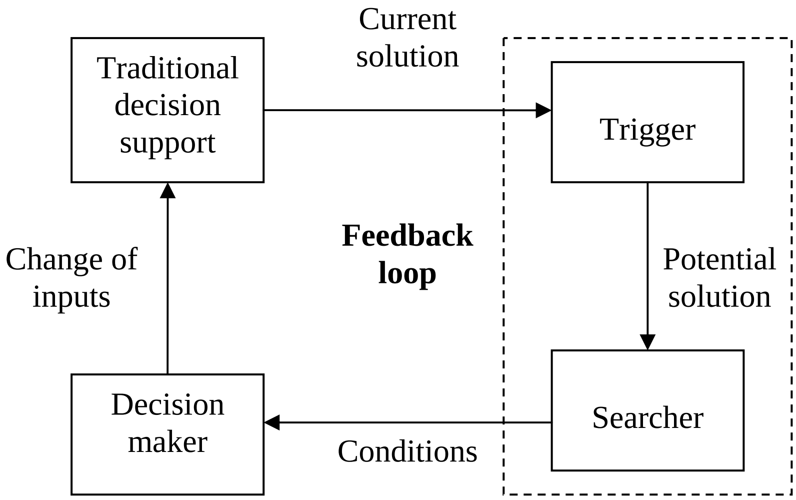


Figure 3.2 Work process of the proposed method

Based on the system's outputs, the trigger compares the outputs to the expected outputs. Then the searching process may start if the outputs are not the expected ones. Constructing a trigger involves how decision-makers establish their decision-making objectives and how these objectives are incorporated into the decision process. Therefore, certain criterion that describes the acceptability of a solution, for example, a value function or a utility function capturing the decision maker's preference, is essential.

Preferences are the decision maker's rankings in terms of desirability for various possible outcomes. They include not only his rankings in terms of the various outcomes which may occur in a decision situation, but also his attitude toward risky outcomes and preferences for outcomes which may occur at various times. They also embody information identifying those factors in a decision situation that are of concern, whether a factor indicates a desirable or undesirable outcome, and how to make tradeoffs among alternative collections of outcomes.

The existence of a value function for scoring alternative sets of outcomes under certainty and a utility function for scoring uncertain outcome bundles is the basic result of the axioms of decision theory. The acceptance of these axioms is implicit in the philosophy and design of decision methods described here. The use of value and utility functions as criteria for decision making has several advantages. If the function is continuous with respect to outcomes, then it is able to handle small differences in outcomes in a consistent manner. This allows the computerized aid to handle an essentially infinite number of possible outcomes, not just those pre-specified, foreseen, and categorized by the system's designers.

If the preference structure can be generated with sufficient generality, then the decision system can attempt to encode attributes of the new situation in terms of the general function, and use the new expression as a basis for decision making in the new situation. The task of developing robust preference models by incorporating deep and fundamental trade-offs is a difficult one. For the foreseeable future, assessment of utility functions for decision aids will necessarily be domain dependent. In fact, the applicability of decision aids such as those envisioned here will, in all likelihood, be limited by the ability to assess an appropriate representation of preferences. Domains in which there is a well developed empirical and theoretical basis for development of utility functions (e.g. financial and engineering decision making and some areas in medicine) are most promising.

Since the trigger provides information about the benefits of the solution which could only be feasible by changing values of some input variables, it is also responsible for supporting decision makers' consideration of the benefits offered by changing inputs in the final stage.

The searcher determines the content of the information exchanging between decision supports and users. It finds out the necessary conditions for the potential solution to be feasible and guide the decision makers to seek information about the input variables related to these conditions. As one of the most popular symbolic reasoning methods, backward chaining can link the targeted potential solution to the conditions needed by tracing back the related rules.

Based on the trigger, searcher and a feedback loop, the proposed method will work according to the following steps to provide intellectual support.

Firstly, the trigger continuously monitors the state of the decision process and automatically identifies the gap between current solutions and desirable ones.

Secondly, the searcher automatically targets the key information aspects by tracking back the rules leading to the current solution.

Thirdly, the feedback loop stimulates decision makers' discovery of changeable points of the inputs through insightful conversations or information exchanges between human and decision supports.

Fourthly, the decision-maker will decide whether to modify the inputs in order to move the outputs closer to the target ones by balancing the costs and benefits by doing so. In operational terms, optimization can be achieved in one of the three ways: First, get the highest level of goal attainment from a given set of resources. Second, find the alternative with the highest ratio of goal attainment to cost or maximize productivity. Third, find the alternative with the lowest cost or smallest amount of other resources that will meet an acceptable level of goals. All these three ways indicate the optimum solution is essentially a satisfied proportion of benefits to costs. Thus in this final stage of the new method, decision makers should follow the principle to explicitly consider the benefits and costs brought by changing the original inputs of the DSS.

Finally, the new information obtained through the feedback loop serves as inputs for another run of inference process. This process will recur starting from the first step until the trigger finds there's no gap between current solutions and desirable ones or the decision maker decides not to change the inputs of the system.

3.4 Active Resource Support

3.4.1 Basic Idea

Decision-making needs specific information, knowledge and other analytical resources. Resource support is essential for providing such resources. Usually, the information and knowledge should be firstly represented in an appropriate manner so that search process can be conducted on the represented information and to solve the decision problem. However there are some problems of providing appropriate resources that initiate the designing of new resources support methods.

Firstly, expert judgments generally serve as the knowledge resource for decision making. Nevertheless, as noted by Anderson et al. (1999), expert judgment must be used with care. Kahneman et al. (1982) , a Nobel Prize winner in 2002, discuss the numerous biases and heuristics that are introduced when humans process information and attempt to provide judgments. Therefore, subjective judgment based knowledge need to be refined, if possible in an objective way to avoid extra human biases. Therefore, the resource support should be able to offer a more objective and rigorous way utilizing the available knowledge about the decision problem.

Secondly, sometimes many criteria are taken into consideration to make a decision. Thus the size of necessary information becomes relatively larger and makes it difficult for the decision maker either to judge all the criteria at the same time or to directly adopt some multiple decision making tools like AHP on the basis of available resources. Therefore, it would be better if new resource supports could have more criteria allowed in the decision-making process for decision makers' customization needs while limited input workload is increased.

3.4.2 Support Method

These benefits of the new resource support idea can be realized by adopting in sequence a set of multivariate analysis tools in statistical field.

Multivariate analysis is employed when researchers need to represent a relative large data set by fewer and easy-to-interpret variables. There are numerous examples of the use of multivariate methods used in the past. They have often been used in the systems approach to study the concept of fit in contingency theory and have been described as the most effective components of configurational theories. Depending on the particular application and the available data, a multivariate method may be applied in the first stage of the quantitative analysis, or may itself be an adequate representation of the theoretical model that one needs to estimate.

In the case of a single data set, principal components analysis proved to be very useful in reducing the dimensionality of the variables' space in applications in psychology, sociology, education, economics and operations research. (Shenhar et al. 2002) For illustration, factor analysis based on principle component approach, as one of the multivariate analysis tools, is to be utilized here.

Firstly, Factor Analysis is adopted. It provides support to multi-criteria decision making in such a way that the number of criteria using for alternative judgment is reduced, which means decision makers' mental workload of comparison will be greatly reduced, while as much information as possible retains. The information is alternative specific and is provided by domain experts or collected by the organization. Part of designed criteria may be overlapped or highly correlated, which means some of them are redundant or superfluous. Too many criteria will make it difficult for system users to consider their preference among all the criteria at the same time.

Secondly, Clustering Analysis is conducted. It's very common that the knowledge about the problem is not sufficient enough for classifying the solutions by experts or decision makers themselves whereas clustering analysis comes to support. This analysis can ascertain the underlying structure of available information. Based on such structure, similar alternative solutions are clustered into same solution group.

Finally, analysis of variance of different groups captures the degree of difference among them. The last two analyses describe how different various solutions are and will facilitate a more efficient searching process for solving decision problems.

3.5 Discussion and Conclusions

The proposed method realizing the new idea of providing intellectual support to decision maker can be considered an artificial intelligence method even though some of its technologies do not formally exhibit intelligence. However, it is definitely useful for designing an intelligent decision-support system.

The method can be added to a conventional decision support system for a more intelligent support to decision makers. It can also be an additional phase of a general decision process for decision makers' utility enhancement. In the next chapter, the method will be incorporated into the design of an Advanced Knowledge-based system as an intelligent component.

CHAPTER 4 ADVANCED KNOWLEDGE BASED SYSTEM WITH ACTIVE DECISION SUPPORT

4.1 Introduction

The architecture of decision support systems was first proposed by Sprague and Carlson (1982) as a macro architectural model with three components data, model, and interface. Later, Turban (1990) revised this model and added expert systems/knowledge-based component to the model. Other researchers (e.g. Dutta 1994, Manheim and Isenberg 1987, Sankar et al. 1995, Silver 1991, Sridhar et al. 1990) have proposed enhanced architectures to encompass particular functionalities not specifically identified in the original macro model. Raghav R. et al. (1994) conclude that the DSS providing high-level cognitive support should be designed as knowledge-based systems.

The architecture to be constructed here is an Advanced Knowledge Based System (KBS) framework, which is an evolution of the Turban model (1990). In addition to the conventional components of traditional KBS, namely, Knowledge Base, Inference Engine, User Interface and an Explanation Subsystem, the architecture involves a Knowledge-Refining component and an 'intelligent' guiding component to enhance its capabilities of providing active decision support. As the most important contributions of this enhanced KBS, the 'intelligent' guiding component and the knowledge-refining component are respectively applying the active intellectual support method and the active resource support method introduced proposed in the previous chapter. These two special components are integrated with those conventional components to generate and provide high-level cognitive support.

This chapter is organized as follows: Section 2 introduces the basic components of a conventional KBS. Section 3 describes the Advanced KBS architecture in detail. Section 4 demonstrates the design process and workflow of the system step by step. Section 5 concludes.

4.2 Conventional KBS

As one of the most important computerized decision support technologies, KBS utilize the pre-input information so that system users are not required to possess knowledge about the problem domain. This kind of structure paves the way for designing next generation decision support. KBS tend to use qualitative knowledge rather than mathematical models to provide necessary supports for the decision situations that usually require expertise.

Almost every KBS contain three major components that are the Knowledge Base, Inference Engine, and User Interface. Some systems also contain additional components, like Knowledge Acquisition Subsystem, Blackboard, Explanation Subsystem and Knowledge-Refining System.

The Knowledge Base contains the relevant knowledge necessary for understanding, formulating and solving problems. It includes two basic elements: (1) facts, referring to what is known about the domain area, such as the problem situation and the theory of the problem, and (2) special heuristic or rules, that direct the use of knowledge to solve specific problems in a particular domain.

The rule-based part of the Knowledge Base is to represent expert knowledge in IF-THEN rules that combine the condition and the conclusion of handling a specific situation. The IF part indicates the condition for the rule to be activated, and the THEN part shows the action or the conclusion if all IF conditions are satisfied. The advantage of rules is that they are easy to understand and new information or knowledge in the form of new rules can be easily added to the Knowledge Base without affecting existing rules.

The Inference Engine is the ‘brain’ of a KBS. It provides a methodology for reasoning about information in the Knowledge Base and for formulating conclusions. In fact, the inference means the process of chaining multiple rules together based on available data. It chooses applicable rules from the Knowledge Base, integrates them, and reasons to find the conclusion.

The User Interface is a friendly, problem-oriented communication part between the user and the computer.

According to Wang et al. (2007), KBS must have the following characteristics: First, representational adequacy, which is the ability to professionally describe all knowledge and to compact with all knowledge in a knowledge base. Second, inferential adequacy, which means the system should be able to inference new rules from some given rules and easily build a new structure. Third, inferential efficiency, which is the ability to efficiently reason, quickly execute and get conclusions. Fourth, acquisitioned efficiency, which means in the system, knowledge should be effectively accessed.

4.3 System Architecture of the Advanced KBS

Following the characteristics instructions mentioned in the previous section, the components of the system and their functions are designed and will be presented in this section as well as the connections and interactions among these components. The system architecture and information flow of the advanced KBS is shown in Figure 4.1.

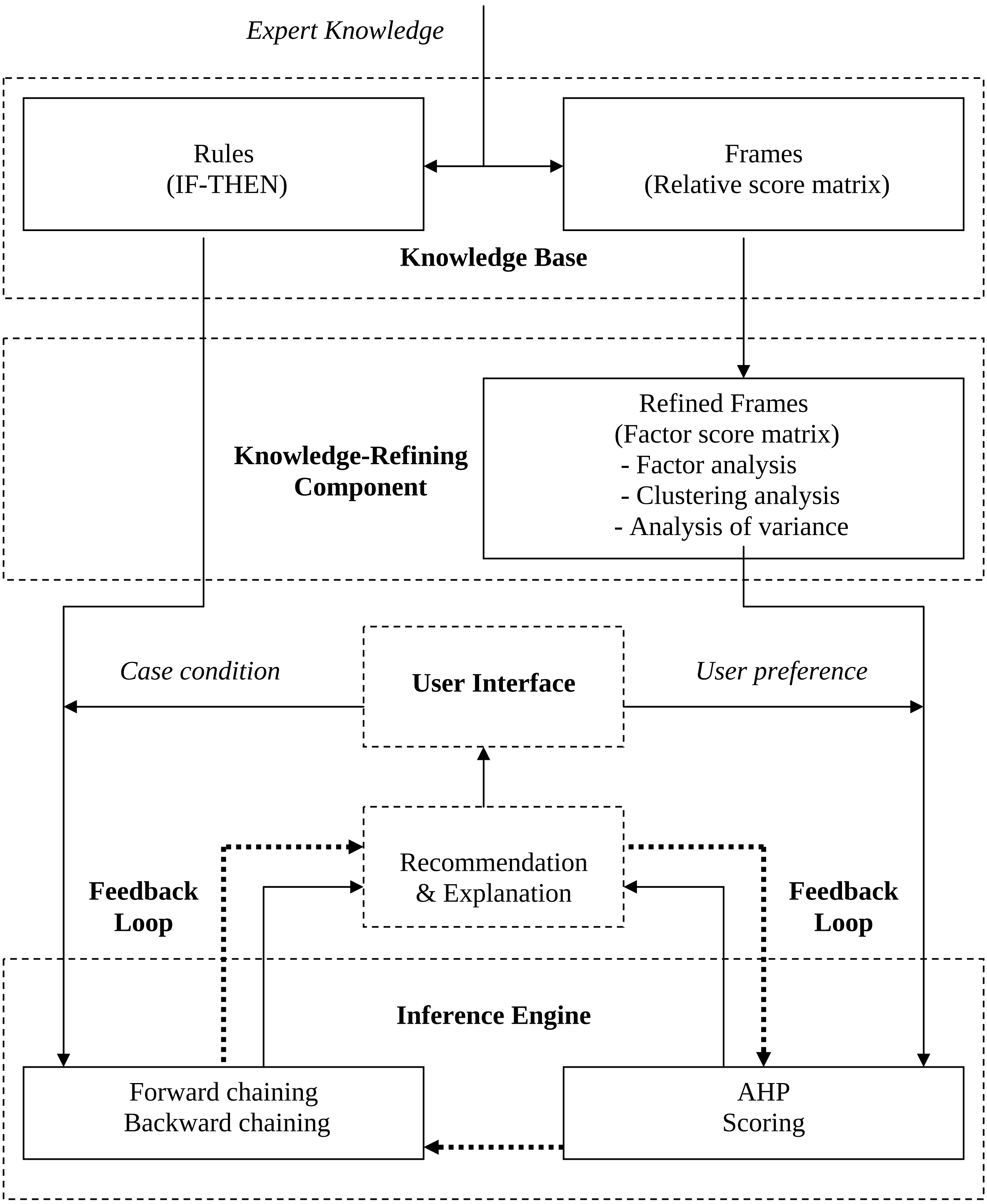


Figure 4.1 Structure of the Advanced Expert System

As clearly shown in the figure, the expert knowledge is input to a hybrid knowledge base, which includes both frames and rules as knowledge representation approaches. In the frame-based part, experts' knowledge is represented by a relative score matrix. The scores in the matrix are used to reflect the properties of different alternatives and serves as input for the knowledge-refining component. In the rule-based part, the knowledge is represented by a set of IF-THEN rules. The IF part indicates the condition for the rule to be activated, and the THEN part shows the action or the conclusion if all IF conditions are satisfied.

According to the figure, the knowledge-refining component deals with the flow of knowledge represented by the relative score matrix. This component applies the proposed active resource support method. It initiates automatically and independently of users' direction. The function of this component is to enable a more accurate knowledge base and a more effective reasoning by the Inference Engine. The mechanism here is just like human experts can analyze their own knowledge and its use, learn form it and improve on it for future consultations.

The general purpose of the statistical knowledge-refining component is to improve objectivity and accuracy of the knowledge base and the efficiency of inference. Specifically, the knowledge-refining component is trying to 'objectively' find out the key features differentiating various alternatives based on their performance under certain criteria, which is defined as the frame part of knowledge on all the alternatives. Since the information in knowledge base largely depends on experts' personal understanding of different alternatives and may lead to systematic bias and errors considering experts may also made subjective mistakes. Therefore, a more objective procedure is needed to revise the obtained knowledge.

Through this component, the system can actively facilitate more efficient use of domain knowledge. Moreover, intellectual support for such purpose is not available so far in commercial KBS. It is still being developed in experimental KBS at several universities and research institutions. (Turban et al. 2005)

The User Interface is designed as a platform for the communication between human decision makers and decision supports. Mainly two kinds of information need to be confirmed by users through the User Interface: One is case condition, which is the specific information related to the decision problem waiting to be solved. This kind of information helps the KBS to provide case specific advices. The other is user preference, which represents the user's attitude to all the criteria and based on which the utility value of all the alternatives to the decision makers can be determined. Such information enables the KBS to offer customized advices, which are more valuable and acceptable to a certain user. The two kinds of information required indicate the KBS developed here is a balanced approach between problem-oriented and costumer-oriented systems approaches. The knowledge together with information acquired from the User Interface will then flow into the Inference Engine and be utilized to reach intermediate conclusions.

As illustrated in the figure, the Inference Engine splits into two parts in order to fully take advantage of two forms of knowledge, rules and frames, and two kinds of information, case condition and user preference. One part of the Inference Engine is based on forward chaining approach, which deals with the case condition and rules in knowledge base. It turns case condition to facts, matches them with the IF part of rule, and then derives case specific conclusions from the rules as feasible solutions. The other part of the Inference Engine is based on AHP and a scoring method, which deals with the user preference and frames from knowledge-refining component. AHP turns the user preference information into criteria weights. Then the refined frame of each alternative is aggregated according to criteria weights into a single utility value and a utility ranking list will be obtained. Combing the results of two parts, feasible solutions with higher utility values will be recommended to the user.

The intelligent guiding component is demonstrated in the figure in a form of feedback loop. It works according to the intellectual support method proposed in the previous chapter. The recommended solutions will be send back to the AHP-Scoring part of the Inference Engine so that the trigger can check whether they are on the top of the utility ranking lists for all the alternative solutions not only the feasible ones. If they are, they will be sent to the User Interface as final advices of the KBS. If not, the feedback loop initiates. Those infeasible solutions with higher utilities than current recommended solutions will be sent to the chaining part of the Inference Engine. Rules applicable to these infeasible solutions will be traced using the backward chaining. Then the IF conditions, which are false according to the original case condition but are necessary for making the conclusions true, will be sent to the User Interface and let the user check whether there are possibilities to change these false conditions to true ones and whether they are willing to cover the cost for such changes. If the answer is no, the original advices are retained. Otherwise, the original advices will be replaced by new solutions with higher utility. The process loops until a final advice is reached.

Through the intelligent guiding component, a higher level of the decision maker may be reached. The component allows the user to consider those alternatives that have higher utility values than the current solution but are originally neglected since some conditions of them are not satisfied.

The explanation component is to trace the responsibility for conclusions to their sources and explain the ES behavior by interactively answering questions like why a certain question is asked by the ES, how a certain conclusion is reached, why a certain alternative is rejected or what remains to be established before a final diagnosis can be determined. It is crucial both in the transfer of expertise and in problem solving.

It is responsible for explaining why the solutions are recommended and how good they are. For the former purpose, the applicable rules and facts will be showed to the users. For the latter purpose, the competence of the top ranking solutions will be explained based on the cluster characterization and differentiating results, which obtained using the active resource support method by the knowledge-refining component. Thus, decision makers will be clear about how much benefit they will get to choose the first ranking model instead of the second one.

4.4 Conceptual Design of the Advanced KBS

The design and work process of the advanced KBS includes four stages that will be introduced in this section step by step. These stages are knowledge representation stage, knowledge refining stage, querying and inference stage, and explanation stage.

Knowledge presentation plays an important role in knowledge reasoning. A well-designed knowledge presentation will affect the performance of a knowledge-based system. There are two parts of knowledge representation stage: one is frame part and the other is rule part. The frame part of knowledge representation stage include three steps to construct the relative score matrix.

The flow chart for this part of the stage is illustrated in Figure 4.2.

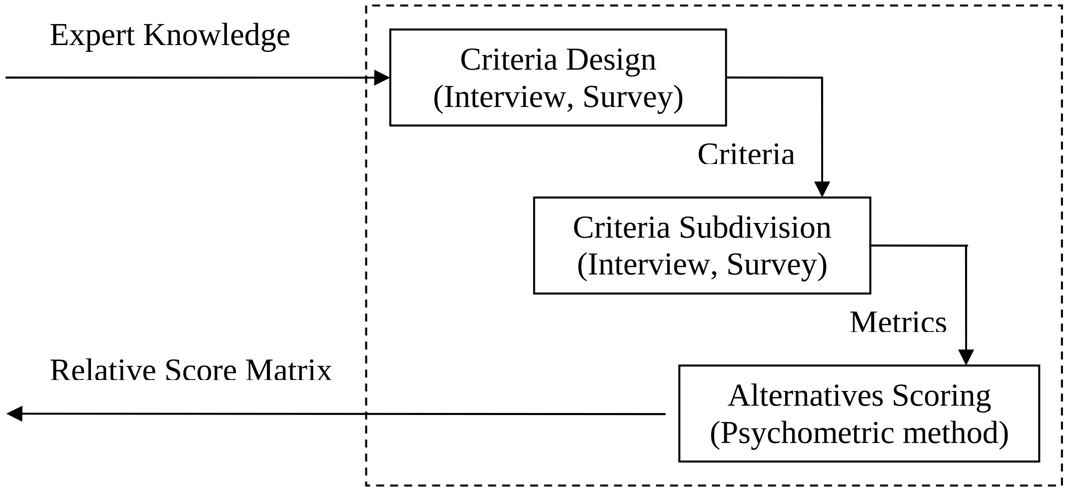


Figure 4.2 Flow chart for the frame part

As shown in Figure 4.2, the first step is criteria design. The guideline for designing criteria here is to reflect the unique requirements of decision problems and the characteristics of alternative solutions as well.

The second step is criterion subdivision. The purpose of this step is to clarify the content of a criterion and to avoid ambiguous evaluation. Each criterion is divided into a group of metrics which can be judged by 'yes' or 'no' according to whether the model for evaluation possesses a certain characteristic or not.

The third step is alternatives scoring. The adopted scoring method here is an accepted psychometric methodology for assigning numerical values to an object in order to measure its properties. (Souder 1972) In this step, firstly, '1' and '0' scores will be assigned to a metric according to the 'yes' and 'no' judgment. Then the scores of the metrics under the same criterion are summed up as the raw score for that criterion. Finally, the raw scores will be divided by the total number of metrics under the same criterion, which is the possible maximum raw score of that criterion, in order to get the relative score for a criterion. After all the alternatives are scored in terms of each criterion using this method, the relative score matrix will be established, which means the frames part of the knowledge base is ready.

The rule part of knowledge representation stage needs to be conducted by experts in the related field and includes two steps.

The first step is to identify the key issues of the decision problem. Different states of these issues will determine the feasibility of certain solutions.

The second step is to construct the rules in the knowledge base. Different states of the key issues identified in the previous step will be the IF part of the rules. The feasibility of alternatives will be the THEN part of the rules.

The knowledge refining stage is designed applying the active resource support method. According to the proposed method, there are three steps in the knowledge refining stage. The workflow is demonstrated in Figure 4.3.

The first step is factor identification and scoring based on Factor Analysis. This step is to structure and refine the raw knowledge represented by frames (relative score matrix). In factor analysis, the relationships among the proposed P criteria are described by a small number of, say K ($K<P$), underlying random quantities called factors. Thus, K key factors can replace the initial P criteria, and the original relative score matrix, consisting of N alternatives' performance on P criteria, is reduced to a factor score matrix consisting of N alternatives' performance on K key factors. In order to identify the factors, the loading L needs to be determined, which can be estimated by a principal component method. Once the loadings L are obtained, factors are identified, and estimated values for the factors themselves, called factor scores, are constructed (Johnson and Wichern 2003).

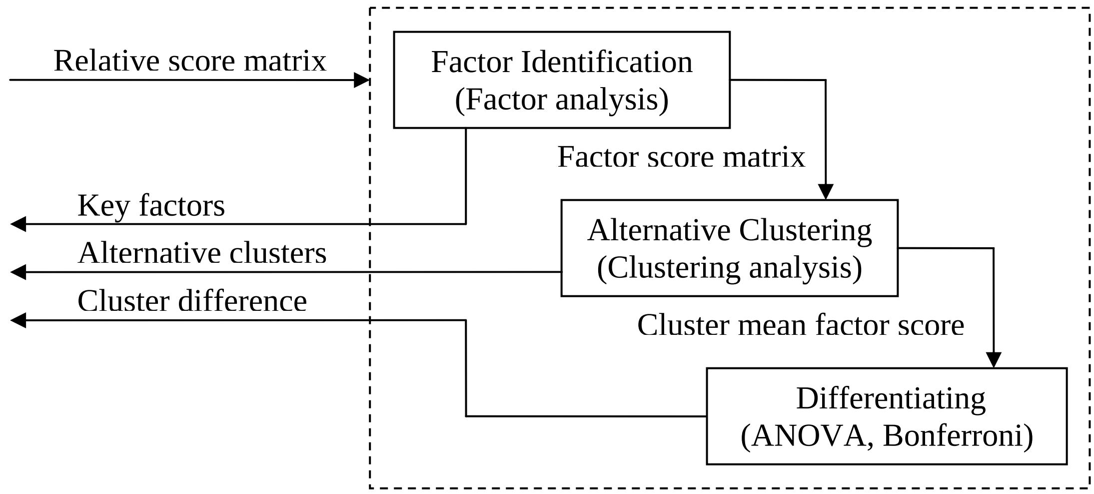


Figure 4.3 Flow chart for the knowledge refining stage

The second step is alternatives clustering using Clustering Analysis. Clustering analysis can be used to discover natural groupings of items. It is done on the basis of similarities and distances (dissimilarities). In this KBS framework, factor score matrix constructed in the previous step is used as input to compute the similarities required by the clustering analysis. Correlation coefficient is used as the similarity measure here. Maximum linkage, one of the agglomerative hierarchical methods, is used as the clustering methods. According to agglomerative hierarchical methods, there are initially as many clusters as the alternatives. The most similar alternatives are first grouped, and these initial groups are merged gradually according to their similarities in their performances on the key factors.

The third step is cluster characterization and differentiating with the help of analysis of variance (ANOVA). After the clusters of alternatives are finally configured, experts will try to find out the score pattern of each cluster based on the factor scores of the alternatives belonging to the relevant cluster. The differences of clusters will be recognized. Then the degree of such differences will be tested using Analysis of Variance. ANOVA can be used to investigate whether the cluster scores are significantly different on each factor. If the significant difference is confirmed, the t-test will be used to identify which pair of solution clusters is significantly different from each other with respect to a certain factor.

There are four steps in query and inference stage. The workflow is presented in Figure 4.4.

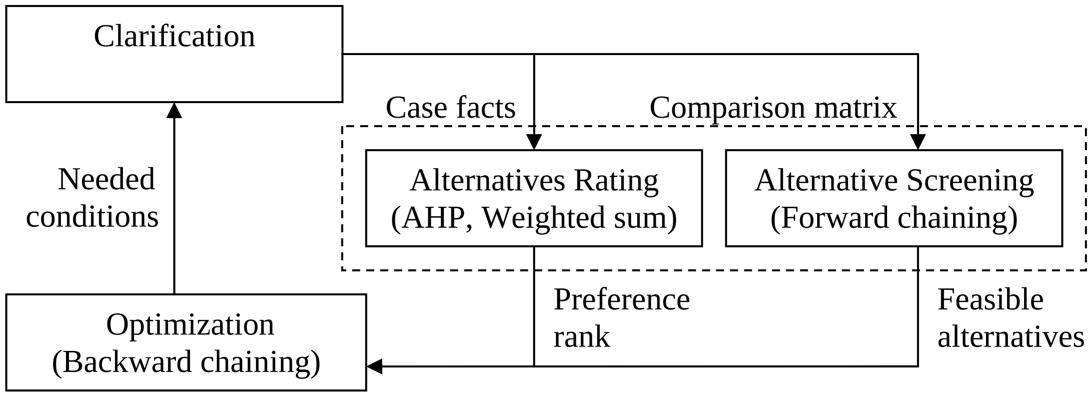


Figure 4.4 Flow chart for the query and inference stage

The first step is case and preference clarification. System users are asked to answer some questions related to the key issues identified in the knowledge representation stage. The answers are then considered as facts of the specific decision problem and will be used to fire rules in the next step. System users are also asked to construct a $K \times K$ pair-wise comparison matrix of the key factors through the User Interface to represent their preference.

The second step is alternatives rating. The comparison matrix developed by the users in the first step serves as the input for AHP, by which the relative importance of the K factors in the rating procedure is assessed. Then, according to this relative importance of the K factors, the mean factor scores of each solution cluster and factor scores of each alternative obtained from the knowledge refining stage are weighted and summed. The weighted sum can be regarded as the utility of a solution cluster or a single alternative and the preference rank of all the clusters and alternatives are made according to this utility value.

The third step is alternative screening. The forward chaining approach is used in this step. By forward chaining, the IF part of a rule is checked with the facts clarified in the previous step. Once all the IF conditions are met, the rule is chosen for deriving the conclusion. If the conclusion derived from the first state is not final, then it is used as a new fact to match with the IF condition of other rules to find a more useful conclusion. This process continues until a final conclusion is reached. Then the feasible solution clusters are obtained.

The fourth step is utility optimization applying the active intellectual support method. According to the proposed method, the preference rank of all the feasible solution clusters is monitored by the trigger and the one with highest rank is picked out. Then, the alternative with highest preference within that cluster will be recommended directly to the user if no other infeasible solution clusters have higher utility values than the current cluster. Otherwise, the conditions determining the infeasibility of these solutions will be traced by the searcher using backward chaining. By tracing the rules taking the infeasible solutions as conclusions, backward chaining starts from identifying the IF conditions that are necessary for making the conclusion true. Those false conditions, according to the original facts clarified in the first step, are picked out for users to have a re-consideration. Users need to consider whether there is a possibility and whether it is economical or sensible to change the states of those key issues to form new facts and enable the infeasible solutions to be feasible. Then the feedback loop continues to work and the flow goes back to the first step of the query and inference stage, the same questions about the key issues will be asked by the User

Interface, and this time the user should answer these questions based on the results of the re-consideration instead of the actual situation of the problem. After such insightful conversations, the third step and the fourth step of the query and inference stage run again until the utility level is optimized. Then the final advices on the solutions are sent to the system user.

The explanation stage includes the following two steps:

The first step is justice demonstration. The applicable rules and matched facts used by forward chaining to reach the final conclusion are demonstrated to the system user the to justify the system's recommendation.

The second step is competence demonstration. Three kinds of information are presented to the system user in this step: First, the revised frame, as the results of the knowledge refining stage, of the recommended alternative; Second, the test result of the differentiation degree between the frame of recommended alternative and other alternatives; Third, the preference rank of the recommended alternative.

4.5 Discussions and Conclusions

The proposed active decision support methods are applied to designing a KBS framework in this chapter. Integrating those active decision support methods make this frame work an intelligent system and named as Advanced Knowledge Based System. It is a hybrid system, since the knowledge base of the system includes both rules and frames as knowledge representation approaches.

The KBS's components and their functions are discussed in detail while two special components of the KBS, applying active intellectual support approach and active resource support approach respectively, differentiate this framework and conventional systems tools. The highlighted two components are: a knowledge-refining component involving a series of statistical tools and an intelligent guiding component to optimize users' utility level. Then design and workflow of these components are introduced step by step and focus has been put on the structure of the two special components. The major contributions of the KBS achieved by the two special components are as follows:

The knowledge-refining component is still an advanced topic that is being studied and no such component is available in the commercial expert system software yet. Furthermore, utilizing statistical tools in the process is a novel way to realize the knowledge refining purpose, although it does not refine the knowledge based on the system's experiences of solving problems like a human expert.

An intelligent guiding component is a new component for knowledge-based systems. When searching for a solution to a decision problem, we usually find feasible ones satisfying the constraints of the problem and stop. However, this component enables the decision maker to have higher utility solution by guiding them to consider the "infeasible" solutions as well. The idea indicated by this guiding component challenges the traditional way solving a decision problem and it can also be incorporated into other decision-support or decision-making tools.

Even without a prototype of the proposed KBS framework, the functions of all the components of the framework can be realized easily by existing commercial software, like SAS and Expert System. Moreover, the framework itself can be applied as a systems approach for multi-criteria decision aiding.

CHAPTER 5 APPLICATION TO R&D MODEL MANAGEMENT *

5.1 Introduction

In previous chapter, a general advanced Knowledge-based System framework is presented, which will be applied to the model guidance in Research and Development (R&D) domain in this chapter. A knowledge-based approach for R&D model guidance in a form of Expert System (R&D ES) will be designed.

In general, products and services have finite life cycle that has continuously been shortening. Thus, R&D, as a way of developing new products, improving current ones and enhancing manufacturing process, is viewed by many companies as central to their survival strategy and becomes increasingly important. If R&D projects are not properly chosen and trimmed, a great amount of resources may be wasted and the organizations may be ruined. Therefore, **R&D project selection is a significant task** for large technology-based corporations and government-funding agencies in order to focus their limited resources on potentially successful projects. Many studies have emphasized the importance of the efficiency of the selection process by which medium and longterm success of such organizations are greatly affected.

R&D project selection is also a complex decision-making process. The topic of modeling for R&D project selection has been a subject of operations research

* Part of this chapter is published as Y. Xia, K.L. Poh and B.W. Ang, 'Systems for R&D Project Selection: A Comparative Evaluation of Methodologies', *Proceedings of the Asia-Pacific Systems Engineering Conference*, Singapore, March 2007.

for more than five decades. A **wide variety of models and techniques have been developed** to facilitate R&D managers' efficient decisions in evaluating, selecting and controlling R&D projects. In the absence of guidance, R&D managers will probably feel short of basis to judge the relative desirability of using one model instead of another. Even they finally choose one model based on their personal preference, it is difficult to justify their decisions (Souder 1972). Thus, a structured, formalized and process based framework is essentially needed for the decision maker to **justify his or her choice of models,** communicate their decisions with others, and to **avoid pressure from various interests groups** involved in project funding.

The advanced KBS framework proposed in the previous chapter is applied to the decision problem here. After constructing the knowledge base by inputting the domain knowledge in R&D project selection field, the general KBS will become an R&D ES. In the knowledge refining stage, the active resource support approach based on multivariate methods, i.e. factor, clustering and variance analysis enables the distinction of suitable models in an objective and holistic way. Furthermore, the knowledge refining component will also allow identification of the effects of several key measurement variables (factors) on different dimensions of models suitability that the more common uni-variate and regression methods have failed to reveal.

The R&D ES will be designed step by step in accordance with the KBS framework. The process consists of four stages that are knowledge representation stage (i.e. models description), knowledge refining stage (i.e. models differentiating), query and inference stage (i.e. models rating) and explanation stage. The models description procedure and models differentiating procedure serve as knowledge base for this approach. Through these two procedures, the theoretical features of all the R&D decision-making models will be analyzed and demonstrated based on the models experts knowledge. The models rating procedure serves as inference engine. The recommendation of models will be given through this procedure based on the decision makers' preference acquired by a user interface. The following are the detail steps for each procedure.

This chapter is organized as follows: Section 2 reviews various kinds of R&D project selection models. Section 3 is a brief survey of previous literature on R&D model guidance. These two parts offer an overview of the resources for expert knowledge in this domain, which will serve as input for this R&D ES. The development work for R&D ES is described step by step according to the proposed approach in Section 4. Section 5 concludes.

5.2 Review of R&D Project Selection Models

Methods and techniques for selecting projects have appeared in the literature for at least 50 years. The number of R&D project selection models, along with user interest in applying them, grew exponentially in the 1950s and 1960s; however, this trend has reversed since the mid-1970s (Souder and Mandakovic, 1986). By reviewing literatures related to R&D management, over a hundred prescriptive project selection models can be identified. Models tend to be either quantitative or qualitative, ranging from rigorous operations research methods to social-science-based interactive techniques. The many different methods of evaluating R&D performance are a reflection of the complexity of R&D activities and the differences that exist among technologies and products.

The review of various kinds of R&D project selection models is stated in Appendix A.

Cooper et al. (2001) showed that those that use more than one selection method have the best results, since no single method has the best attributes in all areas. It appears that the trend in applying selection models is to move away from the application of a single method and to move towards a composite approach of using a number of selection methods. Some researchers hold that improving the understanding of decision processes will bring about a revolution in philosophy of selection methodologies. (Sanchez 1989, Farrukh et al. 2000) Indeed there are some methods already in use that combine economic models with decision theory.

5.3 Review of R&D Model Management

Cetron et al. (1967) summarized and compared 30 models in terms of three aspects: Firstly, a standard set of features describing input and output styles. Secondly, a standard set of characteristics relating to ease of use. Thirdly, the scientific or technical areas of models' applicability. The 30 models they discussed include Decision Theory, Economic Analysis, Operations Research, Mathematical Methodology and Comparative Method.

Cetron (1969) attempted to describe and differentiate the existing R&D models according to how they handle the following 15 features: utility measure; probability of success; orthogonality of criteria; sensitivity; rejected alternatives retention; classification structure; time; strategies; system cross support; technology cross support; graphical display; flagging; optimization criteria; constraints; computer-based. As one might expect, none of the models deals specifically with all 15 features identified by Cetron. Approaches that possess a large number of these features will have to be large and complex. If alternative R&D selection models are evaluated using these 15 features, complex computer-based models have a strong advantage.

Moore and Baker (1969) compared project rankings of three types of models by considering the underlying distribution of project data, time preferences, the number of ranking intervals of categories, and the width of the intervals. The three types of models are Scoring Model, Profitability Index (Economic Model), and Linear Programming Model. They summarized the facts that the models were not being used as the followings: 'The management is not likely to use any model in deciding between projects, the use lies in the range of information generated for making selection decisions'.

Gear et al. (1971) reviewed mathematical programming models that might aid in the selection of a portfolio of projects. The programming models cover Linear Model, Integer Model, Chance Constrained Model, and Dynamic Programming Model.

Souder (1972a) used a methodology to develop performance profiles and assess the usefulness of 41 Operations Research models, which could be classified as Linear Model, Nonlinear Model, Zero-One Model, Scoring Model, Profitability Index and Utility Model. In his another study (Souder 1972b), the author used a scoring system to evaluate the suitability of 26 project selection models, which included Linear Model, Nonlinear Model, Zero-One Model, Scoring Model and Profitability Index. The system was based on five criteria, namely realism (most important), flexibility, capability, ease of use, and cost (the least important), that were measured by a set of more specific characteristics. However, the characteristics used by Souder limit the approach to analyzing only computerized or extremely formal models. Simpler analytical approaches to R&D project selection would not receive fair treatment in his evaluation.

Souder (1973) investigated the perceived utility of four simple, expected values models form the corporate point of view. The results indicated that model selection is highly depended upon the manager's objectives, the life cycle stage of available projects, and the sophistication of the R&D team.

Baker (1974) focused on the practical application of R&D selection models. He concluded that the models "are numerous, unverified empirically, and not used by R&D managers." Baker pointed out some specific problems of the models: First, an R&D selection model should be able to aid hierarchical decisions, since R&D decisions are made in a hierarchical manner. Each level of management makes budget allocation decisions or subject matter decisions at a different level of aggregation. Second, a selection methodology must be capable of incorporating new ideas and information as an increment to an existing R&D project portfolio, since R&D project decisions are made continuously as new ideas are proposed, which is more frequently than once a year. Third, a selection model should treat sufficiently and explicitly R&D projects' three different type of uncertainty. The first, technical uncertainty, is the risk that the product, process, or device will not work. The second is commercial uncertainty, or the risk that the product cannot be economically produced on a commercial scale. The final type of uncertainty is economic, the risk that after it is introduced, the product will not yield economic value to the firm.

Baker and Freeland (1975) provided an assessment of literature on quantitative models for R&D project selection and resource allocation. The authors grouped the comparative approaches, scoring methods and benefit contribution models into a category named Benefit Measurement. The understanding of both the behavioral aspects of the decision process and the effects of benefit interactions was emphasized. Some weaknesses of existing models were discussed and several research areas were identified accordingly: First, inadequate treatment of multiple, often interrelated, criteria. Secondly, inadequate treatment of project interrelationships with respect to both value contribution and resource usage. Thirdly, inadequate treatment of risk and uncertainty. Fourthly, inability to recognize and treat non-monetary aspects. Fifthly, perceptions held by the R&D managers that the models are unnecessarily difficult to understand and use.

Booker and Bryson (1985) comprehensively surveyed the literature of decision methods for project selection with discussion of each kind of method.

Souder and Mandakovic (1986) discussed and compared four groups of project selection models, namely Classical Methods, Portfolio Models, Project Evaluation Techniques and Organizational Decision methods, which represented the steps in the evolution of the philosophy governing the use of project selection models.

Danila (1989) reviewed the main families of R&D project selection in relation to the different categories of firm strategy.

Fahrni and Spatig (1990) attempted to organize the various approaches into an application-oriented guide for determining the most appropriate technique for a particular situation. Five important issues are identified to characterize practical situations faced by managers: To what extent the selection parameters can be quantified, what is the degree of the interdependence among the projects, whether a project needs to satisfy more than one objective and how seriously the risk will be considered. Their framework utilized a binary decision tree to lead to a final 12 methods groups, each of which suits a practical situation featured by the 5 key issues.

Several findings are recognized by reviewing the related literature: Firstly, despite these previous work on models comparison and evaluation, relative little research has been done to investigate modeling of models selection. Especially after 1970's, as the number of R&D decision models is continuously increasing, relevant guidance to these models is far from enough.

Secondly, some studies implementing the models in to real corporations and provide field tests results of some certain model. But such results can only reveal one kind of model's usefulness in the practice. It is hard to implementing several different models in the same company, and the R&D environment of different companies vary greatly from each other, thus these studies still shed little sights on the relative strength of different models over each other.

Thirdly, most of the reviewed literature compare the selection and evaluation models qualitatively and make general recommendation of these models based on the relevant researchers' knowledge. As highlighted by these literature, the choice of an R&D project selection model type may largely depend on the manager's objective, the life cycle stage of the set of available projects, and the way in which the manager views his project selection problem. (Sounder 1973) R&D managers may find it difficult to adapt these general recommendations to the specific requirements of their companies. Thus, it would be better to have a system approach to guide R&D managers make their models selection decisions based on their specific preferences as well as experts' knowledge.

5.4 R&D Expert System Design

5.4.1 Knowledge Representation Stage

According to the design process of the KBS framework presented in the last chapter, the first stage needed to construct an advanced KBS is the knowledge representation stage. For an R&D model guidance ES, this stage is for model description. In the frame part, experts' knowledge of different R&D decision models is represented by a relative score matrix. The scores in the matrix are used to measure the capabilities and reflect the properties of different models. Three steps are followed to construct relative score matrix.

Step 1 criteria design. Criteria reflecting the unique requirements of R&D project selection and the theoretical characteristics of relevant models are compiled from published literature.

Step 2 criterion subdivision. Each criterion is divided into a group of metrics which can be judged by 'yes' or 'no' according to whether the model for evaluation possesses a certain characteristic or not. Interviews with R&D administrators and R&D management scientists will offer relevant information for criteria design and subdivision. Criteria and their metrics used in this system are adapted from sources including Souder (1972) and Poh et al. (2001). These research results are based on personnel interviews and industrial surveys. The final list of criteria and relevant characteristics is illustrated in Figure 5.1.

Step 3 models scoring. In this step, firstly, a '1' or '0' score is assigned to a metric according to the 'yes' and 'no' judgment regarding a model's performance under that metric. Then the scores of the metrics under the same criterion are summed up as the raw score for that criterion. Finally, the raw scores are divided by the total number of metrics under the same criterion. Thus, relative scores for each criterion are obtained. After all the models are scored in terms of each criterion using this method, the relative score matrix is established, which means a draft of the models' capabilities and characteristics is ready. Specific models included to construct this part of knowledge base are described in Appendix B. Table 5.1 shows the detail of the relative score matrix for these models.

After frame part is ready, the **rule part** is constructed as follows.

Step1 key issues identification. Based on the literature review in the previous section, four key issues in R&D model choice are identified as project type, degree of data quantification, decision maker's objective and degree of projects' interdependence.

Realism Criterion
- strategic benefits
- financial benefits
- technical risk
- manufacture risk
- market risk
- premises uncertainty
- resource limits parameter
- budget limits parameter

Usability Criterion
- special persons not needed
- special interpretation not needed
- discrete variables
- low amount of data needed
- easily obtainable data
- computer not needed
- friendly software available

Validity Criterion
- sequential decision nature
- little dependency on subjective opinion
- uncertain judgment allowed
- group decision environment allowed
- new information easily incorporated

Capability Criterion
- multiple time period analysis
- optimization analysis
- simulation analysis
- schedule analysis
- portfolio analysis

Flexibility Criterion
- priority decisions
- termination decisions
- initiation decisions
- budget allocation applications
- project funding applications

Cost Criterion
- low set-up costs
- low personnel costs
- low computer time
- low data collection costs

Figure 5.1 Criteria and subdivision

Table 5.1 The relative score matrix for R&D models

Models	Realism	Capability	Flexibiity	Validity	Usability	Cost
Ch1	0.143	0.000	0.200	0.400	0.857	1.000
Ch2	0.286	0.000	0.200	0.600	0.857	0.750
AHP1	0.714	0.400	0.200	0.200	0.571	0.500
AHP2	0.714	0.400	0.200	0.400	0.714	0.500
Sc1	0.714	0.000	0.200	0.400	0.857	1.000
Sc2	0.429	0.200	0.400	0.400	1.000	1.000
DT1	0.429	0.200	0.600	0.400	0.429	0.750
DT2	0.571	0.400	1.000	0.200	0.143	0.250
DT3	0.714	0.200	0.600	0.600	0.286	1.000
DT4	0.429	0.400	0.600	0.400	0.429	0.500
MAUT1	0.143	0.400	0.400	0.400	0.571	0.500
MAUT2	0.143	0.200	0.400	0.600	0.571	0.500
MAUT3	0.286	0.400	0.200	0.200	0.429	0.500
RO1	0.286	0.600	0.600	0.600	0.143	0.250
RO2	0.286	0.600	0.600	0.600	0.429	0.500
RO3	0.571	0.600	0.600	0.600	0.286	0.500
Ec1	0.429	0.200	0.600	0.400	0.714	0.500
Ec2	0.286	0.200	0.600	0.400	0.571	0.750
P1	0.571	0.400	0.600	0.600	0.429	0.250
P2	0.571	0.400	0.400	0.600	0.429	0.750

For project type, although there are no clear-cut definitions of the different types of R&D, there are some areas into which R&D activities can be grouped. Three broad areas can be defined, according to OECD (1981) and Tidd et al. (1997): basic research, applied research, and experimental development. This classification of R&D then allows the application of the most appropriate tools, since each area has its own properties, such as costs, time span and funding source.

For example, basic research projects are often small forays into potential new technology areas and no application is specified for these projects. A selection system must therefore be able to support and nurture those new technologies and provide a communication of their virtues to appropriate departments. Moreover, by nature, there is little financial information available for such projects and it is not feasible to conduct detailed financial analysis on the merits of such projects, nor is a rigorous risk assessment deemed possible.

When it comes to the degree of data quantification, it is suggested that some models are not entirely suitable for R&D type selection decisions due to a lack of input data, whose type and reliability will ultimately determine the soundness of a decision model. (Moore and Baker 1969, Sharpe and Keelin 1998, Cooper et al. 2000)

As far as the decision maker's objective is concerned, a single-object decision model is obviously not enough for a multi-object decision problem. The common examples for multiple objectives of choosing an R&D model are as follows: The model should include the consideration of balancing between the long term and short term benefit of an organization, the growth and stability of an organization; The model should be flexible to provide financial indexes of the candidate R&D projects as well as non-financial information like their impact on organization's image and culture.

For projects' interdependence, in general, there are three types of interdependence may arise in the R&D environment. The first is due to overlap in project resource utilization, as evidenced by the presence of common equipment, personnel and facilities. The required budget for joint undertakings would thus be less than the individual sums if each were pursued separately.

The second type of interdependency is of a technical nature, where the success or failure, or relative performance, of one project significantly enhances or retards the progress of another.

Finally, effect interdependencies may arise when the value contributions or pay-offs of projects are non-additive. One project aimed at constructing lighter-weight composites, and another, geared toward the development of more economical manufacturing processes, may provide returns that would be dramatically affected by the success of the other. Two projects leading to the commercial realization of products that would ultimately share manufacturing facilities and marketing costs would also have a synergistic effect. The opposite would, of course, be true if the products were direct competitors(Bard 1990).

If the projects are to be selected have only the first type of interdependencies, the degree of the projects' interdependency is defined as low. Otherwise the degree of interdependency is high.

Step2 rules construction. In this step, rules are constructed to reflect the relations among the identified key issues and their impacts on the model choice. These relations and impacts are largely from published literature in the project selection field. Major resources include Lawson et al. (2006), Coldrick et al.

(2005) and Fahrni and Spatig (1990). Twelve rules are built in the knowledge base and illustrated in Figure 5.2.

R1: IF the applications of the projects' results are not specified,
THEN the projects are classified as basic research projects.
R2: IF the applications of the projects' results are specified
and the technologies involved in the projects are not fully understood,
THEN the projects are classified as applied research projects.
R3: IF the applications of the projects' results are specified
and the technologies involved in the projects are fully understood,
THEN the projects are classified as development projects.
R4: IF projects are basic research projects,
THEN the degree of input data's quantification is low.
R5: IF projects are applied research projects or experimental development projects,
THEN the degree of input data's quantification is high.
R6: IF the degree of input data's quantification is low
and degree of projects' interdependence is high,
THEN the programming models should be used.
R7: IF the degree of input data's quantification is low
and degree of projects' interdependence is low
and decision maker has a single objective,
THEN the checklists models should be used.
R8: IF the degree of input data's quantification is low
and degree of projects' interdependence is low
and decision maker has multiple objectives,
THEN the scoring models or the AHP models should be used.
R9: IF the degree of input data's quantification is high
and degree of projects' interdependence is low
and decision maker has a single objective
THEN the economic models or the real options models or the decision tree models should be used.
R10: IF the degree of input data's quantification is high
and degree of projects' interdependence is low
and decision maker has multiple objectives
THEN the scoring models or the programming models should be used.
R11: IF the degree of input data's quantification is high
and degree of projects' interdependence is high
and decision maker has a single objective
THEN the decision tree models or the programming models should be used.
R12: IF the degree of input data's quantification is high
and degree of projects' interdependence is high
and decision maker has multiple objectives
THEN the programming models or the MAUT models should be used.

Figure 5.2 If-then rules in the knowledge base

5.4.2 Knowledge Refining Stage

The second stage is the knowledge refining stage, which includes a series of statistical tools, namely factor analysis, clustering analysis and analysis of variance to differentiate alternative models.

Step 1 factor identification and scoring. Table 5.2 shows the eigen value of the input data matrix's (i.e. the relative score matrix constructed in the first stage) correlation matrix. Firstly, the number of the factors will be determined by the number of the eigen values whose value is greater than one. (Refer to the usual Kaiser criterion, 1960) According to that criterion, two factors retain. As indicated in the last column of Table 5.2, the information carried by the two factors is 65.25% of the original input data.

Table 5.2 Eigen values of the correlation matrix of the input data *

Factor No.	Eigen value	Difference	Proportion	Cumulative
1	**2.79498719**	**1.67499805**	**0.4658**	**0.4658**
2	**1.11998914**	**0.17020924**	**0.1867**	**0.6525**
3	0.94977990	0.27656837	0.1583	0.8108
4	0.67321153	0.39488660	0.1122	0.9230
5	0.27832494	0.09461763	0.0464	0.9694
6	0.18370730		0.0306	1.0000

Then, the factor pattern will be determined by the loadings demonstrated in Table 5.3. According to the table, **Factor 1 = - 0.10523 Realism - 0.11385 Validity - 0.85946 Capability - 0.73649 Flexibility + 0.90622 Usability + 0.81768 Cost;**

* The numbers in the table are obtained through the factor analysis process of SAS.

Factor 2 = - 0.74169 Realism + 0.75257 Validity - 0.02113 Capability + 0.05268 Flexibility + 0.00816 Usability + 0.01648 Cost. The greater the loading is the closer the relationship between the relevant criteria and factor. Since capability, flexibility, usability, and cost have the largest absolute value loadings on the first factor, which means the scores under these four criteria dominate models' performance on the first factor. Therefore the first factor is named as 'Practical' factor. For the same reason, ignoring the criteria with little effect (i.e. the criteria with small absolute value loadings in the second column of Table 5.3), the second factor consists of realism and validity. The second factor is thus named as 'Theoretical' factor.

Table 5.3 Rotated factor loadings on the six criteria *

Rotated Factor Pattern		
	Factor1 'Practical' factor	Factor2 'Theoretical' factor
Realism	-0.10523	**-0.74169**
Validity	-0.11385	**0.75257**
Capability	**-0.85946**	-0.02113
Flexibility	**-0.73649**	0.05268
Usability	**0.90622**	0.00816
Cost	**0.81768**	0.01648

The numbers in Table 5.4 are the communalities of the six criteria. This table shows the percentage of information that two factors explained comparing to the original information reflected by a certain criterion. For example, in the first column, 0.56117943 means the information reflected by the 'Practical' factor and

* The numbers in the table are obtained through the factor analysis process of SAS.

the ‘Theoretical’ factor accounts for 56.117943% of the information reflected by the original criterion ‘Realism’. Based on these communalities, the four criteria constitutes the first factor are explained better and there’s still other information needed to better understanding model’s performance under the realism and validity criteria.

Table 5.4 Communality of the six criteria*

Final Communality Estimates: Total = 3.914976					
Realism	Capability	Flexibility	Validity	Usability	Cost
0.56117943	0.7391245	0.54518714	0.5793172	0.82129977	0.66886829

Finally, the factor score matrix is constructed and illustrated in Table 5.5. The factor score can be regarded as a weighted combination of the original criteria. The weights are determined in the previous Table 5.3 (i.e. the factor loadings). The original 20 x 6 matrix is refined to a 20 x 2 matrix. The bigger the numbers under a factor, the better the criteria performs on this factor.

Step2 models clustering. Since the knowledge concerning the classes of models is sufficient in this case, there’s no need to run the clustering procedure. The models are clustered according to the main theory they based on. Finally, eight model clusters are classified: Checklist model, AHP model, Scoring model, Decision Tree model, MAUT model, Real Options model, Economic Analysis model and Programming model.

Table 5.5 Factor scores of all the models*

Model	'Practical ' factor	'Theoretical' factor
Ch1	1.781	0.758
Ch2	1.405	1.204
AHP1	0.099	-2.169
AHP2	0.238	-1.226
Sc1	1.668	-1.142
Sc2	1.348	-0.167
DT1	0.040	-0.164
DT2	-1.718	-1.560
DT3	0.029	-0.166
DT4	-0.579	-0.203
MAUT1	-0.086	0.711
MAUT2	0.186	1.671
MAUT3	-0.009	-0.749
RO1	-1.609	1.160
RO2	-0.930	1.188
RO3	-1.180	0.232
Ec1	0.133	-0.170
Ec2	0.261	0.316
P1	-0.954	0.243
P2	-0.125	0.234

Step3 cluster characterization and differentiating. Table 5.6 and Figure 5.3 show the difference of cluster scores on the two factors. Cluster scores are the simple average of each model group's factor scores illustrated in Table 5.5. For example, the cluster score of the checklist cluster under the 'Practical' factor,

* The numbers in the table are obtained through the factor analysis process of SAS.

(1.593) is the simple average of the factor scores of Ch1 (1.781) and Ch2 (1.405) under 'Practical' factor in Table 5.5.

Some more statistical tests are run to clarify the degree of such differences. According to the F-test results, the p-value for 'Practical' Factor (i.e. Factor 1) is 0.0004 and for 'Theoretical' Factor (i.e. Factor 2) is 0.0252. This means the eight types of models are statistically different on both factors. According to the t-test, the scores of checklist group and scoring group are statistically higher than any other groups except each other on 'Practical' Factor while the real options group's score is statistically lower than MAUT group and Economic Analysis group on this factor. For the 'Theoretical' Factor, AHP group's score is statistically lower than most of other groups except scoring and decision tree, while decision tree and scoring are statistically higher than checklist and real options. These refined knowledge and information will be utilized in the utility optimization step and explanation stage.

Table 5.6 Cluster scores and characteristics*

Cluster	'Practical ' factor	'Theoretical' factor	Characterization
Checklist	1.593	0.981	very practical and theoretical
AHP	0.169	-1.697	practical but very untheoretical
Scoring	1.508	-0.655	very practical but untheoretical
Decision Tree	-2.227	-2.092	strongly unpractical and untheoretical
MAUT	0.031	0.544	not so practical and theoretical
Real Option	-1.240	0.860	very unpractical but theoretical
Economic Analysis	0.197	0.073	practical and not so theoretical
Programming	-0.539	0.239	unpractical but theoretical

* The numbers in the table are obtained through the factor analysis process of SAS.

5.4.3 Query and Inference Stage

The third stage is the query and inference stage, which is to rate all the project selection models. The workflow contains four steps that are described in the following paragraphs.

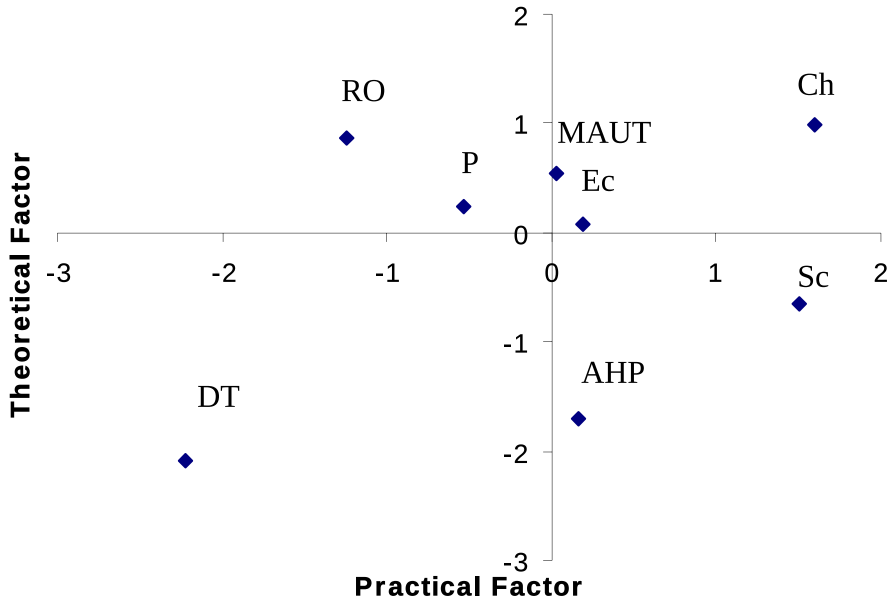


Figure 5.3 Cluster scores

Step1 case and preference clarification. The questions related to the key issues are shown in Figure 5.4.

Q1 Are the application of the projects' results specified? Q2 Are the technologies involved in the projects fully understood? Q3 Is the degree of the project data' quantification low? Q4 Is the degree of projects' interdependence low? Q5 Does the decision maker only have a single objective for the analysis?

Figure 5.4 Sample questions for User Interface

These questions can help to clarify the facts needed by the inference engine of the system. Table 5.7 will be present to the user for another part of query. A number representing the preference of the practical factor over theoretical factor will be put into the right down corner blank. The scale of the number and the interpretation of the factor are illustrated around the comparison table. The result of this part is a completed 1 x 1 pair-wise comparison matrix of the factors. Table 5.8 is used to construct the utility function of the user.

Table 5.7 Comparison table

<table>
<tr><td></td><td>Theoretical factor</td><td rowspan="2">Theoretical factor include:
Validity, Realism

Practical factor include:
Capability, Flexibility, Usability, Cost</td></tr>
<tr><td>Practical factor</td><td></td></tr>
<tr><td colspan="3">Fill in the above blank with a number chose from -9 to 9 representing preference
-9--- -8--- -7--- -6--- -5--- -4--- -3--- -2--- 1--- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9
less important same importance more important</td></tr>
</table>

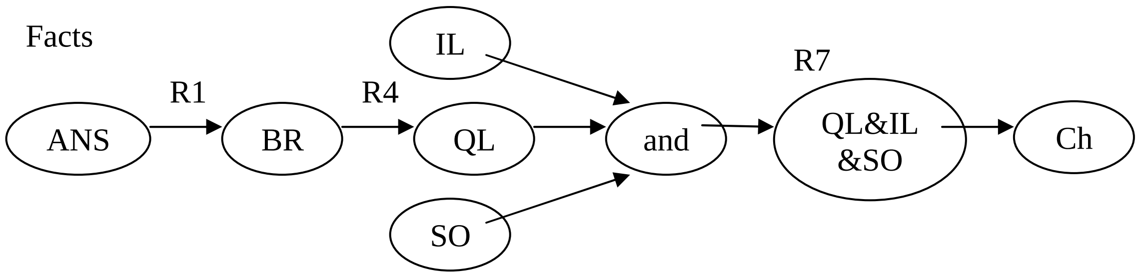
Table 5.8 Utility table

<table>
<tr><td>High practical & Low theoretical
• high usability
• low cost
• low capability
• low flexibility
• low validity
• high realism</td><td>Low practical & High theoretical
• low usability
• high cost
• high capability
• high flexibility
• high validity
• low realism</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">Fill in the above blanks with 1 or 0.
One represents the highest utility level and 0 represents the lowest utility level.</td></tr>
</table>

Step2 alternatives rating. The mean factor scores of each model cluster are weighted and summed up according to the relative importance of the two factors obtained from previous step. Then, the weighted sum is used for ranking of all the models. The ranking results will guide the decision maker to choose a suitable model according to their R&D management requirements.

Step3 alternative screening. Forward chaining is used in this step. A sample inference tree is demonstrated in Figure 5.5. Using this inference tree, the chaining process are as follows: If the user confirmed that the applications of the candidate projects are not specified, the degree of projects' interdependence is low and just want to select a most competitive proposals then these information become facts for the system. According to the first fact and rule 1, the projects are basic research projects.

Then, based on this intermediate conclusion and rule 4, the degree of data quantification is identified as low. Finally based on rule 7, the facts about project interdependence and user's objective, and the intermediate conclusion about data quantification degree, a conclusion of suitable model is reached. Checklist models are recommended.



ANS = the applications of the projects' results are not specified
BR = the projects are classified as basic research projects
IL = degree of projects' interdependence is low
Ch = Checklist model
SO = decision maker has a single objective
QL = degree of input data's quantification is low

Figure 5.5 One inference tree in Knowledge Base

Step4 utility optimization. The preference rank of all the feasible model clusters is checked and the one with highest rank is picked out. Then, the alternative with highest preference within that cluster will be recommended directly to the user if no other infeasible model clusters have higher utility values than the current cluster. Otherwise, the conditions determining the infeasibility of these models will be traced using backward chaining. Those ‘false’ conditions are highlighted for user to have a re-consideration. User needs to consider whether there is a probability and whether it is economical or sensible to change the states of those key issues to form new facts and enable the infeasible models turn out to be feasible. Then the flow goes back to the first step, the same questions about the key issues will be asked by the User Interface, and new facts are clarified by this interaction. Similarly, the third step and the fourth step run again until the utility level is optimized. After that the final advices on the solutions are sent to the system user.

5.4.4 Explanation Stage

The final stage is the explanation stage including the following two steps:

Step1 justice demonstration. First an inference tree is presented. Then the applicable rules and matched facts used by forward chaining to reach the final conclusion are demonstrated to the system user.

Step2 competence demonstration. Figure 5.3 will be presented to the user with the position of recommended model highlighted. The t-test results will be checked whether the factor score of this model is statistically different from other models. Finally, the preference rank of the selected model is presented too.

5.5 Discussion and Conclusions

In this chapter, an expert system for R&D model guidance, named R&D ES is designed using the Advanced Knowledge-based System framework proposed in the previous chapter. As an illustration of knowledge resources for knowledge base construction, various types of R&D project selection models and related literature on R&D model guidance are reviewed. Then the whole design process and work flow of the R&D ES following the KBS framework is described step by step. Focuses have been put on the knowledge representation stage and knowledge refining stage, which are related to the knowledge base and knowledge-refining component construction.

The knowledge base of the R&D ES is a hybrid one involving a rule part and a frame part. The rule part contains the knowledge about what the models can do and the frame part stores the information about how well the models can help in support R&D decision-making. Then the statistical knowledge-refining component compresses the model frames and characterizes the model clusters in the knowledge base to facilitate a more efficient inference process.

However, there are some limitations of the R&D ES architecture here. The expert knowledge input for the system is mostly depends on published literature in R&D domain, which known as documented knowledge. Moreover, the frame part of the knowledge base only includes 20 observations, i.e. 20 different models. Thus, in the future, efforts may be put on collecting more observations and incorporating other kinds of knowledge resources like practitioners' experiences on applying certain models to ensure a more extensive and reliable knowledge base.

In the next chapter, a case study will be discussed to illustrate the functions of this R&D ES. The advantages brought by the active decision support approaches will also be demonstrated through this example.

CHAPTER 6 AN ILLUSTRATIVE EXAMPLE

6.1 Case Background

The case to be studied here is adopted from Rengarajan and Jagannathan's paper (1997). A large R&D organization dealing with different types of research needs a project-selection model to formalize their R&D project-selection process. The organization in this case is the Corporate R&D Division of a company involved in the manufacture of heavy electrical equipment. All the units of the company are located in a single developing country and are widely scattered geographically. The R&D Division is organized into functional groups with specialist manpower, laboratories and computing facilities; it serves the needs of various manufacturing plants and so projects are varied and multidisciplinary.

The function of this division is mainly governed by its research executives. The research executives may determine projects on the basis of trends in their respective fields and future needs. Alternatively, projects may be suggested by the manufacturing plants (based on their existing problems) in which case the plants define only the goal on which research executives plan and execute a project. Thus, the views of the research executives are a strong indicator of the R&D Division's strategic orientation and are included in the project selection process. A project team is usually allocated to each proposed project to do the evaluation. Five typical projects ready to be analyzed are listed as follows.

The scope of Project 'A', taken on request from one of the manufacturing units, is to develop a technology-driven product with an assured future market. The technology developed by the R&D Division will be absorbed by the manufacturing unit for regular production.

Project ‘B’ is also referred by one of the plants and its aim is to develop an import substitute for which demand is not continuous. It enjoys high confidence of success, relevance to existing products, interest of manufacturing plant, penetration into a new market.

Project ‘C’ deals with the study of certain materials used in existing products. The results can help the design of equipment.

Project ‘D’ is to develop an improved version of an existing product. Relevant information is not available as it concerned a new process. Further, the manufacturing plant is not very hopeful of the market for such a product in the near future. Thus, the project is perceived to be of high risk.

Project ‘E’ deals with theoretical investigations useful for design of an existing product. Thus it is a project with a well-identified end use. It is also a short-term project with limited expenses for materials and equipment.

6.2 Application of R&D ES

According to the R&D ES, some facts are clarified through answering the questions offered by a user interface. The questions and relevant answers are illustrated in Table 6.1.

Table 6.1 Q&A through the user interface

Q1 Are the application of the projects’ results specified?	Yes
Q2 Are the technologies involved in the projects fully understood?	No
Q3 Is the degree of the project data’ quantification low?	Not clear
Q4 Is the degree of projects’ interdependence low?	Yes
Q5 Does the decision maker only have a single objective for the analysis?	No

Fact 1: Applications of the projects' findings are clear.

Although the Corporate R&D Division deals with projects with different research types, the main objective of this division is to serve the needs of manufacturing plants, which means in this case the emphasis will be put on plant-oriented projects. Furthermore, the end use of such projects' results is usually clearly defined. For example, as shown in the sample projects' information, Project 'A' involves the development of a well-identified new product and Project 'B' is to develop a substitute product of existing ones.

Fact 2: Technology involved in the projects is not fully understood.

The manufacturing plants suggesting the projects only define the goal of them and the technology involved in the projects to reach these goals are often far from being developed. For example, the objective of Project 'D' is defined clearly as developing an improved version of an existing product. However, as stated in the case, relevant information is not available as this project concerned a totally new process.

Fact 3: Decision makers have multiple objectives.

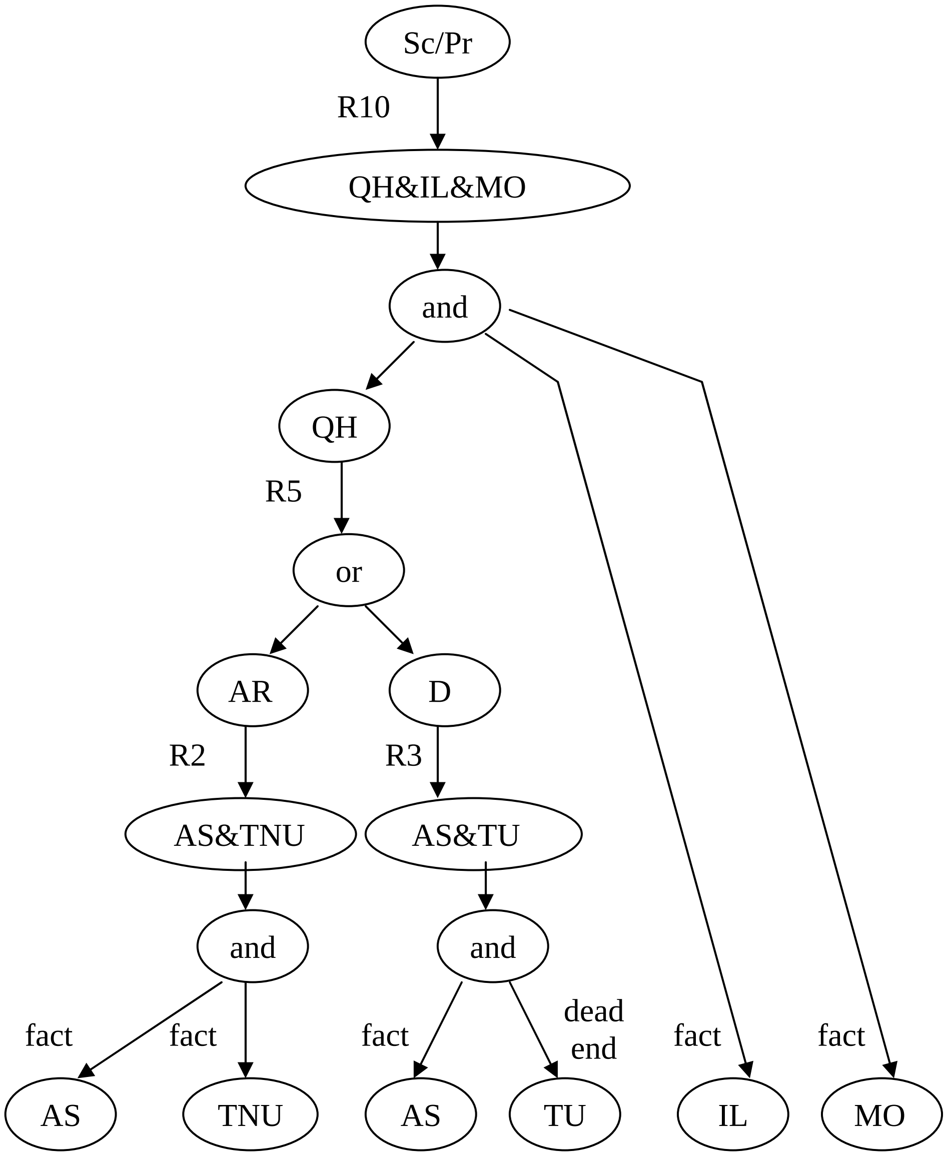
Since the R&D Division is organized into functional groups with specialist manpower, laboratories and computing facilities, the time duration of a project, its manpower consumption and other resource related requirements are of great interests in this case. This makes the selection of projects a balance problem between various objectives.

Fact 4: The degree of the projects' interdependence is low.

Since the projects are usually proposed by different plants and individual team will be assigned to each project, most likely these projects are weakly interdependent.

These facts are now put into the inference engine and produce preliminary recommendations using the forward chaining. The inference tree for this problem is shown in Figure 6.1. According to the forward chaining procedure, we start from the bottom of the tree to check whether the facts are matched with the if-conditions. With the fact 1 and fact 2, rule 3 is no-longer applicable while rule 2 is fired and the intermediate result that the projects are applied research projects are reached. This intermediate result is not the final conclusion we want. Thus, it serves as a new fact and tries to match conditions of other rules. Then rule 5 is found applicable, and a new conclusion that data quantity level is high is deduced. Again this conclusion is regarded as another new fact and basis for rules searching together with fact 3 and fact 4. Finally, rule 11 is found applicable and the scoring models and the programming models are temporarily stored as feasible models.

Then the user is required to input his factor and utility preferences. The inputs are illustrated in Table 6.2 and Table 6.3. Inference engine will give out the second stage recommendation using AHP and scoring based on such preferences. The results are presented in Table 6.4. Among the feasible models identified based on the previous work, the scoring model cluster is recommended to the user, since it offers the decision maker a higher utility than the programming models. Moreover, within the cluster of scoring models, the Sc1 model has a lower aggregated value (-0.44) than the Sc2 model (0.212), which indicates a higher utility to the user. Thus, the Sc1 model, which is exactly the scoring model used by Rengarajan and Jagannathan (1997) in their paper, is recommended to the user based on the current information.



AS = the applications of the projects' results are specified
AR = the projects are classified as applied research projects
D = the projects are classified as development projects
MO = decision maker has multiple objectives
TU = the technology involved in the projects are fully understood
TNU = the technology involved in the projects are not fully understood
QH = degree of input data's quantification is high

Pr = the programming models
Sc = the scoring models

Figure 6.1 An inference tree for forward chaining

Table 6.2 Factor preference clarification

	Theoretical factor	**Theoretical factor** include: Validity, Realism
Practical factor	-3	**Practical factor** include: Capability, Flexibility, Usability, Cost

Fill in the above blank with a number chose from -9 to 9 representing preference

-9--- -8--- -7--- -6--- -5--- -4--- -3--- -2--- 1--- 2 --- 3 --- 4 --- 5 --- 6 --- 7 --- 8 --- 9

less important same importance more important

Table 6.3 Utility preference clarification

High practical and	**High theoretical**	**Low practical and**	**Low theoretical**
• high usability • low cost • low capability • low flexibility	• high validity • low realism	• low usability • high cost • high capability • high flexibility	• Low validity • High realism
0		1	

Fill in the above blanks with 1 or 0.

One represents the highest utility level and 0 represents the lowest utility level.

Table 6.4 Preference rank

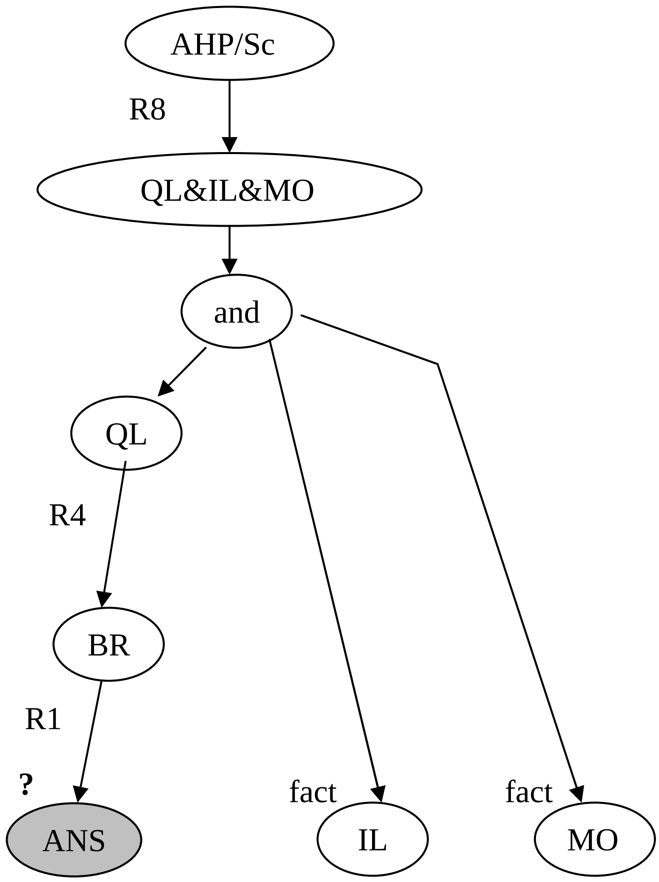
Cluster	Factor1	Factor2	Aggregated value	Utility	Rank
Decision Tree	-2.227	-2.092	-2.126	1.000	1
AHP	0.169	-1.697	-1.231	0.857	2
Scoring	1.508	-0.655	-0.114	0.714	3
Programming	-0.539	0.239	0.044	0.571	4
Economic Analysis	0.197	0.073	0.104	0.429	5
Real Option	-1.240	0.860	0.335	0.286	6
MAUT	0.031	0.544	0.416	0.143	7
Checklist	1.593	0.981	1.134	0.000	8

However, as shown in Table 6.4, the scoring model ranks the third among all the models instead of the first. Therefore, the utility optimization stage initiates. Using backward chaining, first the rules taking the AHP models or the Decision Tree models as conclusions are identified. For the AHP models, rule 8 is applicable while rule 9 and rule 11 are applicable to the Decision Tree models. Then these rules are traced through inference trees illustrated in Figure 6.1 and Figure 6.2.

For the AHP models, as illustrated in Figure 6.1, backward chaining starts from the top of the tree and traces back to rule 8, rule 4 and rule 1. At the bottom of the tree, all the conditions needed to enable the feasibility of the AHP models are in accordance with the original facts except the ‘ANS’, which means the AHP models are designed for low quantification data and suitable for projects with not specified applications.

So the original fact that the applications of the projects’ results are specified has to be changed, or in other words, the highly quantified data may not be fully taken advantage of, if the user wants to use the AHP models.

As shown in Figure 6.2, for the decision tree models, more than one possible way can change its feasibility. One way is through rule 11-rule 5-rule 2 route to the facts ‘AS’ and ‘TNU’, which are original facts, and the conditions ‘IH’ and ‘SO’, which are inconsistent with the original facts input by the user. The other way is



ANS = the applications of the projects’ results are not specified
BR = the projects are classified as basic research projects
MO = decision maker has multiple objectives
QL = degree of input data’s quantification is low
AHP = the AHP models
Sc = the scoring models
IL = degree of projects’ interdependence is low

Figure 6.2 Inference for the AHP models

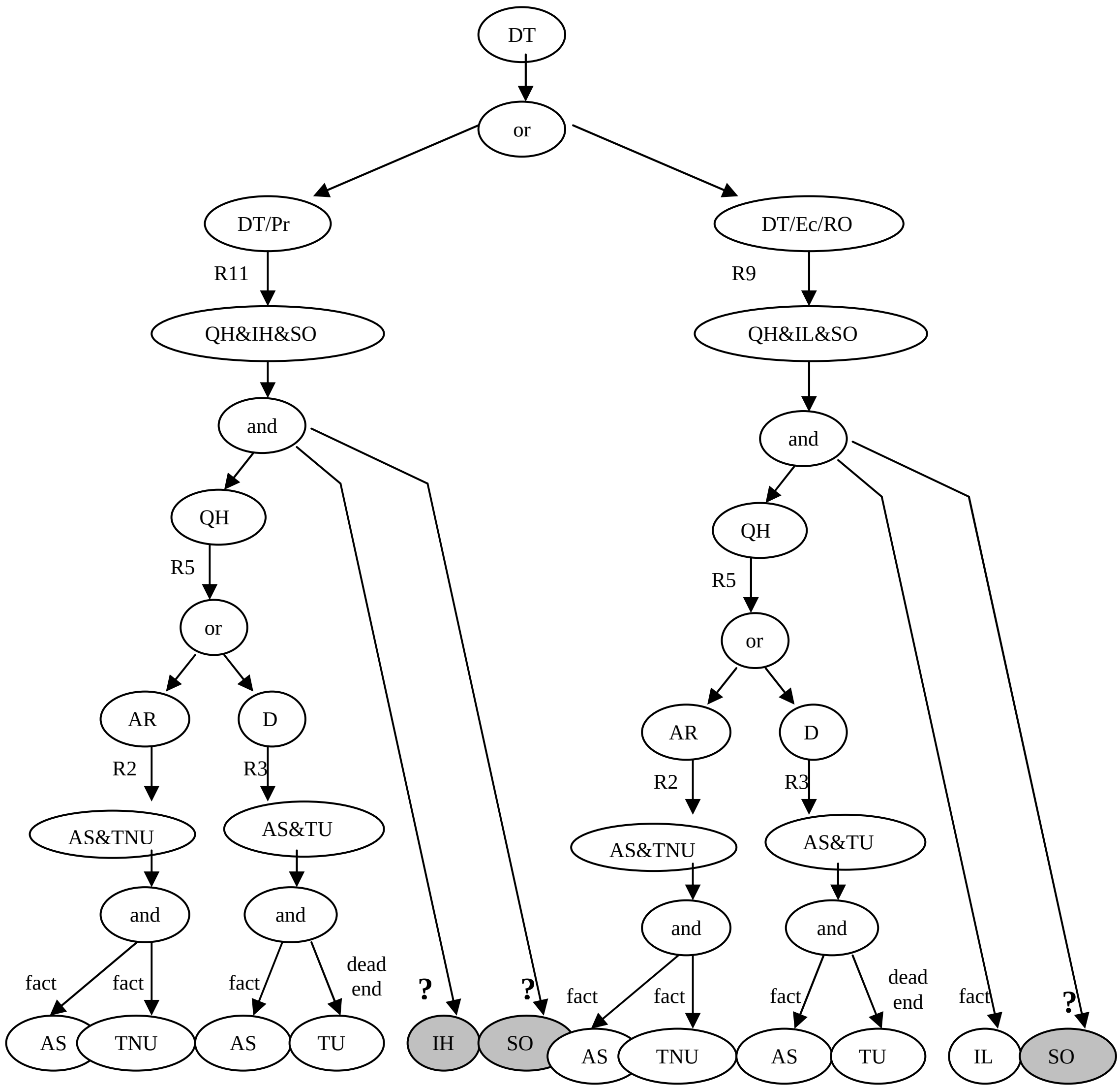
through rule 9-rule 5-rule 2 to the original facts ‘IL’ and ‘AS’ and the condition ‘SO’. All these conditions are highlighted to the user. Obviously, the rule 9-rule 5-rule 2 route requires less change of facts than the rule 11-rule 5-rule 2 route and thus is preferred in the optimization process.

Suppose the decision maker is willing to use one model to achieve one single objective and use another to achieve another objective instead of realizing multiple objectives at one time, but he does not believe the fact that the application of the project are specified can be changed or in other words he is not willing to sacrifice the information offered by the highly quantified input data. According to these considerations, the user answers the questions again with different answers from the previous time. New information is sent to the inference engine, the forward chaining starts again. The ‘ANS’ becomes dead end. Therefore, the AHP models remain infeasible. However, since the ‘SO’ becomes the new fact, all the rules for the rule 9-rule 5-rule 2 route of the decision tree models are fired. Then the decision tree model cluster is added into feasible model set. Due to the higher preference rank, as shown in Table 6.4, the decision tree model cluster is now the preferred group. Since the DT2 model (-1.599) has a lower aggregated value than the other decision tree models in the cluster (DT1-0.113, DT3 -0.117, DT4 -0.297) indicating it has a higher utility value to the decision maker. Thus the DT2 model developed by Rzasa et al. (1990) is finally recommended to the system user.

Moreover, the explanation subsystem will also send the following information to the user demonstrating the justice of this recommendation and the competence of the model: Table 6.4, Figure 6.3 and the refined knowledge that the decision tree model cluster is statistically different from the scoring model cluster on the practical factor.

6.3 Summary

This chapter has described a model guidance example to illustrate the work flow of the whole R&D ES architecture described in the previous chapter. The



AR = the projects are classified as applied research projects
D = the projects are classified as development projects
AS = the applications of the projects' results are specified
TNU = the technology involved in the projects are not fully understood
TU = the technology involved in the projects are fully understood
IH = degree of projects' interdependence is high
IL = degree of projects' interdependence is low
QH = degree of input data's quantification is high

DT= use the decision tree models
Pr = use the programming models
Ec = use the economic analysis models
RO = use the real options models
SO = decision maker has a single objective

Figure 6.3 Inference for the Decision Tree models

R&D ES is applied to guide the mentioned organization to select a suitable model for their R&D management. Through the decision making process, different functions of the R&D ES architecture’s components, especially the intelligent guiding component, are demonstrated.

Preliminary recommendation to the scoring models is given by the system according to the organization’s situation and decision maker's preference. Then, such conclusion is revised by initiating the intelligent guiding component. This component guide the decision maker to consider loosing the constraint for those infeasible models with even higher utility than the current solution. Finally, the new conclusion is justified and explained to the decision maker though an explanation component.

The example illustrates clearly the whole process of applying the proposed R&D ES architecture as a system approach to reach a model recommendation, especially the workflow of the feedback loop working as an intelligent guiding component. How the AHP models and the decision tree models are found to be re-considered when a recommendation to the scoring models is already reached. How the route of tracing back the important conditions of the two models is chosen. How to enable some of the re-considered models to be feasible and why the decision tree models are finally recommended to the system user. All these detail information are demonstrated through solving the model choosing problem in this example, which also in turn proves the efficiency and effectiveness of the proposed R&D ES architecture as well as the active decision support methods.

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Decision-making is a process of choosing among alternative course of action for the purpose of attaining a goal, and decision support shares many important concerns with decision-making. Traditional decision support philosophy has only provided passive supports to decision makers. Therefore, it is necessary to incorporate active roles in decision support tools to improve decision support effectiveness, and to provide active support in decision-making processes that require human mental activities of reasoning and learning.

The overall context of this study is to develop an advanced knowledge-based decision support environment where decision makers and decision support tools can engage in an effective partnership during decision-making process. Such an active decision support environment is visualized in this thesis as a new intellectual decision support tool and a new resource support tool, that are incorporated into a knowledge-based system (KBS) framework. The development integrates the research in the field of statistics, decision support systems, and artificial intelligence.

The active decision supports are designed using general strategies like intellectual support approach and resource support approach but based on unique underlying ideas, which realized by novel support methods. These active decision support methods represent a new trend of decision support philosophy, which emphasize the active participation of decision support tools in decision-making process to provided efficiency support for high-level cognitive tasks involving creativity. To illustrate these notions of active decision support philosophy, proposed support ideas and methods are applied and integrated into a form of Decision Support System, the Knowledge based System, to enhance its functionalities.

The enhanced domain-independent KBS framework has, in addition to the knowledge base, inference engine and user interface components of the traditional KBS, an 'intelligent' guiding component and a statistical knowledge-refining component. The intelligent guiding component is in a feedback form and adopts a new intellectual support idea to identify user-neglected opportunities and guide decision makers to consider more alternatives so that decision quality will be improved. The knowledge-refining component, applying the proposed active support resource method, initiates automatically to extract the information offered by experts using the proposed multivariate-analysis-based resource support tool. The refined information, as stored knowledge, can offer more efficient support to decision makers, especially in multi-criteria decision-making situations with tremendous solution requirements.

The effectiveness and efficiency of proposed active decision support methods are demonstrated by ensuring the enhanced KBS decisional guidance capabilities to support decision makers in providing appropriate judgmental inputs. Selection of the appropriate input value requires user judgment as which level is a more appropriate balance between cost and benefit of a certain alternative. The system provides guidance for the direction of making judgments like on which alternative and on what input variable should decision-makers focus. The guidance is also designed to match to a particular user's needs and the specific decision task on hand.

As an application of the enhanced KBS framework, an Expert System (ES) architecture in the R&D model guidance domain is designed. The general architecture is illustrated clearly with domain dependent knowledge. Then, the R&D ES is applied to a practical model selection problem. The results of the application show that the guidance for judgmental inputs can actually improves decision quality, user learning, and user satisfaction. Furthermore, the knowledge base constructed in this thesis is helpful in making R&D model selection decisions. It can be imported to any ES software as standard knowledge storage.

The new ideas of active decision support and the enhanced KBS can be applied to various areas of decision-making. It could be anticipate that their usefulness will be optimal in the areas, (1) where the task environment is unstructured requiring more judgmental inputs from the decision maker and (2) where the impact of the decision is high, such as strategic management (e.g. R&D management) and crisis management.

In strategic management and planning, top management has to develop comprehensive strategies to cope with the instability, uncertainty, and complexity of the environment. This requires sophisticated and comprehensive understanding of the internal and the external factors to develop strategic plans for long-term direction of the establishment, which will probably results in a large knowledge base of KBS. While a traditional KBS does not adequately support tasks like knowledge structuring and refining, the enhanced KBS can perform these tasks better using its statistical knowledge-refining component.

In crisis management situation, a tendency is to consider a limited number of alternatives and quickly reach a decision. The limited analysis reduces the decision quality by rejecting a correct course of action or accepting a wrong solution to the problem. The enhanced KBS can support the decision-making process by supporting evaluation of more alternatives and evaluating the consequences.

In summary, the new role of the advanced KBS developed here is not to replace the human decision maker but to function as a tool for decision-making by complementing the user's abilities of problem solving in the application domain.

7.2 Future Work

However, one of the major premises of the proposed KBS architecture is all the possible alternatives are pre-identified and the decision task is to choose the best one of them. This premise obviously limits the use of the enhanced KBS, since in some cases that possible alternatives can not identified properly even by domain experts. In such cases, the active decision support should be developed with more advanced techniques, like alternative generation approaches. Recently, some DSS have incorporated intelligent search techniques such as Genetic Algorithms (GA) and Simulated Annealing (SA) for such purpose. Both GA and SA are meta-heuristic search techniques and can be viewed as knowledge discovery techniques because of their search serendipity—identifying new and perhaps unexpected solutions. Incorporating such techniques can probably expand the application fields of the proposed KBS.

Although the conceptual design of the architecture is proposed, a physical KBS computer application needs to be developed to fully exert the architecture. With the accomplished KBS software, some more areas of research, such as studying the impact of the system on the expert and novice decision makers, could also be conducted.

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Appendix A Review of R&D project selection models

The **scoring model** is perhaps the oldest and most familiar class of models to practitioners that still very popular for R&D project evaluation. It has appeared, as a project selection technique and in various forms, in the literature since the 1950's. The most common approach of this model is to score candidate projects with respect to a list of evaluation criteria and combine all the scores belonging to the same project using some algorithm so that a ranking of all the projects can be obtained based on such combined scores. The most popular algorithms used are purely additive or multiplicative.

The scoring model has the following strength: Firstly, it is not so complex as to mystify and hence discourage potential users. Secondly, it can accommodate non-quantitative criteria. Thirdly, it can incorporate peer review into the selection process. Fourthly, it does not require detailed economic data, some of which may not readily be available. Finally, it can be easily customized by an organization to articulate the characteristics it wishes to emphasize. However, the scoring model also has some unresolved issues: Firstly, the figure of merit produced by scoring is not a sufficient measure of a project value and also not a relative value measure; Secondly, purely additive or multiplicative for calculating scores cannot correctly reflect the tradeoffs inherent in the traditional set of R&D project selection criteria. Thirdly, it is only appropriate when there is a low degree of interdependence between projects. Fourthly, generating a 'score' for an R&D project is in some sense arbitrary.

Unlike scoring methods' arbitrary choice of weights, the Analytic Hierarchy

Process (**AHP)** method, developed by Saaty (1980), assumes unidirectional hierarchy relations among decision levels to obtain weights for criteria by pair-wise comparisons at each level. The top element of the hierarchy is the overall goal for the decision model. The hierarchy decomposes to a more specific attribute until a level of manageable decision criteria is met. The hierarchy is a type of system where one group of entities influences another set of entities. Numerous applications have been published in literature since AHP was developed.

The strengths of AHP are as follows: Firstly, it is a relatively simple, intuitive approach that can be accepted by decision-makers as well as a method that can provides rationale for the choice of best alternative. Secondly, it allows for the transformation of qualitative values into quantitative values and performing analysis on them. The weaknesses of AHP are as follows: Firstly, it assumes the decision-making problem can be decomposed in a linear top-to-bottom form as a hierarchy, while it is not always the case in real life. Secondly, it requires the decision maker can compare and provide a numerical value for the ratio of any two elements' merit.

Programming models are usually based on an optimization approach. Given a number of projects and a pool of resources, the portfolio of projects was optimized to a certain criterion. This usually involved the conversion of the attributes of a project into a single monetary value. There is little information on the application of these early models to project selection decisions. The complexity of the models and the problems of application can be a deterrent.

From 1970's to 1980's, the use of **Multi-attribute utility theory (MAUT**) to evaluate important projects is an accepted practice throughout government and industry. (Bard 1989) MAUT (Keeney and Raiffa, 1976) can be utilized to handle problems with a large number of different attributes or types of consequences. The preference of options is obtained by comparing utilities over some relevant attributes or criteria. In this approach, weights and scores are defined and assessed in different ways, while, in AHP, they are not explicitly distinguished. One criticism of this approach is that the individual responses are not always believable.

Compared to the economic analysis method, which models the risk of the project by discounted rate, the traditional **Decision Tree (DT) analysis** structures the problem by assigning all possible outcomes a subjective probability and capturing time and risk preferences using a utility function. Then, the value of an R&D project is subjectively defined as the indifferent buying price of the company. It is useful in R&D projects evaluation because of its power in sequential decision-making situations. The barriers limit the use of decision tree in R&D project evaluation are as follows: First, the discretization of the variables. The standard decision approach needs to discretize the continuous variables in decisions before solve the problem. However, discrete models can appear inaccurate to managers or engineers who tend to think of the decision problem variables as continuous. A discrete approach seems to be distorting the 'real' problem to fit the available analysis tools. Second, the solution difficulties. If there are ten variables in a decision problem and each has five possible levels, then the resulting decision tree will have almost ten million endpoints. Unless the structure of the problem is special, it is very time consuming to solve. Yet, ten variables are not many of a practical management problem. Third, subjectivity in assigning probabilities of different outcomes.

The Economic Analysis method is based on capital budgeting techniques. NPV and ROI are the common representatives of the method. Economic analysis has a good theoretical foundation but the use of it is difficult to be justified due to the difficulties in estimating accurately the contribution of R&D projects and separating them from those of others in monetary terms.

In order to more accurately reflect the uncertainty than the traditional NPV model and keep reflecting the sequential nature of the decision-making situation for R&D managers, the application of **Real Options analysis (RO)** to R&D projects has recently received significant attention. In this method, the value of an R&D project is defined as the market value of a portfolio of securities that exactly replicates the project's payoffs. The investment in an R&D project can be regarded as purchasing a call option on the value of a subsequent result. Therefore, this method emphasizes actively treating future uncertainty as opportunities for financial rewarding rather than a risk of loss in R&D project evaluation.

Appendix B Models in the knowledge base

Ch1 Model: Souder and Mandakovic (1986) built a checklist model that uses $Ti = \sum_j s_{ij}$ represents project i's value, where s_{ij} =1 when project i is judged to meet criterion j and s_{ij} = 0 otherwise. In this model all criteria are assumed to be equally important.

Ch2 Model: Gaynor (1990) provided managers with a list of questions to be answered when selecting R&D projects. The questions put focus on a project itself as a business unit and provide qualitative information to help the selection decision.

Sc1 Model: Rengarajan and Jagannathan (1997) designed a classical scoring method to rank projects having a wide range of objectives and characteristics. Thirteen criteria are identified and weighted through discussion with relevant R&D executives. Projects are evaluated in terms of their contribution to each criterion and the contribution is scaled by the weighting and added together to obtain a total score. All the project evaluation work is done by a project selection committee. The authors claimed that the methodology could be generally applied to large R&D organizations in developing and developed countries.

Sc2 Model: Henriksen and Traynor (1999) proposed a practical scoring tool for R&D project-selection and implemented it in a federal research laboratory. They intended to improve the scoring technique's performance on the first two problems mentioned above. By using a additive/multiplicative combination algorithm, tradeoffs between criteria was explicitly treated. Then the resulting score, representing merit, was combined with a scaled funds request, representing cost, to obtain a value index, which is a relative measure, for each project. An

EXCEL based prototype decision support system realizing the proposed method is developed.

AHP1 Model: Meade and Presley (2002) used the ANP to select R&D projects. In their generic ANP model, the project phase, which is basic, applied or development, and the actors, who will participate in making the decision or will be affected by the decision, are set as two of the intermediate levels in the hierarchy. The influence of the project phase to the actors' preference of measures is modeled as one-way interaction using ANP.

AHP2 Model: Mikhailov and Singh (2003) proposed a fuzzy extension of ANP that was named as FANP. Instead of the classical Eigenvector prioritization method, a new fuzzy preference programming method, which obtains crisp priorities from inconsistent interval and fuzzy judgment was applied. The resulting FANP enhances the potential of the ANP for dealing with imprecise and uncertain human comparison judgments. It allows for multiple representations of uncertain human preferences, as crisp, interval, and fuzzy judgments as input for the decision process and even incomplete sets of pairwise comparisons can lead to a result. Furthermore, the inconsistency of the uncertain human preferences can be measured by an appropriate consistency index. A prototype decision support system realizing the proposed method was developed.

Sinuany-Stern and Mehrez (1987) reviewed several discrete multi-attribute utility models. **MAUT1 Model:** One is developed for selection among interrelated projects. Two independence relations are identified and a type of multiplicative utility function is used. **MAUT2 Model:** Another model is especially designed to conduct selection based on uncertain utility. For such case, the expected utility is used to value projects, which is defined as the sum of the probability of a certain possible outcomes multiplying the utility of having such outcome.

MAUT3 Model: Bard and Feinberg (1989) proposed a two-phase methodology for technology selection and system design. The first phase of their methodology uses deterministic multi-attribute utility theory to rank technological alternatives. Relevant individuals representing different interest groups are interviewed to assess the utility function. Both qualitative and quantitative attributes are considered. The authors believed MAUT was a good start point for technologies identification according to decision maker's risk preference and objectives but not sufficient for defining research programs defining, individual projects selection and resources allocation, that are needed in order to pursue a particular technology.

Pr1 Model: Heidenberger (1996) presented a mixed integer linear programming (MILP) model for dynamic project selection and funding under risk. The model incorporates decision tree concepts. Each candidate project is broken down into important stages where stop/go-decisions and resource allocation decisions are to be made. These projects are described in a stochastic decision tree structure. A type of binary node is used to represent whether a project is chosen and novel type of 'computed-chance' node is designed to characterize how much effort is needed to reach the next project stage with higher successful probability. The efforts are measured in the cost terms, which together with benefit functions, budget of resources constitute the constraints.

Pr2 Model: Badri et al. (2001) developed an integrated project selection model based on 0-1 goal programming. If the value of the decision variable for a project is 1 means the project is selected, otherwise it is not. The constraints include the authors' consideration of benefit related, cost related, risk related and preference related objectives as well as project relations constraints and time constraints.

Then the objective function is set to minimize the deviations of these factors from their ideal level.

DT1 Model: Mehrez (1988) reports on the implementation of the von Neumann-Morgenstern expected utility approach to evaluate and select R&D projects. The uncertainties regarding the profitability of a project are reflected by its expected discounted present worth and the expected utility of the discounted presented worth, based on which the alternative projects are prioritized. A risk-free discount factor and a one-dimensional utility function of money are needed to construct the model. The technological and the marketing risks are measured by the chief researcher's qualitative evaluation.

DT2 Model: Rzasa et al. (1990) presented a portfolio analyzing methodology that has being used by Eastman Kodak. The method is based on decision and risk analysis. An influence diagram is used to identify the uncertainties affect the decision criterion, NPV, and to describe the relationships among them. The outcomes for each uncertainty are modeled using two or three point estimation. Decision trees are constructed for each project and combined to a big tree in order to get a portfolio's ENPV. The distribution of an uncertainty around its expected value will also be identified by the trees and will be a good reflection of downside risk and upside potential. The projects with positive return will be identified. Then, leverages, calculated as expected value divided by expected cost, are computed for each projects, portfolios and additional resources allocated to a project. Based on leverages, the productivity of a project can be measured, optimization within a budget level can be realized by reallocating resources and whether a change in resource level is beneficial can also be determined.

DT3 Model: Hess (1993) reported a model for R&D projects continuing or screening decisions when little data available. The author estimated all the expense and value parameters as well as conditional probabilities of technical, commercial and market success. Then a simple decision tree was constructed to calculate the ENPV for a project based on the estimated parameters. The projects with positive ENPV will be continued when initiation decisions need to be made and projects with higher ENPV will be screened out when selection decisions need to be made. A visual sensitivity analysis is conducted to validate the model results.

DT4 Model: Stonebraker and Kirkwood (1997) proposed a continuous-variable version of the decision tree model and applies the approach to an R&D planning problem. The new approach can directly represent the structure of a decision with continuous and random variables instead of a discrete approximation and can be efficiently solved using standard nonlinear optimization methods.

Ec1 Model: Heidenberger and Stummer (1999) described a model developed by Hess (1985) using the following simple expression for the expected net present value E (NPV): $E(NPV) = -R + P_t(-D + P_c kS \times \int_T^{T+10} e^{-it} dt)$ where R represents applied research cost, P_t is the probability of technical success (technical feasibility), D is development cost (while moving from technical feasibility to commercialization), P_c symbolizes the probability of commercial success (i.e. achieving the forecast profit level), k stands for the gross profit (without R&D cost) as a fraction of sales, S is the average annual sales over the first 10 years, T is the years to commercial introduction, i represents the discount rate and $\int_T^{T+10} e^{-it} dt$ is the cumulative continuous discount factor.

Ec2 Model: Davis and Owens (2003) demonstrated a Discounted Cash Flow

(DCF) model for valuing the United States' federal non-hydro renewable electric R&D program. In their model, a simplified market model should first be constructed to estimate future cash flows of the program. Then assumptions about adopting the results of the program into market are also made. Based on the two aspects of efforts mentioned above, the NPV of the program can be calculated.

RO1 Model: In Smith and Nau's paper (1995), they described an option pricing approach to value risky projects assuming a complete market. The option pricing approach seeks a portfolio of securities that exactly replicates the project's payoffs. The value of the project is then given by the market value of this replicating portfolio.

RO2 Model: Smith and McCardle (1998) integrated a finance-based options valuation approach with Decision Analysis. Both suggest that real option approach can be used to simplify Decision Analysis when some risks can be hedged by trading and to model market risk, and conversely, Decision Analysis techniques can be used to extend the real option approach techniques to model private risk.

RO3 Model: Herath and Park (1999) developed a valuation model incorporating the options approach into a decision tree framework. Two distinct phases of R&D projects are identified as an R&D phase and a commercialization phase. The commercialization decision will be made only when the uncertainty of an R&D phase is resolved. Such sequential decision feature is modeled by a decision tree, while the commercialization decision can be regarded as an opportunity to invest and the R&D project a call option. Therefore, the project can be valued by a formula developed according to the risk-free arbitrage features of the binomial option pricing model and the structure of the decision tree.