A NEURAL EXPERT SYSTEM WITH GOAL SEEKING FUNCTIONS FOR STRATEGIC PLANNING

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ABSTRACT

This paper presents a neural expert system approach to designing an intelligent strategic planning system. The main recipe of the proposed neural expert system is an inference mechanism capable of performing backwards. Four strategic planning portfolio models are considered: BCG matrix, Growth/Gain matrix, GE matrix, and Product/Market Evolution Portfolio matrix. The proposed neural expert system could provide "goal-seeking" functions, which prove to be very useful for unstructured decision-making problems, specifically in strategic planning. Goal seeking functions are realized through the backward inference mechanism, enabling the neural expert system to show the appropriate inputs (or conditions) to guarantee the desired level of outputs. To implement our idea, we developed a prototype system, named StratPlanner, which runs on Windows 2000. Using Korean automobile industry data, we performed experiments under competitively designed situations. Results support our supposition that the neural expert systems approach is useful for performing competitive analyses. Further research topics associated with the current research are also discussed.

INTRODUCTION

Recently, a number of researchers in Operations Research/Management Science (OR/MS) have attempted to build intelligent expert systems for solving a wide variety of problems including production scheduling, finance, personnel, marketing, accounting, etc. (Waterman, 1990). Common motivation underlying this research is to intelligently assist decision-makers who have to solve poor structure problems.

The strategic planning problem is one of many highly ill structured OR/MS problems. In today's business environment, organizations must define a plan for strategic problem solving. In broad terms, strategy is an articulation of the kinds of products the organization will produce, the basis on which its products will compete with those of its competitors, and the types of resources and capabilities the firm must have or develop to implement the strategy successfully (Oliver, 2001). Strategy, in effect, is the managerial action plan for achieving organizational objectives; it is mirrored in the pattern of moves and approaches devised by management to achieve desired performance. Strategy is therefore the "how" of pursuing the organization's mission and reaching target objectives (Thompson and Strickland III, 1990).

Today's managers must think strategically about their company's position and the impact of changing conditions. Organizations must monitor external situations very closely, to determine when the current strategy needs to be changed. They must understand the structure and dynamics of the industry in an effort to make any necessary organizational adjustments (Oliver, 2001). The advantages of successful strategic thinking and conscious strategic planning activities include: (1) providing better guidance to the entire organization on the crucial point of "what it is we are trying to achieve," (2) increasing management’s awareness to change, new opportunities, and threatening developments, (3) providing managers with a greatly needed rationale for steering resources into strategy-supportive, results-producing areas, (4) helping unify the numerous strategy-related decisions by managers across the organization, and (5) creating a more pro-active management posture to counteract the tendency of decisions to be reactive and defensive. The decisive advantage of being pro-active versus re-active is the enhancement of long-term performance. Business history shows that high-performing enterprises often initiate and lead, not just react and defend. They see strategy as a tool for securing a sustainable, competitive advantage, and for pushing performance to superior levels.

Computer-based strategic planning systems play an increasingly relevant role in assisting both the diagnosis of strategic problems likely to threaten the organization's performance, and the suggestion of strategic alternatives to solve those problems. When designing such systems, certain objectives must be considered carefully. First, strategy analysts or managers in organizations should have access to reliable, low-cost, user-friendly instruments - for example, programs running on personal computers. Nevertheless, to meet strategy analysts' requirements, processing time should be relatively short. Since any failure of such systems could prove seriously harmful to an organization's competitive position and performance, both reliability and fault tolerance are crucial properties needing to be satisfied by such computer-based strategic planning systems. At the same time, the strategy analysts must be provided with as much information as possible about how the process is carried out.

In an effort to accomplish these objectives, developers of computer aids for strategy analysts face a variety of problems deriving from the complex nature of strategic planning-related data. Such data is characterized by an intrinsic variability, resulting from spontaneous internal mechanisms or a reaction to occasional external stimuli. Furthermore, most events related to strategic planning result from the interaction of many factors and sub-factors whose different effects are almost indistinguishable.

Strategy analysts are accustomed to such problems, but their skills cannot be easily incorporated into computer programs. Most strategic planning decisions are based on experience as well as on complex inferences and extensive strategic knowledge. Such experience and/or knowledge cannot be condensed into a small set of relations or rules, and this limits the performance of algorithmic approaches or conventional expert systems approaches to many strategic planning tasks. The breadth of strategic planning knowledge is therefore, an obstacle to the creation of symbolic knowledge bases, (for example, IF-THEN rules) comprehensive enough to cope with the diverse exceptions that occur in practice. Experience-based learning, fault tolerance, graceful degradation, and signal enhancement are properties of neural networks that make the neural network-assisted expert systems effective in solving strategic planning problems. This points to a way for implementing reliable computer-based strategic planning systems that can closely emulate a strategy analyst's expertise.

This paper presents the basic part of a prototype neural expert system for diagnosing strategic problems, and suggests strategic alternatives that seem appropriate for current competitive situations. We will focus on two main issues: (1) the design of a neural expert system which is suitable for performing "goal-seeking" analysis and (2) the competence of neural expert systems-driven strategic planning process in real strategic planning situations. Section 2 briefly discusses a basic theory of strategic planning and neural networks. Strategic planning techniques that are used in this paper are introduced in Section 3. Backward inference mechanism is presented in Section 4. In Section 5, architecture of a prototype system is presented. In Section 6, the performance of a prototype system is illustrated with extensive experimental results in the Korean automobile industry. This paper ends with concluding remarks in Section 6.

STRATEGIC PLANNING AND NEURAL NETWORKS

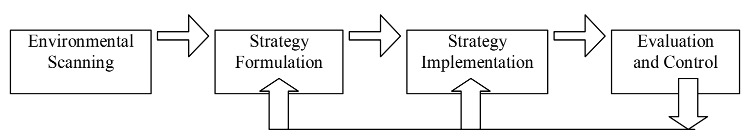
A survey of the huge volume of contemporary practical and theoretical literature on neural network analysis yields the following three observations: (1) There exists a great variety of viewpoints and approaches to neural network analysis (2) A general design principle that will help determine an appropriate architecture of neural networks for a particular application does not exist. It varies with the characteristics of applications (3) Major emphasis has been put upon experimental results obtained from extensive simulations, not upon rigorous theoretical derivations or proofs. These general observations also prevail in neural network applications to OR/MS topics. Literature reporting the neural network applications to the OR/MS problems has begun to appear since the late 1980s. White (1988) suggested a neural network analysis for economic prediction using the IBM daily stock that returns data. Some neural network studies were performed to analyze a stock market prediction (Kamijo & Tanigawa 1990; Kimoto & Asakawa 1990). A current example includes the implementation of a neural network in the strategic planning of a major food industry leader in Taiwan (Chien, Lin & Tan, 1999). In addition, investors have begun using neural networks for currency exchange rate systems, in particular, the UK pound/US dollar exchange rate (Zhang & Hu, 1998). Nevertheless, few studies still exist that use neural networks for solving strategic planning problems.

In a broad sense, neural networks utilize data mining, fuzzy logic, mathematics and software agents in an effort to differentiate technical patterns (Lang, 1999). Neural networks have useful properties such as generalization capability, graceful degradation, heuristic mapping, fault tolerance, multiple inputs, and the capacity to treat Boolean and continuous entities simultaneously (Gallant 1988; Zeidenberg 1990). These vital properties ensure organizational strategy and data are replenished, and rules are redefined (Lang, 1999). Accordingly, the neural networks seem highly suitable for handling strategic planning problems that are characterized by their unstructured nature and uncertainty.

STRATEGIC PLANNING TECHNIQUES

Before strategies can be planned, there must be a sense of organizational-wide innovation. There are four distinct phases that make up an organization's innovation: (1) strategy development, (2) ideation, (3) evaluation, and (4) implementation (Buggie, 2001). Once innovation has been implemented, strategic management planning can begin. Figure 1 depicts the process of strategic management, which consists of four basic elements: (1) environmental scanning, (2) strategy formulation, (3) strategy implementation, and (4) evaluation and control (Wheelen and Hunger, 1992). These processes, in conjunction with the four phases on innovation, create the foreground for a variety of strategic techniques. A number of these techniques have been proposed in previous studies (Abell & Hammond 1979; Glueck 1980; Larreche & Srinivasan 1982; Porter 1980; Rowe, Mason & Dickel 1982). Among them, knowledge-based strategic planning approaches were well reviewed in (Lee 1992; Mockler & Dologite 1991).

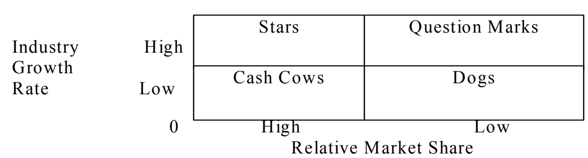
Figure 1.
Basic Elements of the Strategic Management Process



The available methods for strategic planning in literature can be classified into three categories, depending on their focus: (1) portfolio models, (2) profit impact of market strategy (PIMS) analysis, and (3) growth vector analysis. Refer to Rowe, Mason, Dickel (1982) or Lee (1992) for details about these three categories. Portfolio models assist managers in choosing products that will comprise the portfolio and allocate limited resources to them in a rational manner. PIMS analysis is designed not only to detect strategic factors influencing profitability, but also to predict the future trend of return on investment (ROI) in response to changes in strategy and market conditions. Growth vector analysis adopts the idea of product alternatives and market scope to support the product development strategy. This creates the possibility of linking both strategic and international perspectives together. In turn, the organization can build an assurance that relevant business alternatives are considered, strategies are compatible and evaluation/implementation procedures are simplified. The end result lists three strategies that are penetrating a market further with its present products: imitating competitors, introducing current product variants, and innovating entirely new products.

We choose four strategic evaluation methods from portfolio models: BCG matrix, Growth/Gain matrix, GE matrix, and Product/Market Evolution Portfolio matrix. The reasons are: (1) portfolio models have been widely acknowledged among researchers and practitioners and, (2) the four strategic methods selected can provide most of the information that might have been expected from the PIMS analysis and growth vector analysis. The BCG matrix is the single, most popular method. It emphasizes the importance of a firm's relative market share and industry growth rate, and displays the position of each product in a two-dimensional matrix. A more recent adaptation of the BCG matrix is the Mission and Core Competencies (MCC) matrix. The MCC matrix can be utilized to monitor and emphasize claims on all organizational resources (John, 1995). While this adds significant development towards the efforts of strategic planning, the MCC matrix needs to be researched, tested and implemented further. Therefore in this paper, we focus on the heavily researched strategic planning matrix, the BCG matrix. The products within a BCG matrix are called "Stars" "Cash Cows" "Question Marks or Problem Children" and "Dogs" by their position in the matrix as shown in Figure 2.

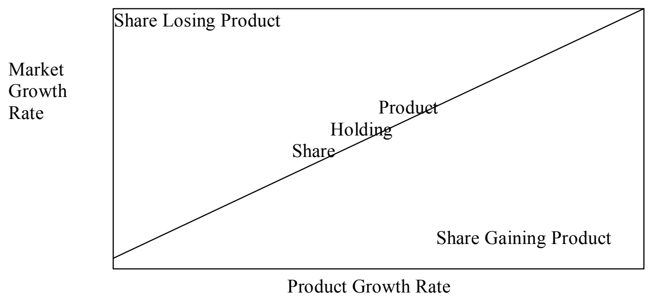
Figure 2
BCG Matrix



Usually the highest profit margins are expected from "Stars," but they are also likely to require high net cash outflows in order to maintain their market shares. Eventually, "Stars" will become "Cash Cows" as growth slows down and the need for investment diminishes as they enter the maturity stage of the product life cycle. "Question Marks or Problem Children" require large net cash outflows to increase the market share. If successful, these products will become new "Stars", which will eventually become the "Cash Cows" of the future. If unsuccessful, these products will become "Dogs" and excluded from the product portfolio. The BCG matrix alone, however, is not sufficient to make the investment decision because the model is too simple to cover all aspects of decision-making. Perhaps the MCC matrix would be more appropriate due to its ability to access numerous organizational resources. Regardless, in many circumstances, factors other than relative market share and industry growth rate play a significant role in production strategy formulation. To compensate for the weaknesses of the BCG matrix, the Growth/Gain matrix, the GE matrix, and the Product/Market Evolution Portfolio matrix are used as well.

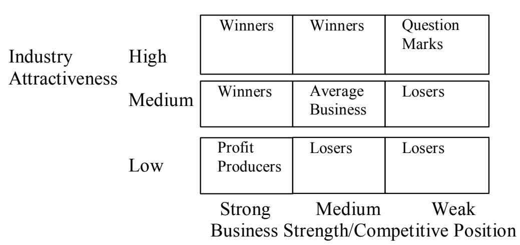
The Growth/Gain matrix indicates the degree of growth of each product against the growth of the market (see Figure 3). Product growth rate is plotted on the horizontal axis and market growth rate on the vertical axis. Share gaining products appear below the diagonal line while share-losing products appear above it. Products on the diagonal line are interpreted as holding the current market share. Alternatively, the graph displaying the trends of the products sales compared with market size may replace the role of the Growth/Gain matrix in a simpler way (Lee 1985).

Figure 3
Growth/Gain Matrix



The composite measures of market attractiveness and business (product) strength are plotted in the GE matrix. In order to construct the GE matrix, managers have to select the relevant factors having significant relationship with industry attractiveness and business (product) strength of the firm. Next they assess the relative weights of those factors depending on manager's judgment, combining the weights to depict composite measures on the GE matrix. Figure 4 shows a 3 x 3 GE matrix chart depicting relative investment opportunity.

Figure 4
GE Matrix Chart



Strategic managers may decide the overall direction of the firm through its corporate strategy by combining market attractiveness with the company's business strength/competitive position into a nine-cell matrix similar to the GE matrix (Wheelen and Hunger 1992). The resulting matrix, depicted in Figure 5, is used as a model to suggest some alternative corporate strategies that might apply to the company's situation. Cells 1, 2, 5, 7, and 8 suggest that growth strategies are either concentrated, which signifies expansion within the firm's current industry, or diversified, where growth is generated outside of the firm's current industry. Cells 4 and 5 represent stability strategies, which are a firm's choice to retain its current mission and objectives without any significant change in strategic direction. Cell 3, 6, and 9 display retrenchment strategies, which are the reduction in scope and magnitude of the firm's efforts.

Figure 5
Contingency Corporate Strategy (Wheelen and Hunger, 1992)

		Business Strengths/Competitive Position		
		Strong	Average	Weak
Industry Attractiveness	High	1. Growth Concentration via Vertical Integration	2. Growth Concentration via Horizontal Integration	3. Retrenchment
	Medium	4. Stability Pause or Proceed with Caution	5. Growth Concentration via Horizontal Integration Stability No Change in Profit Strategy	6. Retrenchment Captive Company or Divestment
	Low	7. Growth Concentric Diversification	8. Growth Conglomerate Diversification	9. Retrenchment Bankruptcy or Liquidation

The GE matrix does not depict as effectively as it might the positions of new businesses that are starting to grow in fledgling industries. In that case, Hofer and Schendel (1978) proposed to use a Product/Market Evolution matrix in which businesses are plotted in terms of their relative competitive position and stage of product/market evolution. It is vital that organizations prepare themselves for all potential stages of the business life cycle, whether the market initiates a technology push or demand-pull. In an effort to meet these competitive stages, the product matrix proposes four main strategies: (1) sub-contracting, (2) cooperation, (3) networking, and (4) joint research (Maisseu, 1995). They also recommended investment strategies at the business level. See Figure 6. The combined use of these four strategic models can provide most of the functions necessary to effectively evaluate corporate and/or business strategies.

Figure 6
Product/Market Evolution Portfolio Matrix and Investment Strategies

Relative Competitive Position

		Strong	Average	Weak	Drop-Out
Stage of Market Evolution	Development Shake-Out	Share – Increasing Strategy			Turnaround Or Liquidation Or Divestiture Strategies
	Growth	Growth Strategy			
	Maturity Saturation Petrifaction	Profit Strategy		Market Concentration and…	
	Decline	Asset Reduction Strategy			

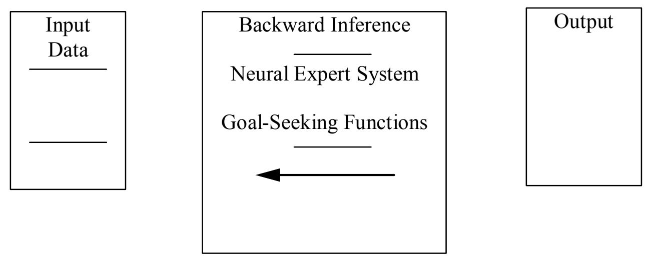
Source: Hofer and Schendel (1978)

INFERENCE MECHANISMS

The multi-phased aspects of strategic planning activities described above indicate that the one-shot, or wholesome approach is not appropriate for effective strategic planning. Rather, to simulate a strategy analyst's reasoning as closely as possible, it would be better to divide the strategic planning-related decision-making processes into a small, relevant number of sub-processes. In this respect, we propose forward inference and backward inference mechanisms to suggest more robust strategies. Forward inference process helps decision-makers perform "what-if" analyses, which are essential for diagnosing the strategic problems and preparing strategic policies against the uncertain future. Backward inference processes provide "goal-seeking" supports that are also useful for decision-makers to accomplish given strategic goals through more effective strategies. In addition, a few studies have researched and implemented a new proposal mechanism for neural networks application. The scenario generator, which is based on both the neural networks theory and the theory of truth value flow inference, possesses the skills to learn and correct organizational mistakes (Li, Ang & Gay, 1997). In theory, this would create the "Ivory Tower" for strategic planning problem solving. However, the studies are few and the available evidence remains inconclusive to warrant any replacement of current mechanisms with the scenario generator. Therefore, this paper strictly focuses on the goal-seeking functions and backward inference process. See Figure 7.

After training the RCP, CCS and GBS neural network modules with appropriate training data, three sets of neural network knowledge base are generated; RCP knowledge base, CCS knowledge base, and GBS knowledge base.

Figure 7
Overall Diagram



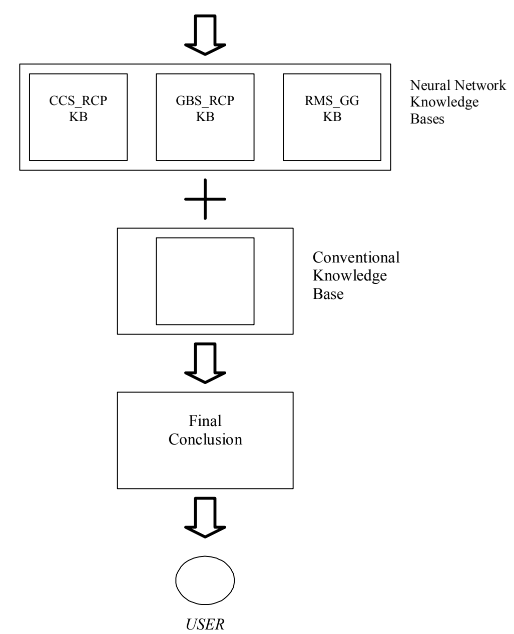
Expert's knowledge are stored in a conventional knowledge base which may include information about various topics, for example, industry environments, socio-economic situations, contingency corporate strategies, competitive position objective, and investment strategy with respect to various strategic situations, etc. Especially, we consider in this paper expert knowledge related to three kinds of areas: contingency corporate strategies, competitive position objective, and investment strategy. Contingency corporate strategies include nine types of strategies: "concentration via vertical integration", "concentration via horizontal integration", "concentric diversification", "conglomerate diversification", "pause or proceed with caution", "no change in profit strategy", "turnaround", "captive company or divestment", and "bankruptcy or liquidation." Each of the six generic types of business strategies involves a different pattern of competitive position objectives, investment strategies, and competitive advantages, which are summarized in Table 1.

Table 1
Characteristics of the Six Generic Business Strategies

Type of Generic Strategy	Competitive Position Objective	Investment Strategy
Share-increasing strategies		
Development stage	Increase position	Moderate investment
Shake-out stage	Increase position	High investment
Other stages	Increase position	Very high investment
Growth strategies	Maintain position	High investment
Profit strategies	Maintain position	Moderate investment
Market concentration and asset reduction strategies	Reduce (shift) position to smaller defendable level (niche)	Moderate to negative investment
Liquidation or divestiture strategies	Decrease position to zero	Negative investment
Turnaround strategies	Improve positions	Little to moderate investment

Backward inference process provides information about the decision making company's positions in the BCG and Growth/Gain matrices. In the backward inference process, we propose three neural network modules: (1) contingency corporate strategy - relative competitive position (CCS_RCP) module, (2) generic business strategy - relative competitive position (GBS_RCP) module, and (3) relative market share - growth/gain (RMS_GG) module. In addition, stage of market evolution (SME) and industry attractiveness (IA) are also used as additional information to CCS and GBS neural network module. Each neural network module consists of one feed-forward neural network trained by the back propagation algorithm, as shown in Figure 8.

Figure 8
Backward Inference Diagram



First, if one of the contingency corporate strategies is selected as a target strategy, the corresponding cell within the GE matrix is determined by a decision-maker. IA value is also determined. With this information, the CCS_RCP module provides information about the competitive position in the market relative to that of the target competitor. The architecture of CCS_RCP neural network module has 14 neurons in the input layer and 4 neurons in the output layer. Output of the CCS_RCP module is then used as input to the RMS_GG module. Figure 9 shows the architecture of the CCS_RCP module.

Figure 9
CCS_RCP Neural Network Module

Input Neurons:
H-S Winners/ H-A Winners/ M-S Winners/ H-Average Businesses/
L-Average Businesses/ Profit Producers/ Question Marks/
M-W Losers/ L-A Losers/ L-W Losers
IA Part ->High/ Medium-High/ Medium-Low/ Low
Output Neurons:
Strong/ Average/ Weak/ Drop-Out

The input neurons of the GBS_RCP module require investment strategies as well as SME information. Output neurons of the GBS_RCP module are those of original RCP module such as Strong, Average, Weak, and Drop-out. The architecture is summarized in Figure 10.

Figure 10
GBS_RCP Neural Network Module

Input Neurons:
Share Increasing/ Growth/ Profit/ Market Concentration and
Asset Reduction/Turnaround/ Liquidation or Divestiture

SME Part -> Development/ Growth/ Shake-Out/ Maturity/ Decline

Output Neurons:
Strong/ Average/ Weak/ Drop-Out

Finally, the input neurons of RMS_GG module require information about the output values of GBS_RCP or CCS_RCP, as well as information about the target competitor's BCG and Growth/Gain matrices. The output neurons of RMS_GG module are specific positions in the BCG and Growth/Gain matrices. Detailed information about the architecture of the RMS_GG module is shown in Figure 11.

Figure 11
RMS_GG Neural Network Module

Input Neurons:
Strong/ Average/ Weak/ Drop-Out
< Competitor >
BCG : Stars/ Cash Cows/ H-Question Marks/ M-Question
Marks/ L-Question Marks/ H-Dogs/ M-Dogs/ L-Dogs
Growth/Gain: Share Gainer/ Share Holder/ Share Loser

Output Neurons:
< Decision Making Company >
BCG : Stars/Cash Cows/ H-Question Marks/ M-Question
Marks/ L-Question Marks/ H-Dogs/ M-Dogs/ L-Dogs
Growth/Gain: Share Gainer/ Share Holder/ Share Loser

After training the CCS_RCP, GBS_RCP and RMS_GG module with appropriate training data, three kinds of neural network knowledge bases are generated; CCS_RCP knowledge base, GBS_RCP knowledge base, and RMS_GG knowledge base.

ARCHITECTURE OF A PROTOTYPE SYSTEM

We developed a prototype system running on Windows 2000. It is coded in Microsoft Visual C++ language. Its main menu is composed of five sub-menus as shown in Figures 12 and 13.

Figure 12
Structure of Main Menu in a Prototype System

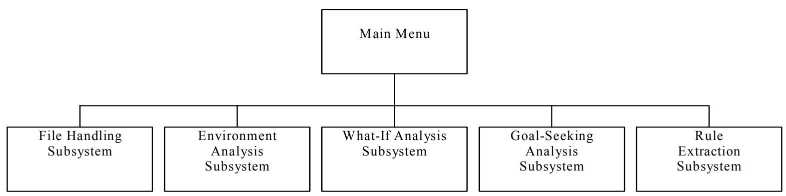
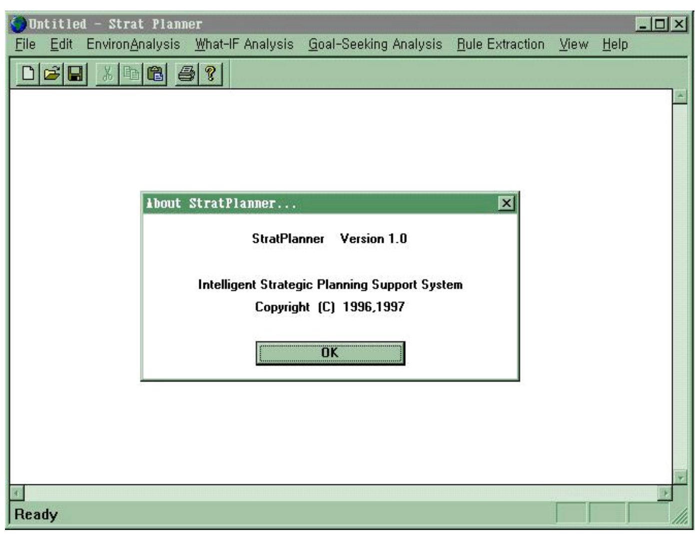


Figure 13
Main Menu Screen



As mentioned in the introduction, we will illustrate the performance of backward goal-seeking analysis. Goal-seeking analysis is performed in the following steps summarized in Figure 14.

Figure 14
Steps of Goal-Seeking Analysis in a Prototype Neural Expert System

Stage 1: GBS-RCP/ CCS-RCP Stage

Step 1. Select a target strategy from either GBS or CCS.
Step 1-1. If GBS is selected,
Step 1-1-1. Open the weight file of GBS-RCP neural network module.
Step 1-1-2. Select a specific GBS strategy.
Step 1-1-3. Input data about stage of market evolution.
Step 1-1-4. Get the result from GBS-RCP neural network knowledge base.

Step 1-2. If CCS is selected,
Step 1-2-1. Open the weight file of CCS-RCP neural network module.
Step 1-2-2. Select a specific CCS strategy.
Step 1-2-3. Input data about industry attractiveness.
Step 1-2-4. Get the result from CCS-RCP neural network knowledge base.

Step 2. RMS-GG Stage.
Step 2-1. Open the weight file of RMS-GG neural network module.
Step 2-2. Input data about competitor's BCG and Growth/Gain matrix.
Step 2-3. Get the result from RMS-GG neural network knowledge base.

REAL LIFE APPLICATION: AUTOMOBILE INDUSTRY IN KOREA

Experiments are performed with Korean automobile industry data, which is considered as a strategically turbulent market. The data is selected to show the performance of a prototype system in a turbulent strategic planning environment. Previous studies by H. Z. L. Li and Hu (2000) have defined such turbulent factors. They include the following: (1) incorrect work, (2) machine breakdowns, (3) re-work due to quality, and (4) rush orders. Table 2 depicts the categories of automobile data used in our experiments.

Table 2: Categories of Korean Automobile Data

Car Type	Company Name		
	KIA	HYUNDAI	DAEWOO
Small	Pride	Excel	Lemans
Compact	Capital Sephia	Elantra	Espero
Medium	Concord	Sonata	Prince
Large	Potentia	Grandeur	Super Salon

Monthly domestic sales data of three companies' passenger cars from May 1990 to August 1994, as well as miscellaneous strategic planning data from May 1990 to August 1994, was collected. The domain knowledge from two experts, a strategy analyst in 'K' automobile company and a strategy expert in a university are also used in this experiment. Table 3 shows the type and description of data used in our experiments.

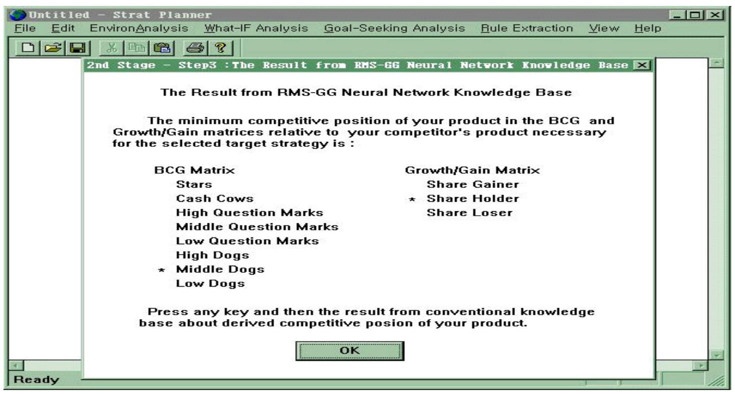
Table 3: Type and Description of Data Used in Experiments

	Type of Data	Description of Data
Quantitative Data	Monthly Sales Data	Market Growth Rate Relative Market Share Product Growth Rate
Qualitative Data	Expert Knowledge	Preparation of Input/Output Pairs used in Supervised Learning Preparation of Desired Output used in Test Knowledge related to three kinds of areas : Contingency corporate strategies Competitive Position Objectives by the typeof Generic Strategy Investment Strategies by the type of Competitive Position Objectives
	Data produced by Neural Network Modules	Relative Competitive Position Position in GE Matrix Position in Product/Market Portfolio Matrix Position in BCG Matrix Position in G/G Matrix
	User's Judgement	Determination of Stage of Market by Car Type Determination of Industry Attractiveness by Car Type Variable Selection Weight Determination

The data set consists of 52 cases divided into 32 cases from May 1990 to December 1992 for the training set and 20 cases from January 1993 to August 1994 for the test set. Another data set is arranged for the differences in production periods. Based on this data, we trained and tested RCP, CCS, GBS, CCS_RCP, GBS_RCP, RMS_GG neural network modules. By using monthly data, this experiment is assumed to be a monthly one-shot.

For illustration of backward inference, consider KIA as a decision making company. Suppose that KIA wants to examine "Profit" strategy for its small type car "PRIDE" comparing it to its competitor DAEWOO's "LEMANS" using data from January 1993. The stage of small car market evolution was analyzed as "Maturity". Using this information, GBS_RCP neural network knowledge base presents "Average" position as a minimum requirement condition. In the second stage, the competitive position of DAEWOO's "LEMANS" was analyzed to belong to "Middle-Dogs" in BCG matrix and "Share Holder" in Growth/Gain matrix, respectively. Based on the results from GBS_RCP neural network knowledge base and the competitive position of DAEWOO's "LEMANS", RMS_GG neural network knowledge base provides that the minimum competitive positions of "PRIDE" for "Profit" strategy comparing to its competitor DAEWOO's "LEMANS" are "Middle-Dogs" and "Share Holder", respectively. The sample screen is shown in Figure 15.

Figure 15
Sample Result of Stage 2 Step 3 in Goal-Seeking Analysis



The current competitive positions of "PRIDE" comparing to its competitor DAEWOO's "LEMANS" are "High-Dogs" and "Share Loser". Therefore, the prototype system displays that the "profit strategy that you consider is adequate for current competitive positions of your product", which is illustrated in Figure 16. Table 5 summarizes the results with additional test cases.

Figure 16
Sample Result of Stage 2 Step 4 in Goal Analysis

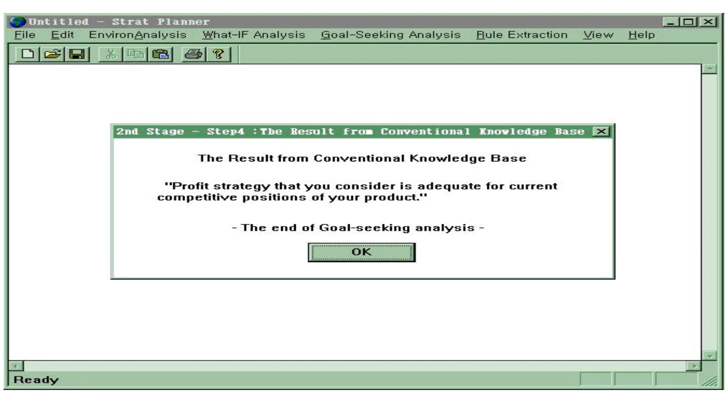


Table 4: Illustration of backward inferencing by GBS_RCP and RMS_GG neural network modules

Test Set	GBS	SME	RCP	Competitor (DAEWOO's "LEMANS")		Decision Making Company (KIA's "PRIDE")			
				BCG	G/G	BCG		G/G	
						Actual	Desired	Actual	Desired
93.01	Profit Strategies	Maturity	Average	Middle -Dogs	Share Holder	Middle -Dogs	Middle -Dogs	Share Holder	Share Holder
02	Profit Strategies	Maturity	Average	Middle -Dogs	Share Loser	Middle -Dogs	Middle -Dogs	Share Loser	Share Loser
03	Profit Strategies	Maturity	Average	Low-Dogs	Share Gainer	Low-Dogs	Low-Dogs	Share Gainer	Share Gainer
04	Profit Strategies	Maturity	Average	Low-Dogs	Share Loser	Low-Dogs	Low-Dogs	Share loser	Share Loser
05	Profit Strategies	Maturity	Average	Middle -Dogs	Share Gainer	Middle -Dogs	Middle -Dogs	Share Gainer	Share Gainer
06	Profit Strategies	Maturity	Average	Middle -Dogs	Share Gainer	Middle -Dogs	Middle -Dogs	Share Gainer	Share Gainer
07	Profit Strategies	Maturity	Average	Middle -Dogs	Share Gainer	Middle -Dogs	Middle -Dogs	Share Gainer	Share Gainer
08	Profit Strategies	Maturity	Average	Middle -Dogs	Share Loser	Middle -Dogs	Middle -Dogs	Share Loser	Share Loser
09	Profit Strategies	Maturity	Average	Middle -Dogs	Share Loser	Middle -Dogs	Middle -Dogs	Share Loser	Share Loser
10	Profit Strategies	Maturity	Average	Middle -Dogs	Share Gainer	Middle -Dogs	Middle -Dogs	Share Gainer	Share Gainer
11	Profit Strategies	Maturity	Average	Middle -Dogs	Share Gainer	Middle -Dogs	Middle -Dogs	Share Gainer	Share Gainer
12	Profit Strategies	Maturity	Average	Middle -Dogs	Share Loser	Middle -Dogs	Middle -Dogs	Share Loser	Share Loser
94.01	Market Concentration	Maturity	Weak	High-Dogs	Share Gainer	High-Dogs	Middle -Dogs	Share Holder	Share Loser
02	Market Concentration	Maturity	Weak	Cash Cows	Share Gainer	High-Dogs	High-Dogs	Share Gainer	Share Gainer
03	Market Concentration	Maturity	Weak	Middle-QM	Share Loser	Low-Dogs	Middle-QM	Share Gainer	Share Loser
04	Market Concentration	Maturity	Weak	Stars	Share Holder	Low-Dogs	Stars	Share Holder	Share Holder
05	Market Concentration	Maturity	Weak	Cash Cows	Share Loser	High-Dogs	Cash Cows	Share Gainer	Share Loser
06	Profit Strategies	Maturity	Average	Low-QM	Share Loser	Low-QM	Low-QM	Share Loser	Share Loser
07	Profit Strategies	Maturity	Average	Cash Cows	Share Gainer	High-Dogs	Cash Cows	Share Gainer	Share Gainer
08	Profit Strategies	Maturity	Average	Low-Dogs	Share Loser	Low-Dogs	Low-Dogs	Share Loser	Share Loser

CONCLUDING REMARKS

In this paper, we proposed a neural expert system capable of performing a backward inference so that strategic planning problems may be solved more effectively. The proposed neural expert system is designed to provide a "goal-seeking" inference function, based on combining the generalization capability of neural networks with an expert system. A prototype system has been developed to prove our approach. Its performance was illustrated with real life data of the automobile industry in Korea. However, much room exists for further research. In this respect, we are currently developing an improved version of the prototype system by incorporating what-if analysis, refined mechanisms of environmental analysis, competitor analysis, and advanced strategic planning models.

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