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A Knowledge-Based Fuzzy Post-Adjustment Mechanism: An Application to Stock Market Timing Analysis

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Abstract

The objective of this paper is to propose a knowledge-based fuzzy post adjustment mechanism so that unstructured problems can be solved more realistically by expert systems. Major part of this mechanism focuses on fuzzily assessing the influence of various external factors and accordingly improving the solutions of unstructured problem being concerned. For this purpose, three kinds of knowledge are used: user knowledge, expert knowledge, and machine knowledge. User knowledge is required for evaluating the external factors as well as operating the expert systems. Machine knowledge is automatically derived from historical instances of a target problem domain by using machine learning techniques, and used as a major knowledge source for inference. Expert knowledge is incorporated into fuzzy membership functions for external factors which seem to significantly affect the target problems. We applied this mechanism to a prototype expert system whose major objective is to provide expert guidance for stock market timing such as sell, buy, or wait. Experiments showed that our proposed mechanism can improve the solution quality of expert systems operating in turbulent decision-making environments.

1. Introduction

Recently, knowledge-based approaches to decision making have been widely acknowledged by researchers and practitioners in OR/MS (Operations Research/Management Science) fields. The role of domain-specific knowledge in expert systems is to provide intelligence which is comparable to that of algorithm in conventional decision support systems. Extensive use of expert systems

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has been observed in a wide variety of OR/MS applications including many unstructured problems such as strategic planning, factory planning and scheduling, financial planning, etc. Especially, we will deal with an issue of improving the expert systems performance in stock market timing (SMART), which is one of highly unstructured problems, by integrating three kinds of knowledge such as user knowledge, expert knowledge, and machine knowledge about SMART. We make such integration more systematically by introducing a fuzzy post adjustment (FPA) mechanism which is a fuzzy logic-based knowledge integration mechanism considering the characteristics of each knowledge type. To help understand our research intention more clearly, let us first overview the previous expert systems for stock investment decisions, which is not exhaustive but meaningful.

PMIDSS (Intelligent Decision Support System of Portfolio Management Decision Making) done by the New York University team (Lee and Stohr 1985) is concerned with investment timing and portfolio selection, and employs mixed knowledge representation schemes encompassing logic, directed network, frames and rules. The PMIDSS is characterized by its ability to support more than one domain such as investment timing, stock selection, and real estate investment, each of which requires different architecture and reasoning as well as model management. FOLIO (Cohen and Liberman 1983) works as a front-end for goal programming model which is capable of ensuring that selected portfolio satisfies sufficiently the investor's goal. If satisfied, it finally allocates the investor's assets to one or more funds of securities, rather than to individual stocks. To enhance system's acceptability, the FOLIO has two functions. The first is interview function which conducts an interview and produces many useful parameters such as tax bracket and proportion of current investments in equity. The second is a forward-chaining (or data-driven) production system which uses expert's heuristic inference rules to infer the investor's goal. Le Courtier developed by the Cognitive Systems Inc. is a rule-based system and commercially implemented expert systems for portfolio selection. The unique aspect of the Le Courtier is a powerful natural language interface. It accepts user's natural language as inputs and interprets them by parser, finally performing the functions with which the user wants to do. The Le Courtier recommends stock purchases, answers factual questions, explains financial terms, responds to statements of personal preferences regarding stock purchases, and analyzes and reviews a large number of accounts. PMA (Portfolio Management Advisor) developed by the Athena Group (1987) advises professional portfolio managers in the construction and maintenance of investment portfolios. The PMA composed of knowledge base, a cognitive interface allowing 'what if' scenarios, and financial planning heuristics provides qualitative reasoning alongside numerical portfolio management methods. ISPMS (Intelligent Stock Portfolio Management System) developed by Lee et al (1989) has three features such as knowledge acquisition by learning-from-example technique, integration of an expert's knowledge with personal preference, and integration of knowledge and preference with the quadratic programming model.

To summarize the discussion mentioned so far, there exist a wide variety of commercial expert systems for supporting stock investment. They all have knowledge base which is composed of domain-specific rules extracted from experts or literature. However, the expert systems reviewed above do not include a formal mechanism for incorporating the effects of external factors that might affect the expert systems performance. They have only conventional uncertainty management methods such as confirmation theory, Bayesian and Dempster-Shafer's models (Buchanan and Shortliffe 1984). Therefore, fuzziness involved in various types of external factors cannot be fully incorporated into the inference process. In this paper, we will focus on considering the influence of external factors involved in the inference process of stock market timing expert systems. The environment within which expert systems work could critically affect the systems performance. If the turbulence of the environment is very high, expert systems may become even inoperative. Therefore, ways to incorporate the effects of the environment into the operative scheme of expert systems must be performed prior to or in parallel with expert systems design. This fact, however, has not received much attention from AI researchers. Fuzzy expert systems are recently introduced to deal with the uncertainty and operative difficulties originating from dynamically changing environment (Zadeh 1983, Negoita 1985, Leung et al. 1989, Graham 1991). The goal of this study is to alternatively propose a knowledge-based FPA mechanism for fuzzily assessing the influence of external factors (expert knowledge) and using it in the inference process of expert systems (user knowledge and machine knowledge). In other words, we will show that it is possible within the framework of knowledge-based FPA mechanism to integrate both human knowledge (user knowledge and expert knowledge) and machine (or computer) knowledge to improve the performance of SMART expert systems.

The SMART problem is famous for its high level of uncertainty and fuzziness (Pring 1985, Braun and Chandler 1987), so that the theoretical or experimental results can be considered as a milestone for similar research works. Specifically, since the stock market environment generically includes many dynamic factors such as economic, social, political, and institutional factors, forecasts for each factor are important to the operative performance of SMART expert systems. Our focus is then on empirically showing that the performance of SMART expert systems can be significantly improved with the knowledge-based FPA mechanism. In the sequel, "performance" indicates the rate of correctly performing the SMART task.

The structure of this paper is as follows. Section 2 discusses the nature of a SMART problem. Operational characteristics of knowledge-based solution are presented in section 3 and procedures of knowledge-based FPA mechanism are given in section 4. Detailed description of experiments is presented in section 5, and this paper is ended with concluding remarks including some further research topics.

2. Target problem

In this section, we will discuss the nature of SMART problem. The SMART problem is basically related to buy-decision or sell-decision in the (stock) market to maximize profits through trading stocks. In the stage of upward trend, investors will want to know when the market turns its trend into downward direction because they want to sell stocks at that point. Contrarily, in the stage of downward trend, investors try to forecast the point at which the market tends to change into upward trend because they want to buy stocks at that point. The SMART problem, therefore, requires a precise interpretation of market behaviors to make decision about when to buy or sell stocks. In this study, three kinds of SMART strategies are considered: Buy, Sell, and Wait. The SMART problem above contains the following two characteristics that make its solution process complex.

〈Inconsistency〉

The SMART-related knowledge or heuristics is inconsistent due to the complex dynamics surrounding the market. For example, though experienced investors usually possess their own expertise about the SMART problem which they believe "certain and time-proven", it becomes ineffective or even useless in some unexpected situations like new government policy and structural change in economics, etc. This inconsistency of the SMART-related human expertise naturally requires the use of machine knowledge which is more consistent and adaptive to new situations. The machine knowledge may be obtained by inductive learning techniques such as ID3 (Quinlan 1986).

〈Uncertainty〉

In the SMART analysis, it is often necessary to make decisions based on uncertain information for several reasons. First, most of the information about listed companies cannot be verified until they announce formal opinion. Secondly, interpretation of news background floating in the market may differ from investor to investor. Thirdly, effects of macro factors such as politics, economics, etc. are hard to estimate due to their stochastic properties. This kind of uncertainty leads to the use of fuzzy set-based approximate reasoning (Zadeh 1983).

The characteristics of the SMART decision problem mentioned above forces us to use a fuzzy logic-driven approach to enhancing the quality of expert systems for solving the SMART problem. In this respect, we propose a knowledge-based FPA mechanism which will be extensively discussed in section 4.

3. Knowledge-based solution

The knowledge-based solution considered in this paper is majorly based on the machine knowledge which is derived from the previous SMART instances by using inductive learning technique (Quinlan 1986).

The general knowledge acquisition method can be classified into two types: knowledge acquisition from expert and knowledge acquisition by inductive learning. In the first type of knowledge acquisition, the knowledge engineers obtain knowledge from domain experts and transform the knowledge into a form that can be manipulated by a machine. Experts about the SMART problem have their own time-proven knowledge, which is called expert knowledge. The knowledge, however, differs from each expert and is hard to be transformed into active inspectable form of performing high value work. The reasons are:

(1) It is based on personal judgment or experience which may be subject to changes in turbulent environment, thereby showing inconsistency.

(2) In general, human experts cannot remember all the important facts related to the SMART problem. They are accustomed to using only small part of those facts that occurred heretofore, resulting in SMART strategy that is imprecise or biased in some aspects.

(3) Expert knowledge is critically dependent on personal tastes. For example, in SMART cases, one may prefer price-related information and the others prefer trade volume-related information. Some may adhere to combined use of price and trade volume information. Considering these pitfalls of expert knowledge, we limit the use of expert knowledge only to building up fuzzy membership functions for various external factors.

In the second type of knowledge acquisition, machine (or computer) automatically generates knowledge with the past instances of application domain, which is called machine knowledge. It is verifiable and rather objective than expert knowledge. In this study, machine knowledge will be majorly used for inference. Although Braun and Chandler (1987) have also experimented the performance of inductive learning approach (or learning from example approach) to the stock market prediction, they considered only use of machine knowledge, ignoring synergistic effects expected from integrating three types of knowledge (i.e., user, machine, and expert knowledge) and FPA mechanism.

4. Knowledge-based fuzzy post-adjustment mechanism

4.1. Background

When trying to solve unstructured problems, we must deal with a large number of information which is interrelated with each other. Some information supports other information or degrades another kind of information. Therefore, we should always be ready to update our original solution when another important but overlooked information is available for our decision-making perception. This is called *opportunism*. Problem solving activity by opportunism is consistently directed toward revising the current problem-solving state when new knowledge or information is observed (Ow and Smith 1987). This opportunism concept is, therefore, suitable for solving the SMART problem. The reasons are:

(1) Information used in the SMART-solving process includes uncertainty and fuzziness, which requires a user's judgment about its usefulness.

(2) A wide variety of conditions surrounding the market always change and move together in a very complicated way to influence the market trend.

(3) Technical indicators (Pring 1985) conventionally used in solving the SMART problem are derived from the historical price and trade volume data. They provide a rough outlook about the market trends to come.

However, without a fuzzy-logic based formal mechanism which guarantees that such opportunism-based problem solving activity yields more improved solution, the SMART problem rich in uncertainty and fuzziness cannot be solved satisfactorily. In this sense, we propose the FPA mechanism to specifically apply the opportunism concept to the SMART problem-solving process (Lee 1991). The main recipe of FPA is that a tentative conclusion derived from the machine knowledge is adjusted by the amount of fuzzy evaluation about external factors affecting the SMART problem-solving process. With this post-adjustment process, the original knowledge-based conclusion or belief can be refined enough to have a real and/or practical sense, which is essential for the successful operation of expert systems dealing with unstructured problems. Pattern recognition-based learning technique was applied to stock market forecasting (Felsen 1975), but it did not consider fuzzification of external factors about stock market and post-adjustment of the knowledge-based strategy.

4.2. External

In this paper, we consider macro external factors surrounding the market, which are fixed for simplicity to four and treated as fuzzy factors to be fuzzified- economy prospects (EP), stock supply and demand (SSD), the amount of currency in the market (AOC), and conditions favorable or unfavorable to market (CFU). EP means forecast about economic situation in the future, which is determined by composite effects of export, GNP, and inflation, etc. SSD is subject to change with capital-increase of listed firms, new list of stocks, institutional investor's investment activities. AOC is determined by four factors: bond yield, call rate of interest, the amount of depositing funds, and monetary policy of government. CFU majorly includes domestic or international political situations (regardless of domestic or international) and news background, which may influence the market movements.

4.3. Fuzzy membership function

To process those four external factors more effectively, we use triangular membership functions. Expert knowledge about the four factors is represented in built-in fuzzy membership functions using verbal expressions. Therefore, a membership function (MF) is required for each factor. Each MF is based on two fundamental linguistic variables such as good and bad. Fuzzy modifiers considered are very and not, and then linguistic variables that can be used in each MF are *very good, good, not good (or not bad), bad,* and *very bad.* Accordingly, expert judgment is expressed in one of five discrete values including 0 (*very bad*), 1 (*bad*), 2 (*not good or not bad*), 3 (*good*), and 4 (*very good*). User knowledge about each factor is incorporated into the built-in MFs above, providing composite fuzzy evaluation of the corresponding factors.

4.4. FPA process

Let us describe the process of knowledge-based FPA mechanism. To test the performance of knowledge-based FPA mechanism, we will consider predicting the four types of stock market stages: Bull stage, Edged-up stage, Edged-down stage, Bear stage. Bull stage and Bear stage indicate a strong upward trend and a strong downward trend, respectively. Similarly, Edged-up stage and Edged-down stage mean a weak upward trend and a weak downward trend, respectively.

Therefore, SMART problem of this paper can be restated as predicting the market stage in the next period. It is worth noting that the period considered in our experiments is a "week" because we use the weekly data. Therefore, the goal of this paper is to show that the performance of SMART problem-solving expert systems could be significantly improved by the proposed knowledge-based FPA mechanism.

For simplicity, let UK, EK, MK denote user knowledge, expert knowledge, and machine knowledge, respectively. We assume that UK is derived from a average (random) user who represents a rational and unbiased decision maker. In specific, we will limit our discussion of knowledge integration based on FPA mechanism to (UK+EK)+MK case, where '+' denotes integration, because (1) this is most general case for integrating UK, EK, MK, (2) MK is handled separately from other two knowledge types and, (3) UK and EK respectively indicate user's and expert's judgment about external factors. Therefore, (UK+EK)+MK indicates that UK is combined with EK and then its result is integrated with MK. Even if UK does not exist, this description can be directly applied to the case of (EK+MK). Theoretical aspects of (UK+EK)+MK are divided into the following two steps.

[Step 1] UK+EK: Procedure of combining UK and EK

Assume that UK and EK have membership functions $\mu_U(x)$ and $\mu_E(x)$ respectively. Let each membership function $\mu(x)$ be a triangular membership function (c, w) where c means central value and w means width. The compositional rule of inference is then to solve the relational equation MAXMIN $\{\mu_U(x), \mu_E(x)\}$. If the four external factors prove to have the values x_1, x_2, x_3, and x_4, the fuzzy membership values are accordingly f_1, f_2, f_3, and f_4. The integration-score is then calculated by summing x_i's multiplied by normalized f_i's. If UK does not exist, then the integration-score means the average of central values of EK. The following procedures suggest how to integrate UK and EK:

(1) For all external factors, assume that the width of EK is 1 stage and also that the width of UK is 1 stage (experienced level), 2 stages (medium level), and 3 stages (beginner level). The judgment whether a user is experienced or medium or beginner is entered by the user. If the user judges that he is experienced, the quality of his judgment about factors is assumed to be same as that of the expert judgment.

(2) Suppose that an average (random) user belongs to medium level. Then UK has a triangular membership function $\mu_U(x_i, 2)$ and EK has $\mu_E(y_i, 1)$ for ith external factor, where there are four factors. The solution z_i is obtained by MAXMIN $\{\mu_U(x_i, 2), \mu_E(y_i, 1)\}$ where z_i has real value ranging form 0 to 4. Then z_i has a corresponding fuzzy value f_i with the triangular MF.

(3) The integration-score S is then derived from the equation

$$S=\sum_i z_i * (f_i/\sum_j f_j)$$

where i, j=1, 2, 3, 4. When UK does not exist f_i becomes 1/4.

[Sep 2] (UK+EK)+MK : Procedure of combining (UK+EK) and MK

The final score S resulting from combining UK and EK(i.e., UK+EK) has 5 stages and MK has 4 stages. To integrate UK+EK and MK, therefore, the score S from (UK+EK) must be transformed into 4 staged-value by one-to-one mapping as follows:

$$T=(3/4)* S+1.$$

Let $\mu_T(x)$ and $\mu_M(x)$ denote respectively membership function of the transformed score of (UK+EK) and MK where x belongs to 4 staged-values. Assume that they have the width of 2 stages. The MAXMIN principle is employed to obtain an optimal solution. The following two procedures suggest how to integrate (UK+EK) and MK practically:

(1) Transform the final score S of UK+EK into four-staged value T.

(2) The final solution from combining (UK+EK) and MK is obtained by solving MAXMIN $\{\mu_T(t, 2), \mu_M(m, 2)\}$ where the solution is one of discrete 4 staged-values. The fuzzy value of the final solution means a belief level for consistency of UK+EK and MK.

Here is an illustrative example to clearly understand the theoretical aspects of knowledge-based FPA process above. Suppose that expert judgment for each external factor EP, SSD, AOC, CFU is respectively good(3), very good(4), good(3), and not good(2). Also assume that user's evaluation for each factor is respectively good(3), good(3), bad(1), and bad(1) with an experienced level of user's quality. Based on these information, we can figure out the triangular membership functions as in the following:

Figure 1 : Membership function for EP factor

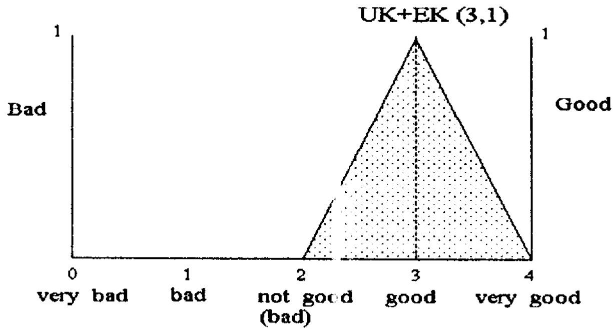


Figure 2 : Membership function for SSD factor

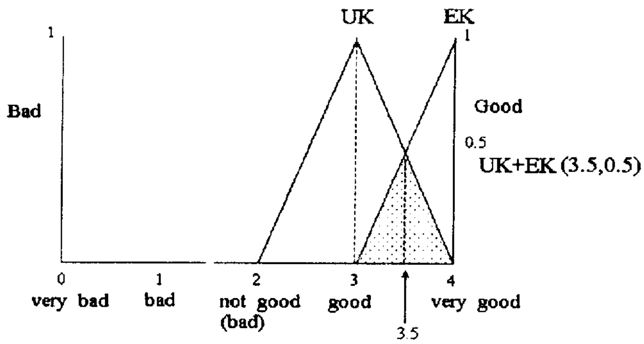


Figure 3 : Membership function for AOC factor

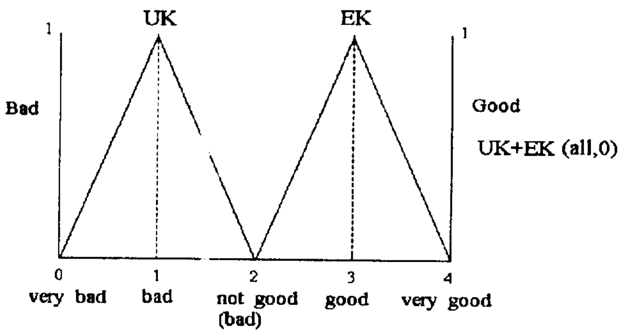
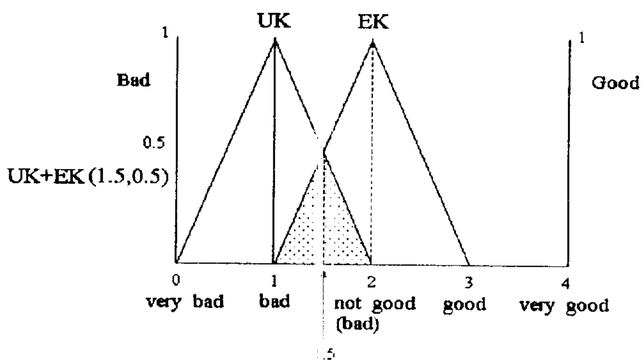


Figure 4 : Membership function for CFU factor



Therefore, the maxmin principle generates 3(1), 3.5(0.5), 0(0), and 1.5(0.5) where the corresponding fuzzy value is in parenthesis. The normalized and weighted sum (S) is

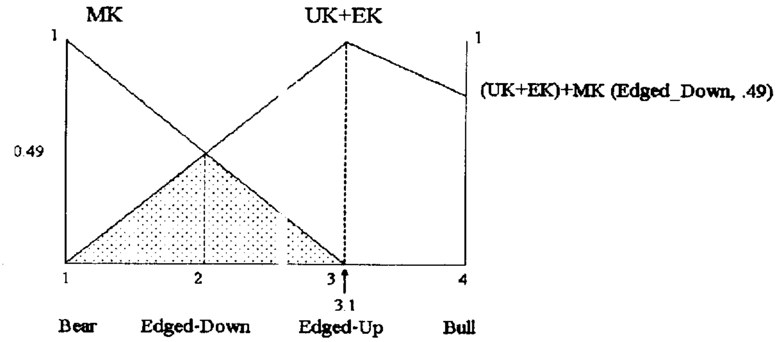
$$S = 3*(1/2) + 3.5*(0.5/2) + 0*(0/2) + 1.5*(0.5/2) = 2.8$$

The sum may be 3 when UK does not exist, while it may be 2 when EK does not exist. For S=2.8, the transformed value T is then obtained as

$$T = (3/4)*2.8 + 1 = 3.1$$

The transformed value 3.1 means that UK+EK is above the outcome "Edged-Up" stage. Assume that the outcome from machine knowledge is "Bear" stage. Let the width of membership function be 2 stages. Then the triangular membership function can be depicted as follows:

Figure 5: Membership function for (UK+EK)+MK



By applying the maxmin principle, we obtain

Max{ (Bear, 0), (Edged-Down, 0.49), (Edged-Up, 0), (Bull, 0)}.

The optimal solution is then an outcome "Edged-Down" stage. Therefore the machine knowledge-based SMART forecast is fuzzily post-adjusted by knowledge-based FPA mechanism from original prediction "Bear" to "Edged-Down".

5. Experiments

5.1. Data

To obtain training and test data for experiments, we used five technical indicators such as MD (Moving average Disparity), PD (Price Disparity), PCR (Price Change Ratio), VD (Volume Disparity), PR (Psychology Rate). Formula for each of them is as follows:

MD = (6 day moving average of KOSPI / 50 day moving average of KOSPI) * 100
PD = (KOSPI / 25 day moving average of KOSPI) * 100
PCR = (positive KOSPI change / (positive KOSPI change + negative KOSPI change)) * 100
VD = (6 day moving average of volume / 25 day moving average of volume) * 100
PR = (days of positive KOSPI change / 12 days) * 100

where KOSPI means Korea Stock Price Index. MD, PD, and VD are related with the power of the market to go upward or downward trend. In other words, if VD is high, then the amount of short-term trade volume data overrides that of mid-term trade volume data. Then the power of the market is enough to go upward trend in a short-term period. In a similar way, MD and PD can be interpreted. PCR and PR describes the power of the market in terms of price.

That is, if PCR or PR is high, then it means that the (stock) price will go upward in the near future. Any combination of technical indicators does not matter for our research purpose because the objective of this study is to show the reasoning process of the proposed knowledge-based FPA mechanism. In addition to the five technical indicators above, there exist a wide variety of technical indicators (Pring 1985)

To obtain the five technical indicators above, we collected a weekly data set of Korea Stock Price Index (KOSPI) and Volume from Jan. 1988 to Dec. 1992, of which 127 weeks turned out bear phases and 109 weeks bull phases. Determining whether a week is bearish or bullish is based on comparing the price of current week with that of previous week. Learning period is from January 1988 to December 1989 consisting of 94 weeks (45 bear-phased weeks and 49 bull-phased weeks), while testing period is from January 1990 to December 1992 composed of 142 weeks (82 bear-phased weeks and 60 bull-phased weeks). Technical indicators were obtained by applying formula above to those price and volume data gathered. We applied sigmoid function below to normalize the technical indicator values into values in (0, 1) because normalization facilitates computational process:

$$y=\frac{1}{1+e^{-(X-\mu)/\sigma}}$$

where y = transformed value,

x = original value,

μ = mean,

σ = standard deviation.

5.2. Sources of knowledge

〈Machine Knowledge〉

To obtain MK through ID3-based machine learning technique (Quinlan 1986, Jackson 1988), we first classified those technical indicators into three stages "Buy", "Wait", and "Sell", depending upon two different criteria such as (0.3, 0.6) for Bearish phase and (0.4, 0.7) for Bullish phase. For example, in case of Bearish phase, it is classified into "Buy" stage, "Wait" stage, "Sell" stage when its value falls in the range (1) [0.0, 0.3], (2) (0.3, 0.6), (3) [0.6, 1.0], respectively. Similar explanation can be applied to the cases of Bullish phase. Determination of either Bullish or Bearish phase depends on whether the price of previous week is less than or greater than that of current week. Also stage classification criteria may change in accordance with the investor's preference and judgment about the market movement.

Secondly, we classified outcome stages into four ones: Bear, Edged-Down, Edged-Up, Bull, depending on the criterion (−3%, 0%, +3%). If the KOSPI return of next week (computed with stock price) is greater than 3%, the corresponding outcome stage is classified as Bull. Similarly, Edged-Up, Edged-Down, Bear, when the KOSPI return is between 0% and 3%, between −3% and 0%, and less than −3%, respectively.

A concept of similarity score is employed in the case of data shortage and heterogeneous outcomes. It is similar to case-based reasoning with partial matching technique. The membership concept is applied to calculating the "feature matching-score" between new case and case base. The case score is computed by the sum of the feature scores. It may be normalized for convenience. For example, we employed the following membership matrix instead of membership function (Figure 6). The column vectors of "Buy", "Wait", and "Sell" play roles of membership function because the stages are of discrete features. Assume that 5 technical features have 3 stages and each outcome has 4 stages.

Figure 6. Membership Matrix for Case-Based Reasoning

		Stage of a case		
C B		buy	wait	sell
A A	buy	1.0	0.5	0.0
S S	wait	0.5	1.0	0.5
E E	sell	0.0	0.5	1.0

Case Base : $B_i(C_{i1}, C_{i2}, C_{i3}, C_{i4}, C_{i5}, O_i)$

ith case base (rule) with 5 feature types and O_i outcome.

New Case:

kth new case with 5 feature types and O_k outcome (unknown).

CS(i, k), which is the case score between B_i, and N_k, is obtained through the following three steps. Suppose that the feature sets of case base and new case are respectively (b, b, w, s, b) and (w, b, b, b, w). Also let the match-weight and the mismatch-weight be 1.0 and 0.0.

Step 1 : Calculation of feature score by membership matrix.

The feature scores of MD, PD, PCR, VD, and PR are 0.5, 1.0, 0.5, 0.0, and 0.5, respectively.

Step 2 : Calculation of similarity score by summing feature scores.

The similarity score is then 0.5 + 1.0 + 0.5 + 0.0 + 0.5 = 2.5.

Step 3 : Calculation of case score by normalization.

The case score is 2.5/5.0 = 0.5, where 5.0 is the total sum of feature scores. Therefore, CS(i, k) becomes 0.5. The exact matching indicates that CS(i, k) is 1.

The decision function may be considered for predicting unknown O_k.

$$D(k) = \text{maximize } CS(i, k) = O_k^*,$$

where D(k) is a decision function of kth case. If D(k) has only one decision, O_k^* is decided as an optimal solution on the basis of MK through exact or partial matching process described above. If D(k) has multiple decisions, we search O_k^* stage adjacent to the average of multiple decisions. It is because outcome stages are discrete and ordinal.

〈Expert Knowledge〉

EK is obtained through expert judgment about the four external factors which were collected from fund managers and weekly investment guide magazine. Scoring these factors into one of 0 (very bad), 1(bad), 2(not good or not bad), 3(good), 4(very good) is needed for EK to be appropriately incorporated into the decision making process.

〈User Knowledge〉

UK depends on user's tastes and/or preference. Therefore, we assume average (random) user to avoid any kind of subjective biases in the process of experiments. During experiments, UK interprets trend of technical indicators or evaluates specific external factor.

Deviation	Bear Phase			Bull Phase			Total		
	UK	MK	MK+EK	UK	MK	MK+EK	UK	MK	MK+EK
0	21(25)	21(25)	33(40)	15(25)	19(32)	24(40)	36(25)	40(28)	57(40)
1	34(42)	44(54)	38(46)	22(37)	22(37)	24(40)	56(40)	66(47)	62(44)
2	21(25)	17(21)	11(14)	15(25)	16(26)	9(15)	36(25)	33(23)	20(14)
3	6(8)	0(0)	0(0)	8(13)	3(5)	3(5)	14(10)	3(2)	3(2)
Average Deviation	1.16	0.96	0.74	1.26	1.04	0.85	1.20	0.99	0.78
Sum	82(100)			60(100)			142(100)		

Table 1. Summarized Results of FPA with Three Knowledge Sources

5.3. Results

We will show empirical results comparing the FPA performance with the use of three kinds of knowledge: UK, EK, and MK. Table 1 summarizes empirical results of three kinds of knowledge-based FPA in the two cases of Bull phase and Bear phase, where the figure in parenthesis represents column percentage. Also UK column means UK-based FPA results, MK-based FPA results, (MK+EK)-based FPA results. Deviation indicates the degree of difference from actual outcome stage. For example, deviation 0 means that system-guided outcome stage correctly predicts actual outcome stage.

MK+EK column assumes that UK-based FPA makes no decision for four external factors as if UK does not exist. It is difficult to define UK because there exist a wide variety of users showing different tastes of investment. Therefore we assumed average (random) user to avoid any kind of subjective biases in the process of experiments. To show the theoretical calculation employed in UK column, let p, p, p, p respectively denote proportion of four outcome stages in the experimental period: Bear, Edged-Down, Edged-Up, Bull. By definition, sum of p through p becomes 1. Then the probability of outcome stages for each deviation can be computed theoretically as follows:

if Deviation = 0, then $P = (1/4)*(p1+p2+p3+p4) = 1/4$
if Deviation = 1, then $P = (1/4)*(p1+p4) + (2/4)*(p2+p3)$
$= 1/4 + (1/4)*(p2+p3)$
if Deviation = 2, then $P = (1/4)*(p1+p2+p3+p4) = 1/4$
if Deviation = 3, then $P = (1/4)*(p1+p4)$

Our test period has the distribution as follows

Phase	P_1	P_2	P_3	P_4
Bear Phase	.22	.35	.33	.10
Bull Phase	.25	.33	.15	.27
Total	.23	.35	.25	.17

5.4. Discussion

Based on the amount of average deviation shown in Table 1, we obtained the following findings:

(1) For all kinds of knowledge, the performance in Bear phase surpasses the performance in Bull phase. This is due to data sensitivity and knowledge sensitivity. The former depends on the data structure in experimental period and the latter on the knowledge structure used in experiment. The ratios between average deviations of Bear phase and Bull phase are 0.921(UK), 0.923(MK), and 0.871(MK−EK). Three phase-ratios are below 1.0. This seems to indicate that the current system is going to show more accurate prediction when the market trend changes downward than when the market trend is in the upward direction. But the phase-ratio of UK may be affected by data structure in a specific time do-

main, not by knowledge structure. The fact that the phase-ratio of UK is similar to that of MK indicates that a significant phase sensitivity exists only in EK.

(2) For all phases and total, however, MK always shows better performance than the single use of UK and MK+EK better than MK which indicates that UK<MK<MK+EK. Therefore we can conclude that combining MK and EK results in more efficient knowledge type which can robustly meet the market turbulence.

(3) Since it is natural and logical that the performance with UK is lower than that with EK, we can obtain the following first relationship

UK<UK+MK<(UK+EK)+MK<MK+EK.

where '+' denotes 'integrated use' and parenthesis indicates that two types of knowledge are first integrated and then used. Therefore (UK+EK) means that two types of knowledge UK and EK are integrated for the combined use. The reason why UK is first integrated with EK, not with MK is twofold: (1) both UK and EK require human thought and judgment and (2) not only the number of knowledge in MK can be reduced by manipulating the data instances but also it is easy to apply fuzzy concept. Anyway, this relationship leads to the second relationship:

UK<UK+MK<MK<MK+EK.

Therefore we can conclude that

1) performance with UK-based FPA may be improved by MK and EK.
2) performance with MK-based FPA may be improved by EK.
3) performance with (UK+MK)-based FPA may be improved by EK.
4) MK and (UK+EK) + MK have no preference order.

Through the empirical tests above, we proved that there exist at least one MK or EK which is superior to UK. Therefore, the performance with UK may be improved by incorporating the single or combined use of MK and EK. This indicates that the efficiency of the FPA concept proposed can be verified provided that there exists either MK or EK of good quality. It is noteworthy that either MK or EK means one among the infinite number of possible MKs or EKs, indicating that incorporating a certain MK or EK into the decision making process results in better performance than the single use of average UK. However, since UK used herein is limited to follow the average concept, there might exist such a UK which surpasses MK and EK.

Those experimental results shed a promising light on the expert systems design such that the knowledge-based FPA mechanism is useful for integrating MK and EK in a synergistical way. In other words, the performance of expert systems could be improved by combining MK with EK within the proposed FPA mechanism.

6. Concluding remarks

This paper proposed a knowledge-based FPA mechanism to improve the quality of expert systems solution. It is based on three kinds of knowledge: user knowledge, expert knowledge, and machine knowledge. By integrating these kinds of knowledge, the knowledge-based FPA mechanism helps to fuzzily incorporate the possible influence of external factors and provide more improved solution. After applying to the SMART problem, we concluded that the proposed knowledge-based FPA mechanism using both machine knowledge and expert knowledge can aid in enhancing the quality of expert systems solution significantly. We are now developing a more advanced method of intelligently solving SMART problem by using both fuzzy neural networks and fuzzy cognitive map.

7. References

[1] BRAUN, H and J. S. CHANDLER (1987), Predicting Stock Market Behavior through Rule Induction: An Application of the Learning-from-example Approach', *Decision Sciences,* 18, pp. 415-429.

[2] BUCHANAN, B. G. and E. H. SHORTLIFFE (1984), Rule-Based Expert Systems, *Addison-Wesley,* 1984.

[3] COHEN, P. R. and M. D. LIBERMAN (1983), 'A report on FOLIO: An Expert Assistant for Portfolio Managers, '*Proceedings of the International Joint Conference on Artificial Intelligence,* pp. 212-214.

[4] *The Courtier System,* Cognitive Systems Inc.

[5] FELSEN, J. (1975), 'Learning Pattern Recognition Techniques Applied to Stock Market Forecasting', *IEEE Transactions on Systems, Man, and Cybernetics,* 5, pp. 583-594.

[6] GRAHAM, I. (1991), 'Fuzzy Logic in Commercial Expert Systems-Results and Prospects', *Fuzzy Sets and Systems,* 40, pp. 451-472.

[7] JACKSON, A. H. (1988), 'Machine Learning, *Expert Systems,* 15, pp. 132-150.

[8] LEE, J. B. and E. A. STOHR (1985), 'Representing Knowledge for Portfolio Management Decision Making', *Proceedings of 2nd Conference on Artificial Intelligence Applications,* Miami.

[9] LEE, J. K., S. C. CHU and H. S. KIM (1989), 'Intelligent Stock Portfolio Management System', *Expert Systems,* pp. 74-87.

[10] Lee, K. C. (1991), 'Fuzzy Post-Adjustment of Knowledge-Based Solution', *Proceedings of International Fuzzy Engineering Symposium,* Yokohama (Japan).

[11] LEUNG, K. S., W. S. F. WONG and W. LAM (1989), 'Applications of a Novel Fuzzy Expert System Shell', *Expert Systems,* 6 (1), pp. 2-10.

[12] NEGOITA, C. V. (1985), *Expert Systems and Fuzzy Systems,* The Benjamin/Cummings Publishing Company.

[13] OW, P. S. and F. SMITH (1987), 'Two Design Principles for Knowledge-Based Systems', *Decision Sciences,* 18, pp. 430-447.

[14] PRING, M. J. (1985), *Technical Analysis Explained,* McGraw-Hill.

[15] THE ATHENA GROUP (1987), 'Portfolio Management Advisor', *Expert Systems,* 4, p. 54.

[16] QUINLAN, J. R. (1986), 'Induction of Decision Trees', *Machine Learning,* 1, pp. 81-106.

[17] ZADEH, L.A. (1983), 'The Role of Fuzzy Logic in the Management of Uncertainty in Expert Systems', *Fuzzy Sets and Systems,* 11, pp.199-227.