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Synthesis of Machine Knowledge and Fuzzy Post-Adjustment to Design an Intelligent Stock Investment System

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Abstract

This paper proposes two design principles for expert systems to solve a stock market timing (SMART) problems : machine knowledge and fuzzy post-adjustment. Machine knowledge is derived from past SMART instances by using an inductive learning algorithm. A knowledge-based solution, which can be regarded as a prior SMART strategy, is then obtained on the basis of the machine knowledge. Fuzzy post-adjustment (FPA) refers to a Bayesian-like reasoning, allowing the prior SMART strategy to be revised by the fuzzy evaluation of environmental factors that might affect the SMART strategy. A prototype system, named K-SISS2 (Knowledge-based Stock Investment Support System 2), was implemented using the two design principles and tested for solving the SMART problem that is aimed at choosing the best time to buy or sell stocks. The prototype system worked very well in an actual stock investment situation, illustrating basic ideas and techniques underlying the suggested design principles.

1. Introduction

In the last decade, significant change has been observed in problem-solving perspective in the fields of management science, that is, a shift away from general purpose algorithmic approaches to the use of problem domain-specific knowledge. In the fields of expert systems, this new perspective has been used most extensively, allowing a wide variety of related researches and softwares to use more flexible and heuristic knowledge specific to target problems [13]. However, designing expert systems is nontrivial and requires very complex expertise [9], especially for the case of unstructured problems which are difficult to resolve due to their complex

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heuristics and existence of various factors affecting the solution process.

In this paper, two design principles are proposed for designing expert systems aimed at solving a SMART problem, one of the highly unstructured problems. The design principles are (1) machine knowledge which allows a knowledge-based SMART strategy in an objective way and (2) fuzzy post-adjustment by which environmental factors affecting the SMART problem solving process are fuzzily evaluated and the knowledge-based SMART strategy is revised accordingly. The principles proved very useful in dealing with fuzziness and uncertainty intrinsically included in the SMART problem. To the best of our knowledge, this study seems the first attempt to explicitly propose the fuzzy post-adjustment of knowledge-based solution and then apply the FPA technique to the design of expert system aimed at solving the SMART problem which shows typical characteristics of unstructured problems.

In the next section we will describe the nature of the SMART problem and then discuss the two proposed design principles in detail. We will also address the particular design features of a prototype system, K-SISS2, and give an overview of how it works in an experimentally designed situation.

2. The SMART Problem

2.1 Nature

The SMART problem is basically related to buy-decision or sell-decision in the (STOCK) market to maximize profits in trading stocks. In the stage of upward trend, investors will want to know when the market turns its trend into downward direction because they are willing 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, four kinds of SMART strategies are considered : ***Buy***, ***Sell***, ***Hold***, and ***Wait***. ***Buy*** and ***Sell*** may be interpreted literally, while ***Hold*** means that an investor should hold the current stocks without any investment actions and ***Wait*** indicates that he should prepare for taking ***Buy*** or ***Sell*** action. By adding ***Hold*** to SMART strategy, we can avoid making impatient SMART action. The SMART problem above contains the following two characteristics that make its solution process complex :

(1) ***Inconsistent human experitse***. 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 such as 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 can be obtained by applying inductive learning [11, 12], which is one of the artificial intelligence techniques, to historical SMART instances. This learning technique helps maintain most-updated knowledge suitable for solving SMART problem in current market situations.

(2) *Incomplete information*. In the SMART analysis, it is often necessary to make decisions based on incomplete information for several reasons. First, most of the information about listed companies cannot be verified until they announce formal opinion about it. Secondly, the investors' interpretation of the news background floating in the market may differ from each other. Thirdly, it is hard to estimate the effects of the changes in domestic/international political and socio-economical factors because of their stochastic properties. This incompleteness leads to use of fuzzy set-based approximate reasoning [15].

2.2 Unstructuredness

Decision problems in the fields of managemet science can be majorly grouped into two types : (1) structured decision problems that can be expressed as a set of steps to follow, a flowchart, a decision table, or formulae, and therefore the solution procedures may be preplanned or prespecified, and (2) unstructured decision problems that have no preestablished decision procedures because the related decision process is too changeable to allow us to preestablish a stable decision procedure. The SMART decision problem belongs to the unstructured decision problems due to the nature mentioned above. This typical unstructuredness of the SMART problem leads us to consider the design principles described in the next section that we employed in prototyping an expert system for solving the SMART problem.

3. Two Design Principles

3.1 Machine Knowledge

Experts of the SMART problem have their own time-proven knowledge, which is called in this study ***human expertise***. Even in a group of experts, however, their expertise is different from each other, and it is hard to transform the expertise into an active inspectable form that can be used in performing high value works. The reasons are :

(1) Human expertise is based on personal judgment or experience which may be subjective to change with turbulent environment and thereby shows inconsistency.

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

(3) Human expertise is critically dependent on personal tastes. That is, in building SMART strategy, one may prefer price-related information and others may prefer trade volume-related information. Some may adhere to combined use of price and trade volume information in SMART decision-making.

Meanwhile, the SMART-related data can also provide useful basis for forming a ***machine knowledge***, which is verifiable and more objective than human expertise. The effectiveness of machine knowledge can be revealed especially in data-rich situation : when a massive amount of historical data about specific SMART problems are given to a human expert, he cannot operate them effectively due to insufficient memory. But, if an inductive learning is applied to the data, then a set of machine knowledge can be extracted, which is compact and consistent with the given data. Therefore, integrated use of machine knowledge and human expertise may result in better performance than a single use of human expertise or machine knowledge. In addition, by combining these two knowledge sources, we can expect synergism in a sense that some situations unknown to the machine knowledge can be recognized by human expertise and vice versa, thereby enhancing the system performance. Braun and Chandler [3] proposed a learning-from-example approach to stock market prediction similar to SMART, but they considered only the use of machine knowledge and ignored synergistic effects expected from integrating machine knowledge and FPA.

3.2 Fuzzy Post-Adjustment

Problem-solving activity by nonmonotonic reasoning is consistently directed toward revising the current problem-solving state when new knowledge or information is observed [4, 8, 14]. Nonmonotonic reasoning is, therefore, suitable for solving the SMART problem which has the following situations :

(1) Information used in the SMART-solving process shows uncertainty and fuzziness, which requires a decision-maker (DM)'s judgment about its usefulness. This makes it impera-

tive to reason with imprecise knowledge.

(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[10] conventionally used in solving the SMART problem are derived from the historical price and trade volume data. They provide approximation about the market trends to come.

In this sense, we propose FPA mechanism to specifically apply the nonmonotonic reasoning concept to the SMART problem-solving process. The main recipe of FPA is that a tentative conclusion derived from the machine knowledge is adjusted by the amount of fuzzy evaluation of environmental factors affecting the SMART problem-solving process. With this post-adjustment process, the knowledge-based conclusion or belief can be refined enough to have a real and practical sense, which is essential for successful expert systems dealing with unstructured problems. Pattern recognition-based learning technique was applied to stock market forecasting [5], but it did not consider fuzzification of stock market's fuzzy factors and post-adjustment of knowledge-based strategy.

4. Design Methodology

In this section we describe the application procedures of the two design principles employed in the design of a prototype system for solving SMART problem, K-SISS2. We begin with the hybrid knowledge-based inference and then discuss fuzzy evaluation process of environmental factors affecting the SMART strategy, a primary step of incorporating the nonmonotonism into K-SISS2. Finally, detailed steps about post-adjustment or revision of the knowledge-based strategy are presented.

4.1 Machine knowledge-based inference

The inference procedure in K-SISS2 mainly uses a machine knowledge base. The machine knowledge is constructed by an inductive learning, an induction process for extracting definite rules from a large number of historical SMART examples. To illustrate the induction process, we present training examples shown in Quinlan [12].

Table 1. Training examples

No	Attributes				Class
	Outlook	Temperature	Humidity	Windy	
1	sunny	hot	high	false	N
2	sunny	hot	high	true	N
3	overcast	hot	high	false	P
4	rain	mild	high	false	P
5	rain	cool	normal	false	P
6	rain	cool	normal	true	N
7	overcast	cool	normal	true	P
8	sunny	mild	high	false	N
9	sunny	cool	normal	false	P
10	rain	mild	normal	false	P
11	sunny	mild	normal	true	P
12	overcast	mild	high	true	P
13	overcast	hot	normal	false	P
14	rain	mild	high	true	N

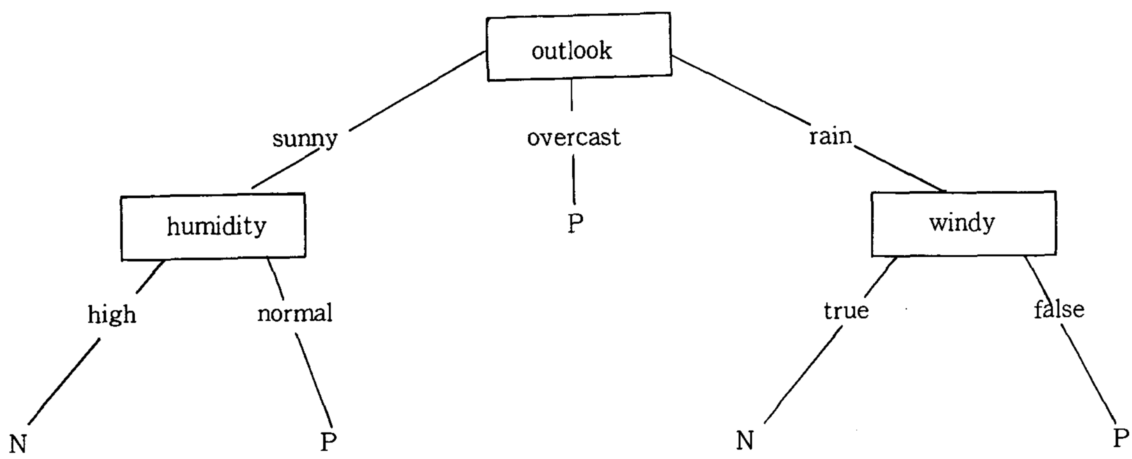

Figure 1. Decision tree by inductive learning

After applying inductive learning approach to the examples in Table 1, decision tree can be obtained as in the Figure 1. Organizing rules from Figure 1 yields machine knowledge in the following List 1.

List 1. Machine knowledge extracted from the training examples in Table 1

Rule 1 :	IF	outlook	= sunny
	AND	humidity	= high
	THEN	class	= N
Rule 2 :	IF	outlook	= sunny
	AND	humidity	= normal
	THEN	class	= P
Rule 3 :	IF	outlook	= overcast
	THEN	class	= P
Rule 4 :	IF	outlook	= rain
	AND	windy	= true
	THEN	class	= N
Rule 5 :	IF	outlook	= rain
	AND	windy	= false
	THEN	class	= P

Machine knowledge acquisition process above gives us several interesting implications about knowledge acquisition which has been regarded as a major bottleneck in developing expert systems. First, conversion from the decision tree to machine knowledge is intrinsically mechanical. Secondly, machine knowledge is consistent with all the examples. Thirdly, machine knowledge is compact and its size is also considerably small. The reasons are twofold : (1) redundancy asssociated with the examples is trimmed away by the information-theoretic filtering process of inductive learning [3, 11, 12], and (2) all the information hidden in a large number of examples is therefore condensed into the form of machine knowledge.

To construct the machine knowledge used in K-SISS2, we used five technical indicators such as SONA chart (SONA), ratio of price disparity (PD), price-volume composite indicator (PVCI), psychological ratio (Psy.), and ratio of volume disparity (VD). Refer to Lee [6] for detailed remarks about PVCI and see Pring [10] for the others. Excerpt of machine knowledge is shown in List 2. It is noteworthy that different from the four SMART strategies (buy, hold, wait, sell), the state of technical indicators in IF clause is classified into ***buy***, ***pause***, and ***sell***, where Pause means a wait-and-see strategy for calmly watching the market movement.

List 2. Excerpt of machine knowledge used in K-SISS2

RULE 34 :	IF	SONA	= Pause
	AND	Price_Disparity	= Buy
	AND	PVCI	= Buy
	AND	Volume_Disparity	= Buy
	THEN	Strategy	= Wait
RULE 35 :	IF	SONA	= Pause
	AND	Price_Disparity	= Buy
	AND	PVCI	= Buy
	AND	Volume_Disparity	= Pause
	THEN	Strategy	= Buy

4.2 Fuzzy Post-Adjustment

4.2.1 Motivation

When operating in a turbulent environment like stock market, the expert systems often yield solution that does not make sense, because environmental factors such as economics, political affairs, and regulations cannot be fully considered in building the KB of expert systems. This lack of information about environmental factors frequently causes so called a *mesa effect*, implying that expert systems cannot provide solution when the problem characteristics deviate even slightly from the originally expected problem domain. Recently, Lee [7] has suggested a neural network knowledge base to reduce the mesa effict. In this paper, a fuzzy set-logic approach is proposed to post-adjust the knowledge-based solution by evaluating the environmental factors surrounding the stock market.

4.2.2 Environmental factors

In this paper, environmental factors surrounding the market are fixed for simplicity to four and treated as fuzzy factors to be fuzzified : economy prospects (EF), stock supply and demand (SSD), the amount of funds affording to buy stocks (FAB), 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. FAB is determined by four factors : bond yield, call rate of interest, the amount of depositing funds, and monetary policy of government. CFU majorly includes political situations (regardless of domestic or international) and news background, which may influence the market movements.

4.2.3 Two-staged fuzzification

To process those four environmental factors more effectively, we used two-staged fuzzy resolution approach. In the first stage, expert's opinion 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***, then linguistic variables that can be used in each MF become ***very good***, ***good***, ***not good*** (or ***not bad***), ***bad***, and ***very bad***. Accordingly, expert's opinion is expressed in one of five integer values ranging from 1 (***very bad***) to 4 (***very good***), in which 3 represents a linguistic variable ***good***, 2 ***not good*** (or ***not bad***), and 1 ***bad***. To easily represent ***good*** or ***bad*** opinion in its sign (positive sign for ***good*** and negative sign for ***bad***), final MF for each factor is determined by subtracting ***very bad*** MF from ***very good*** MF, which makes corresponding membership value range from -1 to 1. In the second stage, DM's judgment about each factor is incorporated into the built-in MFs above, providing composite fuzzy evaluation of those factors surrounding the market. Advantages derived from combining expert's opinion with DM's own judgment are twofold : 1) it may prevent one-sided inference by expert's opinion from being directed toward extreme strategy against DM's intention or tastes and 2) the way of appropriately incoroprating DM's own opinion into expert's opinion is essential for proper reflection of DM's personal propensity to invest in building SMART strategies. It should be noted that expert's opinion about market environmental factors is limited to the Korea Stock Market case, but that it surely does not restrict the applicability of this two-staged fuzzification process to other cases.

4.2.4 Fuzzy evaluation

Now let us describe each membership function (MF) for the four environmental factors.

Economy prospects : Expert's judgment about this factor is that various internal or external factors surrounding Korea economy will collectively cast a gloom over its prospects in the near future. To incorporate this kind of expert's opinion about economy prospects into MF, corresponding MF is accordingly designed to be skewed to ***bad***. MF for ***good*** is formulated as Max($-1+0.5x$, 0) and MF for ***bad*** as Max($1-0.25x$, 0), respectively. Figure 2 shows graph of both ***bad*** and ***good*** MFs.

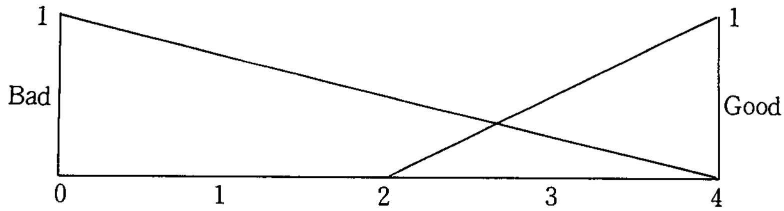

Figure 2. Membership function for "Economy Prospects"

Therefore, composite MF can be obtained by subtracting ***bad*** MF from ***good*** MF as the following :

$$\text{Composite MF for EP} = \begin{cases} -2+0.75x, & 2 \le x \le 4 \\ -1+0.25x, & 0 \le x < 2 \end{cases}$$

where a variable x represents DM's response ranging from 0 to 4.

Stock supply and demand : Experts agreed that stock supply will be reduced due to listed company's self-restraint to issue new stocks in order to boost the market's revitalization. MF for this factor is therefore skewed to ***good*** so that expert's opinion is represented into MF for SSD. MF for ***good*** is Max($0.25x$, 0) and MF for ***bad*** is Max($1-0.5x$,0), respectively. Figure 3 depicts two MFs.

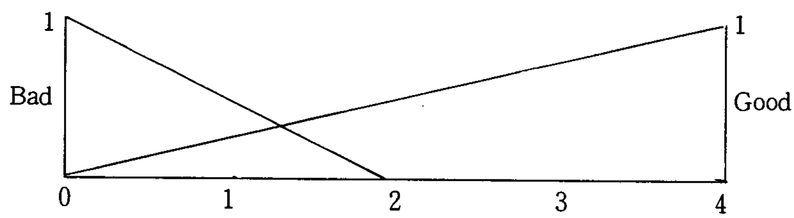

Figure 3. Membership function for "Stock Supply and Demand"

Composite MF is then obtained by "***good*** MF − ***bad*** MF", resulting in :

$$\text{Composite MF for SSD} = \begin{cases} 0.25x, & 2 \le x \le 4 \\ -1+0.75x, & 0 \le x < 2 \end{cases}$$

Amount of funds affording to buy stocks : Experts' general view about this factor is that market funds will undergo retrenchment due to overall economic decline and government's monetary regulation. This somewhat pessimistic forecasts about FAB factor leads us to design MF for FAB factor to be skewed to ***bad***. ***Good*** MF designed as $\mathrm{Max}(-1/3+x/3, 0)$ and ***bad*** MF as $\mathrm{Max}(1-x/4, 0)$. Figure 4 depicts two MFs.

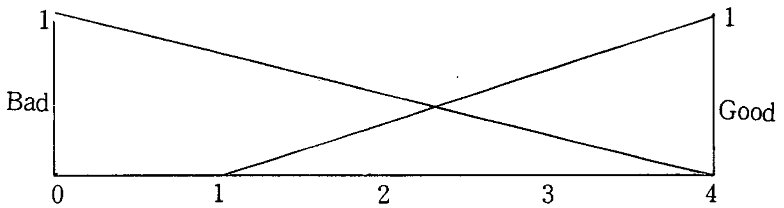

Figure 4. Membership function for "Amount of Funds Affording to Buy Stocks"

Composite MF is obtained by subtracting ***bad*** MF from ***good*** MF, yielding :

$$\text{Composite MF for FAB} = \begin{cases} -1.33+0.58x, & 1 \le x \le 4 \\ -1+0.25x, & 0 \le x < 1 \end{cases}$$

Conditions favorable or unfavorable to market : Experts agree that the effects of favorable conditions on market trends may be offset by those of unfavorable conditions. ***Good*** MF is $\mathrm{Max}(x/4, 0)$ and ***bad*** MF $\mathrm{Max}(1-x/4, 0)$. Therefore MF for this factor can be formulated as

$$\text{Composite MF for CPU} = -1+0.5x, \quad 0 \le x \le 4.$$

Figure 5 shows two MFs.

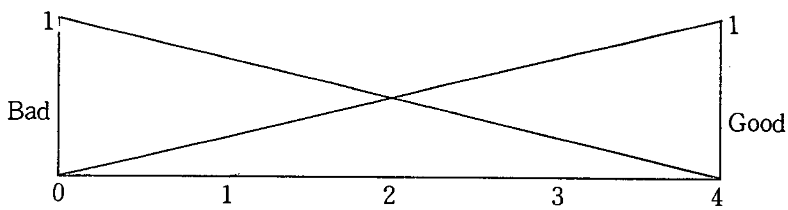

Figure 5. Membership function for "Conditions Favorable or Unfavorable to Market"

After all the fuzzy membership values (FMV) are computed for each fuzzy factor, it is necessary to organize these four FMVs into a single numerical value which represents expert's overall judgment about four fuzzy factors above. For this purpose, we used ***weighted average*** method in which appropriate weights are assigned to each factor according to its relative importance which is also determined by expert. In this paper, we simply assigned equal weight to each factor, that is, 0.25. In this way, a composite fuzzy membership value (CFMV) is obtained which reflects synthetic effects of all the fuzzy factors upon the market trends.

4.2.5 Fuzzy post-adjusting rules

The extent of FPA depends on the CFMV which is obtained in fuzzy evaluation of environmental factors. Due to a reason described above, the CFMV lies between -1.0 and 1.0 which sharply differs from conventional membership value falling between $[0,1]$. We divided the CFMV range into three intervals ; pessimistic interval $[-1.0, -0.3]$, neutral interval $[-0.3, 0.3]$, and optimistic interval $[0.3, 1.0]$. The FPA is thenperformed according to the following three rules :

(1) If CFMV $\in$ pessimistic interval, then adjust *Sell* strategy into *Sell* strategy, *Buy* strategy into *Wait* strategy, *Hold* into *Sell*, and *Wait* into *Wait*.

(2) If CFMV $\in$ optimistic interval, then adjust *Sell* strategy into *Hold* strategy, *Hold* into *Hold*, and *Wait* into *Buy*, *Buy* strategy into *Buy* strategy.

(3) If CFMV $\in$ neutral, then accept the strategy drawn from the machine knowledge.

In this way, the final SMART strategy is obtained after applying this FPA process, which becomes more realistic and appropriate because both turbulence and dynamics intrinsic to stock market are considered through FPA mechanism.

5. Experimentation

A prototype system K-SISS2 was coded in pascal language which is suitable for structured system design and graphical display on PC. K-SISS2 is a backward-chaining and deductive. Besides, it is graph-guided system because each of technical indicators is graphically displayed on the screen so that DM can determine the state of each technical indicator more user-friendly.

Step 1 : Graphic display for five indicators

This step allows DM to perceive the current state of indicators they are concerned with. To help DM identify indicator values on a specific date, the system is equipped with a graphic-scanning function which moves through a graph.

Step 2: ***Machine Knowledge-based inference***

K-SISS2 interacts with DM through a dialogue window on which system questions about state of indicators are displayed. According to DM's response, inference engine derives a conclusion and stores it in memory. After investigating graphs of indicators, DM is prompted to input one of three responses : s(sell), p(pause), and b(buy), into which DM should classify the state of each technical indicator, as already mentioned in section 4.1. At this point, we must stress a fact that this interactive dialogue management technique is necessary for correspondingly solving the SMART problem because interpretation of an indicator value may change with the DM's propensity to invest or subjective view about market trends. Aggressive investor, for example, who likes to take a risky behavior and sometimes succeeds in making a profit exceeding the market would evaluate the indicator value very progressively, implying that he tries to sell at the highest point of the indicator graph and buy at the lowest point. Contrary to this, in the case of defensive investor, band-width between selling position and buying position on the indicator graph is certainly narrow compared to the aggressive investor's case.

Step 3: ***Fuzzy evaluation of market fuzzy factors***

At this stage, four environmental factors are evaluated by fuzzy set logic. The system also tries to get DM's opinion about these factors and then incorporate it into built-in membership function for each factor. This acquisition of DM's judgment about each factor is necessary because it will be more synergistic and bias-free to combine expert's judgment with DM's judgment about factors. After all the factors are evaluated, final composite fuzzy value is computed.

Step 4: ***Post-adjustment***

According to the fuzzy evaluation, machine knowledge based strategy is adjusted as described in the previous section. The directions of post-adjustment are ***reinforcing***, ***excitatory***, and ***inhibitory***. Reinforcing adjustment occurs when the SMART strategy suggested after post-adjustment is the same as the machine knowledge-guided strategy, while excitatory adjustment is made in case when upward market trend is expected. Inhibitory adjustment is activated when downward market movement is forecasted. Then a final SMART strategy for DM to take is obtained such as ***Sell***, ***Buy***, ***Hold***, and ***Wait***. Solution process of K-SISS2 can be summarized into the following four steps as depicted in Figure 6.

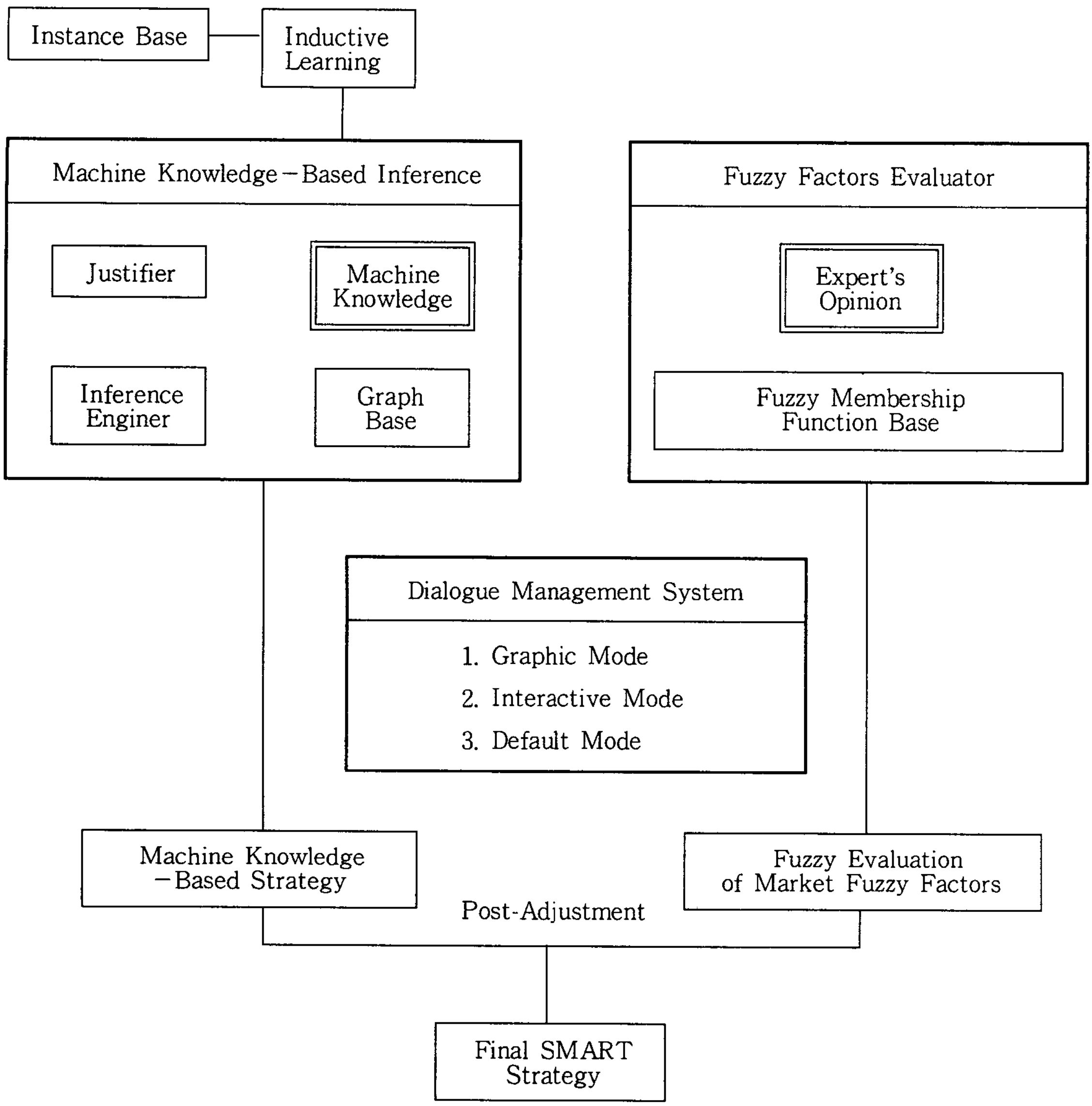

Figure 6. Solution process of K－SISS2

Experiments were performed using the price and trade volume weekly data (Jan. 1987－Dec. 1989) collected from Korea stock market. Machine knowledge was extracted from this data and integrated with human expertise. Test data totaling 72 cases were collected on a weekly base covering the period Feb. 13, 1990－July 30, 1991. 36 cases of them proved *new* by the prototype system and experimental results with the remaining 36 cases are summarized in Table 2.

Table 2. Summary of Experimental Results

Correct	24(67%)	Bull Phase	11(69%)
		Bear Phase	13(65%)
Incorrect	12(33%)	Highly Incorrect	4(11%)
		Medium Incorrect	5(14%)
		Slightly Incorrect	3(8%)

Correct rate 67% is meaningful compared to the result reported in Braun and Chandler [3] in which best SMART expert records 64−65% in annual average. The cases "Slightly Incorrect" proved that market forecast (one week later) is slightly different from the actual one, but that the SMART strategy based on FPA is insightful. Therefore, if the cases "Slightly Incorrect" are considered favorably, correct rate increases to 75%.

As already mentioned in section 4.1, K-SISS2 allows a DM to select one from three responses (sell, pause, buy) for his own opinion about the state of each technical indicator. Rigorously speaking, however, DM's opinion will be different from each other according to his propensity to invest : aggressive or defensive, which may affect the performance of K-SISS2. We displayed graphically a criterion shown in Table 3 to help DM determine the state of technical indicators during experimentation of K-SISS2. The criterion is a widely-accepted one among SMART experts, and it may also change adaptively according to the state of stock market : bearish or bullish. Since this criterion is provided only for reference DM may refer to, DM has not to follow this criterion obligatorily.

Table 3. Input Criterion for Five Technical Indicators

Input	SONA	PD	PVCI	VD	Psy
buy	SONA<-1	PD<97	PVCI<40	VD<80	Psy<40
pause	-1≤SONA≤1	97≤PD≤102	40≤PVCI≤60	80≤VD≤120	40≤Psy≤60
sell	1<SONA	102<PD	60<PVCI	120<VD	60<Psy

The directions of FPA are ***reinforcing***, ***excitatory***, and ***inhibitory***. Reinforcing adjustment occurs when the knowledge-based strategy is supported by the FPA-based SMART strategy, while excitatory adjustment is made in the case when the knowledge-based SMART strategy is modified into aggressive one after FPA process. Also inhibitory adjustment is activated when the knowledge-based SMART strategy becomes defensive after FPA process is applied. Table 4 presents the excerpt of detailed experimental results with 10 test cases. Asterisk mark means skip by inference engine due to the compactness of machine knowledge and bold-faced columns indicate system response to DM's inputs.

Table 4. Excerpt of Experimental Results

Machine Knowledge-Based Inference						Fuzzy Evaluation of Market Factors					FT	FPA-based SMART Stra.	Actual Market Trend
SONA	PD	PVCI	VD	Psy.	Stra.	EP	SSD	FAB	CFU	CFMV			
b	p	p	p	b	Wait	1	1	1	1	-.56	R	Wait	E-Down
p	p	p	s	b	Wait	1	3	3	2	.102	R	Wait	Bear
b	p	p	p	p	Buy	2	2	3	3	.227	R	Buy	E-Up
s	s	*	*	*	Sell	1	2	1	2	-.23	R	Sell	Bear
p	p	s	p	p	Wait	2	0	1	1	-.68	R	Wait	Bear
b	b	b	b	b	Buy	1	1	0	1	-.62	I	Wait	E-Up
s	s	*	*	*	Sell	0	3	3	2	.040	R	Sell	Bear
p	b	b	b	*	Wait	1	2	1	1	-.37	R	Wait	E-Up
s	s	s	p	p	Sell	3	3	3	2	.352	E	Hold	Bull
p	p	p	s	p	Hold	2	1	1	2	-.37	I	Sell	E-Down

FT column indicates one of the three FPA types : reinforcing (R), excitatory (E), and inhibitory (I). The last column shows the market trend realized in one-week later, where E-Down and E-Up stands for Edged-Down and Edged-Up, respectively. The FPA-based SMART strategies are meaningful considering the actual market trends in one-week later.

6. Concluding Remarks

In this paper, we discussed the application of two design principles-machine knowledge and FPA-to the design of a SMART problem-solving expert system. By using the machine knowledge, we were able to obtain a knowledge-based SMART strategy that is more objective and rather insensitive to misleading market fluctuations. Nonmonotonic reasoning was accomplished through FPA mechanism by which machine knowledge-based SMART strategy is revised. Through experiments with a prototype system K-SISS2, we found that the two design principles proposed in this study have high applicability to unstructured decision making problems such as SMART because of an ability to deal with the fuzzy information. Besides, since our design principles do not require either complex design of inference mechanism or special knowledge representation suitable for processing fuzzy information, they have a design simplicity which may lead to cost and time efficiency in designing expert systems capable of dealing with fuzziness. In summary, the attractive properties mentioned so far are based on three reasons : fuzzy post-adjustment of a knowledge-based problem solving, the use of fuzzy set logic for representing uncertain or indefinite environmental information, and machine learning which extracts hidden knowledge from a set of historical instance.

The prototype system K-SISS2 is an extended version of K-SISS [6]. As an extension of this study, we are now incorporating functions of selecting an optimal portfolio for "Buy" strategy that depends on DM's propensity to invest (for instance, risk-taking, risk-averse, and risk-neutral).

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