

Fuzzy Rule-Based Stock Trading System

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Abstract— Our study investigates the generalization capability of fuzzy rule-based trading systems and conducted an empirical study on Taiwan's stock market during 1991/1/1-2010/12/31. The empirical conclusions are as follows (1) The investment performance in the training period is much better than that in the testing period, which exhibits over-learning. (2) The symmetry rules approach demonstrates that the pure price trend trading system is better than the pure volume trend trading system and hybrid price-volume trend trading system. The pure volume trend trading system is the poorest system. (3) The asymmetry rules approach demonstrates that the trading system optimized in one period may be performed poorer in another period. The pure price trend buy-rule combined with the pure volume trend sell-rule has good performance in 1991-2000 but acts poorly in 2001-2010.

Keywords-fuzzy rule; market timing; stock market; moving average; over-learning

I. INTRODUCTION

The stock market is a high-risk market. The reason is that too many factors affect the stock prices, making them hard to predict. Nearly a dozen years, many artificial intelligence methods, such as artificial neural networks [1], genetic algorithms [2,3], and hybrid approach [4], have been applied to the stock price forecast and the buy-sell decision-making. These studies first attempt to establish a stock price forecast system, and then use the forecast system to develop the buy-sell decision system. Because of the unpredictability of the stock prices, the effect of such a study has its limitations [5-15].

Recently, some studies [16, 17] adopted new ways of thinking to directly construct the buy-sell decision system, instead of developing a stock price forecast system, and indicated that this strategy can effectively enhance investment performance. Although this thinking may seem unreasonable, but it is feasible if we consider it from the perspective of control theory. Just like most people can learn driving through practice, but very few people really understand vehicle dynamics. In other words, most people can't accurately predict the movement of the vehicle, but still capable of making decisions (control the steering wheel).

The fuzzy rule-based systems (FRBS) are decision-making systems combining the non-linear model of fuzzy rules and the stock trading simulation mechanism. FRBS use the strategy of optimization to skip the construction of stock price forecast system and directly develop the buy-sell decision system. The rationale is to employ the fuzzy rule-based system as the decision system. The technical indicators based on daily stock prices and trading volume are employed as the system inputs, and the buy-sell decision indicator as the system output. When these technical indicators trigger the fuzzy buy-rule, a buying decision is recommended; when these indicators trigger the fuzzy sell-rule, a selling decision is suggested. This study adjusted the parameters in these fuzzy rules to optimize the performance to produce the decision-making system. The steps of building FRBS are detailed as follows:

1. Build the fuzzy rule-based trading system

There are the buy-rule and the sell-rule in the system. Each rule has some adjustable parameters, such as membership function shape parameters, rule trigger thresholds, and weights of conditions.

2. Optimize the fuzzy rule-based trading system

Alter the adjustable parameters in the system to maximize the profits under the simulated environment of using the historical stock market data in the training period.

3. Evaluate the fuzzy rule-based trading system

Use the optimized adjustable parameters in the system, and evaluate the profits under the simulated environment in the testing periods.

4. Determine the best parameters

Choose the parameters that have the best performance during testing periods.

Because of the changing nature of stock markets, the decision-making system generated from the fuzzy rule-based approach can only be guaranteed for generating good profits in the training period, but it is not guaranteed to produce good profits in the future. The future performance of this original decision-making system is suspicious. Therefore, to objectively prove that the generated decision-making system has good performance in the future, the historical stock market data must

be divided into several parts, for example, four parts. Every time we use one of the parts as the “training period” and the others as the “testing periods” as shown in Fig. 1. In the second step of FRBS, several fuzzy rule-based systems are generated, according to the profits, in the training period. In step three of FRBS, the profits produced in the testing periods are used to evaluate which systems can be generalized to the testing periods. That is, if we can generate a system that not only has good performance in the training periods but also has good performance in the testing periods, then we can expect this system will generate good profits in the future.

Our study aims to examine whether FRBS have the generalization capability. Section 2 describes the rationale of fuzzy rule-based stock trading decision system. Section 3 examines the investment performance of FRBS in the testing periods. Section 4 contains concluding remarks.

Period 1	Period 2	Period 3	Period 4
Period 1	Period 2	Period 3	Period 4
Period 1	Period 2	Period 3	Period 4
Period 1	Period 2	Period 3	Period 4
1991-1995	1996-2000	2001-2005	2006-2010

Figure 1. Cross-Evaluation Approach (the gray boxes represent the training periods, and the white ones are testing periods)

II. FUZZY RULE-BASED STOCK TRADING SYSTEM

A. The calculation of technical indicators

Although there are thousands of technical indicators can be used in the stock market, the moving averages of price and volume are essential. A moving average is calculated by adding the security's prices for the most recent N time periods and then divided by N. It smooths out a data series, making it easier to spot trends.

The Moving Average Indicator (MAI) and Moving Average Volume Indicator (MVI) are defined as follows

$$MAI_{m,n} = \frac{MA_m}{MA_n} \quad (1)$$

$$MVI_{m,n} = \frac{MV_m}{MV_n} \quad (2)$$

where MA_m and $MA_n = m$ -day and n -day moving average of closing prices; MV_m and $MV_n = m$ -day n -day moving average of trading volume. In this study, we adopted $m=1$ and $n=50$.

B. The fuzzy rules

There are two rules in the system

Buy-rule: IF MAI is big and MVI is big Then buy

Sell-rule: IF MAI is small and MVI is small Then sell

The membership functions are defined as follows

$$\mu(MAI \text{ is big}) = \frac{1}{1 + \exp(-MAI)} \quad (3)$$

$$\mu(MVI \text{ is big}) = \frac{1}{1 + \exp(-MVI)} \quad (4)$$

$$\mu(MAI \text{ is small}) = 1 - \mu(MAI \text{ is big}) \quad (5)$$

$$\mu(MVI \text{ is small}) = 1 - \mu(MVI \text{ is big}) \quad (6)$$

where

$$MAI = \frac{MAI_{m,n} - 1}{k \cdot \sigma_{MAI}} \quad (7)$$

$$MVI = \frac{MVI_{m,n} - 1}{k \cdot \sigma_{MVI}} \quad (8)$$

where σ_{MAI} and σ_{MVI} are the standard deviations of $MAI_{m,n}$ and $MVI_{m,n}$ in the recent n days, and k is the membership function shape parameter.

We use the weighted summation instead of minimization for the “and” operation; that is the fuzzy rules triggered based on the following rules

$$\begin{aligned} &\text{If } w_{MAI-Buy} \cdot \mu(MAI \text{ is big}) + w_{MVI-Buy} \cdot \mu(MVI \text{ is big}) \\ &> \theta_{buy} \quad \text{Then Buy} \end{aligned} \quad (9)$$

$$\begin{aligned} &\text{If } w_{MAI-Sell} \cdot \mu(MAI \text{ is small}) + w_{MVI-Sell} \cdot \mu(MVI \text{ is small}) \\ &> \theta_{sell} \quad \text{Then Sell} \end{aligned} \quad (10)$$

where θ_{buy} and θ_{sell} are the rule trigger thresholds, and we assumed

$$\theta_{sell} = \theta_{buy} = \theta \quad (11)$$

and $w_{MAI-Buy}$ and $w_{MVI-Buy}$ are the weights of conditions in the Buy-rule; $w_{MAI-Sell}$ and $w_{MVI-Sell}$ are the weights of conditions in the Sell-rule, and we assume

$$w_{MVI-Buy} = 1 - w_{MAI-Buy} \quad (12)$$

$$w_{MVI-Sell} = 1 - w_{MAI-Sell} \quad (13)$$

The fuzzy rule response surfaces are shown in Fig. 2. When the k , membership function shape parameter, is close to 0, then the system is close to crisp system instead of fuzzy system. The weights of conditions control the slope direction of the response surface.

III. THE RESULTS OF FRBS IN TAIWAN STOCK MARKET

We use daily data of the Taiwan Stock Market Index (TAIEX) from 1 Jan 1991 to 31 Dec 2010 as shown in Figure 3. Totally 5297 individual data were collected. The data are divided into four parts by timing and are shown in Figure 1. This research considers the profit or loss in the training period and in the testing period.

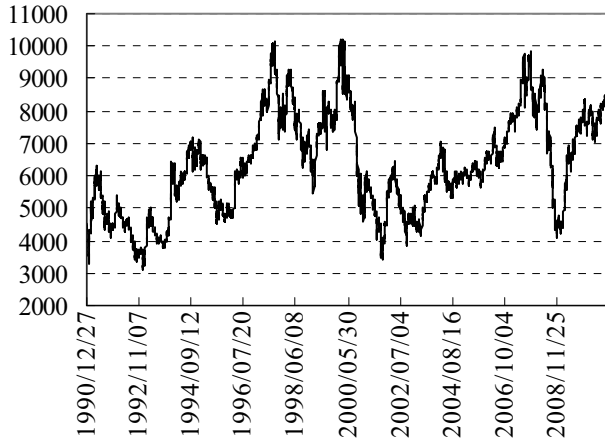


Figure 3. TAIEX (1991/1/1-2010/12/31)

Figure 3 exhibits the stock market fluctuating in the training and in the testing periods, which show the representativeness of the data. Every time we use one of the parts as the “training period” and the remaining ones as the “testing periods”. Several fuzzy rule-based systems are produced based on the profits generated in the training period, and then the profits in the testing period are used to evaluate which systems can be generalized to the testing periods.

Because the objective of this study is to develop a decision-making system with high investment performance in Taiwan's stock market; therefore, the transaction costs refer to the practical stock transaction costs in Taiwan. These costs include

transaction fees of purchasing accounting for 0.1425% of the buying price; the transaction fees and trading tax of selling account for 0.1425% and 0.3% of the selling price, respectively. The profits (annual return) of buy-and-hold strategy in the 4 parts are 4.0%, -1.7%, 6.7%, 6.5%, respectively.

A. The symmetry rules approach

In this approach, we assume that the weights of conditions of the buy-rule and the sell-rule are the same.

$$w_{MAI-Buy} = w_{MAI-Sell} = w_{MAI} \quad (14)$$

We firstly use 0, 0.3, 0.5, 0.7, 1 for the w_{MAI} , and change the rest of adjustable parameters, the membership function shape parameters k (0.1, 0.2, ..., 1) and rule trigger threshold θ (0.5, 0.55, ..., 0.95), in the system to maximize the profits under the simulated environment of using the historical stock market data in the training period. To avoid the profit comes from few trades, we eliminated all the results whose number of trade is less than 60 times in the 20 years (60 times for buy and 60 times for sell). Then we use the optimized adjustable parameters in the system and evaluate the profits under the simulated environment in the testing periods. The results are shown in Table 1. In this table, we use the profit gain, the gap between the annual return of the system and the buy-and-hold strategy, to evaluate these systems.

To objectively prove that the generated decision-making system has good performance in the training period, we use the average profit gain produced in the testing periods to evaluate the system. Because we exclude the profit gain generated in the training periods, the average profit gain can objectively be used to evaluate the performance of the system. If we can generate a system that not only has good performance in the training periods, but also has good performance in all the testing periods, then we can expect this system will generate good profits in the future. We also use the standard deviation of profit gain to evaluate the stability of the system. Finally, we use the ratio of the average profit gain to the standard deviation of profit gain to measure the total performance for a specific weight. The results show that when the weight is varied (0, 0.3, 0.5, 0.7, and 1), the generated profit gains in the training periods are 8.0, 7.1, 7.0, 7.3, and 6.8, and the ratios are 2.14, 1.20, 1.51, 1.85, and 3.40, respectively. On the other hand, in the testing periods, when the weight is changed (0, 0.3, 0.5, 0.7, and 1), the produced profit gains are 3.0, 1.8, 2.6, 3.6, and 5.5, and the ratios are 0.74, 0.54, 0.56, 1.03, and 3.09, respectively. The investment performance in the training period is much better than that in the testing period, which exhibits over-learning.

The results show that 1.0 is the best weight of conditions. That is, the best fuzzy rule is the rule containing only the MAI conditions, and the MVI conditions are not included in the system. Figure 4-7 show its performance. The initial capital is 10000. All these four optimized fuzzy rule sets can obtain fairly high final cumulated capital.

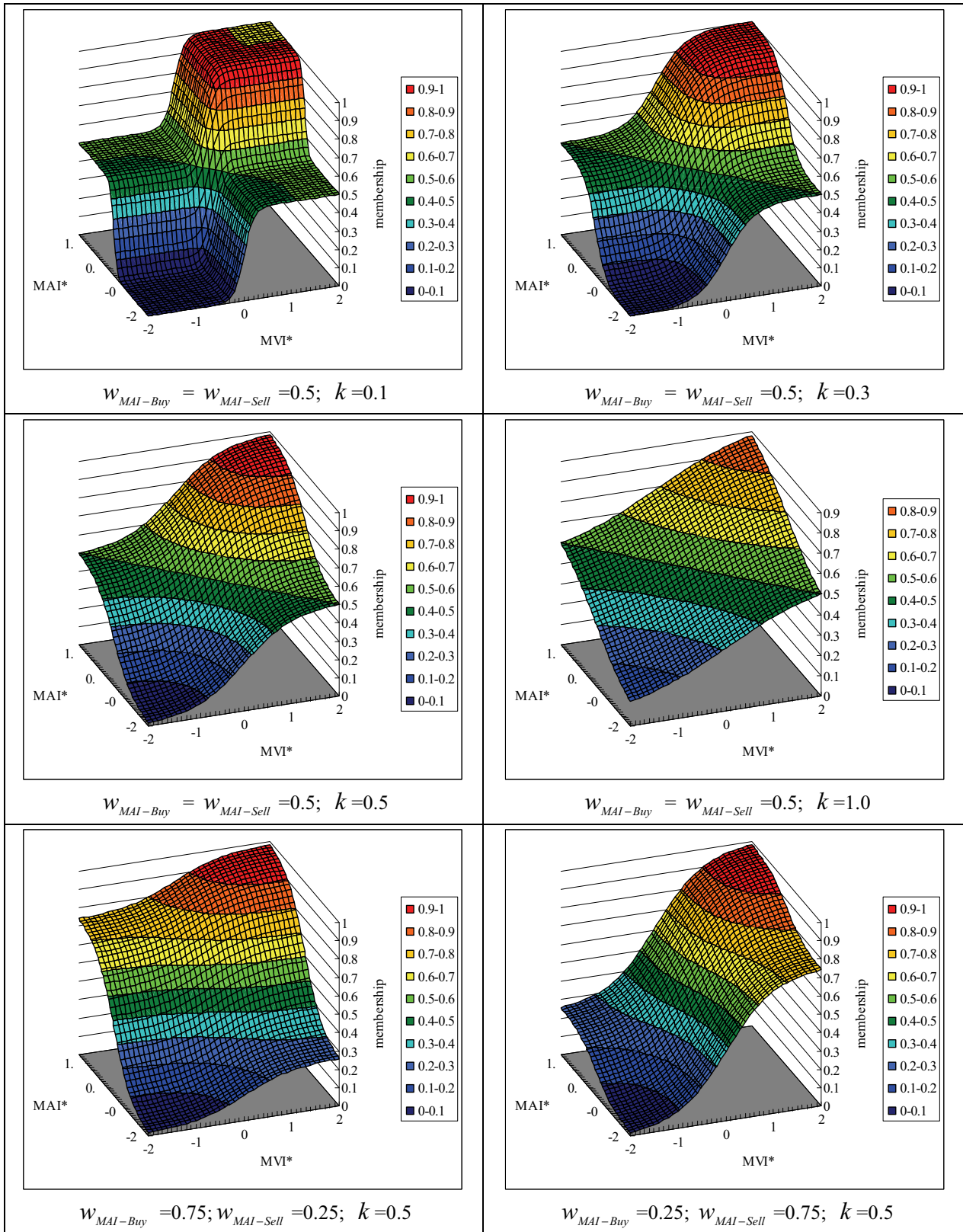


Figure 2. Fuzzy rule response surface

TABLE 1. The Results of FRBS: Symmetry Rules Approach

weight pair	Train Period	Opt. θ	Opt. k	Test period				Avg profit gain	Std of profit gain	Ratio
				1	2	3	4			
(0,0)	1	0.7	1	8.5	5.9	2.7	2.4	8.0 3.0	3.7 4.0	2.14 0.74
	2	0.65	1	1.4	12.8	0.2	-6.0			
	3	0.7	0.9	6.7	8.0	3.9	1.4			
	4	0.8	0.7	3.1	8.8	1.1	6.7			
(0.3,0.3)	1	0.75	0.6	12.4	7.6	-0.9	-2.0	7.1 1.8	5.9 3.3	1.20 0.54
	2	0.75	0.1	4.5	12.0	-1.3	-0.1			
	3	0.65	1	3.5	3.2	2.1	-2.9			
	4	0.9	0.1	4.5	5.0	0.5	1.8			
(0.5,0.5)	1	0.6	1	9.0	5.2	-1.6	-2.5	7.0 2.6	4.6 4.6	1.51 0.56
	2	0.6	0.3	6.7	12.4	-6.5	-0.6			
	3	0.85	0.1	3.9	4.7	2.0	4.1			
	4	0.9	0.1	8.5	7.5	1.1	4.5			
(0.7,0.7)	1	0.7	0.3	10.6	5.4	0.6	5.1	7.3 3.6	4.0 3.4	1.85 1.03
	2	0.55	0.5	6.7	10.2	0.1	-2.3			
	3	0.6	0.3	4.9	9.2	2.1	0.5			
	4	0.85	0.1	6.4	4.7	1.1	6.4			
(1,1)	1	0.8	0.1	8.7	5.8	3.3	6.0	6.8 5.5	2.0 1.8	3.40 3.09
	2	0.7	0.2	8.2	7.0	4.0	4.5			
	3	0.7	0.2	8.2	7.0	4.0	4.5			
	4	0.6	0.3	6.4	5.4	2.7	7.6			

(The bold values are based on the training period; the rest of the values are based on the testing periods.)

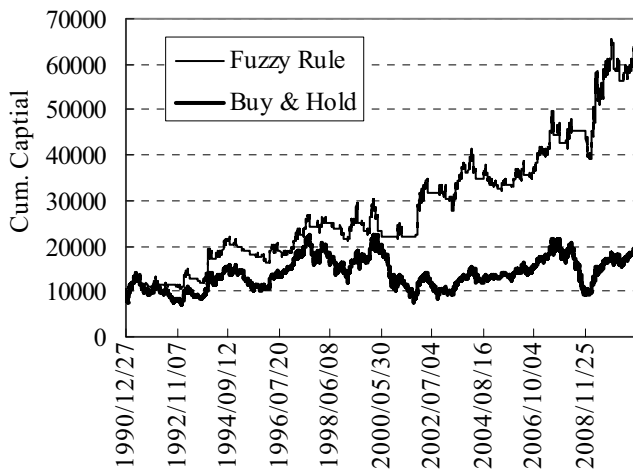


Figure 4. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,1) in the 1st period (1991-95).

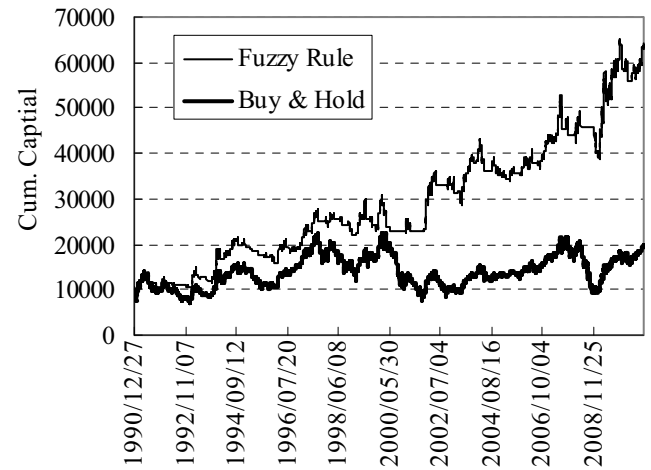


Figure 5. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,1) in the 2nd period (1996-00).

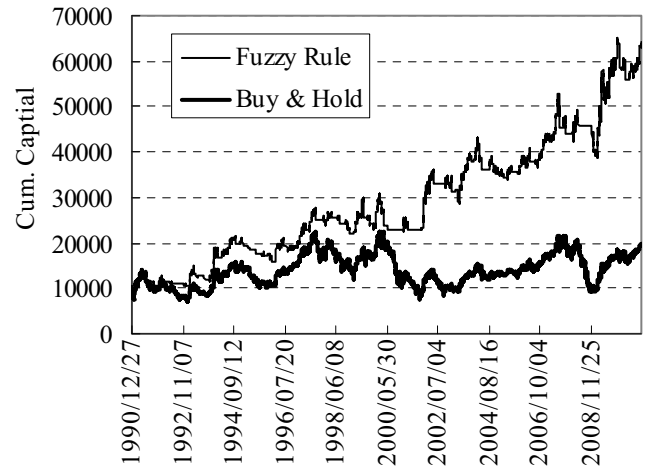


Figure 6. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,1) in the 3rd period (2001-05).

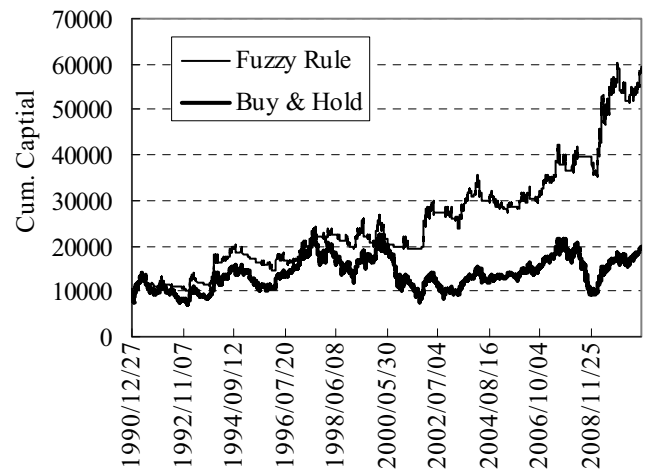


Figure 7. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,1) in the 4th period (2006-10).

B. The asymmetry rules approach

In this approach, we assume that the weights of conditions of the buy-rule and the sell-rule are different. We try the buy weight and the sell weight pair=(0,1) and (1,0). The results are shown in Table 2. Figure 8-11 show the cumulated capital employing the optimized fuzzy rule set with the weight pair (1, 0), which is the pure price trend buy-rule combined with the pure volume trend sell-rule, in the four different periods. Although these four optimized fuzzy rule sets can obtain rather high final cumulated capital, but the systems generated from the period 1 (1991-1995) and period 2 (1996-2000) have relatively poor performance in period 3 (2001-2005) and period 4 (2006-2010), which demonstrates that the optimized trade system produced from one period may be performed poorer in another period. We also use different weights such as 0, 0.05, 0.1, 0.15, 0.2,..., 1. Therefore, there are totally $21 \times 21 = 441$ weight pairs. The pair of (0.8, 1) has the highest ratio of the average profit gain to the standard deviation of profit gain. However, it also exhibits over-learning.

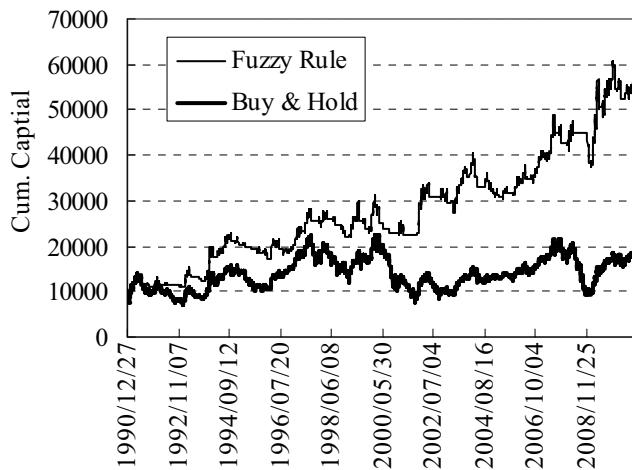


Figure 8. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,0) in the 1st period (1991-95).

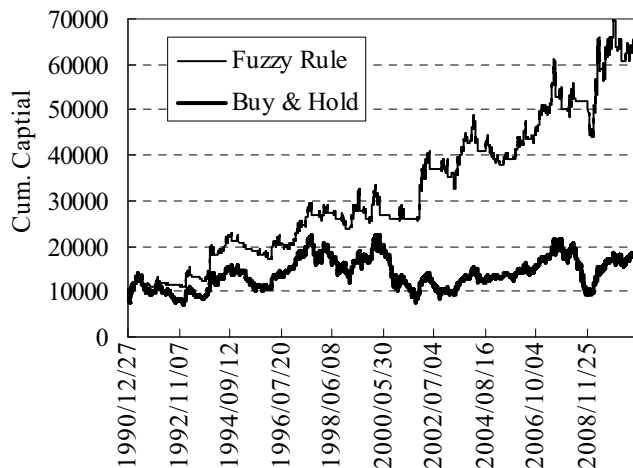


Figure 9. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,0) in the 2nd period (1996-00).

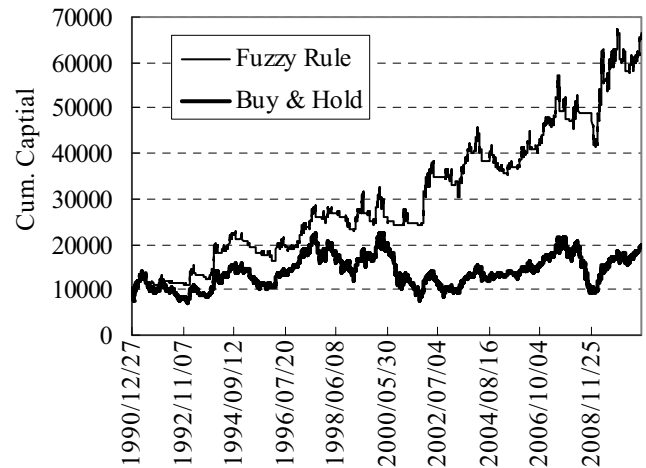


Figure 10. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,0) in the 3rd period (2001-05).

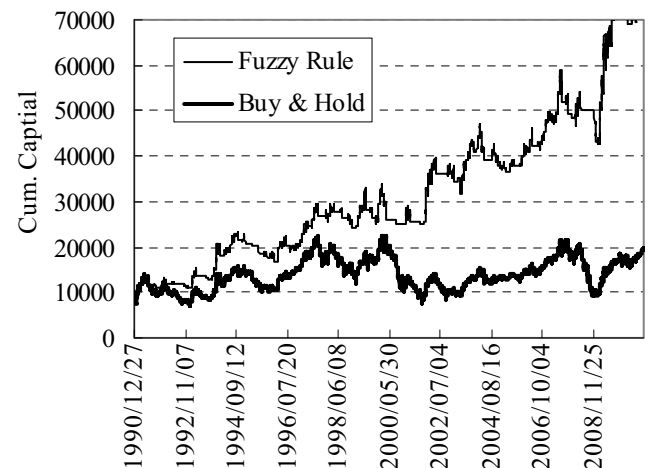


Figure 11. The cumulated capital employing the optimized fuzzy rule set with the weight pair (1,0) in the 4th period (2006-10).

IV. CONCLUSION

Our study investigates the generalization capability of fuzzy rule-based trading systems and conducted an empirical study on Taiwan's stock market during 1991/1/1-2010/12/31. The empirical conclusions are as follows:

1. The investment performance in the training period is much better than that in the testing period, which exhibits over-learning.
2. The symmetry rules approach demonstrates that the pure price trend trading system performs better than the pure volume trend trading system and hybrid price-volume trend trading system. The pure volume trend trading system has the poorest performance.

TABLE 2. The Results of FRBS: Asymmetry Rules Approach

weight pair	Train Period	Opt. θ	Opt. k	Test period				Avg profit gain	Std of profit gain	Ratio
				1	2	3	4			
(0,1)	1	0.55	1	7.2	7.1	1.9	3.3	5.9 3.1	2.7 3.0	2.18 1.03
	2	0.95	0.1	3.2	9.1	-0.1	0.0			
	3	0.65	0.4	5.2	9.0	3.2	2.4			
	4	0.65	0.2	3.5	2.8	-1.5	4.2			
(1,0)	1	0.95	0.1	13.3	8.4	0.8	-2.7	7.7 4.7	6.4 5.0	1.20 0.95
	2	0.7	0.2	11.7	13.1	-0.3	0.2			
	3	0.7	0.1	6.2	10.9	1.7	2.6			
	4	0.7	0.1	6.2	10.9	1.7	2.6			
(0.8, 1)	1	0.8	0.1	10.9	6.7	1.5	4.7	7.9 5.6	3.26 2.7	2.50 2.04
	2	0.7	0.2	5.6	9.7	1.8	6.1			
	3	0.6	0.4	9.4	8.5	3.7	5.9			
	4	0.6	0.5	7.9	7.1	1.4	7.4			

(The bold values are based on the training period; the rest of the values are based on the testing periods)

3. The asymmetry rules approach demonstrates that the optimized trading system in one period might act poorer in another period. The pure price trend buy-rule combined with the pure volume trend sell-rule has fairly good performance in the period of 1991-2000, but has poor performance in 2001-2010.

The deterioration of the investment performance may be resulted from that the 5-year training period is not long enough to gather sufficient patterns to build general model; or maybe the 5-year testing period is too long and the stock market structure has been changed during the time, which also makes the developed trading system cannot be applied to the testing period. Apparently, it is not easy to use the current framework to overcome the problem of over-learning. Researchers have to solve this problem through different approaches.

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