Genetic Programming for the Investment of the Mutual Fund with Sortino Ratio and Mean Variance Model*

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***Abstract*—In this paper, we propose two genetic-programming-based models that improve the trading strategy for mutual funds. These two models can get better returns and reduce risks. The first model increases the return by selecting funds with high Sortino ratios and allocates the capital equally, achieving the best annualized return. The second model also selects funds with high Sortino ratios, but reduces the risk by allocating the capital with the mean variance model.**

Most importantly, our model utilizes the genetic programming to generate feasible trading signals to gain return, which is suitable for the market that changes anytime. To verify our model, we simulate the investment for mutual funds from January 1999 to December 2009 (11 years in total). The experimental results show that our first model can gain return from 2004/1/1 to 2008/12/31, achieving the best annualized return 9.11%, which is better than the annualized return 6.89% of the previous approach. In addition, our second model with smaller downside volatility can achieve almost the same return as previous results.

***Keywords*-fund; global trend indicator; monitoring indicator; Sortino ratio; genetic programming; annualized return.**

I. Introduction

More and more investors are interested in investing financial products such as stocks, futures and mutual funds in recent years. However, the financial market is so complex with nonstationary and chaotic data series, thus it is full of risks. It is hard for investors who lack comprehensive investment information to get return in the market.

To get good return in the financial market, many researchers have applied artificial intelligence techniques and soft computing methods such as *support vector regression* (SVR) [4], [16], *support vector machine* (SVM) [3], [11], [4], *genetic algorithm* (GA) [5], [15], *genetic programming* (GP) [12], *artificial neural network* (ANN) [5], [6] and so on to prediction of trends or values of the market. By using these methods, one may can extract the rules or patterns hidden in the market.

In this paper, we confine our investment to mutual funds. A fund pools money from many investors, and then it invests the money in stocks, bonds, securities, assets, or some combination of these investments. Investors can reduce the loss risk by investing their money in a wide variety of funds, or by choosing the appropriate timing to sell or buy the shares of these funds.

In this paper, we desire to study how to find the best portfolio for each period, and how to allocate the capital to the portfolio until the best timing to sell. First, we measure the *Sortino ratio* [14] of each fund and choose the funds with higher Sortino ratio as our portfolio. The Sortino ratio, which only penalizes the returns that are negative or below a user-defined target, is a modification of the *Sharpe ratio* [13]. The Sortino ratio is better than the Sharpe ratio as a measure of portfolio risk when the distribution of excess returns is skewed [1]. Second, we use the *mean-variance model* [9] to decide how to allocate the capital to funds, by which we can reduce the risks as much as possible. Third, we use historical data series to decide when to redeem our portfolio.

Tsai *et al.* [15] Proposed the *global trend indicator* (GTI) to evaluate the trend of mutual funds, and then they applied the genetic algorithm to select funds. Their return performance is better than the *buy-and-hold method* and the *4433 rule*. In this paper, we propose two models that utilize *genetic programming* to generate effective trading signals. With these trading signals, the first model increases the annualized return by selecting funds with high Sortino ratios and allocates the capital equally. To reduce the risk, we devise the second model, which also selects funds with high Sortino ratios, but allocates the capital with the mean variance model.

The first proposed model gets better returns than Tsai's results. The second proposed model can achieve almost the same return as Tsai's results with a lower risk.

The rest of this paper is organized as follows. In Section II, we will present some background knowledge of this paper, including Sortino ratio, mean variance model and genetic programming. In Section III, we will propose our two models, both of which improve Tsai's result by adopting effective trading signals generated by genetic programming. In Section IV, we will show some benchmarks, and present the experimental results of our two models. Finally, the conclusion of this paper will be given in Section V.

II. Preliminaries

In this section, we will give an introduction to portfolio theory, mean variance model, Sortino ratio, and genetic programming, which serve as the background knowledge and will be used in the following sections.

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A. Portfolio theory

Investment is a trade-off between return and risk. The risk in the investment is the variance of the expected return. Investors always prefer to have their return as high as possible, but to have the risk as low as possible at the same time. However, an investment with high return usually accompanies with high risk. Markowitz [9] proposed the mean variance model which laid the foundation of portfolio theory.

B. Mean Variance Model

The portfolio problem deals with how to allocate capital among several assets. Markowitz [9], [10] proposed the *mean variance model (MV model)* for solving the problem. The principle of the MV model is to use the expected return of a portfolio as the investment return, and to use the covariance of returns of the portfolio as the investment risk. The MV model is based upon the assumption that investors are risk-averse.

The definition of the MV model is described as follows:

$$\begin{cases} \text{minimize } \lambda \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \cdot w_j \cdot \sigma_{ij} - \\ \qquad (1-\lambda) \sum_{i=1}^{n} w_i \cdot E(R_i), \\ \text{subject to } \sum_{i=1}^{n} w_i = 1, \end{cases} \tag{1}$$

where $E(\cdot)$, w_i, σ_{ij}, R_i, n, and λ are the expected value operator, the weight of capital allocated to the ith asset, the covariance of the expected return between the ith and jth assets, the historical return of the ith asset (usually obtained from historical price series), the size of the portfolio (number of assets), and the inclination of the investor, respectively.

In the definition of the MV model, $\lambda = 1$ represents that the investor is risk-averse, which results in less expected return of the portfolio. In contrast, $\lambda = 0$ represents that the investor is risk-willing, which results in more expected return of the portfolio.

C. Sortino Ratio

The Sortino ratio [14] only considers the downside volatility as the risk. The formula for the *Sortino ratio* is described as follows:

$$SemiVariance = \frac{1}{n_s} * \sum_{R_i < R_{MAR}} (R_i - R_{MAR})^2, \tag{2}$$

$$Sortino\ ratio = \frac{E(R_i) - R_{MAR}}{\sqrt{SemiVariance}}, \tag{3}$$

where $E(\cdot)$, R_{MAR}, R_i, and n_s denote the expected value operator, the minimum acceptable return, the returns of the ith invested asset, and the total number of assets whose values are below R_{MAR}. With the Sortino ratio, we can find out the assets that have better performance in the past, and the assets that have higher probability to gain return in the future, which can be used to construct our portfolio.

D. Genetic Programming

The *genetic programming* (GP) [7], [8] is an evolutionary algorithm which extends the *genetic algorithm* (GA) by supporting nonlinear structures such as trees. Similar to GA, GP optimizes the population by the principles of natural selection.

In GP, the trading strategy can be obtained by traversing the tree structure. The tree structure used in GP is constructed from a predefined set of functions. In the tree structure, function nodes contain operators such as '$+$', '$-$', '$\times$', '$/$', '$>$', '$<$', '$=$', and terminals represent parameters and constants.

The steps of evolutions in GP are summarized as follows.

1) *Initialization*: The initial population is composed of trees which are generated randomly.
2) *Selection*: The basic idea is that the higher fitness value an individual has, the more likely the individual is to be selected to produce offspring. The selection mechanism is usually done by the roulette-wheel method.
3) *Reproduction*: Reproduction simply makes an exact copy of the selected individual, and puts it in the new population.
4) *Crossover*: Crossover is applied to two selected individuals, and it is used for reproducing new individuals. The most common approach for crossover in GP is the *subtree crossover*. Usually, internal nodes are more likely than terminals to be selected as crossover points. To perform the crossover between two trees, random subtrees are respectively selected from the father tree and the mother tree. Then, the father's subtree is replaced by the mother's subtree, and the new individual is the offspring.
5) *Mutation*: Mutation is applied to only one individual, and it increases the diversity of the population. The most common approach for mutation is the *subtree mutation*. In the subtree mutation, a mutation point (the root of a subtree) is randomly selected from the individual. To perform the mutation, the subtree connected to the mutation point is replaced by a randomly generated tree. The new individual is the result of mutation.

III. Fund Investment with Genetic Programming

In this section, we propose two models for investment. The first model can gain return from 2004/1/1 to 2008/12/31, achieving better return than Tsai's method [15]. The second model lowers the risk with the MV model, but achieves almost the same return as Tsai's result. In our models, the funds which can be invested are measured with the *Sortino ratio*, and some of them are selected as our portfolio. The capital in the portfolio is allocated equally (the first model) or allocated with the MV model (the second model). The risk among the funds can be reduced with the MV model by allocating different weight to each fund. For the timing of buying, holding, or selling the portfolio, we refer to the signals generated by genetic programming.

A. The Flow Chart of Investment

The flow chart of our investment is shown in Figure 1. In each trading period (here we adopt one week), we check whether the fund market is open or not by checking the function $isMarketOpen(t)$ [15]. The function $isMarketOpen(t)$ returns "true" if the number of tradable funds at time t is greater than 10% of all funds issued before time t. Otherwise, this function returns "false". If $isMarketOpen(t)$ returns "true", we will derive a trading rule (by GP) that generates signals for deciding the timing of buying, holding, or selling. If $isMarketOpen(t)$ returns "false" and the trading period is one week, we will trade at time t_b, where t_b is the nearest day before t that $isMarketOpen(t_b)$ returns "true".

In bull market, we buy or hold the funds. Before investing, the rank of funds are determined by the Sortino ratio. Then, according to the rank of funds, inferior funds that are held in our portfolio will be replaced by superior funds. In bear market, all the funds in our portfolio will be redeemed.

B. Selecting Funds with the Sortino ratio

In this paper, we set the R_{MAR} in Equation 3 to zero, which means that we only consider the negative return as the risk of investment.

If we decide to purchase funds at date t and there is no fund in our portfolio, then the top fn funds in the last tp months (ranked by the Sortino ratio) are selected.

Assume there are some funds already in our portfolio F and the ranks of their Sortino ratios are from 1 to $|F|$ in the beginning. We define a *redeeming threshold*, denoted as γ, for replacing inferior funds. Our portfolio is updated by the following steps.

1) Set the initial trading date to t. Rank the Sortino ratios for all funds in the last tp months before t.
2) Redeem the holding funds (if any) whose ranks fall outside the top $\gamma \times |F|$, and replace them by better funds which do not exist in our portfolio. Note that if the new funds get negative returns in the last tp months, these funds are not chosen.
3) If t is the date for the end of investment, then go to Step 4. Otherwise, set $t = t + 7$ (one day) and go to Step 2.
4) Report the results.

C. Allocating the Capital with the Mean Variance Model

To allocate our capital with the MV model, we assume that there are some funds in our portfolio, and that the returns of funds in the market will be reflected by their historical price series.

Assuming that the $\lambda = 1.0$, we solve Equation 1 to get the best weights of capital of the funds in our portfolio. The capital is reallocated when some funds are redeemed and some new funds are added into the portfolio, until the end of investment.

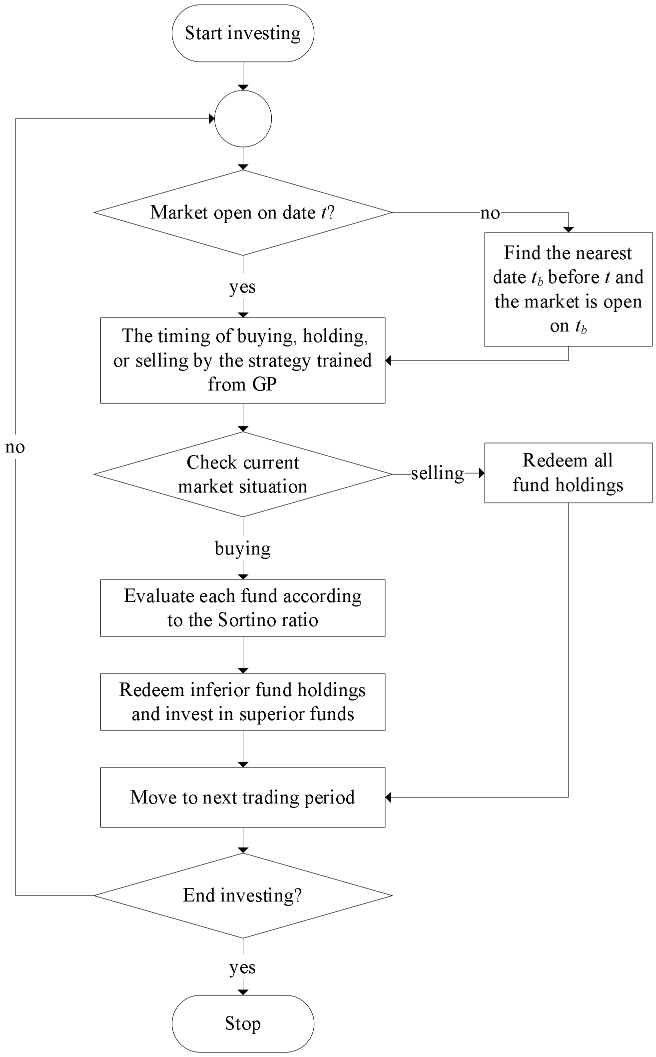

Figure 1. The flow chart for investing funds.

D. Determining the Timing with the Genetic Programming

The function set of our method for GP contains the operators for calculating the trading signals. We involve the operators '$>$', '$<$', '$=$', '$\geq$', '$\leq$', 'and', 'or' here.

In addition, because the transaction fee has great impact to the return, we put the weekly monitor index (MI) [15] in our terminal set to avoid over-trading. Assume that we can buy and sell the global trend indicator (GTI) [15] index, and the transaction fee is 3% in each transaction.

Our fitness function in GP is to maximize the return of GTI. Because GTI represents the situation of the market, we can gain return when the trend of GTI goes up. With GP, we can first obtain a function that generates trading signals (*true* or *false*) to get the best return of GTI in the training period. Next, we adopt this function to determine the action we should take at date t. The action can be interpreted as follows.

- **buying**: If the signal of t is *true* and the signal of $(t - 7)$ is *false*, then we select appropriate funds as our portfolio and allocate the capital to them with our method.

- **selling**: If the signal of t is *false* and the signal of $(t-7)$ is *true*, then we redeem all the funds in our portfolio.
- **holding**: If the signal of t is *true*, the same as the signal of $(t-7)$, we replace the inferior funds with the superior ones. If the signal of t is *false*, the same as the signal of $(t-7)$, we do nothing, which means that we are waiting for the timing of buying.

This procedure will be performed every day until the end of the investment.

IV. Experimental Results

A. Data Collection and Preprocessing

The testing dataset which contains the profiles and the *net asset values* (NAV) of funds is taken from FundDJ [2].

The training period for finding appropriate parameters of our model, and the testing period for testing the return performance are set from 1999/1/1 to 2003/12/31, and from 2004/1/1 to 2009/12/31, respectively. The detailed information of our dataset is described as follows.

1) The dataset contains only the funds which can be bought and sold in Taiwan.
2) We consider only equity funds and A-type funds, and the trading currency is US dollar.
3) Nine funds whose IDs are CTZ14, IAE01, IAE02, FTZ17, CTZ34, PAZ65, PAZ83, PAZ85, and TLZ27 are removed beacause of their extremely unstable NAVs.

The numbers of funds in our training and testing datasets are 107 on 1999/01/01 and 648 on 2009/12/31, respectively.

B. Experimental Results with the Sortino Ratio on the Buy and Hold Strategy

In our experiment, we search for the parameters of the training period, including the portfolio size N, the redeeming threshold γ, and tp for ranking the Sortino ratios. Then the parameters which get better return in the training period are applied to the testing period.

In the beginning of each year, the portfolio (of size N) is constructed according to the Sortino ratios in the last tp months. The funds are updated with the redeeming threshold γ in the investment. In the end of the same year, all funds in the portfolio are redeemed, and the return of the year is calculated. In this way, we can find out the parameters N and γ that can earn higher return in the training period.

We discuss various parameters with $N = \{5, 10, 15, 20\}$ for the portfolio sizes, $tp = \{3, 6, 12\}$ for ranking Sortino ratios, and $\gamma = \{10\%, 20\% \ldots 90\%\}$ for the redeeming thresholds. To test the downside volatility, we compare the average of negative returns, whose details are described as follows. Because the trading period of our model is one week, we calculate the return ROI_{1w} on Friday each week. For example, suppose the investment period is from 1999/1/1 to 1999/12/31, and the value of our portfolio in the beginning is 100.0. Assume the value of portfolio on 1999/1/4, 1999/1/11, 1999/1/18 are 102.4, 101.6, and 99.2, respectively. Then the ROI_{1w} on 1999/1/4, 1999/1/11, 1999/1/18 are 2.4%, -0.78%, and -2.36%, respectively. In this way, we get 52 ROI_{1w} values each year. To represent the downside volatility, we calculate the average of negative returns. The smaller the average of negative returns is, the more stable of the value of the portfolio in the investment period is.

In our experiment, we get the result that the buy and hold strategy gets higher return with $tp = 6$ and $\gamma = 70\%$. The results for $N = \{5, 10, 15, 20\}$, $tp = 6$, and $\gamma = 70\%$ are shown in Table I. From Table I, we know that the more assets we invested in, the less risk we will take (from the values of AVGNEG), but we also get the less returns.

Table II
The parameters of genetic programming.

Population size	300
Number of generations	250
Initial method	equal mix of Full and Grow method
Selection method	roulette wheel
Reproduction number	3
Crossover rate	90%
Mutation rate	50%
Max depth	5

C. Experimental Results with Sortino Ratio on the Genetic Programming

In this experiment, we adopt the trading signals generated by the genetic programming (GP) for buying and selling funds. In the training period, we obtain better parameters and the best trading function that generates effective trading signals. These parameters and this trading function are then applied to the testing period.

The elements in the function set and terminal set of GP are $\{>, <, =, \geq, \leq, and, or\}$ and $\{-1.0, -0.9 \ldots 0.9, 1.0, weeklyMI(t), weeklyMI(t-7)\}$, respectively.

Assume we can buy and sell the global trend indicator (GTI) index and the transaction fee is 3% in each transaction. The fitness function of our GP is to maximize the return of GTI in the training period. The parameters of GP are shown in Table II and the format of each obtained trading function (an encoded solution) in GP is described in Equation 4.

$$\begin{array}{l} \text{IF } buying\ rule > 0 \text{ AND} \\ \quad selling\ rule \leq 0 \text{ THEN} \\ \quad signal(t) \leftarrow true \\ \text{ELSE IF } buying\ rule \leq 0 \text{ AND} \\ \qquad\qquad selling\ rule > 0 \text{ THEN} \\ \quad signal(t) \leftarrow false \\ \text{ELSE} \\ \quad signal(t) \leftarrow signal(t-1) \\ \text{END IF} \end{array} \tag{4}$$

If the buying rule and the selling rule are of opposite signals, which means the two rules have the same opinion,

Table I
THE RETURNS AND AVERAGE OF NEGATIVE RETURNS FOR $N = \{5, 10, 15, 20\}$, $tp = 6$, AND $\gamma = 70\%$ IN THE TRAINING PERIOD FROM 1999/1/1 TO 2003/12/31. HERE EQ REPRESENTS THAT THE CAPITAL IS ALLOCATED EQUALLY, MV REPRESENTS THAT THE CAPITAL IS ALLOCATED WITH THE MV MODEL ($\lambda = 1.0$), ROI REPRESENTS THE RETURN OF INVESTMENT, AND AVGNEG REPRESENTS THE AVERAGE OF NEGATIVE RETURNS.

year	$N = 5$		10		15		20	
	ROI	AVGNEG	ROI	AVGNEG	ROI	AVGNEG	ROI	AVGNEG
1999 EQ	139.64%	-2.64%	116.08%	-2.37%	92.50%	-1.89%	83.03%	-1.80%
1999 MV	291.72%	-2.34%	113.66%	-1.34%	113.53%	-1.34%	113.12%	-1.32%
2000 EQ	1.42%	-2.76%	-8.25%	-2.42%	-7.31%	-2.29%	-9.93%	-2.57%
2000 MV	14.28%	-2.50%	6.44%	-2.49%	3.92%	-1.98%	2.19%	-2.20%
2001 EQ	-0.50%	-1.88%	-0.43%	-1.62%	-1.69%	-1.60%	-3.99%	-1.49%
2001 MV	-4.52%	-1.98%	-3.03%	-0.72%	-1.61%	-0.70%	-5.26%	-0.80%
2002 EQ	6.09%	-2.56%	-2.18%	-2.36%	-4.37%	-2.35%	-1.32%	-1.96%
2002 MV	12.12%	-2.52%	-19.98%	-1.63%	-20.03%	-1.60%	-15.88%	-1.77%
2003 EQ	28.27%	-1.57%	18.23%	-1.53%	24.23%	-1.51%	31.85%	-1.44%
2003 MV	34.35%	-1.98%	11.32%	-1.01%	12.77%	-1.07%	15.22%	-0.87%
2004 EQ	15.30%	-1.56%	11.87%	-1.63%	15.23%	-1.76%	11.08%	-1.64%
2004 MV	17.50%	-1.52%	17.47%	-1.43%	11.83%	-0.96%	11.83%	-0.96%
2005 EQ	21.92%	-1.68%	27.65%	-1.68%	24.96%	-1.43%	29.71%	-1.63%
2005 MV	11.75%	-1.12%	14.26%	-1.18%	11.68%	-1.71%	14.94%	-1.69%
2006 EQ	20.15%	-2.76%	15.31%	-2.30%	14.01%	-2.52%	14.22%	-2.30%
2006 MV	25.99%	-2.54%	10.55%	-2.20%	19.63%	-1.93%	14.21%	-1.84%
2007 EQ	40.97%	-4.11%	39.97%	-3.70%	36.91%	-3.43%	34.11%	-3.26%
2007 MV	42.28%	-3.14%	6.24%	-2.80%	6.39%	-2.66%	10.33%	-2.73%
2008 EQ	-72.56%	-5.75%	-68.67%	-5.40%	-65.79%	-5.20%	-65.07%	-4.81%
2008 MV	-70.97%	-6.04%	-64.88%	-5.18%	-55.49%	-4.02%	-46.39%	-3.75%
2009 EQ	62.11%	-2.27%	62.11%	-2.27%	62.11%	-2.27%	62.11%	-2.27%
2009 MV	62.11%	-2.27%	62.11%	-2.27%	62.11%	-2.27%	62.11%	-2.27%

then the trading function generates either a true or false signal. Otherwise the market situation is considered as ambiguous, and the current signal remains the same as the previous signal.

We run the GP 100 times and select the best profitable trading functions in the training period for $N = \{5, 10, 15, 20\}$, $tp = 6$, and $\gamma = 70\%$. The training results and testing results of these functions are shown in Table III.

Most of the trading functions that are generated by GP can get profits both in the training and testing period, because GTI index is the average weight index of all funds, and the funds we selected usually take high percentage of GTI index. Hence the trading functions which can get high profit by trading GTI index usualy can get high profit in trading funds.

The buying and selling rules of the best trading function generated by GP are shown in Table IV. According to these results, we know that most profitable trading functions in the training period can also obtain good results in the testing period, and the value of portfolio is more stable when the capital is allocated by our MV model, since the average of negative returns is smaller.

To end this section, we compare the performance of our models with various models. The results are shown in Table V, where the period for computing ROI_{cum} (cumulated ROI) and AR_{cum} (annualized ROI) is from 2004/1/1 to 2008/12/31. One can see that in Table V, our models outperform other strategies.

Table III
THE RETURNS OF THE BEST PROFITABLE STRATEGIES GENERATED BY THE GP WITH $N = \{5, 10, 15, 20\}$, $tp = 6$, AND $\gamma = 70\%$. HERE EQ REPRESENTS THAT THE CAPITAL IS ALLOCATED EQUALLY, MV MEANS THAT THE CAPITAL IS ALLOCATED WITH THE MV MODEL ($\lambda = 1.0$). THE TRAINING PERIOD IS FROM 1999/1/1 TO 2003/12/31, AND THE TESTING PERIOD IS FROM 2004/1/1 TO 2009/12/31.

Model	training ROI	testing ROI
$N = 5$ EQ	509.61%	100.33%
$N = 5$ MV	432.44%	91.89%
$N = 10$ EQ	315.14%	94.83%
$N = 10$ MV	140.78%	99.91%
$N = 15$ EQ	276.59%	106.09%
$N = 15$ MV	46.55%	99.34%
$N = 20$ EQ	287.98%	125.68%
$N = 20$ MV	184.08%	116.72%

Table IV
THE BUYING AND SELLING RULES OF THE BEST PROFITABLE STRATEGIES GENERATED BY GP IN THE TRAINING PERIOD FROM 1999/1/1 TO 2003/12/31.

buying rule	$((MI(t) > 0.8) = (MI(t-7) > 0.7)) > MI(t-7)) \leq MI(t)$
selling rule	$MI(t-7) < 0.7$

V. CONCLUSION

In this paper, we propose two effective models for investment. Our models select funds with the Sortino ratio and determine the timing to buy and sell funds with genetic programming. Our first model with equally allocated capital can gain return from 2004/1/1 to 2008/12/31, achieving the best annualized return 9.11%, which is better than the

Table V
PERFORMANCE COMPARISON FOR VARIOUS MODELS FROM 2004/1/1 TO 2008/12/31. HERE GP AND GA REPRESENT THE GENETIC PROGRAMMING AND THE GENETIC ALGORITHM, RESPECTIVELY.

Model name	ROI_{cum}	AR_{cum}
The 4433 rule	-27.50%	-6.23%
MSCI world price index	-11.21%	-2.35%
S&P 500 composite price index	-18.51%	-4.01%
Sortino ratio on the buy and hold (Equally, $N = 5, tp = 6, \gamma = 70\%$)	-34.67%	-8.16%
Sortino ratio on the buy and hold (MV model, $N = 5, tp = 6, \gamma = 70\%$)	-31.66%	-7.33%
Our first model on GP (best strategy, $N = 5, \gamma = 70\%$)	54.62%	9.11%
Our second model on GP (best strategy, $N = 5, \gamma = 70\%$)	31.82%	5.68%
Tsai's model by GA (constant weight, $N = 35, \gamma = 70\%$)	39.53%	6.89%
Tsai's model by GA (constant weight, $N = 45, \gamma = 70\%$)	37.35%	6.55%
Tsai's model by GA (constant weight, $N = 55, \gamma = 70\%$)	33.78%	5.99%

annualized return 6.89% obtained by Tsai's approach [15]. Our second model that uses the MV model lowers the risk, but still gains the return almost the same as Tsai's result. That is, our second model is more stable than Tsai's model.

In the future, we want to find a more suitable way to allocate the capital, because investors may prefer some funds to others in their portfolio, and they may like to invest more capital in these funds. In addition, we also want to increase the performance of our trading function by improving the function and terminal sets used in the genetic programming. By using different kinds of sets, we may get better return from the investment.

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