Applied Mechanics and Materials *Online: 2014-06-10*
ISSN: 1662-7482, Vols. 571-572, pp 318-325
doi:10.4028/www.scientific.net/AMM.571-572.318

A Mutual Fund Investment Method Using Fruit Fly Optimization Algorithm and Neural Network

Tsui-Hua Huang [1, a], Yungho Leu [2,b]

[1] No.43, Sec. 4, Keelung Rd., Da'an Dist., Taipei 106, Taiwan

[2] No.43, Sec. 4, Keelung Rd., Da'an Dist., Taipei 106, Taiwan

[a]h11431@hotmail.com, [b]yhl@cs.ntust.edu.tw

Keywords: Mutual Fund, Data Envelopment Analysis, Fruit Fly Optimization Algorithm, General regression neural network, neural network and linear regression.

Abstract. This paper presents a method to construct a profitable portfolio of mutual funds for investors. This method comprises two stages. In the first stage, the DEA, Sharpe and Treynor indices of mutual funds and the monthly rates of return (ROR) of mutual funds are used to select a mutual fund portfolio. In the second stage, the linear regression model, the Fruit Fly Optimization Algorithm (FOA) and the General Regression Neural Network (GRNN) are used to construct a prediction model for the net asset values of each of the constituent mutual funds of the portfolio. The trade decision of a selected mutual fund is then made based on the rise or fall of its net asset value. The empirical results showed that, compared to other combinations, the combination of using Sharpe index for portfolio selection and the GRNN optimized with FOA for net asset value prediction offered the best accumulated return rate for the mutual fund portfolio investment.

Introduction

Investment tools such as stocks and bonds are very sensitive to the fluctuation of the market. An investor needs to possess enough financial background to be able to gain profit from the stock and bond markets. In contrast, a mutual fund collects capital from many investors and consigns it to professional managers for investing. With sound financial knowledge and in-depth understanding of the industry, a mutual fund manager can usually renders high return rate for their investors. In addition, a mutual fund is a very flexible investment tool due to its low investment barrier, easy handling procedure and easy cashable characteristics. After the investors have selected a mutual fund, they can purchase the mutual fund on a systematic investment plan (SIP) basis or on a one-time investment basis. For one-time investment, an investor gain profits by buying a fixed number of units of the fund at a lower price and sell them at a higher price through catching the pulse of the stock market. On the other hand, with a systematic investment plan, an investor commits to investing a fixed amount of money at a regular interval. With SIP the investor benefits from purchasing units of fund with low average cost and the power of compounding. Over a long investment horizon, SIP tends to deliver attractive returns.

To diversify the risk on mutual fund investment, we propose to construct a simple mutual fund portfolio over several efficient mutual funds. To construct the portfolio, three Taiwan's stock-based mutual funds that are listed on the Taiwan Economic Journal (TEJ) database are selected. Many performance indices can be used for mutual fund selection. For example, if the investment risk is not considered, return rate is a good selection criterion. However, if the investment risk is considered, Sharpe and Treynor performance indices are better than the return rate. Furthermore, if more than one factor is considered, the Data Envelopment Analysis (DEA) can be used for mutual fund selection. To compare the effectiveness of different selection criteria, we use rate of return, Sharpe's and Treynor indices and DEA in mutual fund selection.

Having constructed a mutual fund portfolio, we simulate trading of the portfolio. We first predict the price (net asset value) of the mutual fund of the portfolio on a daily basis. If we predict a price rise in the next day, we buy the mutual fund in the next day with the closing price of the previous day for a value of the total investment. We then sell the investment before the market closes. If we predict a price fall in the next day, we operate in the reverse direction by selling the mutual fund first at the opening of the market and then purchasing the mutual fund before the market closes.

To predict the price of a mutual fund portfolio, we adopt methods from artificial intelligence. It has been noted that though the traditional quantitative methods are useful for financial engineering prediction, they are not as powerful in predicting problems which show a non-linear input/output relationship Leorey et al. Leorey et al. [10]. In contrast, artificial intelligence methods such as neural networks and genetic algorithms can handle problems with non-linear input/output relationship. Therefore, in this research, we use the fruit fly optimization algorithm and the general regression neural network to build a prediction model for the price of a mutual fund portfolio.

The rest of the paper is organized as follows. We address the related work in Section 2. In Section 3, we present our research architecture. Section 4 describes the prediction model. The empirical results and analysis are shown in Section 5. Finally, Section 6 gives the conclusion and suggestions of this paper.

Literature Reviews

For the purpose of making higher profit, this paper will focus on selecting a mutual fund portfolio and constructing a prediction model for the net asset value of a mutual fund in a trading strategy, the reference literatures are discussed in the following.

2.1 Traditional performance indices of mutual funds

The Sharpe index is developed based on Capital Asset Pricing Model, which is an index to measure the excess return of per unit investment after adjusting its total risk. The larger the index value, the better the performance of the mutual fund under analysis. Some investors thought that for a mutual fund the non-system risk should have already been diversified. Therefore, the Treynor index, which measures the excess return after adjusting systematic risk instead of total risk, was proposed.

Treynor[9] used 20 mutual funds to describe the application of the Treynor performance index. Sharpe[19] used the annual data of 34 mutual funds to study the difference between Sharpe and Treynor indices and found that Treynor index was consistent with the Sharpe index.

2.2 Mutual fund selection using data envelopment analysis

Data envelopment analysis is frequently used in financial engineering. For example, Murthi et al. [2] used the excess return as the output, and transaction fee, handling fee, turnover rate and standard deviation as the inputs of the DEA to examine the correlation between the DEA investment portfolio efficiency index (DPEI) and other traditional methods. The result shows a high correlation between DPEI and each of the Sharpe index, Jensen index and the Morningstar. McMullen and Strong [11] used return rate as the output, and standard deviation, minimal investment value, transaction fee and sale fee as the inputs of the DEA to select portfolios stock mutual funds. Razieh Bahrani et al. [15] applied DEA to evaluate the efficiency of several companies. Fethi and Pasiouras [12] found that DEA is widely used in the assessment of bank performance.

2.3 Applications of artificial intelligence in optimization and investment

Artificial intelligence can be dated back to 1957, and it was not popular until Hopfield neural network [7] was designed in 1980. It needs not to meet a lot of assumptions of multivariate analysis, and can handle different types of data. Many researchers have used it to set up investment strategies. Recently, many researchers have also applied the artificial intelligence in solving optimization problems.

Chen et al. [16] generalized the traditional portfolio selection problem as an investment strategy portfolio problem. They therefore proposed a new combination encoding format and its corresponding shrinking crossover operator for solving the investment strategy portfolio problem. Chang et al. [8] proposed to use investment satisfied capability index (ISCI), an index borrowed from the Process Capability Indices (PCI) of quality management, as a parameter for the investor to screening a set of investing stocks. Afterwards, the particle swarm optimization (PSO) algorithm was applied to allocate the capital of the investment among the selected stocks. This method allowed the investor to specify his desired return rate and selected a portfolio that satisfied the desired return rate. Pan [18] proposed a hybrid method which used the principal component regression (PCR) model, genetic algorithm and the general regression neural network to predict the price of a stock.

Artificial intelligence algorithms such as ant colony algorithm (Chang et al. [16]), particle swarm algorithm (Chang et al. [8]) and fruit fly algorithm (Pan [17]) have been used in optimization. In this paper, we applied Pan's Fruit Fly Algorithm combined with the General Regression Neural Network (FOAGRNN) to build a prediction model for an investment strategy.

Research method

3.1 Research architecture

The research architecture of this paper is shown in Figure1. The first step of this research is to select three mutual funds of stocks to form an investment portfolio. Then an investment strategy is applied to the investment portfolio to trade the mutual funds on a daily basis. Finally, we analyze the performance of the investment strategy.

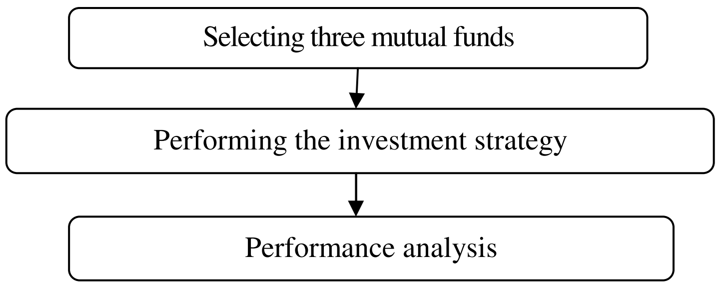

Fig. 1 Research architecture

In order to construct an effective portfolio, not only the rate of return of the recent month, but also the Sharpe and Treynor indices and the data envelopment analysis (DEA) are used. After selecting the investment portfolio, artificial intelligence models, including general regression neural network, Fruit Fly Optimization Algorithm optimized General Regression Neural Network, are used to predict the NAVs in the investment strategy. Besides, a linear regression model, which served as a benchmark, is also used to predict the NAVs in the investment strategy.

3.2 The prediction model

In this research, in order to compare the prediction result between general regression neural network and fruit fly optimization algorithm combined general regression neural network prediction neural network, traditional linear regression estimation model is additionally selected to perform the performance comparison.

The prediction model for the net asset value of a mutual fund is shown in the following equation.

$$\mathrm{NAV}_t = \mathrm{F}(\mathrm{NAV}_{t-1}) + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \sigma^2), \tag{1}$$

where NAV_t and NAV_{t-1} are the closing net asset values of a mutual fund at time t and time t-1, respectively, and ε_t is the random noise.

To decide the above-mentioned prediction model, we carefully examined the autocorrelation functions (ACFs) and the partial autocorrelation functions (PACFs) of different mutual fund time series in this research. We found that all the mutual fund time series in this research fitted the AR(1) time series model. That is, the closing NAV of a mutual fund of the next day depends only on the closing NAV of its previous day. Furthermore, for all the nine mutual funds in this research, we adopted the Multivariate Regression Splines (Friedman [5]) to extract the key influential variables for a regression with the 6-previous-period closing NAVs (i.e., a time series with lag order 6) as the independent variables and the current closing NAV as the dependent variable, we found that 100% key influential factor is due to the closing NAV of the previous day. Being an AR(1) model, a simple linear regression model is enough for the prediction of the NAV of a mutual fund. A simple linear regression model is shown in the following:

$$F(NAV_t) = \beta_0 + NAV_{t-1} * \beta_1 + \varepsilon_t, \tag{2}$$

where β_0 and β_1 are the intercept and the slope of the model, respectively; ε_t is the random noise.

In this research, a linear regression model is used as a benchmark for artificial intelligence prediction models.

3.4 Performance evaluation

3.4.1 The directional symmetry

The directional symmetry is used to measure the coincidence in the directions of tendency (i.e., up or down) of the forecasted values and the actual values. DS is defined by the following formula:

$$DS = \frac{\sum_{t=1}^{n} dt}{n} * 100, \quad \text{where} \quad dt = \begin{cases} 1 & \text{if}(A - A_{t-1}) * (F_t - F_{t-1}) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where A_t and A_{t-1} are the actual values at time t and time t-1, respectively; F_t and F_{t-1} are the forecasted values at time t and time t-1, respectively. A good trend forecasting is a forecasting with a large DS.

3.4.2 The return rate on investment

Having constructed a mutual fund portfolio, we simulate trading of the portfolio. We first predict the opening net asset value (NAV) of a mutual fund of the portfolio on a daily basis. If we predict a rise in the closing NAV of the next day, we buy the mutual fund in the next day with the closing NAV of the previous day for a value of the total investment. We then sell the investment before the market closes. Conversely, If we predict a fall in the opening NAV of mutual fund in the next day, we operate in the reverse direction by selling the fund first at the opening of the market in the next day and then purchasing the fund before the market closes. The daily rate of return is shown as follows:

Daily return rate:

$$r_t = (NAV_t - NAV_{t-1})/NAV_{t-1} \tag{4}$$

where r is Daily rate of return at time t; NAV_t and NAV_{t-1} is the net asset values of mutual fund at time t and time t-1, respectively. The accumulated return rate is defined as follows:

Accumulated return rate:

$$R = \prod_{t=1}^{N} (1+r_t) - 1, \tag{5}$$

where R is the accumulated return rate.

The Fruit Fly Optimization Algorithm.

4.1. The Concept

The Fruit Fly Optimization Algorithm (FOA) [17] is a new evolutionary algorithm for optimization. It is based on the food searching behavior of a fruit fly which has better smelling and vision capabilities than any other species.

In searching of food, a fruit fly can use its sensitive vision to find the food and the company's flocking location, and then flies toward the food (shown in Figure 2). The FOA proposed by Pan allows only two dimensions in direction and distance, while in this paper we expand it into three dimensions.

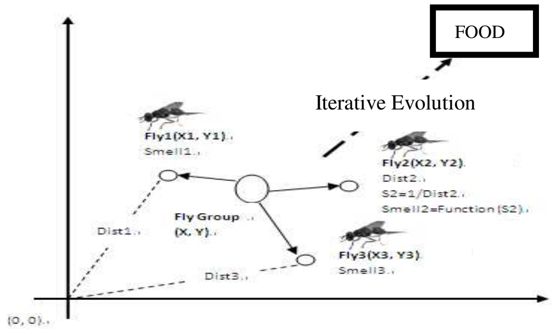

Fig. 2 Illustration of group iterative food searching of fruit fly [17]

4.2 Optimizing the GRNN by FOA

The General Regression Neural Network (GRNN) uses functional approaching method to solve a problem (Specht [4]). This article proposes to use FOA to adjust the smoothing parameter (spread) value of the GRNN.

When the spread value of a GRNN is small and its radial basis function is relatively steep, the GRNN will make the weights vector neurons, that are closer to the input, to have an output that are bigger than other neurons. The network will react to the target vector that is the closest to the designed input vector. The more the spread value increases, the more glacis the slope of radial basis function will become, and many neurons can be reflected into the inputs vector. The action of the network is like to take the weighted mean of the target vector, and the designed input vector is closest to the new input vector. Because of the above, when the spread value becomes bigger and bigger, more and more neurons will contribute to the average value, resulting in a more glacis network function.

For the proposed GRNN optimized by FOA prediction model, we adopted the MATLAB GRNN toolbox and the modified MATLAB program by Pan [17]. The procedure of the GRNN optimized by FOA is illustrated in the following.

First, we randomly generate a swarm of fruit flies with random initial positions, and then give them random directions and distances to look for food with their sensitive organs. The number of iterations and the population size are set to 100 and 10, respectively. In the beginning, the food location is unknown, therefore each fruit fly first estimates the distance with the origin, and then calculate the value of smell concentration. This value is the reciprocal of the 3-D distance.

Secondly, substitute the spread of GRNN with the smell concentration value; input the training data, and get the output value of the GRNN; calculate the difference between the real output and the output of the GRNN. Find the root mean square error of the difference; determine the fruit fly with the maximum smell concentration, and retain the best smell concentration value of the fruit fly swarm.

Thirdly, repeat the above-mentioned steps except the step of generating fruit flies' initial positions. If the smell concentration of the current iteration is better than the smell concentration of the previous iteration, replace the best smell concentration with the smell concentration of the current iterat*ion.*

Empirical result and analysis

5.1 Description of variables

The data used in this research is acquired from Taiwan Economic Journal. After deleting mutual fund with insufficient data, there are 318 mutual funds left. The data used in this research are the monthly average of the net values (NAVs) of the mutual funds of 2012. To construct better portfolio for trading, we use the Sharpe and Treynor indices and the data envelopment analysis (DEA) method, respectively, to select the top-3 mutual funds for the portfolio. Noting that for DEA the only output variable is recent monthly return rate of a mutual fund, and the input variables are annualized standard deviation, turn-over rate of the buy in a single month, turn-over rate of the sell in a single month, direct transaction cost rate, expense ratio, beta value, and the net asset value of the mutual fund.

To construct a prediction model, we used 290 consecutive NAV values of each of the selected mutual fund, including 232 values in 2012 and 58 NAV values in 2013. Note that we use the 232 NAV values in 2012 as the training data set and the 58 NAV values in 2013 as the testing data set. We performed 58 NAV predictions and compare the performance of the prediction models.

5.2 The mutual funds selected by different methods

The top 3 ranked mutual funds selected by different selection methods are shown in Table 1. As shown in Table 1, there are same mutual funds selected by different methods. Totally, we have nine different mutual funds selected for constructing mutual fund portfolios in this research.

Table 1. Top-3 ranked mutual funds selected by four selection methods

DEA	▪ Manulife Asia Pacific Mid & Small Cap ▪ SinoPac Luxury and Lifesty ▪ Hua Nan Global Luxury Goods
Sharpe Index	▪ ING Global Biotech & Health Care ▪ Allianz Global Investors Global Biotech Fund ▪ ING Thailand
Treynor Index	▪ ING Indonesia Star ▪ FSITC Malaysia ▪ Allianz Global Investors Global Biotech Fund
Rate of return	▪ ING Thailand ▪ Allianz Global Investors Global Biotech Fund ▪ Paradigm Small Capital Fund

5.3 Investment performance analysis

In this research, real data are used to simulate the result, after repeated test of 10 times of the result, fruit fly optimization algorithm combined general regression prediction model shows a stable value on the rate of return and hit rate analysis and the general regression neural network prediction model shows larger fluctuation on the rate of return and the hit rate analysis, we take the average value of 10 times of the empirical result for analyzing the performance.

5.3.1 Return rate analysis

Table 2 shows the accumulated return rates for different combinations of selection methods and prediction models. It is shown that the combination of the Sharpe index selection method and the fruit fly optimized general regression neural network model (FOA+GRNN) offers the highest accumulated return rate (35.46%). Among the prediction models, the FOA optimized GRNN offers the highest average accumulated return rate (28.85%). Furthermore, it is also shown in Table 2 that the average accumulated return rate of the artificial intelligence methods, including FOA+GRNN and GRNN, offer better performance than the traditional linear regression method does (19.61%>-5.08%).

Table 2. Rate of return analysis of all kinds of investment strategies

Portfolio selecting method \ Prediction method	FOA+GRNN	GRNN	Linear regression
DEA	22.25%	11.26%	1.68%
Sharpe index	35.46%	11.69%	-12.78%
Treynor index	24.51%	6.42%	-5.15%
Rate of return	33.18%	12.07%	-4.06%
Average	28.85%	10.36%	-5.08%

5.3.2 The directional symmetry of different methods

As shown in table 3, the combination of the FOA optimized GRNN and the Sharpe index offers the highest DS, which means that this combination has the highest accuracy in trend prediction. This accounts for the highest accumulated return rate offered by this combination. On average, the FOA optimized GRNN offers the highest averaged DS (72.7%) compared to that of GRNN (56.09%) and linear regression (41.81%). Furthermore, the artificial intelligence methods offer better DS than the traditional linear regression method does (64.40%>41.81%).

Table 3 Hit rate analysis of all kinds of investment strategies

Portfolio selecting method \ Prediction method	FOA+GRNN	GRNN	Linear regression
DEA	66.09%	57.18%	49.43%
Sharpe index	81.03%	56.90%	33.91%
Treynor index	67.82%	53.28%	39.66%
Rate of return	75.86%	57.01%	44.25%
Average	72.70%	56.09%	41.81%

Conclusions and suggestions

In this paper, we have proposed an investment strategy of mutual fund. We first select a portfolio of stock-based mutual funds from the market using performance indices such as Sharpe and Treynor indices, monthly return rate and data envelopment analysis. We then use the general regression neural network which is optimized by the fruit fly optimization algorithm to predict the net asset value of each mutual fund in the portfolio. Based on the predicted value, a simulated trading of the mutual fund portfolio is performed. The empirical results showed that: (1) the portfolio selected by the Sharpe's index outperformed the portfolio selected by any other performance indices or methods, and (2) the simulated trading with the net asset value of mutual fund predicted by the general regression neural network optimized with the fruit fly optimization algorithm offered the highest accumulated return rate compared to other prediction methods.

References

[1] A.Charnes, W. W. Cooper and E. Rhodes: Measurement the Efficiency of Decision Making Units. European Journal of Operational Research Vol. 2, Issue 6 (1978), p.429-444.

[2] B.P.S. Murthi, Yoon k. Choi and Preyas Desai: Efficiency of Mutual Funds and Portfolio Performance Measurement: A Non-Parametric Approach. European Journal of Operational Research, Vol. 98, Issue 2 (1997), p.408-418.

[3] Chien-Jen Huang, P-W Chen and W-T Pan: Multi-stage Data Mining Technique to Build the Forecast Model for Taiwan Stocks. Neural Comput. & Applic., Online First TM (2011).

[4] D.F. Specht “A General Regression Neural Network”, IEEE Trans. Neural Networks, Vol.2, No.6 (1991), p.568-576.

[5] J.H. Friedman: Multivariate adaptive regression splines. Annals of Statistics, Vol.19, No.1 (1991) p.1-141.

[6] Jiah-Shing Chen, Jia-Li Hou, Shih-Min Wu and Ya-Wen Chang-Chien: Constructing investment strategy portfolios by combination genetic algorithms. Expert Systems with Applications, Vol. 36, Part 2 (2009), p.3824–3828.

[7] J.J. Hopfield: Neural Networks and Physical Systems with Emergent Collective Computational Abilities. Proc. Natl. Acad. Sci. Vol. 79, No.8 (1982), p.2554-2558.

[8] Jui-Fang Chang: Using investment satisfaction capability index based particle swarm optimization to construct a stock portfolio. Information Sciences, Vol. 181, No.14 (2011), p.2989–2999.

[9] J. L. Treynor: How to Rate Management Investment Funds. Harvard 84 Business Review, Vol. 43 (1965), p. 63-75.

[10] Leorey Marquez and Tim Hill: Function Approximation Using Backpropagation and General Regression Neural Networks. In Proceeding of the Twenty-Sixth Hawaii International Conference on System Science, Vol. 4 (1993), p.607-615.

[11] McMullen, Patrick R. and Robert A. Strong: Selection of Mutual Funds Using Data Envelopment Analysis. Journal of Business and Economic Studies, Vol. 4, Issue 1 (1998), p. 1-12.

[12] Meryem Duygun Fethi and Fotios Pasiouras: Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. European Journal of Operational Research, Vol. 204, issue 2 (2010), p.189–198.

[13] M. J. Ferrell: The Measurement of Productive Efficiency. Journal of theRoyal Statistical Society, Vol. 120, Part 3 (1957), p.253-281.

[14] Peng-Wen Chen, Wei-Yuan Lin, Tsui-Hua Huang and Wen-Tsao Pan: Using Fruit Fly Optimization Algorithm Optimized Grey Model Neural Network to Perform Satisfaction Analysis for E-Business Service. Applied Mathematics & Information Sciences, Vol. 7, No. 2L (2013), p.459-465.

[15] Razieh Bahrani and Nader Khedri: Evaluation of Relative Efficiency and Performance of Companies Using Data Envelopment Analysis (DEA) Approach. Elixir International Journal, Elixir Fin. Mgmt. 56 (2013) , p.13299-13304.

[16] Ruay-Shiung Chang, Jih-Sheng Chang and Po-Sheng Lin: An ant algorithm for balanced job scheduling in grids. Future Generation Computer Systems, Vol. 25, Issue 1 (2009), p. 20–27.

[17] Wen-Tsao Pan: A New Fruit Fly Optimization Algorithm: Taking the Financial Distress Model as An Example. Knowledge-Based Systems, Vol.26 (2012), p.69-74.

[18] Wen-Tsao Pan: Performing stock price prediction use of hybrid model. Chinese management studies : CMS.-Bingley : Emerald, Vol. 4, Issue 1 (2010), p.77-86.

[19] W. F. Sharpe: Mutual Fund Performance. Journal of Business, vol. 39, No. 1, Part 2 (1966), p. 119-138.