MNFS-FPM: A Novel Memetic Neuro-fuzzy System Based Financial Portfolio Management

Ernest Lumanpauw, Michel Pasquier, and Chai Quek

Abstract—Portfolio management consists of deciding what assets to include in a portfolio given the investor’s objectives and changing market and economic conditions. The always difficult selection process includes identifying which assets to purchase, how much, and when. This paper presents a novel Memetic Neuro-fuzzy System for Financial Portfolio Management (MNFS-FPM) which emulates the thinking process of a rational investor and generates the optimal portfolio from a collection of assets based on a chosen investment style. The system consists mainly of two modules: the Generically Self-Organizing Fuzzy Neural Network realizing Yager inference (GenSoFNN-Yager), to predict the expected return of each asset, and a memetic algorithm using simplex local searches (MA-NM/SMD) to determine the optimal investment weight allocation for all assets in the portfolio. Experimental results on Dow Jones Industrial Average (DJIA) stocks show that the proposed system yields better performance compared to that of existing financial models: statistical mean-variance analysis and Capital Asset Pricing Model (CAPM).

I. INTRODUCTION

FINANCIAL portfolio management means to control a collection of securities or instruments held by either an institution or an individual [1]. An investor with certain objectives has a sum of money to be invested for a particular length of time known as the holding period. At the end of the holding period, the investor will sell the securities and perhaps reinvest. Securities in a portfolio can be in the form of stocks, bonds, options, foreign currencies, commodities, or other assets which are expected to bring forth returns to the investor.

The renowned mean-variance model for portfolio selection, introduced by Markowitz in 1952 [2], has been widely used in finance and is considered to be one of the most important foundations of modern portfolio theory.

\[
\bar{r}_p = \sum_{i=1}^{N} w_i \bar{r}_i 
\]

(1)

\[
\sigma_p = \left[ \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij} \right]^{1/2}
\]

where \( \sigma_{ij} = \rho_{ij} \sigma_i \sigma_j \) (2)

subject to \( \sum_{i=1}^{N} w_i = B. \) (3)

According to (1)-(3), the portfolio’s expected return or mean \( \bar{r}_p \) is determined by the expected return \( \bar{r}_i \) of each individual security and the proportion \( w_i \) of each security in a portfolio of \( N \) assets. The portfolio expected risk or volatility \( \sigma_p \) is determined by three factors: the proportion \( w_i \) of each security in the portfolio, the standard deviation \( \sigma_i \) of each security from its expected return, and the correlation \( \rho_{ij} \) between the deviations for each pair of securities in the portfolio. \( \sigma_{ij} \) is known as the covariance and measures how much returns on asset securities \( i \) and \( j \) move in tandem. Finally, the sum of the proportion of each security must be equal to budget \( B \), which for simplicity is usually set to 1. The solution to this problem is an optimal weight allocation for each instrument \([w_1, w_2, ..., w_N]\) which satisfies the predefined objective set by the investors.

While this model has enlightened investors’ understanding of portfolio selection in terms of risks, returns, and efficient frontier [1], two major challenges remain in the area of portfolio selection: on the one hand, the estimation of return, volatility, and correlation values of stock components and, on the other hand, the design of a computational process or strategy to demonstrably realize that optimal portfolio.

The accurate estimation of stock component values forms the foundation of the portfolio selection process, since the estimated values are used critically during the process of generating an optimal portfolio. Reliable information will help investors foresee which stocks will bring positive returns (or lower risks) and allocate accurately the amount of investment money on those stocks. Conversely, inaccurate information will result in a misleading portfolio to be generated i.e., that will perform well below expectation. Various techniques, such as fundamental analysis [3], technical analysis [4], time series analysis [5], Support Vector Machines (SVM) [6, 7], neural networks [8, 9], fuzzy theory [10-12], neuro-fuzzy systems [13], and genetic programming [14] have been proposed and used with varying results.

Finding an optimal portfolio which satisfies the predefined objectives may become a complex and multidimensional search problem, especially when it involves a large number of stocks. The search process may by time-consuming and, due to a complex a search landscape, many search or optimization techniques may fail to generate optimal results e.g., when prone to be trapped in local optima. Various techniques, such
as greedy search, Newton method [15], and evolutionary algorithms [16-18], have been employed to find optimal portfolios of different number of stock components.

In this paper, a novel portfolio management system which synergizes the learning and predictive capabilities of a neuro-fuzzy system [19] and the optimization capability of a memetic algorithm (MA) [20, 21], termed Memetic Neuro-fuzzy System for Financial Portfolio Management (MNFS-FPM), is proposed to serve as a decision support tool for real-world portfolio management. It should be noted that in this model we do not intend to capture every detail of the investor’s thinking process. This would be neither feasible, given that due to emotional or psychological aspects investors may react differently in a given situation, nor desirable, due to the computational issues arising from the model complexity. Instead, we aim at encapsulating the generalized investment process and focus on the functional and decision making aspects involved in investment and portfolio management.

The system consists of two modules: the hippocampus-inspired Generic Self-organizing Fuzzy Neural Network realizing Yager inference (GenSoFNN-Yager) [22] and a memetic algorithm which uses simplex local searches (MA-NM/SMD) [23]. First, the GenSoFNN-Yager is used to predict the expected return of each individual asset based on historical return values. Then, the MA-NM/SMD is applied to determine the optimal investment weight allocation for each asset in the portfolio that satisfies the investor’s objectives.

This paper is organized as follows. Section II outlines the proposed memetic algorithm, MA-NM/SMD. Section III reviews the architecture and learning procedure of the GenSoFNN-Yager. Section IV describes in detail the proposed portfolio management model. Section V presents extensive experimental results using the proposed portfolio management system on Dow Jones Industrial Average (DJIA) stocks. Results in terms of actual return and risk as well as Sharpe ratio [24] are presented and compared against those evaluated using other financial approaches: statistical mean-variance analysis [1] and Capital Asset Pricing Model (CAPM) [25-27]. Finally, Section VI concludes this paper.

II. MA-NM/SMD

Memetic Algorithm (MA) is a population-based approach for heuristic search in optimization problems [21]. It is a combination of genetic algorithm [28, 29] and local search method (GA-LS) which often finds better solutions and searches more efficiently than GA alone [30]. Traditionally, MA searches are based on the use of genetic algorithm and a single local search method. In this work, the approach of using multiple local search methods, namely Simplex Search of Nelder and Mead (NM) [23] and Sequential Multi-Directional Search (SMD) [31], is investigated. NM and SMD are variants of Simplex Search, a widely used optimization method that uses only the objective function values.

The Simple Random Walk Scheme MA [32] is a more effective search where, at any one time only one out of a pool of local search methods is selected at random and executed. We adopt the same approach to randomly execute NM local search, SMD local search, or no local search at each decision point. The two local search methods are placed into a catalog and, each time prior to the execution of local search in MA, a random number \( k \in [0, 2] \) is generated to decide which local search is to be used. NM search is selected when \( 1 \leq k \leq 2 \) and SMD when \( k = 2 \); no local search is performed when \( k = 0 \).

In canonical MA, the local search is performed rigidly, i.e. on each individual of the GA population for a fixed number of evaluations, in every generation. Experiments on various benchmark problems have shown that the evolutionary process of GA typically consists of a rapid convergence phase, during which the fitness value improves significantly from generation to generation, followed by a slow convergence phase, during which the GA performance deteriorates notably. From this observation, we propose to postpone the use of local search until the rapid convergence phase ends, since until then the GA alone performs effectively. Not only execution of local search during this phase may not be efficient or have little effect to the overall search process, but also it would add to the computational cost.

Let \( \Delta_{\text{max}} \) be the minimum rate of change of best fitness value between two generations. In each generation, we calculate \( \Delta_n \) the rate of change of the best fitness value between two generations, as per (4), where \( \text{Fitness}^* (n) \) is the best fitness value in the \( n^{th} \) generation. If \( \Delta_n < \Delta_{\text{max}} \) then local search is performed. Heuristically, we set \( \Delta_{\text{max}} = 0.01 \). The workings of MA-NM/SMD are outlined in Fig. 1.

\[
\Delta_n = \left( \frac{\text{Fitness}^* (n) - \text{Fitness}^* (n-1)}{\text{Fitness}^* (n-1)} \right) \leq \Delta_{\text{max}}
\]

Fig. 1. Working principles of MA-NM/SMD.

For the purpose of reproducibility and after comparing with other GA variants on several benchmark functions, the DemeGA from the C++ GA Library (GAlib) by Wall [33] is
used. Implementations of NM and SMD are adopted from C++ Direct Searches Library [34].

III. GENSOFNN-YAGER

The GenSoFNN-Yager [35] is a neuro-fuzzy system [19] with a generic connectionist structure, extended from the Generic Self-organizing Fuzzy Neural Network (GenSoFNN) [36] to realize the Yager fuzzy inference scheme [37]. The network, specifically modeled after the operations of the hippocampal region of the brain [38], is a global learning memory system which employs online sequential learning [35].

A. Architecture

The GenSoFNN-Yager consists of five layers of nodes, as illustrated in Fig. 2. Input nodes in layer 1 and output nodes in layer 5 represent input and output linguistic variables, respectively, while nodes in layers 2-4 define the fuzzy rule base. The linguistic term nodes in layer 2 and 4 represent the antecedents and consequents of the fuzzy rules, respectively, and each rule node in layer 3 represents a single fuzzy rule.

B. Learning Procedure

Training the GenSoFNN-Yager is a single-pass process that consists of three phases. During the self-organizing phase, the system performs unsupervised cluster analysis of the problem data using the Discrete Incremental Clustering (DIC) algorithm [36] to construct input and output fuzzy labels. Next, the rule formulation phase employs the RuleMap algorithm [36] to derive the fuzzy rule base, linking input and output labels. Finally, the parameter learning phase employs the back-propagation learning algorithm [39] to refine the model.

IV. MNFS-FPM

A. Architecture

A block diagram of the MNFS-FPM is shown in Fig. 3, which illustrates the following three operational steps.

1) GenSoFNN-Yager, using supervised learning, predicts the expected return of each asset for the subsequent year based on historical return data.
2) MA-NM/SMD searches for the optimal asset allocation for each stock based on the predicted return values from GenSoFNN-Yager and pre-computed volatility and correlation values of all stocks.
3) Performance of the portfolio is computed in terms of actual return, volatility (risk), and Sharpe ratio by substituting the weights, actual return, volatility, and correlation values of its stock components into (1)-(3).

B. Chromosome Representation

The real-valued chromosome encoding the DJIA stock allocation is depicted in Fig. 4, where each gene corresponds to the weight \( w_i \in [0.0, 1.0] \) of each stock.

C. Fitness Function Formulation

Two different fitness functions portray different investor characteristics, namely: (1) a risk-seeking investor who seeks to maximize return and (2) a risk-averse investor who seeks to minimize portfolio risk.

Although the objective of the risk-seeking investor is to maximize return, setting the fitness function of the MA-NM/SMD to solely maximize return must be avoided since the algorithm may end up investing 100% of the wealth into a single asset. Not only this would contradict the very notion of portfolio (or tenet of portfolio management), but also it might yield disastrous results with the investor losing a larger amount of money. A more realistic approach is to set the fitness function to maximize the Sharpe ratio [40], used to measure how well the return on investment compensates the investor for the risk taken. It is defined in (5), where \( E[R] \) is the expected return of the portfolio, \( R_j \) is the risk free rate of return (often assumed constant throughout the investment period), and \( \sigma \) is the risk of the portfolio. Substituting (1) and (2) into (3), the fitness function of the risk-seeking investor is defined as per (6) hereafter.
\[
S = \frac{E[R] - R_f}{\sigma} \quad (5)
\]

Maximize \[
S = \frac{\sum_{i=1}^{N} w_i \bar{r}_i - R_f}{\left( \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij} \right)^{1/2}} \quad (6)
\]
subject to \[
\sum_{j=1}^{N} w_i = 1
\]

For the case of risk-averse investor, it should be noted that the investor’s ultimate goal is still profit, but by suppressing the risk level as low as possible by avoiding volatile assets. Therefore, the fitness function is set to minimize the standard deviation of the portfolio (7).

\[
\text{Minimize } \sigma_p = \left( \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij} \right)^{1/2} \quad (7)
\]
subject to \[
\sum_{i=1}^{N} w_i \bar{r}_i > R_f \text{ and } \sum_{i=1}^{N} w_i = 1
\]

D. Performance Evaluator

A risk-free asset [1], i.e. financial instrument with near-zero risk, is often set as a preliminary benchmark to measure the effectiveness of different portfolio models. In practice, the US Treasury bill (T-bill), an instance of risk-free assets, is commonly used as benchmark, since it yields an average 5% annual return with near-zero risk. Therefore, any portfolio that yields less than 5% return annually is hardly worth the risk, since one can simply invest in T-bill instead.

Measurements in terms of actual return, volatility (risk/variance), and Sharpe ratio are conducted to assess the performance of a portfolio. The Sharpe ratio [40] is arguably the most insightful since it measures how well the return of investment compensates the investor for the risk taken. In general, investors prefer portfolio which has high return, low volatility/risk, and high Sharpe ratio.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Simulation Settings

The following settings are applied in all experiments:

1) The entire wealth (100\%) is invested and no borrowing is allowed.
2) Investment is only for long term, thus no short selling is allowed.
3) The portfolio is evaluated yearly and return/loss from the previous year will not be brought forward.
4) Two different types of investors are considered: risk-seeking and risk-averse investors.

Comparisons are made with other portfolio models: equal weight, statistical mean-variance, and CAPM, as summarized in Table I.

![Table I: Summary of Different Portfolio Models](image)

The equal weight model is without forecast and simply allocates wealth equally to all assets. The MVA_5 and MVA_10 use statistical average and standard deviation as return and volatility estimators defined in (8) and (9) respectively. The return and standard deviation in the CAPM model is estimated using (10) and (9) respectively. The MNFS-FPM utilizes GenSo-FNN-Yager as the return predictor and (9) to estimate volatility. For the GenSoFNN-Yager, return prediction is based on previous 10 return values. However, since the yearly return data is limited, monthly return values from 1992 to 2001 are used as training set. Finally, for all models (except equal weight), the portfolios are constructed using MA-NM/SMD with settings listed in Table II.

![Table II: Parameter Settings of MA/NM-SMD](image)
B. Data Preprocessing

The Dow Jones Industrial Average (DJIA, NYSE: DJI) is the oldest continuing and the most widely quoted US stock market index, comprising thirty of the largest and most widely held public companies in the United States. DJIA stock price data from 1992 to 2006 obtained from the Center for Research in Security Prices (CRSP) [41] is used throughout the simulation.

For each stock, its monthly and yearly return values \( R(t) \) are calculated using formula (11). In the event of stock split, adjusted return is calculated using formula (12), where SR (Split Ratio) usually occurs in the form of 2:1, 3:1, 3:2, 5:4, and so forth.

\[
R(t) = \frac{\text{Price}(t) \times \text{SR} - \text{Price}(t-1)}{\text{Price}(t-1)} \quad (12)
\]

\[
R(t) = \frac{\text{Price}(t) - \text{Price}(t-1)}{\text{Price}(t-1)} \quad (11)
\]

C. Case 1: Risk-seeking Investor

As observed in TABLE III, despite having similar objectives, different models generate different number of stocks. This implies that different forecast values of individual stocks affect the outcomes of the portfolio structure. The equal weight model always generates portfolios which have the most number of stocks, followed by CAPM. On the other hand, the MNFS-FPM almost constantly generates portfolios which have the least number of stocks. This can be viewed as a good indicator that portfolios formed by the proposed system are in line with the objective of maximizing return. This is because maximizing return indirectly implies having fewer stocks in the portfolio and allocating a bigger proportion of wealth into the individual stocks.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal Weight</td>
<td>[30, 30, 30, 30, 30]</td>
</tr>
<tr>
<td>MVA_5</td>
<td>[17, 4, 3, 4, 2]</td>
</tr>
<tr>
<td>MVA_10</td>
<td>[7, 7, 6, 6, 8]</td>
</tr>
<tr>
<td>CAPM</td>
<td>[24, 23, 21, 25, 19]</td>
</tr>
<tr>
<td>MNFS-FPM</td>
<td>[4, 5, 3, 2, 2]</td>
</tr>
</tbody>
</table>

TABLE IV shows that over the 5-year period, the MNFS-FPM yields significantly higher average investment profit compared to other financial models. In addition, as shown in Fig. 5, the profit of the proposed portfolio management system is consistently higher compared to that of other financial models for every year except 2002.

Due to an unavoidable event called stock market downturn of 2002 [42-44], worldwide stock exchanges crashed and experienced sharp drop in stock prices. This is a concrete illustration of systematic risk [1] which is unavoidable. In this kind of situation, the market is almost totally unpredictable. This is further confirmed by the facts that other investment models also suffer from significant losses, but not as severe as in our approach due to their more diversified portfolio composition.

Conversely, in 2003, the market condition is bullish (booming). In this year, the MNFS-FPM yields a massive profit of 85.62%, much greater than other investment models. This signifies that the proposed system selects and allocates investment amount wisely based on predicted return values by GenSoFNN-Yager. For the remaining years (2004-2006) the MNFS-FPM always yields higher investment profits compared to other investment models. These can be ascribed to more accurate forecast of return values using GenSoFNN-Yager.

As observed in TABLE V, portfolios generated by the MNFS-FPM present on average a much higher risk level compared to those generated by MVA_5 and MVA_10, but still slightly lower compared to those of equal weight and CAPM. Fig. 6 shows that risk level of portfolios generated by MNFS-FPM increases and fluctuates from year to year, different from that of other models which is relatively stable.

![Fig. 5. Actual profit of different portfolio models for Case 1.](image-url)
However, this was expected since the investor is risk-seeking and his/her objective is to maximize return without putting any restrictions on risk.

### TABLE V
**Actual Variance (Risk) Comparison Between Different Portfolio Models for Case 1.**

<table>
<thead>
<tr>
<th>Year</th>
<th>Equal Weight</th>
<th>MVA_5</th>
<th>MVA_10</th>
<th>CAPM</th>
<th>MNFS-FPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>2.09</td>
<td>0.06</td>
<td>0.25</td>
<td>1.51</td>
<td>0.25</td>
</tr>
<tr>
<td>2003</td>
<td>3.08</td>
<td>0.71</td>
<td>0.01</td>
<td>2.88</td>
<td>2.23</td>
</tr>
<tr>
<td>2004</td>
<td>3.85</td>
<td>0.63</td>
<td>0.75</td>
<td>3.83</td>
<td>2.69</td>
</tr>
<tr>
<td>2005</td>
<td>3.50</td>
<td>0.69</td>
<td>0.69</td>
<td>3.80</td>
<td>4.01</td>
</tr>
<tr>
<td>2006</td>
<td>3.48</td>
<td>0.17</td>
<td>0.82</td>
<td>3.88</td>
<td>6.01</td>
</tr>
</tbody>
</table>

Avg. Var.

- Equal Weight: 3.20
- MVA_5: 0.45
- MVA_10: 0.63
- CAPM: 3.18
- MNFS-FPM: 3.04

![Fig. 6. Actual risk of different portfolio models for Case 1.](image)

The Sharpe ratio values in Fig. 7 are obtained by substituting average return and average risk values into (5). From the figure, we observe that the Sharpe ratio of MVA_5 is negative. This signifies that its average return within five years is less than that of T-bill. This also implies that it is better to invest in T-bill and get 5% return annually with near-zero risk, rather than to invest in portfolios generated using MVA_5. It is also clearly evident that the Sharpe ratio of MNFS-FPM is significantly higher than that of other portfolio models. The high Sharpe ratio value implies that portfolios generated by MNFS-FPM have the highest reward-to-risk ratio, and investing in portfolios generated using MNFS-FPM is worth bearing the risks.

Based on encouraging actual average investment profit and Sharpe ratio which are much higher compared to those of other portfolio models, we can conclude that the predictive capability of GenSoFNN-Yager helps the MNFS-FPM to satisfy the investor’s objective to maximize returns.

### TABLE VI
**Number of Stocks of Different Portfolio Models for Case 2.**

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal Weight</td>
<td>[30, 30, 30, 30, 30]</td>
</tr>
<tr>
<td>MVA_5</td>
<td>[12, 7, 7, 9, 8]</td>
</tr>
<tr>
<td>MVA_10</td>
<td>[8, 6, 6, 7, 8]</td>
</tr>
<tr>
<td>CAPM</td>
<td>[9, 6, 6, 7, 7]</td>
</tr>
<tr>
<td>MNFS-FPM</td>
<td>[14, 5, 8, 6, 30]</td>
</tr>
</tbody>
</table>

### TABLE VII
**Actual Profit Comparison Between Different Portfolio Models for Case 2.**

<table>
<thead>
<tr>
<th>Year</th>
<th>Equal Weight</th>
<th>MVA_5</th>
<th>MVA_10</th>
<th>CAPM</th>
<th>MNFS-FPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>-19.95</td>
<td>-2.24</td>
<td>-2.58</td>
<td>-10.63</td>
<td>-22.70</td>
</tr>
<tr>
<td>2003</td>
<td>35.17</td>
<td>8.53</td>
<td>8.67</td>
<td>20.06</td>
<td>46.59</td>
</tr>
<tr>
<td>2004</td>
<td>2.40</td>
<td>2.43</td>
<td>0.15</td>
<td>6.19</td>
<td>6.58</td>
</tr>
<tr>
<td>2005</td>
<td>2.04</td>
<td>-1.28</td>
<td>-0.24</td>
<td>-2.31</td>
<td>-5.48</td>
</tr>
<tr>
<td>2006</td>
<td>15.22</td>
<td>4.26</td>
<td>4.85</td>
<td>10.88</td>
<td>20.43</td>
</tr>
</tbody>
</table>

Avg. Profit

- Equal Weight: 6.98
- MVA_5: 2.34
- MVA_10: 2.17
- CAPM: 4.84
- MNFS-FPM: 9.08

![Fig. 7. Sharpe Ratio of different portfolio models for Case 1.](image)

**D. Case 2: Risk-averse Investor**

As observed in TABLE VI, in contrast to previous case, the MNFS-FPM now almost constantly generates portfolios which have the most number of stocks compared to other models. This can be viewed as a good indicator that portfolios formed by the proposed system are in line with the objective of minimizing risk, which is usually achieved by means of diversification (investing in more number of stocks).
Similar to previous case, the unavoidable loss in 2002 is due to the stock market downturn of 2002. Consequently, other investment models also suffer from significant losses. In this case, however, all portfolio models incur less severe losses compared to the situation in Case 1. This indirectly shows that the objective of minimizing risk is satisfied.

From TABLE VIII, we observe that on the average portfolios generated by the MNFS-FPM have rather high risk level compared to those generated by MVA_5, MVA_10, and CAPM, but still much lower compared to that of equal weight. Comparing with the average risk in Case 1, we can see that the average risk is now suppressed from 3.04% to 1.33%. As observed in Fig. 9, the risk level of portfolios generated by MNFS-FPM is still quite fluctuating from year to year. However, it is not appropriate to look only from the risk perspective since the investors’ main interest is monetary profit. Therefore, a more appropriate way is to compare in terms of reward-to-risk ratio by looking at the Sharpe ratio.

TABLE VIII
ACTUAL VARIANCE (RISK) COMPARISON BETWEEN DIFFERENT PORTFOLIO MODELS FOR CASE 2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Equal Weight</th>
<th>MVA_5</th>
<th>MVA_10</th>
<th>CAPM</th>
<th>MNFS-FPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>2.09</td>
<td>0.01</td>
<td>0.02</td>
<td>0.13</td>
<td>0.07</td>
</tr>
<tr>
<td>2003</td>
<td>3.08</td>
<td>0.08</td>
<td>0.07</td>
<td>0.33</td>
<td>1.20</td>
</tr>
<tr>
<td>2004</td>
<td>3.85</td>
<td>0.06</td>
<td>0.18</td>
<td>0.28</td>
<td>0.74</td>
</tr>
<tr>
<td>2005</td>
<td>3.50</td>
<td>0.08</td>
<td>0.12</td>
<td>0.24</td>
<td>0.76</td>
</tr>
<tr>
<td>2006</td>
<td>3.48</td>
<td>0.15</td>
<td>0.13</td>
<td>0.32</td>
<td>3.89</td>
</tr>
<tr>
<td>Avg. Var. (%)</td>
<td>3.20</td>
<td>0.08</td>
<td>0.10</td>
<td>0.26</td>
<td>1.33</td>
</tr>
</tbody>
</table>

Fig. 10 shows that despite having low risks, the MVA_5, MVA_10, and CAPM have negative Sharpe ratio values. This is because average profits generated by those models are lower than the 5% rate of T-bill. This also implies that it is more preferred to invest in T-bill and achieve 5% return annually with near-zero risk, rather than to invest in portfolios generated using MVA_5, MVA_10, or CAPM. From the figure, it is clearly evident that the Sharpe ratio of MNFS-FPM is significantly higher than that of other portfolio models. The high Sharpe ratio value implies that portfolios generated by MNFS-FPM have the highest reward-to-risk ratio, thus worth bearing the risks.

VI. CONCLUSION
This paper presents a portfolio management system which synergizes novel learning and predictive features of neuro-fuzzy system and optimization capability of memetic algorithm. In this approach, a hippocampus-inspired neuro-fuzzy system (GenSoFNN-Yager) is employed to predict expected return of individual asset based on historical data, the results of which are subsequently processed by the MA-NM/SMD to determine optimal asset allocation in the portfolio that satisfies the predefined investment objectives.
Experimental results using DJIA stock data demonstrate the advantages of the proposed framework in comparison with other popular financial models, e.g. statistical mean-variance analysis and CAPM.

REFERENCES