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Optimization of the Mutual-Fund Portfolio of Tehran Stock Exchange Using Artificial Neural Networks and Genetic Algorithm

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Abstract: The purpose of present research is to predict the return of mutual funds listed in Tehran Stock Exchange by a linear panel data regression model and a nonlinear model based on artificial neural networks then optimizing the portfolio consisting of these mutualfunds using Genetic Algorithm (GA). Using 13 factors affecting mutual fund returns as input data to both pooled regression and ANNs results showed the predictability of mutual fund returns by both methods using these factors but ANNs had a better performance. The results showed that GA can be used for mutual-fund portfolio selection and the superiority of GA method on Markowitz approach. Portfolio size had no significant effect on the results and GA had a better performance at all levels. GA had a markedly better performance than linear methods when portfolios were more diversified. So, investors can use nonlinear models such as ANNs to predict mutual-fund returns. Also investors can use nonlinear methods such as GA to build optimal portfolios. This research provides new insights into mutual funds and their driving factors in Iran's emerging market. It is also a new approach to using nonlinear ANNs for prediction of mutual-fund returns and using GA for portfolio optimization.

Key words: Mutual fund Neural Networks (NNs), Genetic Algorithm (GA), portfolio optimization, panel data, factors

INTRODUCTION

Thenmozhi (2006) cited that there is a nonlinear relationship between past and future returns and an accurate mechanism is required to predict future returns. Artificial Neural Networks (ANNs) are an effective tool in economic analyses due to their ability to estimate complex nonlinear functions. A large number of studies have shown that ANNs are effective for pattern recognition and classification due to their nonlinear and non-parametric characteristic. They are also widely used in analysis of financial data (Vaisla and Bhatt, 2010). A neural network can work with parallel inputs and can manage a large set of data at a fast rate. Its main power lies in its ability to detect multidimensional nonlinear relationships in data and recognize patterns and irregularities (Chang *et al*., 2009). Changes in capital market returns have a nonlinear patterns and thus neural networks are more appropriate for modeling them. Their main advantage is that they can model a nonlinear process without any previous knowledge of it (Vaisla and Bhatt, 2010).

Portfolio optimization is another challenging issue in finance. Selecting asset weights in a portfolio for achieving the expected risk and returns makes it even more complex. In response to this problem, Harry Markowitz proposed the so-called mean-variance model for determining efficient portfolios which give maximum return for a given risk or minimum risk for given return (Sefiane and Benbouziane, 2012). There are various methods for portfolio optimization in the literature but it is difficult to predict risk and returns and create optimal portfolios using traditional approaches due to the complexity of factors that affect them. Linear methods are unable to correctly understand nonlinear behaviors and are only appropriate for quadratic functions with one purpose. But the question is what happens if a function has more than one purpose, i.e., maximizing returns and minimizing risk? certain AI-based methods such as GA have recently been developed to address this problem (Sefiane and Benbouziane, 2012). GA is a search heuristic that mimics natural selection and can be used in nonlinear optimization and for non-smooth and even discontinuous functions (Lin and Gen, 2007).

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Artificial Neural Networks (ANNs) are learning algorithms inspired by biological neural networks and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Some of the main features of ANNs are: network structures, parallel processing ability, distributed memory, fault tolerance, collective solution and learning ability (Li, 1994).

GA is a search heuristic that is used to find useful solutions to optimization and search problems (Dehghani and Vafayi, 2008). Unlike most traditional optimization methods that stop after the first local optimum is found, GA continues the search until a global optimum is located (Momeni, 2013).

This research examines the factors that affect mutual fund returns and compares the predictive power of panel data regression (pooled) and ANNs. An attempt is also made to create an optimal portfolio from mutual-fund stocks using GA and to compare this method to traditional approaches. The effect of portfolio size is also examined. This study has implications for optimal resource allocation, portfolio risk management and control and shareholder wealth maximization. An effective system for predicting returns can attract new investors and accelerate economic growth. Moreover, selecting an optimal portfolio from mutual funds can help create multi-class mutual funds and develop the country's financial instruments. Obviously the variety of mutual funds encourages investors to participate in the capital market.

Literature review: Javed and Iqbal (2008) examined the factors that affect Swedish mutual fund performance. The results showed that higher risk (measured by beta and standard deviation) leads to higher returns. They also showed that fund size influences fund performance as larger funds have higher investment diversification and economies of scale than smaller funds. Moreover, management tenure was positively associated with fund performance.

Afza and Rauf (2009) examined the variables that influence Pakistani mutual fund performance. The results showed that size has no significant effect on fund performance. Also age had a positive but insignificant effect on fund performance with old funds performing the same or slightly better. However, lagged return, liquidity and 12B-1 fee had a significant effect on fund performance.

Yim (2002) compared neural networks with time series models for forecasting stock returns. RMSE, MAE and the Chong and Hendry encompassing test were used to evaluate forecasts. The results suggested that ANNs are superior to traditional models.

Wang (2009) integrated a new hybrid asymmetric volatility approach into ANNs Option-Pricing Model to improve stock price forecast. The results showed that the proposed model had higher predictive power than other volatility approaches.

Yang (2006) incorporated a GA into a state dependent dynamic portfolio optimization system. The algorithm significantly improved expected return estimation accuracy and improved the overall portfolio efficiency over the classical mean-variance method. Similarly, Lin and Gen (2007) designed a GA to solve the multi-objective optimal portfolio selection problem and proved its effectiveness.

Lazo *et al.* (2000) used a hybrid genetic-neural system to for portfolio selection. The 12 assets were selected from a total of 137 assets using a GA and the efficiency of each selected asset was predicted using neural networks. Finally, the optimal weight of each asset was determined by another GA and validated the effectiveness of the approach for portfolio selection and management. Given this review, the present research tries to address the following hypotheses:

- Neural networks have higher predictive power than regression models for mutual-fund returns forecast
- Mutual-fund portfolio selection using GA significantly improves portfolio performance compared to traditional models

MATERIALS AND METHODS

Design: The present research is a descriptive ex post facto study.

Variables

Dependent variable: Mutual fund returns is the dependent variable and is calculated as follows:

$$RNAV_{it} = \frac{NAV_{it}-NAV_{it-1}}{NAV_{it-1}} \quad (1)$$

where, $RNAV_{it}$ is the revalued net asset value (returns) for fund i in time t, NAV_{it} is the net asset value for fund i in time t and NAV_{it} is the net asset value for fund i in time t-1.

Independent variables: Based on the theoretical background and past research, 13 independent variables were used in this study.

Ex-post sharpe ratio (reward-to-variability ratio): Sharpe ratio or reward-to-variability ratio is one of the best measures of mutual fund performance that examines it by adjusting for its risk. Higher sharpe ratio indicates better performance (Rahnama *et al*., 2011). This ratio is calculated as:

$$S_a = \frac{R_a - R_b}{\sigma_a} \tag{2}$$

Where:

R_a = The portfolio return
R_B = The risk-free rate
σ_a = Standard deviation

Ex-post treynor ratio (reward-to-volatility ratio): Treynor ratio is a risk-adjusted measure of return based on systematic risk. It is calculated as:

$$T = \frac{r_i - r_f}{\beta_i} \tag{3}$$

Where:

r_i = The portfolio i's return
r_f = The risk-free rate
β_i = The portfolio i's risk

Jensen's alpha: Jensen's alpha represents the average return on a portfolio over the theoretical expected return. It is calculated as:

$$a = R_i - [R_f + \beta_i (R_M - R)] \tag{4}$$

Where:

R_i = The portfolio return
R_f = The risk-free rate
β_i = The portfolio beta
R_M = The market return

Best period ratio: Best period indicates the numbers of days in a given period duringwhich a fund's returns have been higher than market returns. The higher the ratio, the better is the fund's performance.

Fund size: Fund size is calculated using in Eq. 5:

$$\begin{aligned} &\text{Fund size} = \text{In (Fund value)} \\ &\text{Fund value} = \text{NAV} \times \text{Number of total issued} \\ &\qquad\qquad\text{investment units} \end{aligned} \tag{5}$$

Mutual fund growth: An important factor in the success of mutual funds is growth in the net value of their total assets. Growth is calculated as the total fund value at time-t less the total fund value at time t-1 divided by total fund value at time t-1.

Management tenure: This variable is calculated from the annual ranking reports provided by the Tehran Stock Exchange. Management experience affects fund performance.

Average monthly return: Average monthly return is another measure of fund performance. With higher average monthly return there is a higher tendency to invest in the fund. This variable is calculated as the ratio of total return by fund age in months:

$$\text{Total return} = \frac{NAV_i - NAV_0}{NAV_0} \tag{6}$$

Individual investors' ownership: This variable is calculated as the percentage of individual investments in fund i during the period-t.

Fund age: Fund age is equal to the number of month since the fund began its operations.

Market return: Market return is calculated as:

$$R_M = \frac{\text{Closed end price}_t - \text{Closed end price}_{t-1}}{\text{Closed end price}_{t-1}} \tag{7}$$

Systematic risk: Beta is used as a measure of systematic risk:

$$\beta = \frac{Cov(r_i, r_m)}{\sigma^2 r_m} \tag{8}$$

Percentage of cash assets: This index is a measure of the fund managements approach to using risk-free assets with lower return or risky assets with higher return. Lower percentage of cash assets indicates better fund performance:

$$\text{Cash assets (\%)} = \frac{\text{Cash+Bond+Certificate of deposit}}{\text{Total accets}} \tag{9}$$

Also, Markowitz's model is used for portfolio optimization with the following variables.

Expected return: It is calculated as the mean weight of the expected return for each asset:

$$E(R_p) = \sum_{i=1}^{n} x_i E(R_i) \tag{10}$$

Where:

R_p = The return on the portfolio
R_i = The return on asset-i
x_i = The weighting of component asset i

Portfolio return variance: This is a measure of portfolio risk and is calculated as:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij} \quad (11)$$

where, δ_{ij} is the correlation coefficient between the returns on assets i and j.

Covariance: Covariance is a measure of the correlation between each pair of assets:

$$\sigma_{ij} = \sum_{k=1}^{n} h_k \left[R_{i,k}\text{-}E(R_i)\right]*\left[R_{j,k}\text{-}E(R_j)\right] \quad (12)$$

Combining assets that have lower positive correlation can reduce portfolio risk. The final model is as follows:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij}$$

Subject to:

$$E(R_p) = \sum_{i=j}^{n} x_i E(R_i)$$
$$\sum_{i=1}^{n} x_i \quad (13)$$
$$x_i \geq 0 \text{ for } i = 1, 2, ...,$$

The final step is to evaluate the performance of portfolios using the Sharpe ratio.

Population: The population of this research consisted of all the mutual funds listed on the Tehran Stock Exchange (TSE) in the period 2010-2012 (N = 30). Data were collected from TSE's database, each individual fund's website and the financial information processing of Iran.

RESULTS AND DISCUSSION

Returns forecast using a linear approach: Pooled regression was used in this approach. The results of F-test and Hausman test showed that a fixed showed that a random effects model is more appropriate. The results of estimating the model are provided in Table 1.

According to the data in Table 1, the model is significant at the 95% CI. However, best period ratio, management tenure and individual investors' ownership are not significant. Moreover, Jensen's alpha, growth, market returns and average monthly return are the strongest predictors of mutual fund returns. The adjusted coefficient of determination is 0.6065, indicating that about 60% of changes in the dependent variable can be explained by independent variables. Also the Durbin-Watson statistic indicates the lack of auto-correlation between the residuals.

Table 1: Predicting mutual fund returns using a linear approach

Variables	Coefficients	SD	t-values	Sig.
Intercept	0.116449	0.0501960	2.319912	0.0208
Sharpe ratio	0.000432	0.0001710	2.523048	0.012
Treynor ratio	-0.005946	0.0023840	-2.494033	0.013
Jensen's alpha	-0.072092	0.0200520	-3.595202	0.0004
Best period ratio	0.000316	0.0169410	0.018656	0.9851
Fund size	-0.013886	0.0048710	-2.850972	0.0046
Growth	0.047198	0.0071240	6.625142	0.0000
Percentage of cash assets	-0.000322	0.0001540	-2.088257	0.0374
Management tenure	0.003552	0.0037020	0.959481	0.3379
Individualinvestors' ownership	0.000069	0.0002430	0.283399	0.7770
Fund age	0.000719	0.0000246	2.917133	0.0037
Market return	0.553747	0.0399320	13.867180	0.0000
Systematic risk	0.010114	0.0041340	2.446370	0.0149
Average monthly return	0.826244	0.1952440	0.195482	0.0000
R^2		0.6439770		
Adjusted R^2		0.6066501		
Durbin-watson statistic		1.9208370		
F-statistic		17.1836800		
F-test Sig.		0.0000000		

Returns forecast using ANNs: ANNs are data-driven self-adaptive methods in that there are few a priori assumptions about the models for problems understudy. They learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe (Thenmozhi, 2006). ANN procedure for forecasting returns was carried out in Clementine 12.0 software and is described.

Data preprocessing: Importing raw data can reduce the accuracy and speed of ANNs. Therefore, input data were normalized to improve the network's efficiency:

$$NX_i = \frac{X_i\text{-}\min X_i}{\max X_i\text{-}\min X_i} \quad (14)$$

Designing the ANN: The best network structure can be identified through trial and error (Monajemi *et al*., 2009). It involves the following steps.

Network type and learning method: This research utilized a Multilayer Perceptron (MLP) with a back propagation learning algorithm. Such a network is a universal approximator. That is, it can represent a wide variety of functions when given appropriate parameters (Hornik, 1991). The 70, 15 and 15% of the data were randomly selected and assigned to training, validation and testing subsets.

Activation function and stopping criteria: The activation function of a node defines the output of that node given an input or set of inputs. It injects some level of nonlinearity into the network. Sigmoid activation function is the best function for the hidden layer of the MLP used in this research. Finally, the stopping criteria are 10% error, maximum 250 cycles and 5 min time. The network stops when each of these conditions is satisfied.

Network architecture and evaluation criteria: The number of hidden layers and its neuron scan only is determined through trial and error. However, Mean Squared Error (MSE), Root-Mean-Square error (RMSE) and coefficient of determination (R^2) can be used to evaluate the models and determine if the number of layers and neurons is optimal:

$$MSE = \frac{\sum_{i=1}^{n} e_i^2}{n} \quad (15)$$

$$RMSE = \sqrt{MSE} \quad (16)$$

where, n is is the number of data in the training data set or the cross-validation data set and e_i^2 is the difference between predicted and actual outputs.

According to the data in Table 2, the best possible condition occurs when R^2, MSE and RMSE are 0.973, 0.00022937 and 0.01514498, respectively. Therefore, an MLP with three hidden layers and a 5-6-7 neuron architecture is the best model. Using this model, 97.30% of changes in the dependent variable can be explained by the independent variables.

Testing the first hypothesis: Here, we compare the coefficients of determination in linear and nonlinear models. The results show that the ANN has a higher explanatory power with an adjusted R^2 of 97.30% compared to the regression model with an adjusted R^2 of 60%. Thus, the first hypothesis is accepted at the 95% CI.

The results also indicate that the said evaluation measures can be used to predict the mutual fund returns and Jensen's alpha, growth, market return and average monthly return are the strongest predictors.

Optimal portfolios: Matlab software was used to identify optimal mutual fund portfolios. First a portfolio with 3 mutual funds was randomly selected. Then a new 3-asset portfolio was selected and this process continued until no 3-asset portfolio could be selected. In the next step, the number of assets in each portfolio increased one by one. Finally, 66 random portfolios with different sizes and without replacement were created. These portfolios were then optimized using linear and nonlinear methods and evaluated using the sharpe ratio.

Designing the GA: The nonlinear approach to portfolio optimization involved a GA with the following characteristics.

Initial population and fitness function: The size of the initial population is usually determined through trial and error. In this research, the initial population size is 100. The purpose of the designed algorithm is to select a portfolio that achieves maximum return at minimum risk with the least possible correlation between the selected assets (Modares and Mohammadi, 2007).

Selection: This operator selects chromosomes from the population for reproduction. This is done via "roulette wheel selection". In this approach, chromosomes with higher fitness are more likely to be selected.

Crossover: Crossover is the main operator for reproduction of chromosomes. This operator, similar to its natural counterpart, produces new candidates whose components (genes) are taken from the parents. The crossover rate in this research is 0.80.

Table 2: The results of nonlinear modeling using ANN

No. of hidden layers	No. of neurons in the 1st layer	No. of neurons in the 2nd layer	No. of neurons in the 3rd layer	R^2	MSE	RMSE
1	3	0	0	0.9443	0.00046953	0.02166874
1	4	0	0	0.9554	0.00038091	0.01951694
1	5	0	0	0.9465	0.00045144	0.02124715
2	3	4	0	0.9503	0.00041865	0.02046083
2	4	5	0	0.9571	0.00036140	0.01901042
2	5	6	0	0.9675	0.00027606	0.01661512
3	3	4	5	0.9423	0.00048551	0.02203440
3	4	5	6	0.9487	0.00043312	0.02081145
3	5	6	7	0.9730	0.00022937	0.01514498

Table 3: The results of t-test for paired samples (linear and nonlinear optimization)

Paired difference test							
			95% CI				
Mean	SD	SE	Lower bound	Upper bound	t-statistic	df	Sig.
-0.6734	0.74783	0.09205	-0.85725	-0.48957	-7.316	65	0.000

Table 4: The results of t-test for paired samples (small, medium and large portfolios)

Paired difference test								
				95% CI				
Size	Mean	SD	SE	Lower bound	Upper bound	t-statistic	df	Sig.
Small	-0.43073	0.51306	0.07648	-0.58487	-0.27659	-5.632	44	0.000
Medium	-0.66347	0.75057	0.20817	-1.11704	-0.20990	-3.187	12	0.008
Large	-2.05465	0.11623	0.04109	-2.15183	-1.95748	-49.998	7	0.000

Mutation: Mutation is a genetic operator used to maintain genetic diversity from one generation of chromosomes to the next. This operator alters one or more gene values in a chromosome from its initial state. The mutation rate in this research is 0.10.

Stopping criteria: The algorithm stops if there are no improvements in 100 successive generation.

Testing the second hypothesis: The t-test for paired samples was used to examine the difference between the performances (Sharpe ratio) of linear and nonlinearapproaches. The t-statistic has a n-1 degree of freedom and is calculated as:

$$t = \frac{\bar{d} - \mu_d}{S\bar{d}} \tag{17}$$

$$S_{\bar{d}} = \frac{S_d}{\sqrt{n}} \tag{18}$$

The results are provided in Table 3. The data indicate that there is a significant difference between the linear and the nonlinear approach and thus the second hypothesis is accepted at the 95% CI. That is, using GA significantly improves portfolio performance compared to traditional methods. GA can be used in mutual fund portfolio selection and optimization.

The effect of portfolio size: Here, the optimal portfolios are divided into small (3-10 assets), medium (11-20 assets) and large (>21 assets) categories and the effect of size on portfolio performance is examined using t-test for paired samples (Table 4).

The results show that the GA has a significantly better performance in all small, medium and large portfolios. Moreover, this superior performance is more evident in larger and more diversified portfolios as the mean difference is about 43% in small portfolios about 66% in medium portfolios and 205% in large portfolios.

CONCLUSION

The purpose of the present research was to compare the predictive power of a linear regression model and a nonlinear model based on Artificial Neural Networks (ANNs) and to optimize the mutual-fund portfolio of Tehran Stock Exchange using genetic algorithm. The results showed that mutual fund returns can be predicted using 13 measures (i.e., Sharpe ratio, Treynor ratio, Jensen's alpha, best period ratio, fund size, growth, average monthly return, management tenure, percentage of cash assets, fund age, systematic risk, individual investors' ownership and market return). This is consistent with the results of Javed and Iqbal (2008), Afza and Rauf (2009) and Saidi *et al.* (2010). It was also shown that Jensen's alpha, growth, market return and average monthly return were the strongest predictors of mutual fund returns.

Another finding was that both pooled regression and ANN can predict mutual fund returns but ANN had a better performance. This is consistent with the results of Refenes *et al.* (1994), Hill *et al.* (1996), Lendasse *et al.* (2000), Yim (2002), Wang (2009), Rai and Chavoshi (2003), Sinai *et al.* (2005) and Azar and Karimi (2010) on stock return forecast.

Moreover, GA and Markowitz's model were compared in terms of portfolio optimization using sharpe ratio. The results showed that the GA could be used for mutual fund portfolio selection and optimization and these portfolios were superior to those created by the traditional approach. This is consistent with the results of Mahfoud and Mani (1996), Yang (2006), Lin and Liu (2008), Aranha and Iba (2009), Chang *et al*. (2009) and Modares and Mohammadi (2007) on portfolio optimization using GA. The GA can adapt to a dynamically changing search space and find the optimal solution without changing the population or the parameters. GAs is inspired by nature and use principles of evolutionary biology such as natural selection and reproduction as guidelines to evolve a population of solutions to a given problem (Dehghani and Vafayi, 2008).

Finally, the effect of portfolio size was examined. The results showed that the GA had a significantly better performance than the traditional method in all small, medium and large portfolio categories. Also, the difference was more noticeable in larger and more diversified portfolios. This is consistent with the findings of Garkaz *et al*. (2010). Conversely, Chang *et al*. (2009) found that smaller portfolios are more efficient than larger ones.

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