Risky Portfolio Selection through Neural Networks

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Abstract

The major aim of this research is to achieve a more appropriate investment model in portfolio selection for risk taker investors. In this research Markowitz model is the base for comparison in the Portfolio theory, which can construct an optimum portfolio on the basis of the special assumptions. In the present study, along with Markowitz model, the created models through the Artificial Neural Networks (ANN) are applied. Then they have been compared with Markowitz model in several cases of investment. The learning pattern for neural networks is "back propagation". The portfolios consist of twenty shares in the Tehran Stock Exchange (www.tse.ir), which has been studied for a period of thirteen months. In both Markowitz and ANN portfolios, there is a significant difference between the daily return and the outcome of the investment at the end of the investment period in the test set. Both of these two models are statically and dynamically applied, and in both cases the neural networks' portfolios outweighed the Markowitz's portfolios. In this research, the suggested portfolios are for the risk takers and the major goal is to maximize the portfolios' return. The risk of the portfolios constructed by the neural networks is less than those of the Markowitz model. Furthermore, the transaction costs have not been computed in the Markowitz and neural networks. This study shows that employment of neural networks in portfolios selection can be effective.

Key words: Portfolio, Investment, Markowitz Model, Neural Networks

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1. Introduction

The major tools of financial decision-making include prediction and optimization techniques, which are the most important ones in this regard. A good predictive technique provides a good estimate to the return of a share in the future. Most of predictive techniques used in the finance are statistical and econometrics techniques which are normally recognized as static and linear. An optimization model presents before hand a value of decision variables for a formulated model in advance.

Moreover the optimization techniques used in the finance are often those used in the operations research, whether linear or non-linear .In this article, a methodology is selected and used in predicting, selecting and constructing a portfolio in the Tehran Stock Exchange (TSE).

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In this approach, both the Markowitz model and neural networks have been used as tools for prediction and optimization.

Part two explores the investment process in portfolios selection by using the Markowitz model. In part three, the neural networks techniques are explained briefly. Part four introduces the research method. Part five compares the consequences of using the neural networks with the Markowitz model the risk-taker investor from the risk-taker investor's point of view.

2. Markowitz Model

One of the major methods used for investment analysis in portfolios construction is analyzing the efficient set of investments which has been initiated by Harry M. Markowitz. In such an analysis the relationship between shares in a portfolio and the relevant interaction is of prime importance .Each portfolio represents an investment opportunity. Figure (1) shows a set of portfolios in a two-dimensional space of the expected rate of return and the standard deviation. On this bullet, some points are definitely preferred to the others: e.g. instead of an equal risk (standard deviation), a higher expected rate of return is preferred and instead of an equal expected rate of return a lower risk is preferable. The bullet-shaped curve is named minimum variance set. The upper segment of this curve is called the efficient set, with a certain level of standard deviation, which has the highest expected rate of return.

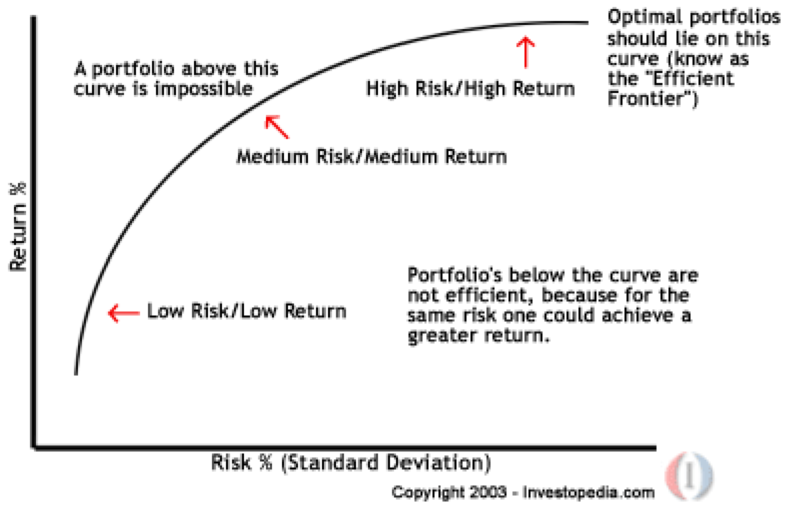

Figure (1): Different portfolios from two shares in a minimum variance set.

In order to obtain the portfolios of the minimum variance for a certain level of rate of return, it is necessary to solve the following non- linear programming problem:

$$\text{Min } \sigma^2(r_p)$$

ST:

$$E(r_p) = \sum_{j=1}^{M} x_j \; E(r_j)$$

$$\sum_{j}^{M} x_j = 1$$

$$x_j \geq 0$$

In this problem, there is not short-selling, and the goal is to minimize the risk—but the problem of maximization of rate of return can also be brought up with some modification. Since the key element in this article is determination of portfolios for risk-taker investors, the problem may be formulated as follows:

$$\text{Max } E(r_p) = \sum_{j=1}^{M} w_j \, E(r_j)$$

$$\sum_{j=1}^{M} w_j = 1$$

$$w_j \geq 0$$

In this problem, there exists no risk (standard deviation). Thus, the only criterion for decision-making is return maximization, which is suited for the risk taker investors. Any such investors will select the extreme point of the efficient set.

3. Neural networks

The study of the Artificial Neural Networks began in 1943 by Warren S. McCulloch & Walter Pitts. Since the aim of the artificial intelligence is to develop the humanly used paradigms or algorithms for machines, the artificial intelligence emulates the human brain performance.

One neuron (nervous cell) is a certain biological cell, which processes the data (figure 2). This cell is made up of a body of cells, Axon and Dendrites. The neuron receives signals (simulators) through dendrites (recipients) from the environment or from other neurons, and transmits the created signals by a body of cells, through Axon (sender). At the end of them, there are synopses. A synopsis is a basic structure and a functional unit between two neurons (one neuron at Axon, the other at Dendrite).

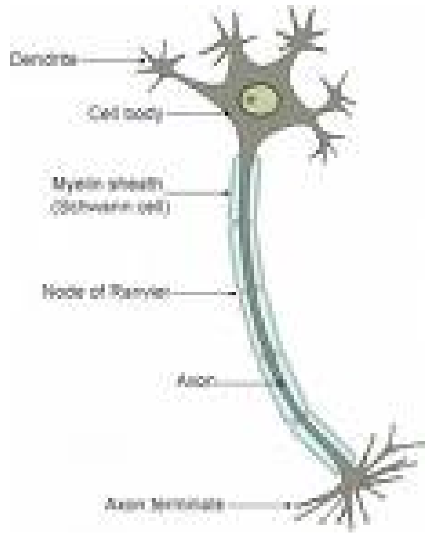

Figure (2): a nervous cell

Synoptic connections can be corrected by passing signals through them whereby synopses may be engaged in learning process from their share of work. This historic dependence in synoptic connections acts as memory and may provide a response to the memory accordingly.

The first artificial neuron was presented by McCulloch & Pitts (figure 3) which is derived from the natural neuron. The inner connections and communications, i.e. the input and outputs, shape models out of Dendrite and Axon, communicative weights represent synopses and activity function, which estimate the body performance.

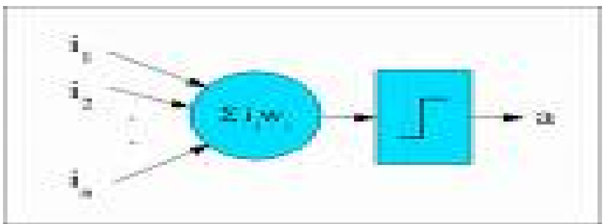

Figure (3): The first artificial neuron was presented by McCulloch & Pitts

One of the major features of the artificial neural networks, whose function approximates more to that of human beings, is the power of learning. The neural networks use basic rules (like input-output links) out of a set of interpretive models for learning in place of pursuing a set of rules defined by an expert. In order to understand or design a learning process, first it is essential to have a model of the environment in which the network is involved. Such a model is named “learning algorithm”. Second the learning rules governing the updating process, or in other words, networks weight updating process should be known.

One of the most important learning algorithms in the neural network is the "back propagation algorithm" which per se is based on the rule of “error – correction”, and for the gradual decrease of error, where the actual output of (y) network is not equal to the desirable output (d), the neural weights can be corrected by using the error sign of (d-y).

Considering the way the neurons stand out , their interrelationship, the neural networks characterize a specific architecture out of which a well- known one is the multi–layer perception network where by the data direction is why they are called “Feed-forward neural network".

4. Research Method

Investment model aided by neural networks data was primarily collected from the stock market. The data was selected from the documents belonging to corporations.

In Tehran Stock Exchange, in order to obtain the rate of return and preprocessed data, the models of neural networks were designed and share weights for risk taker investor determined.

4.1. Data collection

The data used an “inputs” of the network is related to price shares and dividends. This data covers twenty corporations available at Tehran Stock Exchange which are involved in various industries from 21 March 1990 to 18 May 2005.

4.1.1 Training Set

A portion of the data colleted from 21 March 1990 to 3 April 2006 has been selected as a training set.

4.1.2. Test Data

The second portion of the data has been used for testing the model, so as to indicate its credibility, which is named “test set".

4.2.1. Data preprocessing

The primary data has been used to obtain the rate of return on shares which is the main variable in the portfolio selection. Thus the return of each corporate share has been computed with the following ratio.

$$R= \frac{(P_1 - P_0) + DIV}{P_0}$$

In this formula, "R" is the rate of return, $P_1$and P_0 are respectively the share price at the end and in the beginning of the period; and DIV, the dividend in that period. The computation of the return is for a simple reason, that is because the return is a more suitable criterion than price, and reflects other share profits as well.

The next portion of preprocessing is to obtain the moving average and other factors affecting the return of shares (security). One of the other network inputs is the five-day moving average of each security which had been calculated from the outset.

4.3. Neural Network Designing

Since The network inputs have been allocated for twenty securities including 20 returns and 20 moving averages per day and whilst the foreign exchange price (dollar) as well as general index at Tehran stock Exchange along with the five-day moving average were considered to be effective factors on the input layer, was 44. The number of neuron on the output layer, with respect to the weight of securities in the portfolio which included twenty securities, was twenty. The number of hidden layers consists of two layers.

Therefore, upon conduct of various tests, the network architecture was selected to be a four layer Perceptron network (figure 4).

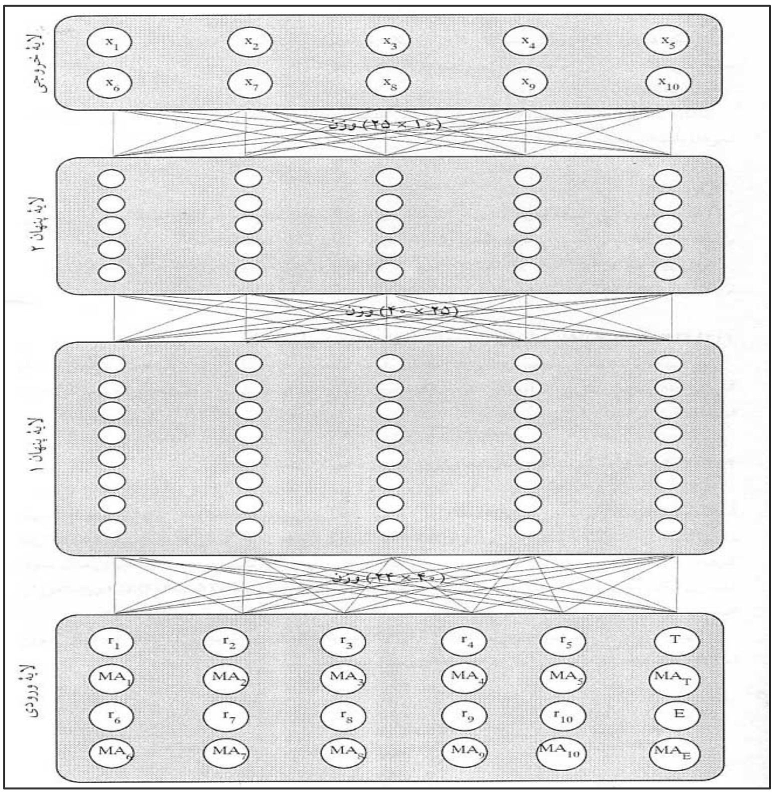

Figure (4): The four-layer network architecture for twenty shares

Such networks also can continue to make a prediction in the course of optimization process.

4.3.1. Determining the desired output and Network Training

The multi layer Percetron networks with back propagation learning algorithm needs a desired output. Considering the network role in making a prediction in the course of optimization, it had to determine the appropriate weight of each security in the portfolios of the next day.

The training set covered a desired output to ensure that the network could compare its own output with it and correct itself .The network operates highly efficiently when it corrects a hundred percent (one) weights to a security whose return reaches the highest record next day. Also the security weight with the highest return will be (one) and the weight of other securities (zero), it is noteworthy that this research did not permitted the short selling.

Considering the fact that the required output is between zero and one, the activity function of neurons has been chosen in sigmoid and the network was trained by drawing on the data of the training set, considering a large amount of data, the overtraining was not conducted.

4.3.2. Network Testing

The network was tested by exploiting the remaining data called the test set. The following two strategies were evaluated:

A) Static Network evaluation

In this strategy, network weights did not change after training by training set and remained constant and was exploited for the rest of the test. Only new inputs were added to the network and then outputs with the same weights were explored.

B) Dynamic Network evaluation

In this strategy, all previous patterns including trainings and test patterns were taught to the network. In other words, to determine the weights on the T^{th} day, all former data related to the previous days along with desired output were entered into the network. Therefore, the network could identify its errors to weights.

5. Comparing the Results of Neural network with Markowitz Model

The designed model is merely for the sake of risk-taker investors thus a portfolio with the highest risk must be chosen from the portfolios presented by Markowitz model.

In the present research, the risk parameter (standard deviation) was omitted from the Markowitz model and them the model was used the outcome of the intended model was computed in two ways as follows:

(a) Markowitz model

In this model, the parameters of the anticipated output, standard deviation, and securities covariance were computed with the aid of the existing data in the training set. They were used until the end of the investment period, i.e. the relevant parameters were estimated for a single investment period (equivalent to the training set). Then the weights in the portfolio with the highest output were determined from the whole investment period.

5.1. Comparing the outcome of High risk investments in the static Markowitz portfolio and the neural network

The outcome of investment in the daily Markowitz portfolios has increased the assets of the investor to as much a high figure as1.375 of his initial capital after 324 days. But the outcome of investment in the neural network daily portfolios has changed the investors’ assets to as much a high figure as 2.8407 of his initial capital after 324days.

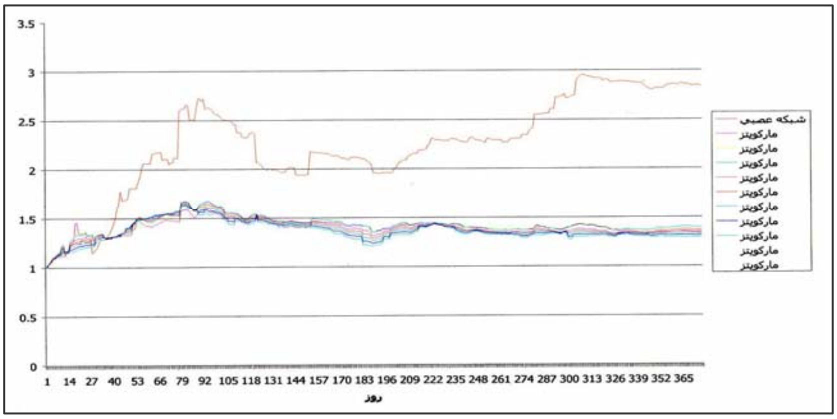

Figure (5): the outcome of High risk investments in the Markowitz portfolio and the neural network

6. Conclusions

The surveys conducted from 21 March 1990 to 21 November 1997 on the portfolios made up of ten shares in Tehran Stock Exchange can demonstrate the behavior of the share returns as follows:

- The behavior of the afore-mentioned share return is not full stochastic, but it follows a specific trend; such behavior could represent that the shares market has chaotic behavior with regard to mere random one. The emergence of regularity, therefore, in irregularities, will help agents marshal the people toward achievement of more return. It is not an easy task to discover such regularity. In this behavior, there is a fairly high degree of hope to the past for estimation of the future.
- Since the stock market behavior is not linear but it is non-linear thus, the linear models are unable to describe the share return behavior. The systems can simply recognize a major portion of the system, which is non-linear. Each share is inspired by diverse factors and conditions which are sometimes systemic and at times non-systemic with unique models of import as well.
- The parameters of Markowitz model, which are comprised of expected return of portfolios, variances and covariances, must be estimated. In a non-linear model, it is very unlikely for the initiative model to reach an optimum point even if all parameters have been well-estimated.
- The Markowitz model rely on the shares interrelationship connections for the selection of an optimal portfolio.However the rate of return of each share is not only influenced by other stocks but other factors, in particular hidden factors, which have not been covered in the Markowitz model.

Since the artificial neural networks are independent of the model, have non-linear behavior and have the capability to accept all variables affecting the return, they are moreover, dynamic and appropriate instrument for prediction, optimization, and classification of shares.

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