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PORTFOLIO OPTIMIZATION USING NEURO FUZZY SYSTEM IN INDIAN STOCK MARKET

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Abstract: This paper describes a portfolio optimization system by using Neuro-Fuzzy framework in order to manage stock portfolio. It is great importance to stock investors and applied researchers. The proposed portfolio optimization approach Neuro-Fuzzy System reasoning in order to make a more yields from the stock portfolio, and hence maximize return and minimize risk of a stock portfolio through diversification and right investment allocation to the particular stock under uncertainty. To evaluate the performance of forecasting and optimization system, BSE Sensex index of India considered as benchmarks in this study to measure efficient forecasting models. The results show that the proposed Neuro Fuzzy system produces much higher accuracy when compared to other portfolio models.

INTRODUCTION

Recently, many researchers pay their attention to portfolio optimization problem in the area of finance, particularly in stock market. Portfolio optimization is an approach of stock portfolio management, which maximizes the return and at same time, it minimizes risk.

Portfolio Management involved with discovering the combination of financial assets or stocks that meets an investor's necessities and needs the best. Portfolio management can be viewed as discovering combination of stocks that provide an investor the ideal trade-off between expected return and risk associated with it. In portfolio management or portfolio optimization, profit is commonly evaluated as rate of return on investment, i.e., the percentage vary of the initial investment. Portfolio management is often to minimize as much risk as achievable, or to reach the highest feasible returns or both.

Portfolio optimization should consider realistic constraints such as portfolio size, transaction costs, or additional demands from investors rapidly, which adds a complexity level that exceeds regular optimization methods. Conventional prediction techniques (Statistical linear and regression models) often fail to forecast future values when the characteristics of the time series are non-linear and chaotic. New techniques have developed that improve the accuracy of non-linear time series forecasting, known as soft computing based methods. If the system is non-linear, these techniques have the potential to allow a feasible solution through its expert approach to self-organization. It has been noticed that these techniques generate better results than the statistical approaches when the time-series is chaotic [1] [2] .

Neuro-Fuzzy System architecture is formulated based on the theory of fuzzy logic and fuzzy set[3]. It is integrated with two intelligence systems, i.e. Fuzzy Inference System (FIS) and adaptive neural network system in such an approach that the neural network-learning algorithm is applied to establish the parameters of the fuzzy inference system. Neural networks are statistical non-linear data modeling tools which

can get and simulate any input-output relationships and can be trained to discover complex patterns in data. FIS is the process of creating the mapping from a recognized input to desired output using fuzzy logic.

The financial applications of soft computing techniques have concerned a lot of interest in last few years. It had grown clear to many stock market viewers that soft computing tools, particularly those from the domains of ANFIS or neuro-fuzzy computing systems were frequently discovering relevance in the stock markets [4] .

Neuro-Fuzzy system is an integrated system applying the adaptive neural networks with hybrid learning algorithms and the fuzzy inference system. Neuro-Fuzzy system incorporates the advantages of FIS and ANN. Moreover, the Neuro-Fuzzy system applying simple fuzzy if-then rules can simulate the qualitative characteristics of human knowledge and can be appropriate for human to utilize, and can deal with nonlinear and uncertainty problems [5] .

Neuro-fuzzy systems are described by the combination of fuzzy sets and systems techniques and neural networks. Neuro-fuzzy system shows the capability of fuzzy systems to simulate explicitly the linguistic concepts, uncertainty, and the knowledge of human experts, also achieving fuzzy reasoning together with the learning capabilities and noise robustness of neural networks [6].

In this study, we considered BSE Sensex data and 30 stocks data listed in BSE SENSEX (including both price and volume data) were collected at regular intervals.

PORTFOLIO OPTIMIZATION

Portfolio optimization is a primary issue in asset management and it handles with suitable investment allocation to minimize risk and maximize return of a stock portfolio through diversification[11]. Stock Portfolio optimization in asset management is a significant activity for forecasting stock movements to earn superior return.

Measuring Risk and Return of a Portfolio:

If an investor decided to invest together a portfolio that includes both kinds of assets: risky asset and riskless or risk-free asset. A risk-free asset is specified as an asset that has the smallest level of risk among all the existing assets[8]. In other terms, it is "risk-free" comparative to the other assets. A standard practice among investment advisor is to select a Government bond or bank interest rate as a representation of a risk-free asset[12,13]. In this study, we considered that risk-free return rate is 8% based on Indian Government bond.
w = proportion of risky asset in portfolio
(1-w) = proportion of risk-free asset in portfolio
Accordingly, the return of the portfolio is calculated as follow:

$$R_p = w.R_r + (1-w)R_f \tag{1}$$

Where, R_r = return of risky asset

R_f = return of risk-free asset

We can calculate the risk or standard deviation of the investor's portfolio as follows:

$$\sigma_p = \sqrt{w^2 \cdot \sigma_r^2 + (1-w)^2 . \sigma_f^2} = w \cdot \sigma_r \tag{2}$$

We can also measure the weight (or proportion), w, in terms of the standard deviation of the risky asset and the portfolio.

$$w = \frac{\sigma_p}{\sigma_r} \tag{3}$$

If an investor decided to invest in a portfolio that contains only multiple risky asset and without riskless or risk-free asset.

In this case, the return of the portfolio (R_p) will be determined as follows:

$$R_p = w_1 R_1 + w_2 R_2 + ... + w_n R_n = \sum_{i=1}^{n} w_i R_i \tag{4}$$

Therefore, the expected return of the portfolio is measured from the weighted average of the expected return of the independent assets:

$$E(R_p) = \sum_{i=1}^{n} w_i \times E(R_i) \tag{5}$$

NEURO-FUZZY SYSTEM

Recent studies recognized that non-linearity exists in stock market data. Nonlinear models such as soft-computing models provide superior prediction results than linear models. Neuro-Fuzzy System can be believed as strong alternative to various soft computing models for forecasting stock price. Neuro-Fuzzy combines the advantages of ANN and fuzzy logic system that can be employed in the design of the forecasting system. Fuzzy logic systems easily deal with problems such as interpretation on a high-level than ANN [7]. A fuzzy logic system is an intelligent system described by a set of if-then rules and they apply the linguistic terms. Neuro-Fuzzy has emerged by integrating the superior learning capability of ANN and better reasoning ability of fuzzy logic.

In the beginning, the fuzzy system fuzzifies the given inputs to values at interval [0, 1] with a set of membership functions (MF). After that, fuzzy logic inferred it through fuzzy if-then rules. The fundamental part of fuzzy system is the fuzzy inference engine, which can be applied for constructing fuzzy rules[9]. The syntax of fuzzy rules is :

$$R^j = if\ \ x_1\ is\ MF_1^i\ and/or\ x_2\ is\ MF_2^i\ and/or............x_j\ is\ MF_j^i\ then\ z^j\ is\ MF_0^i$$

Jang proposed Neuro-Fuzzy, which made up of five layers: fuzzy layer, product layer, normalized layer, defuzzy layer, and summation layer[3]. The architecture of Neuro-Fuzzy model used in this thesis is shown in Figure 1. The nodes described by a square, named adaptive nodes, have parameters sets that can be adjustable, whereas the circle-shaped nodes are named fixed nodes, have parameter sets that should be fixed. The Neuro-Fuzzy system architecture has five layers, nodes in layers 1 and 4 are adaptive, and nodes in remaining layers are fixed.

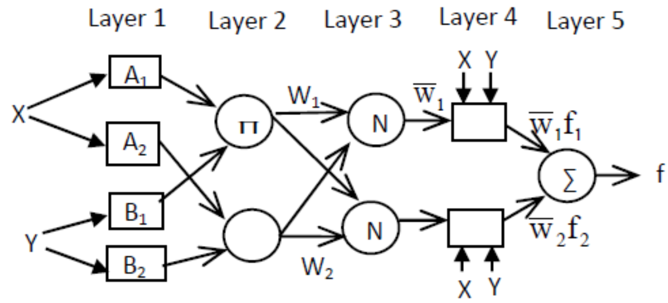

Figure 1. Architecture of Neuro-Fuzzy system

Layer 1: Each node in this fuzzy layer is an adaptive node, marked by square. a, b and c are premise parameters which define the membership function of the node. The node function described as

$$O_i^1 = \mu A_i(x), \qquad i=1,2 \tag{6}$$

Where x is the input node.

Layer 2: Each node in this product layer applies a scaling factor to incoming signals and sends the product out, represented by circle.

$$O_i^2 = w_i = \mu A_i(x) \cdot \mu B_i(y), \qquad i=1,2 \tag{7}$$

Layer 3: Every Node on this normalized layer calculates the weights according to the ratio of the ith fuzzy rule's firing strength to the combine of all fuzzy rules' firing strengths:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \qquad i=1,2 \tag{8}$$

Layer 4: Each node in this de-fuzzy layer is an adaptive node, noticed by square, which execute the linear arrangement of system input signals x and y by implies of consequent parameters a , b, and c, as described in the below equation

$$O_i^4 = \overline{w_i} z_i = \overline{w_i}(a_i x + b_i y + c_i), \qquad i=1,2 \tag{9}$$

Layer 5: Only one fixed node is in this summation layer, marked by square, which calculates the output signal as the summing up all signals.

$$O_i^5 = \sum_i \overline{w_i z_i} = \frac{\sum_i w_i z_i}{\sum_i w_i}, \quad i=1,2 \tag{10}$$

EXPERIMENTAL SETUP AND RESULTS

In this experiment, we considered BSE (Bombay Stock Exchange) SENSEX (Sensitive Index) of India for our experiment that plays an important role in emerging stock market. Both training and testing data sets are shown in Table I.

Table 1. Training and test data

INDEX	***Training data***		***Test data***	
	From	***To***	***From***	***To***
BSE SENSEX	March 2010	July 2010	August 2010	December 2010

Technical indicators are used to predict future price trends of the stock by discovering the trend from early movements. Our portfolio optimization module Neuro-Fuzzy produces the buying and selling signals based on the results of the technical indicators. Among various technical indicators, we have used well-recognized technical indicators, such as Exponential Moving Average (EMA), Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI) are used to measure the price trend [10,14]. The initial fuzzy rule is evaluated by the forecasting system with technical indicators formulating the following fuzzy rules.

If *Price* is *Very High* and *Exponential Moving Average* is *Low* and *RSI* is *Very High, then rating =0.25 (sell)*

If *Price* is *Low* and *MACD* is *high* and *RSI* is *Very low, then rating =0.75 (buy)*

The following Figure 2 shows the overall process of Neuro Fuzzy (Sugeno) model for stock market prediction.

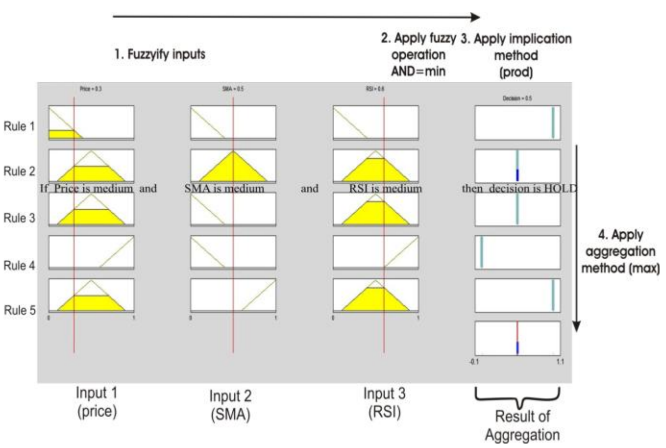

Figure 2: Overall process of Sugeno fuzzy model

The logic of our Neuro-Fuzzy portfolio optimization model is described in pseudo code as follows:

Begin:

Select portfolio size, where N > 5

Construct and diversify the portfolio based on past performance for minimizing risks.

DO calculate the return $R_i < \frac{1}{N}(\sum_{i=1}^{N} R_i)$ and *rating* of individual stock periodically.

IF $R_i < \frac{1}{N}(\sum_{i=1}^{N} R_i)$ and *rating* <0.50

Sell poor performance stock.

ELSE

Buy best performance stocks for matching portfolio size

ENDIF

UNTIL portfolio return= = expected return. i.e. R_P = $= E(R_P)$

END

Where R_i = return of individual asset.

Our proposed portfolio strategy is compared with other three portfolio models. The first portfolio is equal weight model is without prediction and just assigns investment equally to all stocks.The second portfolio is momentum-investing portfolio. Every 30 days, the portfolio is rebalanced to keep the top 25% of stocks. It buys high return stocks and sells poor return stocks over the previous four months. Final, buy and hold strategy is constructed by arbitrarily choosing particular stocks from 30 stocks in which selected stocks has the equal ratio of investment.

Table 2: Portfolio performance

Month	***Profit (%)***			
	Equal Weight	***Momentum Investing Portfolio***	***Buy-and-Hold Strategy***	***Neuro - Fuzzy***
Aug 2010	-19.09	-7.22	-13.70	-33,80
Sept 2010	34.17	14.82	33.05	85.67
Oct 2010	2.40	9.21	7.25	11.80
Nov 2010	2.04	-4.25	2.42	13.67
Dec 2010	15.22	8.67	17.50	21.56
Average Profit	6.948	4.246	9.304	33.175

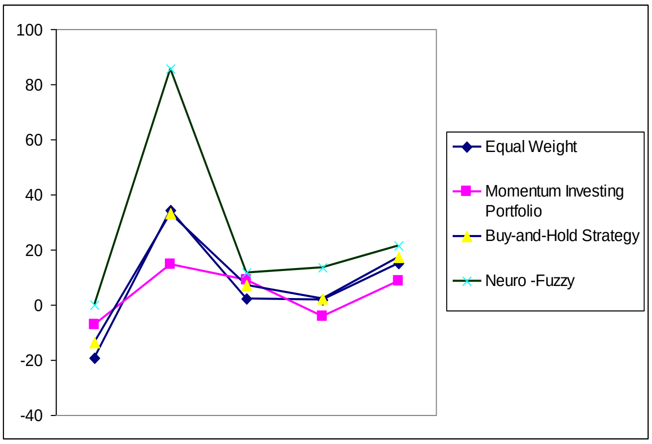

Figure 3: Portfolio returns

Table II shows that over the 5-month period, the Neuro-Fuzzy system provides considerably superior average investment return compared to other portfolio models. In addition, as shown in Fig. 2, the profit of the Neuro-Fuzzy portfolio optimization system is constantly higher compared to that of other portfolio models for every month except August 2010.

CONCLUSION

In this paper, we extend the Neuro Fuzzy system to solve the portfolio optimization problem. The proposed approach is validated by BSE Sensex stock index. Experimental results show that the performance of the stock portfolio models, as evaluated by its return on investment and risks. However, the results acquired using the proposed Neuro-Fuzzy system in performance evaluation experiments applying real stock market data profited significantly higher return on investment values compared against other portfolio models. This showed that applying the proposed portfolio optimization with Neuro-Fuzzy portfolio optimization model yielded superior returns than other portfolio models.

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Short Bio data for the Author

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