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A CONCEPTUAL MODEL FOR PORTFOLIO MANAGEMENT SENSITIVE TO MASS PSYCHOLOGY OF MARKET

Milad Jasemi [a], Ali M. Kimiagari [b], A. Memariani [c]

[a] Department of Industrial Engineering, Islamic Azad University, Masjed Soleyman Branch, Masjed Soleyman, Iran,
[b] Department of Industrial Engineering, Amirkabir University of Technology, Hafez avenue, Tehran, Iran
[c] Department of Industrial Engineering, Bu-Ali Sina University, Hamedan, Iran
Corresponding author: Milad Jasemi, Miladj@aut.ac.ir

In an effort to model stock markets, many researchers have developed portfolio selection models to maximize satisfaction of investors. However, still this field suggests the need for more accurate and comprehensive models. Development of these models is difficult because of the unpredictable economic, social and political variables that surely affect manners of stock markets. The portfolio model developers have escaped the inspired complexity by some simplifying assumptions like absolute rationality of investors. In this paper a conceptual model for portfolio optimization is presented. Some important features of the model in comparison to others are: 1) Consideration of investors' emotion or psychology of market that is arisen from the 3 above mentioned factors; 2) Significant loosing of simplifying assumptions about markets and stocks; 3) Ability of managing portfolio even according to any specified time interval. As a matter of fact the model is a modular one with modules that are designed in a way that the model can be used for both purposes of portfolio selection and management without the problems that are common in most of the previous ones.

Keywords: Portfolio management; Portfolio selection; Psychology of market; Conceptual model; Technical analysis.

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1. INTRODUCTION

Modern portfolio theory is an effort for evolution of traditional principles in portfolio selection. Portfolio theory has been organized to overcome the challenge of assigning one's wealth among different assets (Deng et al., 2005). In mathematical programming asset is a random variable with a stochastic distribution for future returns and portfolio is a linear combination of these variables (Liu and Shenoy, 1995), or in other words every way of diversifying money among several assets is called a portfolio (Fernández and Gómez, 2007). Recognizing the best portfolio of assets is one of the major challenges of financial world (Ballestero et al., 2007) and is called portfolio selection. As a matter of fact, portfolio selection is the process of making a portfolio that maximizes the investor's satisfaction [(Fernández and Gómez, 2007), (Huang, 2007), (Elikyurt and Ozekici, 2007), (Huang, 2008)].

The researchers who develop portfolio models try to maintain a balance between level of reality in their models and handleability of such expectations in a model. These two criteria have reverse relation, i.e. more realistic a model is to be developed; less handleable it is and vice versa. On the other hand there is a sensible harmony between advances in modeling techniques and improvement of portfolio theory in both of the cited criteria. That is, new portfolio models are considering more and more of the real conditions that have been ignored by previous scholars.

In spite of continuous contributions of scholars in development of better models, still they are not completely applicable in real world. Much of the inapplicability or in better words the low confidence interval of portfolio models is because of the gap between realities of market and assumptions of such models. Many of the assumptions are made because the optimization techniques that have been used in such models are not developed exclusively for the field of portfolio theory. The problem of portfolio optimization has been simplified significantly in order to be explainable by the techniques. This simplification has resulted in disappointing applications of the models by stock traders.

According to the mentioned shortcomings, the following deeds seem effective to fill the gap considerably:

1. Considering the stock market psychology in portfolio optimization models.
2. Loosing of restricting assumptions in portfolio models, for instance on distribution of data, direction of variations, manner of market development and so on.
3. Increasing flexibility of models for responding daily events or even events of shorter time intervals.
4. Decreasing reliance on raw past data and moving toward processing of them for particular purposes like forecasting.

This paper is going to develop a conceptual model that seems potential to meet the mentioned challenges.

2. BACKGROUND

According to Konno and Yamazaki (1991) modern portfolio theory is based on the pioneer works of Markowitz (1952), Markowitz (1959) and Sharpe (1963). Markowitz portfolio optimization model in spite of theoretical notability has never been used extensively for making large-scale portfolios (Konno and Yamazaki, 1991). If the exact expectations of future returns and correlation of returns for each couple of stocks is accessible and returns having a symmetric distribution, Markowitz model could be nominated to achieve a reliable result. It is completely apparent that the mentioned conditions are impossible so considerable amount work has been directed to Markowitz model in order to make it more practical. For example to respond the challenge of deriving a real covariance matrix for stocks returns, Hirschberger et al. (2007) has designed a procedure for random development of covariance matrices. Another main problem with Markowitz model is the computational difficulty that a large scale quadratic programming problem with a dense covariance matrix has (Parra et al., 2001). Because of these shortcomings, Markowitz model has seen many developments in the following directions (Deng et al., 2005):

- Alternative portfolio selection models.
- Equilibrium models such as Capital Asset Pricing Models (CAPM) developed by Sharpe (1964), Lintner (1965), Mossin (1966) and Sharpe (1970) or Arbitrage Pricing Theory formulated by Ross (1976) and developed by Huberman (1982) and Connor (1982). In such models that are also called Factor models, random return of stock is a linear combination of some common factors plus a random variable that is usually different for different stocks (Connor and Korajczyk, 1995).

Since the proposed model of this paper categorized in first group, the paper pays special attention to its literature. Some of the alternative models with minor changes are Mean-Semivariance, Mean-absolute deviation, Mean-Variance-Skewness or Mean-Variance with some logical constraints and if more fundamental changes are going to be considered we come to Robust Optimization, Markov chain, Multi objective decision making (MODM), Possibility and Fuzzy theory or Minimax modeling of portfolio optimization.

2.1 Robust Optimization

Portfolio selection is a highly uncertain problem. Uncertainty is because of stock price estimation. Robust optimization is a method that assumes uncertain parameters are in a continuous and convex region. This kind of modeling supports portfolio selection when there is shortage of information and several assessment criteria (Liesio et al., 2008).

Ben-Tal and Nemirovski (1999) as a practical example for robust linear programming model, solved the stock selection problem that had been solved by Scenario-based optimization method previously and showed that results of robust modeling are more attractive. Ben-Tal et al. (2000) present a robust modeling of multi-period portfolio selection problem. Bertsimas et al. (2004) developed a robust portfolio selection model for symmetric and dependent return rates. El Ghaoui et al. (2003) developed a robust matrix programming model with VaR criterion. Halldorsson and Tutuncu (2003) modeled and solved a nonlinear programming portfolio selection problem with semi-definite constraints. Oguzsoy and Güven (2007) presents a robust optimization for short term modeling of portfolio beside anomalies for an index of Istanbul Stock Exchange and US dollars returns.

2.2 Markov Chain

According to Elikyurt and Ozekici (2007), Markov modeling of a stochastic financial market goes back to Pye (1966). Some studies have presented models with stochastic interest rates that are modeled by markov chain. For example Norberg (1995) and Elliott and Mamon (2003) do the same work in a continuous time environment.

There are studies for risk sensitive portfolio optimization in markov markets in three states of observed, nonobserved and partially observed factors. For example Di Massi and Stettner (1999) consider the problem in discrete time partially observed conditions with infinite horizon. Bielecki et al. (1999) first study discrete time multi-state markov chain and then discuss its application to portfolio management. Bielecki and Pliska (1999) challenge the optimum dynamic policies for controlled markov processes and Stettner (1999) generally studies the portfolio optimization. Nagai and Peng (2002) consider dynamic optimization of portfolio with partial information during infinite horizon and at last Stettner (2004) optimized the portfolio with factors that partially or completely have been observed.

In some studies continuous time markov chain with a discrete state space has been used for portfolio selection and stock transaction problems. For example Zhang (2001) used the approach of sell optimization to study stock transaction and Bauerle and Rieder (2004) in environment of markovian stock price and interest rate perform portfolio optimization.

As a new study in markov field, Elikyurt and Ozekici (2007) consider a market with completely obvious states by a markov chain. They study several multi-period portfolio optimization models with a portfolio that consists of a risk free asset and a number of risky assets.

2.3 MODM

Portfolio selection is a usual multi-objective problem (Parra et al., 2001). Steuer and Na (2003) present a categorized bibliography about applications of multiple criteria decision making techniques in field of financial management. They got that 69% of published papers had used goal and multi-objective programming and 29% of them had been involved in portfolio selection problems (Ben Abdelaziz et al., 2007). For the first time Lee and Lerro (1973) used goal programming for portfolio selection (Parra et al., 2001). Kumar et al. (1978), Lee and Chesser (1980) and Levary and Avery (1984) also applied goal programming for portfolio selection problem.

Among multi-objective stochastic programming applications, Muhlemann et al. (1978) present a formulation of stochastic multi-objective linear programming under uncertainty for portfolio selection and Tamiz et al. (1996) present a two stage goal programming model for portfolio selection. Ogryczak (2000) developed Markowitz model by designing a multi-objective linear goal programming. Ballestero (2001) presents a formulation of stochastic goal programming based on utility function and mean-variance model. In this study the problem is solved by combining standard expected utility theory and a lean weighted linear goal programming model. Aouni et al. (2005) introduce decision maker preferences explicitly and apply chance constrained programming for stochastic goal programming model. They show their formulation by an example from portfolio selection field. Prakash et al. (2003) apply a polynomial goal programming in which investor's preferences for Skewness can be added to model, to determine the best portfolio of capital markets in some continents. Ben Abdelaziz et al. (2007) present a model for portfolio selection when some parameters are random and normal. They work on a chance constrained compromise programming, that combines compromise programming model and chance constrained programming approach.

2.4 Fuzzy and Possibility Theory

Fuzzy Theory

When the characteristics are inaccurate, fuzzy theory is a good option (Parra et al., 2001). So the field of financial management that is full of inaccuracies has found this theory an appropriate one to solve its complicated problems. The significance of fuzzy theory contribution in portfolio theory advances is noticeable to the extent that Huang (2007) says there have been only two directions for evolution of the theory, one in stochastic environment and the other in fuzzy environment. For example Parra et al. (2001) developed a fuzzy goal programming that encompasses three criteria of return, risk and liquidity.

For investors, fuzzy and randomness often are combined with each other. For example a stock return is assumed to have Normal distribution but its parameters are fuzzy. It should be noted that there is not much research in application of random fuzziness to model and solve portfolio selection problems (Huang, 2007). Tanaka et al. (2000) represent two new portfolio selection models based on fuzzy probabilities and possibility distributions respectively. Huang (2008) represents two new models for portfolio selection in which stock returns are random variables with fuzzy information. In this study also a hybrid intelligent algorithm has been developed to solve the optimization problem.

Possibility Theory

According to Tanaka and Guo (1999) possibility portfolio selection models were initially proposed by Tanaka et al. (1995) and Tanaka and Guo (1997) while these models can reflect portfolio expert knowledge. Tanaka and Guo (1999) consider a portfolio selection problem that is based on upper and lower exponential possibilistic distributions. Both of distributions have been chosen to reflect the expert knowledge in portfolio selection problems. Carlsson et al. (2002) apply a possibilistic approach to select the portfolio with highest utility score. Zhang and Nie (2004) develop an admissible efficient portfolio model in which admissible errors are dependent to risk and asset returns to reflect the uncertainty of the real world.

2.5 Minimax

Among the researches that have chosen minimax approach to study portfolio selection problems, Sengupta (1989) has done the job on basis of game theory but Dembo (1990) applies scenario analysis. Young (1998) minimizes the maximum loss during all past periods for a specified level of return and Ghezzi (1999) applies immunization approach to do the job. In this study the problem has been formulated as a maximin optimum control problem that is solved by dynamic programming. Cai et al. (2000) minimizes the maximum risk of individual assets. Deng et al. (2005) have made a new minimax model for portfolio selection in conditions of randomness uncertainty and data approximation. In this approach the best portfolio is the one that maximizes the worst possible expected returns.

3. LITERATURE

Academic researches have paid an acceptable attention to portfolio models that leads to continuous evolution of the theory. But as can be seen in part 2, experts of each field have analyzed the portfolio selection problem from their own perspective of expertise. So they have to simplify the complex problem of portfolio optimization to make possible the modeling and solving of it. For example there are some unrealistic and simplifying assumptions in stochastic programming, robust optimization and markov modeling, on distribution of parameters, change direction of uncertain parameters, and manner of relationship between future and present respectively. That is portfolio optimization problem plays the role of a case study for these techniques. As a matter of fact such deeds have benefited expertise field of the techniques more than the field of portfolio theory. As a result of this approach, the models have not been welcomed by stock traders and there is a significant gap between products of academic community and what the stock market practitioners apply.

The new versions of these models as can be seen in previous part, have tried to fill the gap but again because of the fact that the techniques are not initially developed for the uncertain and particular field of finance, the applicability of them in real cases is not satisfactory. So a new portfolio selection model that is designed particularly to optimize a portfolio is highly and highly needed. This new kind of model must be capable of encountering the following challenges:

1. One of the basic assumptions that scholars have made for their models is the assumption of absolute rational behavior of investors. That is emotion has no effect on investors decision making. But both of experiments and experiences have proven the necessity for entrance of psychological effects of markets into portfolio models. That is decisions made by traders struggling in the midst of the financial markets may not be as heartless as they are seemed to be [http://ssm-vm010.mit.edu/media/snow04-08-02.htm]. Lo and Repin (2001) study the importance of emotion in the decision-making process of professional practitioners of stock market by measuring their physiological characteristics like skin conductance, blood volume pulse during live trading sessions while simultaneously capturing real-time prices from which market events can be detected. In their sample that was 10 traders, they found different physiological responses during different states of the market and across the 10 traders. According to their results even the most hard-boiled trader has heart palpitations during volatility events, and less experienced traders can react emotionally to a broader swath of market behavior [http://ssm-vm010.mit.edu/media/snow04-08-02.htm]. So it is highly critical for portfolio models to encompass the emotional factors of market but how?
2. The world of finance never waits for anybody or never adapts itself with assumptions of scholar's models; rather scholars themselves must obey its circumstances. Any simplifying assumption about the market behavior however small and partial may reduce the reliability of results considerably. So an ideal model is the one without any restrictive assumption like previously cited ones.
3. Nowadays flexibility of models is needed more than anytime in the past. Winkler (1989) agrees and justified his belief as follows:

> "I prefer, however, to take the view that, in many situations, there is no such thing as a 'true' model for forecasting purposes. The world around us is continually changing, with new uncertainties replacing old ones. As a result, the longer-term search for a 'true' model is doomed to fail in many cases because unanticipated changes prevent us from enjoying the luxury of getting to the longer term in a stable environment. This suggests that models should be adaptive, but even adaptive models only represent our best state of knowledge at a given time; they do not represent the 'truth' in any sense."

This century is time of rapid and discontinuous changes with new risks. Time pressures and rush of events make us design and apply adaptive, unified and efficient decision support systems (Leigh et al., 2002). Most or even all the available models can not do well with this challenge. Because they assume future state of stock markets are in accordance with past state of them (Tanaka and Guo, 1997) but the past data have limited applicability (Ballestero et al., 2007). Efficient and practical portfolio models must be flexible and capable of rapid responses to market changes.

4. THE MODEL

The proposed model of this paper that is to be potential in addressing the three main mentioned challenges is a modular one as is depicted in Figure 1. The model consists of three main phases; two for filtering inefficient portfolios and stocks and one to integrate their outcomes.

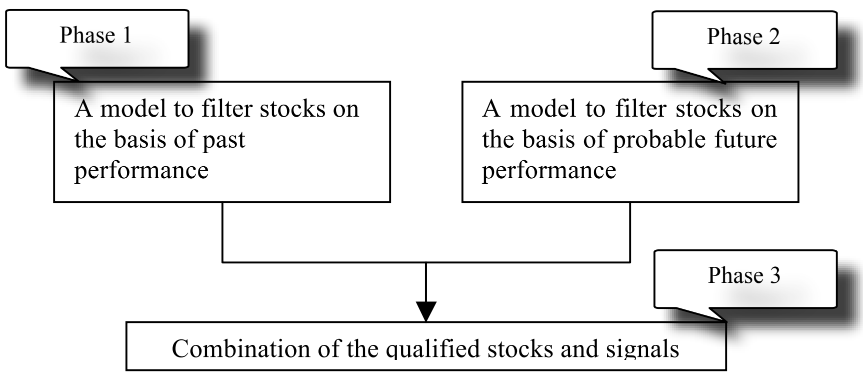

Figure 1. Block diagram of the 3 phase model

Despite phases 2 and 3, phase 1 is a familiar module in portfolio models. In fact in modern portfolio theory it is natural to calculate the risk-reward frontier first and then help the investor to select the portfolio that best satisfies his risk and return preferences. But the main work of specifying the utility function of investor for choosing the most attractive point on the frontier still remains a critical issue (Ballestero et al., 2007).

As was mentioned before the nature of phases 1 and 2 are the same and both of them have the mission of filtering. The slight difference between them is the time horizon they focus on. Phase 1 referees the stocks according to their past performance while phase 2 considers their future performance. Meanwhile before discussing phases1 to 3, because of the leading role of market psychology in contributions of the paper, part 4.1 describes it.

4.1 Market psychology

Markets are influenced at times by emotionalism of stock traders. As John Manyard Keynes stated, “there is nothing as disastrous as a rational investment policy in an irrational world”(Nison, 1991).

For making the model sensitive to psychology of market like any other factor, three following steps should be taken:

1. Defining the factor

Generally the intention from market psychology is mass psychology. For example mass psychology is a support to money applicability in market. Why is money, with no inherent worth, exchanged for something real like material? It is because of a shared psychology. Everyone believes it will be received, so it is. One time this shared or mass psychology disappears it becomes worthless.

2. Measuring the factor

Fundamental analysis only provides a gauge of the supply/demand situations, price/earnings ratios, economic statistics, and so forth and there is no psychological component involved in such analysis (Nison, 1991). According to definition that was presented in previous part and intangibility of the psychological factor, Technical Analysis (TA) is capable of providing a good mechanism to measure the irrational or emotional components that are present in all markets (Nison, 1991). TA that is also known as charting technique has been part of financial deeds for many years and many people believe it is the main shape of investment analysis (Chavarnakul and Enke, 2008). Generally there are three approaches to benefit from market. First one is the principle of efficient market and random walk theory. Second one is fundamental analysis and the last one is TA that assumes prices have a trend and the analysis try to discover it (Yao and Tan, 2000). Although there has been much academic opposition toward TA, it has been proved that TA for stock prices is powerful and has a considerable popularity among economists and practitioners. It is because of the equilibrium that TA maintains among human, politic and economic events (Chavarnakul and Enke, 2008).

3. Entering the factor to the model

Since the basis of TA for giving signals including selling, buying or holding is mass psychology analysis of market, if the result of a portfolio model is affected by outcomes of a TA processor, naturally the model would be an emotional one. And designated intensity of the influence determines the level of sensitivity to psychology of market. For doing so in this paper the second phase, the future performance filtering, in which each stock is processed technically, is devised. Part 4.3 discusses this module in detail.

4.2 Phase 1: Past performance filtering

Deriving efficient frontier (EF) on basis of historical information is an essential initial step to remove inefficient portfolios otherwise the complexity of decision making increases considerably (Ballestero et al., 2007). The collection of portfolios that have maximum return at a specified level of risk or have minimum risk at a specified level of return is called efficient frontier (Markowitz, 1952) and Ballestero and Romero (1996) recommend maximizing investors expected utility on EF. Our methodology also considers EF as one of its phases. The general well known model in literature to derive EF is as follows.

$$Min \quad Risk\left(P\left(x_1,\ldots,x_n\right)\right)$$

$$\sum_{i=1}^{n} x_i = 1 \qquad \ldots \qquad (1)$$

$$\sum_{i=1}^{n} x_i \bar{r}_i = R_d \qquad \ldots \qquad (2)$$

$$\sum_{i=1}^{n} y_i = a \qquad \ldots \qquad (3)$$

$$l_i y_i \le x_i \le u_i y_i \qquad i = 1,\ldots,n \qquad \ldots \qquad (4)$$

$$x_i \geq 0 \quad i = 1,2,\ldots,n \qquad \cdots \qquad (5)$$

$$y_i = \begin{Bmatrix} 1 & x_i > 0 \\ 0 & x_i = 0 \end{Bmatrix} \qquad \cdots \qquad (6)$$

where

$Risk$: Risk function

x_i : Investment share of stock i in the portfolio

$P(x_1,\ldots,x_n)$: The portfolio whose shares of stocks are $x_1,\ldots,x_n$

$\bar{r}_i$: Indicator of stock i past performance

a : Pre-determined number of stocks in the portfolio

R_d : Indicator of the portfolio past performance

l_i : Lower admissible limit for investment in stock i

u_i : Upper admissible limit for investment in stock i

In the model, constraints 1, 2 and 5 are necessary but constraints 3, 4 and 6 that are also discussed by Perold (1984) are optional. The model also lets decision makers to choose any risk measure or any definition for $\bar{r}_i$ in their models.

The literature has introduced the arithmetic average of past returns of stock i as a definition for $\bar{r}_i$ but the definition does not encompass the entire situations and is not a basis for many investors to decide on. Investors may use maximum or minimum or any other statistics of past returns as a measure for assets performance. For instance a person who invests in lottery tickets considers the max potential return as an indicator of the asset return. Because the expected value of a lottery ticket return is less than many other investment opportunities even with smaller risks. The main reason for applying arithmetic average in approximately all the portfolio models is mutual dependency of risk and return measures in such models. As a matter of fact the efficient frontier is the result of equilibrium between return and risk. More realistic the risk measure is, you are freer in selecting return measure. For example if you apply the variance measure for risk, you should use the arithmetic average of past returns for rational results as Markowitz did. So because of the importance of risk measures in application of efficient frontier model that is one of the 3 phases of our model, the popular risk measures of literature that any of them can be used in the proposed methodology of this paper are going to be discussed.

In field of portfolio theory, Variance, Semivariance, Probability of an Adverse Outcome (PAO), Value at Risk (VaR), Conditional Value at Risk (CVaR) and Lower Partial Moments (LPM) are the most well known risk measures.

Before Markowitz (1952), investors in spite of their acquaintance with concepts of risk and return did not quantify them. After that mathematical analysis of portfolio management developed considerably and variance became the most accepted mathematical definition for risk (Huang, 2008). According to this definition if r is the expected return of asset and μ is the expected value, asset investment risk equals with $V[r] = E\left[(r-\mu)^2\right]$.

The measure of semivariance has been introduced to financial literature by Markowitz (1959). This measure evaluates the variability of returns that are less than average. The mathematical description of SV is as follows:

$$SV[r] = E\left[\left[(r-\mu)^-\right]^2\right],$$

where

$$(r-\mu)^- = \begin{cases} r-\mu, & if \quad r \leq \mu \\ 0 \quad , & if \quad r > \mu. \end{cases}$$

This measure pertains to downside risk measures category. The downside risk concept is becoming more and more popular and portfolio models based on this kind of measure are known as post-modern ones (Grootveld and Hallerbach (1999). According to Grootveld and Hallerbach (1999) the general idea of downside risk is that left-hand side of a return distribution involves risk while the right-hand side contains better investment opportunities.

The safety first measure formulated by Roy (1952) that is called Probability of an Adverse Outcome is probably the most known downside risk measure in literature of investment (Grootveld and Hallerbach, 1999). This measure defines risk as the probability of falling of an asset value below a pre-specified level. If b and r_0 denote the pre-specified level and distance respectively, mathematical definition of the measure is like Eq. (1). (Huang, 2008)

$$\Pr\{(b-r) \geq r_0\} \qquad \cdots \qquad (1)$$

According to PAO the above probability and $(b-r)$ are called risk and loss of investment respectively.

The measure of VaR has much similarity to PAO that Huang (2008) considers it as another description of PAO. The main difference is that Roy's measure output is a probability but VaR output is an expression of loss that can be described in any way. If β is a pre-determined level for probability, $\beta - VaR$ of a portfolio will be the minimum amount of α in the way that the loss of investment, with probability of $(1-\beta)$, does not exceed α (Rockafellar and Uryasev, 2000).

Some undesirable characteristics of VaR like lack of subadditivity or convexity caused development of CVaR by Rockafellar and Uryasev (2000). $\beta - CVaR$ is the conditional expectation of losses that are more than $\beta - VaR$ (Rockafellar and Uryasev, 2000). Figure 2 describes schematically two measures of VaR and CVaR.

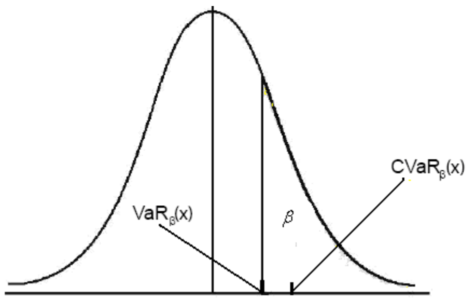

Figure 2. VaR and CVaR on Loss distribution chart

Bawa (1975) introduced a general definition of downside risks in form of LPM and Fishburn (1977) developed the (α,τ) model (Grootveld and Hallerbach, 1999). This measure of order α around τ is defined in Eq. (2).

$$LPM_\alpha(\tau;R) \equiv \int_{-\infty}^{\tau} (\tau - R)^\alpha dF(R) = E\ \{(\max\ [0, \tau - R\ ])^\alpha\} \quad \dots \quad (2)$$

where $F(R)$ is cumulative distribution function of the investment return R and τ is the target parameter. In the measure, $\alpha = 1$ concerns a risk-neutral investor and separates risk seeking from risk adverse behavior (Fishburn, 1977).

After deciding which constraints to be used in EF model and designating a gauge for stock past performance and selecting the appropriate risk measure, phase 1 will be applicable. After solving the EF model for different amounts of R_d and drawing the resulting points, the intended efficient frontier will be yielded. The time horizon of this phase is a subjective parameter and can be of any length from 7 days to 10 years but it is recommended to be between 3 and 36 months.

4.3 Phase 2: Future performance filtering

As was referred to in 4.2 evaluating stocks according to past performance is a routine work but what about future performance? Is it necessary to find out about the future status of stocks before proposing the final portfolio? Surely it is. Scholars have not paid enough attention to future in their models because of many difficulties that are embedded in forecasting. In fact they assume future state of stock markets completely obeys its past trend or manner, the assumption that is difficult to be accepted in stock markets with continuous variations (Tanaka and Guo, 1999). It is true that there are many works in field of forecasting and predicting stocks return but the lacuna of an integrated portfolio selection model that may be capable of considering the future performances of stocks is felt. In this paper for filling the gap, one of the 3 phases is dedicated to this task. In reality the given phase accomplishes two important missions of the conceptual model simultaneously. First, making the model sensitive to psychology of market and secondly finding the inefficient stocks that are going to experience a fall in future.

In simple words the reason for devising phase 2 in the model is to equip the model with a forecasting mechanism that contributes to the final results (of the portfolio optimization model) that are not only on basis of stocks past performances and their future conditions also influence selection of them at the current time. For example consider two stocks of 1 and 2 that according to indicators of past performance are the same while the future state of stock 2 is superior to stock 1. In these conditions without phase 2, two stocks have no difference but with it stock 2 is prior to stock 1 in composing a portfolio. The example shows how phase 2 can contributes to get better results. But the reason for choosing TA as forecasting mechanism, as was discussed before is its sensitivity to psychology of market. So phase

2 is a TA expert or in better words is a TA processor that forecasts the future trends of stocks by considering mass psychology of market. After feeding the necessary data to this phase, for each stock there will be a signal to buy, sell or hold that stock .i.e. the outputs of this phase are some signals. A selling signal for a stock means that phase 2 tends to filter it while a buying signal shows better status of that stock in future.

The inputs of this phase are determined by kind of TA that has been selected. For example if the candlestick charting technique is used the input data for each stock would be high, low, open and close prices of last 2 or 3 days. Or if moving average whether simple, weighted or exponential is used, scholars should determine the number of reference days.

It is to be noted that for development of the phase, there is no limit on technique or indicator that is considered for TA processor and the main point of this phase is its output signals to buy, sell or hold the corresponding stock. Naturally the better this system is designed, more reliable the results will be. The TA processor can also be a combination of several techniques that their results are interpreted to one of the three mentioned signals according to a pre-specified rule. For instance Chenoweth et al. (1996) have discussed some of such rules.

Phase 2 is equipped with TA by means of Artificial Intelligence (AI) as is depicted in Figure 3. Performing TA in financial markets by using AI have been surveyed by some researchers with promising results. Lee and Jo (1999) develop an expert system of candlestick charting analysis to forecast the best timing of stock market. Fernandez-Rodrıguez et al. (2000) study the applicability of a simple technical rule on the basis of neural networks. Yao and Tan (2000) present some documents for applicability of neural network models for prediction of exchange rate of currency. In this study time series data and technical analyses like moving average to achieve movement principles of exchange rate of currency, are fed to a neural network. Leigh et al. (2002) show the prospect for application of modern approach of hybrid methods for assessment of buying opportunities in stock market by TA and neural network. Lam (2004) studies the applicability of neural networks especially back propagation algorithm for integration of fundamental and TA for forecasting of financial performance. Chavarnakul and Enke (2008) used a neural network for performing equivolume charting technique and as the most recent work in this field Jasemi et al. (2010) presents a new model to do stock market timing on the basis of a supervised feed-forward neural network and the technical analysis of Japanese Candlestick.

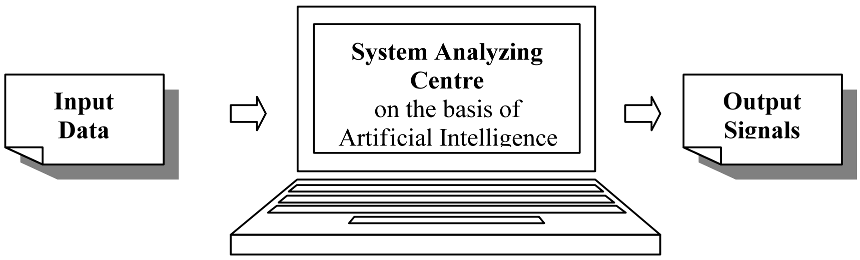

Figure 3. The future performance filtering module of the model

At last it should be noted that any shape of AI including neural network, expert system, genetic algorithm and fuzzy theory can be used. Meanwhile this module is run for each stock independently of others, i.e. it should be applied n times per each run of the model where n is number of stocks that we are going to select the best portfolio from.

4.4 Phase 3: Integration phase

Inputs of this phase are outputs of phases 1 and 2. As was discussed before the output of phase 1 is an EF that represents some qualified portfolios and the output of phase 2 is n signals associated with n stocks. At first glance it is appeared that the outputs of first two phases are not cognate. One delivers portfolios and the other delivers signals, so there should be another stage in the model in which these two kinds of outputs are combined to give an applicable result. In fact phase 3 exactly does this task. There are two options for development of this phase as follows.

1- Rule-Mathematical Programming

According to this structure, phase 3 is combination of a rule and a mathematical programming as is depicted in Figure 4. In the figure Pi denotes the ith portfolio of EF from phase 1, sii denotes the TA signal for ith stock and SSi denotes the ith stock that passes the rule.

In this structure the rule output is only several stocks without specification of their shares. These stocks will compose the optimal portfolio after being fed to the mathematical programming that can be chosen from the mentioned models in part 2. There are infinite rules that can be developed and they are completely subjective and experience based. A typical rule can be as follows:

Assume a stock trader who wants a portfolio with 3 stocks ($a = 3$) while $n = 10$. After running phase 1, Table 1 that presents 20 portfolios of the efficient frontier is achieved. According to the table investment shares of stocks in the 4th portfolio (P4) from EF is as follows: 41% in stock1 (S1), 1% in S2, 11% in S3, 19% in S4 and so forth.

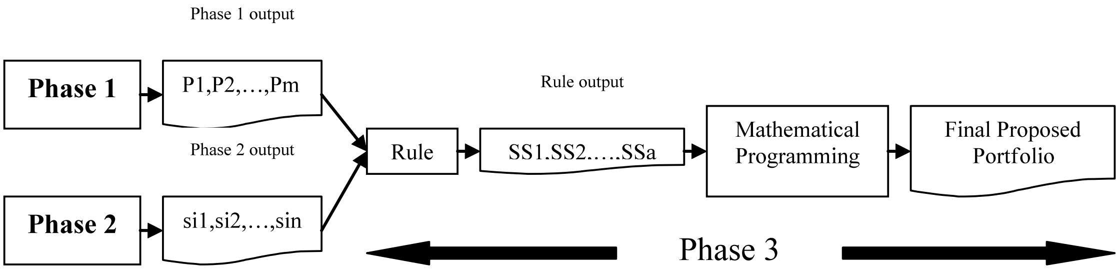

Figure 4. The Rule-Mathematical Programming structure of phase 3 in the model

Table 1. Stocks shares of 20 efficient portfolios in percentage

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
P1	16	2	8	15	31	17	0	8	2	1
P2	6	14	12	25	23	2	2	6	2	8
P3	34	1	14	21	8	0	8	4	6	4
P4	41	1	11	19	0	0	6	10	7	5
P5	0	2	22	24	20	20	0	3	7	2
P6	24	10	16	6	7	0	10	15	4	8
P7	0	2	3	13	3	46	5	14	7	7
P8	34	6	2	0	2	26	20	0	2	8
P9	26	1	35	0	0	31	7	0	0	0
P10	13	7	43	19	0	9	0	2	1	6
P11	27	17	0	3	3	19	4	15	3	9
P12	25	11	0	0	26	38	0	0	0	0
P13	20	7	28	21	10	0	5	0	0	9
P14	0	0	38	0	40	0	1	15	0	6
P15	12	1	11	3	24	22	9	13	1	4
P16	13	8	32	1	13	0	18	3	3	9
P17	30	4	4	20	0	27	0	0	6	9
P18	0	8	0	0	46	0	6	34	1	5
P19	7	15	5	28	43	0	0	0	0	2
P20	0	12	8	9	5	0	19	10	30	7

Again assume that after running the second phase, S1, S2, S6 and S9 got selling signal, S3, S4, S5, S7 and S10 got buying signal while S8 got holding signal. The outputs of each phase will be converted to some scores and then integration will be fulfilled by Eq. (3).

$$Ss_i = Ssp_i + Ssf_i \quad \text{...} \quad (3)$$

where

Ss_i: Total score of stock i

Ssp_i: Past performance score of stock i

Ssf_i: Future performance score of stock i

Ssp_i is equal to summation of investment percentages of stock i in all 20 efficient portfolios as is formulated in Eq. (4).

$$Ssp_i = \sum_{j=1}^{20} Sp_{ij} \quad \text{...} \quad (4)$$

where

Sp_{ij}: Investment percentage of stock i in jth efficient portfolio and at last Ssf_i gets three scores of +40, -40 and 0 for a buying, selling and holding signal respectively. According to Eq.s (3) and (4), Table 2 shows the stocks scores. For example S1 gets score of 328 from its past performance, equals to summation of figures of the second column in Table 1, and score of 40 from its future performance because it got a buying signal from phase 2.

Table 2: Sorted stocks according to their total scores

	S1	S6	S5	S3	S4	S2	S8	S9	S7	S10
Ssp	328	257	304	292	227	129	152	82	120	109
Ssf	40	40	-40	-40	-40	40	0	40	-40	-40
Ss	368	297	264	252	187	169	152	122	80	69

Table 2 says that $(SS1, SS2, SS3) = (S1, S6, S5)$. That is the final proposed portfolio will be a combination of three stocks of S1, S6 an S5.

2- Rule-Rule

According to this structure, phase 3 is combination of 2 rules without mathematical programming as is depicted in Figure 5.

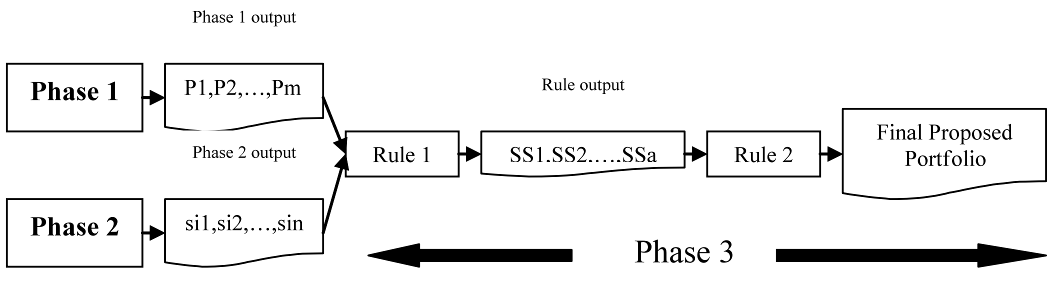

Figure 5. The Rule-Rule structure of phase 3 in the model

In this structure the functions of rule 1 and rule 2 are completely similar to the functions of rule and mathematical programming in previous structure respectively. Again there are infinite rules of 1 and 2 that can be developed. A representative combination of rule 1 and rule 2 can be as follows:

Consider the example described in 4-4-1. Here Eq. (5) can represents rule 2.

$$Sp_i = \frac{m_i Ss_i}{\sum_{k=1}^{n} m_k Ss_k} \qquad \ldots \qquad (5)$$

where

Sp_i : Percentage of investment in stock i in the final proposed portfolio

$$m_i : \begin{cases} 1 & if \quad rank(S_i) \le a \\ 0 & if \quad rank(S_i) > a \end{cases}$$

$rank(S_i)$: Rank of stock i among all stocks according to the criteria of total score (Ss)

a : pre-determined number of stocks in final proposed portfolio

n : Total number of stocks that are evaluated for investment

Whereas in our problem $a = 3$ and ranks of S_1, S_6, S_5 are less than 4 (≤ 3), so Sp_1, Sp_6 and Sp_5 are calculated as 40%, 32% and 28% respectively.

Hitherto the major points of the given conceptual model particularly functions of the phases have been discussed in detail. The remainder of the paper will focus on the point of model ability for portfolio management.

4.5 The management ability of the model

Because of variation in future expectations of stocks, in most cases portfolio optimization is limited to edition of the current portfolio. Edition means buying, selling or holding of stocks (Xia et al., 2000) that is called portfolio management (Parra et al., 2001). So can a portfolio selection model manage a portfolio? Yes it can but with some inadequacies like significant amount of repetitive work or low sensitivity of the results to new data.

For example to manage a portfolio daily with a portfolio selection model it is solved every day and then new results should be compared with previous (yesterday) results. If a stock was present in yesterday portfolio but is absent in new one, it should be sold. In opposite conditions the stock should be bought in the amount that the new portfolio specifies. And at last if a stock is present in both portfolios (the new and yesterday); amount of it should be set according to the new portfolio. If this procedure is applied, with any time period like minutely, hourly, daily, weekly and so forth, portfolio management have been done by a portfolio selection model.

In our model from the perspective of portfolio management much of the task is done by phase 2 that is a TA processor. Since usually the input data of TA processors are from time intervals of less than one week, so the sensitivity of the model to new data will be much more than the portfolio selection models that their input data are from time intervals of several months. And on the other hand exactly for the same reason each data is fed to model less times and so the amount of repetitive work reduces considerably.

About the role of the first phase in portfolio management it is to be noted that there should be an initial portfolio for being edited. Much of this task, i.e. presenting an acceptable initial portfolio, is done by the first phase. If the stocks data of T time units are fed to phase 1, this phase should be applied every T_1 time units where $T_1 \leq T$.

The flowchart for portfolio management according to the conceptual model of this paper is shown in Figure 6.

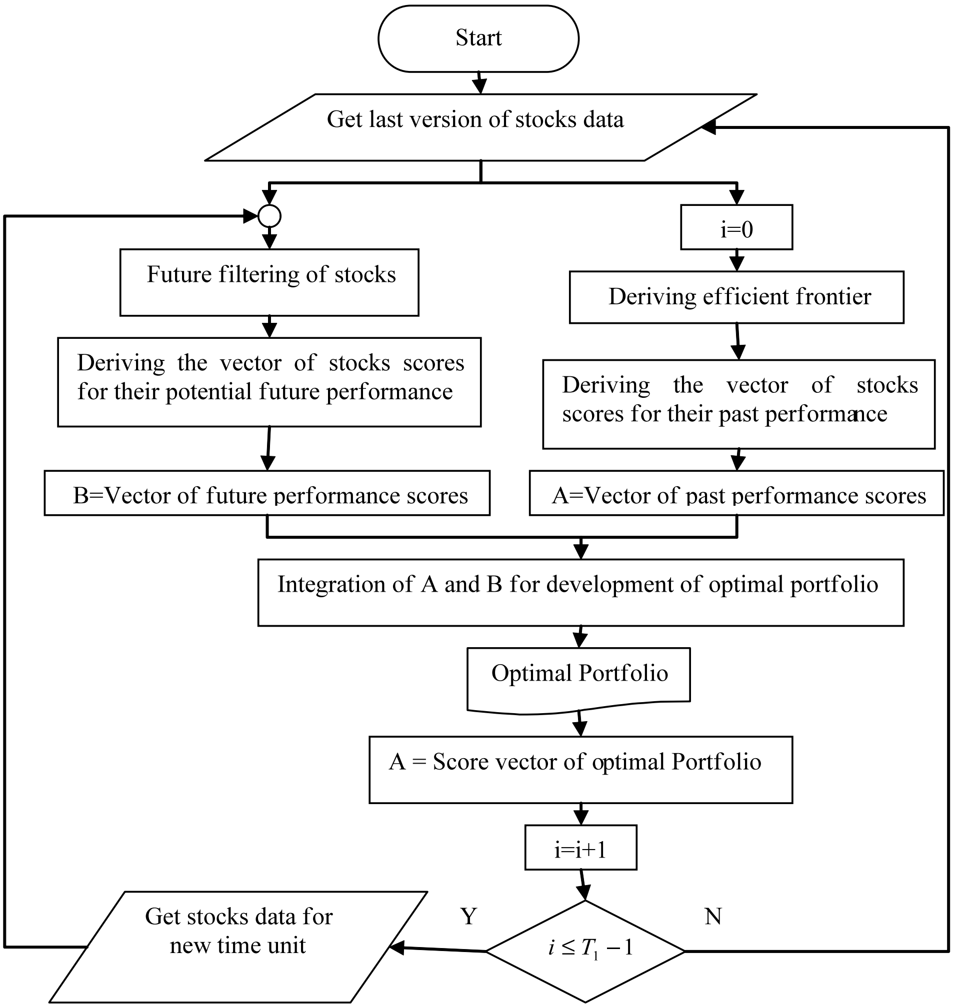

Figure 6. The portfolio management model flowchart

According to Figure 6 at first step the data should be fed to model. For past performance filtering the last T data for each stock that is usually closing price are used and fed to model in a time. According to these data the model yields the efficient frontier. For future performance filtering the necessary data in accordance with the selected TA are fed to AI system in n times to get the TA signal for each stock.

According to outputs and the pre-defined rule, optimal portfolio is resulted and at this time the first run of model is finished. The next run of the model will be after a time unit. For example if a day is used as time unit, the next run of the model will be tomorrow. After a time unit, new data are added to data base and the new package of data are fed only to AI system just like the previous step to get the new score vector of future performance. In this stage the score vector of past performance is replaced with the last optimal portfolio score vector. In next runs of model this vector will be replaced by score vector of new optimal portfolios to give the optimal portfolio after each run. This procedure continues for T_1 times. And after that every thing will start like the first run but with new data.

5. INSIGHTS FOR PRACTITIONERS

Portfolio managers have the responsibility of recognizing the best portfolio of assets that is one of the major challenges of financial world. Any study that helps this group of managers in better fulfillment of their mission has been welcomed by literature. This paper also concentrates on this area and tries to improve the mentioned models to

- ✓ Become more dynamic and suitable for mission of management. It is to be noted that most of portfolio models focus on task of selection or optimization, not management, but the focal point of this paper is management of a portfolio.
- ✓ Become emotional and sensitive to mass psychology of market.
- ✓ Become free of many limiting assumptions that are common in previous portfolio models.

If the three above mentioned aspects are responded well we can expect a revolution in portfolio models. Naturally the origination of any applied model is a conceptual model as has been done in this paper i.e. a conceptual model that seems potential for the challenges is presented.

6. CONCLUSION

In this paper after a review of portfolio selection models, some of the major shortcomings of these models that have caused their unwelcomeness in real markets have been discussed. To improve the level of such models, a conceptual model for portfolio management is presented that seems effective to the challenges. In a nutshell the major innovations can be summarized as follows.

- Being sensitive to psychology of market by applying TA and AI. So the model results will be affected by emotional state of market.
- Being free of any simplifying assumption on distribution of stocks return, state of market, variation direction of parameters and so on.
- Being the most adaptive to the changing environment. The model is designed in a way that is able to respond to the environmental factors even minutely. As a matter of fact the managerial nature of the model is the result of this ability.

To prove efficiency of the model, there is need for running comprehensive experiments to evaluate its performance in comparison with other well known portfolio models. As a matter of fact trying to fit the model in a given market to get better results than previous models would be a good research after this paper.

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BIOGRAPHICAL SKETCH

M. Jasemi accomplished his B.Sc. in Industrial Engineering at Iran University of Science and Technology, Tehran, Iran (1999_2003), and M.Sc. in Industrial Engineering at Sharif University of Technology, Tehran, Iran (2003_2005). He obtained his Ph.D. in Industrial Engineering from Amirkabir University of Technology, Tehran, Iran (2005_2010). Currently, he is an Assistant Professor at Industrial Engineering Department at Islamic Azad University, Masjed Soleiman, Iran. His research interests are Financial Engineering, Risk Management, Investment Analysis and Inventory Control.

Ali M. Kimiagari accomplished his B.Sc. in Economy at Tehran University, Iran (1976), and M.Sc. in Industrial Management at Paris Dauphine University, France (1976-1977). He obtained his Ph.D. in Industrial Management from Paris Dauphine University, France (1977_1981). Currently, he is an Associate Professor at Industrial Engineering Department at Amirkabir University of Technology, Tehran, Iran. His research interests are Economy, Risk Management and Investment Analysis.

A. Memariani accomplished his B.Sc. in Mathematics at Bangalore University, India (1984), and M.Sc. in Mathematics at Meerut University, India (1986). He obtained his Ph.D. in Mathematics (O. R.) from Banaras Hindu University, India (1993). Currently, he is a Professor at Bu-Ali Sina University. His research interests are Multiple Criteria Decision Making, Fuzzy Systems, Decision Support Systems, Data Envelopment Analysis and Data Mining.