A New Efficient Metaheuristic Model for Stock Portfolio Management and its Performance Evaluation by Risk-adjusted Methods

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ABSTRACT

In this research, we proposed a new metaheuristic technique for stock portfolio multi-objective optimization employing the combination of Strength Pareto Evolutionary Algorithm (SPEA), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Arbitrage Pricing Theory (APT). To generate the more precise model, ANFIS has implemented to envisage long-term movement values of the Tehran Stock Exchange (TSE) indices including TSE TEPIX and TSE TEDIX making use of technical indicators. The SPEA is exerted to choose several characteristics of technical indicators that these types of chosen essential characteristics strengthen the overall performance of the forecasting model. This research applied the suggested model in Tehran Stock Exchange. The research sample contains panel data for top 50 Companies of Tehran Stock Exchange over a ten-year interval from 2007 to 2017. The efficient procedures on actual market information are examined and explain the performance of the offered model under true limitations from the experiential assessments; we clearly discover that SPEA-ANFIS-APT forecasting technique considerably performs better than the other portfolio optimization models. The suggested hybrid optimization approach provides considerable enhancements and also innovation in the portfolio management and investment strategies under unpredictable and uncertain stock exchange without human interference, with a diversification procedure, thereby supplying satisfactory and ideal returns with minimum risk. Furthermore, the planned portfolio model SPEA-ANFIS-APT attains appropriate and acceptable functionality among diverse portfolio models despite oscillations in a stock exchange conditions. In comparison with the outcomes of various other approaches, the supremacy of the offered model is approved.

Keywords: Stock portfolio management, multi-objective optimization, SPEA, ANFIS, APT

1. Introduction

Portfolio optimization is truly one of the essential matters in finance. There are many studies in the literature on this matter. The majority of these studies is endeavoring to create the Markowitz model far more practical for main model choice or endeavoring to solve it for comparatively optimal portfolios. In this article, technical indicators have been appended to the Markowitz mean-variance model. The technical indicators are surely one of the determinative factors for investing in the stock exchange, as well as meanwhile, and they perform a significant role in buy/sell stocks signals (Björk et al., 2014). There are numerous ways to solve the problem of the portfolio optimization nevertheless virtually not any of them considers the combined model which presented in the current article. The trouble of choosing Portfolio is truly one of the essential research matters in the Finance field. The principal objective of the portfolio selection is to choose the finest compound of assets which will generate the higher expected return while to ascertain a satisfactory degree of risk. The precursor within this field of study is Markowitz, while he represents the mean-variance portfolio method by a quadratic optimization issue under linear boundary circumstances (Markowitz, 1952). The principal purpose of Markowitz's labor is to achieve optimal asset distribution across a range of assets while minimizing risk together with maximizing returns on the expected portfolio (Markowitz, 1999). The difficulty of the portfolio optimization is a recognized complicated issue that is happening in finance. The issue is selecting an optimal collection of assets to minimize risk coupled with maximizing the return. This article suggests a new model for this issue. The advent of a novel type of optimization approaches, termed Metaheuristics, represents a key revolution in optimization. These types of approaches apply to all sorts of combinatorial issues and also can be reconciled to persistent troubles. They permit experts to discover a beneficial solution. Metaheuristic approaches are employed to solve large difficulties. These approaches generally are divided into two categories: First, the particular algorithms which are typified by way of knowledge area for a particular problem. Second the general algorithms which can be used for the broad variety of troubles.

Consequently, numerous investigation actions considering trouble of the portfolio optimization concentrated on the application of these meta-heuristics, which generate effective solutions and also dominate the intricacy of this trouble. Various theoretical advancements have attempted to expand and solve this model by utilizing mathematical modeling techniques.

In this research, the TSE TEPIX and TSE TEDIX indices have been taken into account in our experience, which performs a vital factor in the developing equity market. We have additionally taken into account the TSE TEDPIX indices that are the combination of two indices mentioned. A novel portfolio management methodology combining SPEA, ANFIS and APT has been proposed in this investigation for stock price forecasting and the portfolio optimization in Iran stock exchange. The model comprises three modules:

1) The SPEA module for optimizing multi-objective portfolios.
2) The ANFIS module to forecast the future price of every stock.
3) APT module to find the optimal allocation of assets to minimize risk combined with maximizing the return

Forecasting the stock market is considered a complex and arduous work because of skepticism in the motion of the stock market. In accordance with many scientific studies, price changes trend is not fortuitous. Alternatively, they act extremely dynamically and nonlinearly. Besides that, the capability to prognosticate stock motion and also accurate worth of stock prices, in the long run, are the key elements in Investment strategies. All of the investor requirements must be assessed at the appropriate time.

Technical indicators are employed to identify the behavior patterns and tendencies investors and their effect on the stock's future price motion from previous motions.(Abbondante, 2010)

The SPEA-ANFIS prognostication module creates the trading signals utilizing the technical indicators, comprising four main collections: Trend indicators, Moment indicators, Volatility indicators, Volume indicators.

APT is a substitute for the CAPM to describe the return on assets or portfolios. It had been introduced by the Stephen Ross (Ross, 2013) , and over time, the APT has gained popularity due to comparatively plain suppositions. Nevertheless, APT is much more arduous to employ in action since it needs a large number of data and also intricate statistical examination.

In this study, we used from MathWorks MATLAB R2017b for the presentation of the model. The coding of our model has been described in the Appendix.

Figures A1 to A8 are also employed to compute the technical indicators which are incorporated in the Appendix.

The rest of this paper is organized as follows: Section 2 summarizes the literature and in Section 3, the methodology of research and offered model are expressed. In Section 4, we will provide the final results of the model and in Section 5, concludes the paper with discussion and conclusions.

2. Literature Review

Among the research that has been done on this topic, we investigated the related articles and will refer to them in the next paragraphs. From the first articles dealing with the applying of Metaheuristics Algorithms to the problem of the portfolio optimization, we examine it from Eddelbüttel (Eddelbüttel, 1996). This article describes the index tracking issue, that is, how to multiply the tendencies of a reference index in a destination portfolio. The purpose of this research is to minimize the variance in yield spreads between the benchmark and the tracking portfolio. However, empirically, these expected yield premiums are predefined, and the portfolio is selected regarding fewer stocks. The solution to this problem is difficult to calculate, so the author has resorted to a hybrid genetic algorithm. In the first stage of every descendant, the assets in the portfolio are picked by the genetic algorithm. After that, the optimum weights of these chosen stocks are described by a quadratic programming solver. This approach is empirically employed on "German Stocks Index" (DAX) with daily basis closing prices. Chang et al.(Chang et al., 2000) focus on solving the portfolio optimization issue of mean-variance, consisting of cardinality limitations and also weight limitations. To achieve their targets, the authors utilized three algorithms: Genetic Algorithm, Tabu Search and Simulated Revealing. The consequence of this research implies that the existence of cardinality limitations is a discontinuous effective limit. The effective limit is thus formed by a mathematical programming technique and according to all unlimited case combinations. The authors indicate that several parts of the efficient frontier are concealed, so the utilization of the suggested Meta logistics reveals that the genetic algorithm functions are more desirable than other algorithms utilized. Chan et al., (Chan et al., 2002) examine a multi-phase portfolio optimization issue in the utilization of genetic algorithms. Crama and Schyns (Crama and Schyns, 2003) utilize a simulated mitigation algorithm to solve the problem of optimizing the portfolio by systematically introducing restrictions. Lin et al. (Lin et al., 2005) appends deal expenses to the project optimization issue and utilize a particle swarm optimization technique to solve it. Chen et al., (Chen et al., 2006) improve a limited issue in the portfolio optimization and solve it with a method to optimize the particle swarm. Nevertheless, Thong (Thong, 2007) employs an ant colony algorithm for the same issue.

Ruiz-Torrubiano and Suarez (Ruiz-Torrubiano and Suárez, 2007) deal with the Mean-Variance method with cardinality limitations and also weight limitations for every asset or even category of assets. The authors utilize a hybrid technique. Firstly, they utilize an evolutionary algorithm to search for the optimal combination of the assets in the goal portfolio. Secondly, they utilize a quadratic programming solver to determine the optimal weight assigned to every selected asset. Additionally, the conventional targets of other programs, Aranha and Iba (Aranha and Iba, 2007) have pursued a different goal that minimizes transaction costs between two consecutive intervals. For empirical utilizing, authors NIKKEI employ monthly historical outcomes and also the NASDAQ indices, and as Metaheuristics they trigger genetic algorithms. By accidental programming, Hochreiter (Hochreiter, 2008) contains uncertainty in his portfolio approach. To solve this issue of optimization, the author utilizes the metaheuristic genetic algorithm. Chang et al., (Chang et al., 2009) examine the issue of the portfolio optimization from the perspective of risk aversion. Four kinds of risk criteria are utilized within this article: variance, semi-variance, mean absolute deviation as well as variance with asymmetry. To solve this issue, the authors utilize a metaheuristic genetic algorithm. The algorithm employed is typified by a binary competition choice, a uniform crossover and a replacement procedure where the poorest individuals are substituted by the descending chromosomes. The empirical ramifications for this work indicate that any improvement in cardinality means an improvement in computational time. Moreover, the effective limits of lower cardinality dominate those of higher cardinality. Yu et al. (Yu et al., 2010) employ a demo system to seek an optimal asset allocation that maximizes the benefits for non-life insurers. The authors progress a novel evolutionary algorithm that considers the multi-periodic situations in the asset allocation issue. They indicate that their strategy is more efficient in comparison with other algorithms that optimize issues with single periods. Ardia et al.(Ardia et al., 2010) and Krink and Paterlini (Krink and Paterlini, 2011) examine multi-objective issues with portfolio optimization with actual limitations and solve the issue consistent with a hierarchy of stochastic research by differential evolution. Antonio et al. (Briza and Naval Jr, 2011) provide a stock dealing structure that utilizes the MOPSO of financial indicators. This paper is intended to examine the applying of multi-objective optimization for historical stock dealing. Based on historical information, the structure optimizes the weight of numerous technical indicators for two objective functions including the profit percentage and the Sharpe ratio. The planned MOPSO structure worked much better than the structure optimized by NSGA-II. Bermúdez et al.(Bermúdez et al., 2012) introduce a novel method that extends the genetic algorithms of their conventional optimization field to the fuzzy ranking approach to choose efficient portfolios with limited cardinality. The uncertainty of the performance of a particular portfolio is modeled utilizing fuzzy sets, and a downside risk function is employed to explain the investor's risk aversion. The authors utilize information collection from the Spanish stock exchange to demonstrate the efficiency of our method to the portfolio selection issue. Furthermore, historical securities information, specialist views, and valuations as well as, different traders settings are incorporated into the portfolio selection procedure, So that the individual priority of the investor is mirrored by an optimistic-pessimistic parameter. To Jun Li et al. (Li and Xu, 2013) discuss the multi-objective portfolio selection model with unclear random yields for investors based on three criteria: return, risk, and liquidity.Prevent the trouble of assessing a great number of effectual solutions and assuring the choice of the ideal answer, a compromise-based genetic algorithm was developed to resolve the suggested method. Additionally, a numerical instance is given to demonstrate the offered algorithm. Lwin et al. (Lwin et al., 2014) offered the algorithm which is compared to four multi-objective scalable algorithms consist of the NSGA-II, SPEA-2, PESA-II and PAES. Outcomes are revealed for in public accessible OR library datasets from seven market indices. Sara et al. (Shalan and Ykhlef, 2015) suggest a novel intelligent hybrid scalable algorithm that incorporates cloning with particle band optimization to optimize the portfolio. Subsequent, they demonstrate the outcomes of the suggested solution via findings carried out in the Saudi stock exchange (Tadawul). The main objective of Rubén et al. (Saborido et al., 2016) is to solve the MDRS portfolio selection method as a completely limited optimization problem with three objectives, to analyze the effective portfolios that optimize the three measures concurrently. To achieve this, they suggest novel mutation, crossover, and repair operators for scalable multi-objective optimization that are particularly created to produce practical strategies to the MDN issue. They compound the operators offered in the evolutionary algorithms NSGAII, MOEA/D, GWASF-GA and evaluated their efficiency for Spanish stock exchange. To decrease the intricacy of the portfolio optimization on a large scale, two asset screening techniques have been performed by B. Y. Qu, et al. (Qu et al., 2017) that take into account the return and risk of individual assets. To examine the efficiency of the offered approaches, a multi-target scalable scaling algorithm according to decomposition (NMOEA/D) and other types of commonly used common objective scaling algorithms are utilized and checked. Six tests with various parameters are accomplished. The outcomes indicate that the simulation time is decreased with the suggested techniques, whereas the performance of the exchange is substantially upgraded.

3. Methodology

3.1. Multi-objective Optimization

Optimization models are playing an extremely important character in financial decisions. To facilitate the presentation, the mathematical coding models are split into| two principal groups, which are single-portfolio optimization and multi-objective portfolio optimization. MOPO is a multivariable decision space that addresses mathematical optimization issues where numerous objective functions must be optimized concurrently (Gunasekaran et al., 2013). Multi-objective optimization has been utilized numerous aspects of science, like finance and economics, where optimal decisions must be made in the event of compromise between two or more contradictory goals.

For a non-trivial multi-objective optimization issue, it does not have any particular solution that optimizes each goal concurrently. In this instance, the objective functions are contradictory and there are lots of optimal solutions from Pareto.

Investigators explore multi-objective optimization issues from different perspectives, and as a result, there are various solution targets in their execution and solution. The objective may be to discover an agent set of optimal Pareto solutions and quantify the considerations to achieve the various targets and find a solution that meets the intellectual priorities of a human decision maker.

Mathematically, a multi-objective optimization issue can be formulated in below form:

$$\text{Min } ((f_1(x), f_2(x), \ldots, f_k(x)) \qquad \text{s.t. } x \in X,$$

Whereas the integer $k \geq 2$ is the quantity of objectives and the collection X is the possible collection of decision vectors. Usually, the possible collection is described by certain limitation functions. Furthermore, the vector-valued objective function is oftentimes considered as $f: X \rightarrow R^k$, $f(x) = (f_1(x), \ldots, f_k(x))^T$. A component $x^* \in X$ is a possible answer; a possible answer $x^1 \in X$ is told (Pareto) control one other answer $x^2 \in X$, if**:**

- $f_i\ (x^1) \leq\ f_i\ (x^2)$ for all those indices and $i \in \{1,2,\ldots,k\}$ and
- $f_j\ (x^1) < f_j\ (x^2)$ for leastwise one index $j \in \{1,2,\ldots,k\}$.

An answer $x^1 \in X$ is named Pareto optimal if there is no other solution to controls it.

3.1.1. Mathematical Formulation for Stock Portfolio Optimization

Recently, the investigation society has made considerable advancement in the portfolio optimization. One of the benefits was the recognition of valuable and effectual methods for resolving the mathematical issue model with portfolio optimization. Methods can be categorized into two principal classes: exact techniques and heuristic techniques.

To do this study, a combination of two techniques was employed to resolve the portfolio optimization model.(Ruiz-Torrubiano and Suárez, 2010)

The correlation coefficient ρij is utilized to gauge the effectiveness of portfolio diversification that value is between 1 and −1. If the correlation coefficient is −1, the diversification is at the maximum efficiency; otherwise, the diversification is at the minimum efficiency.

The correlation coefficient of the two assets is calculated as follows:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i\ \sigma_j}$$

The expected return for the portfolio is gauged by the mean-weighted of the expected return on the independent assets using the aforesaid notional circumstances.

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

The risk (variance) of the three asset portfolios is calculated as follows:

$$\sigma_p^2 = w_1^2\ \sigma_1^2 + w_2^2\ \sigma_2^2 + w_3^2\ \sigma_3^2 + 2\ w_1\ w_2\ \sigma_{12} + 2\ w_1\ w_3\ \sigma_{xy} + 2\ w_2\ w_3\ \sigma_{23}$$

$$\sigma_p^2 = \sum_{i=1}^{3} w_i^2\ \sigma_i^2 + 2\sum_{i=1}^{2}\sum_{j=i+1}^{3} w_i\ w_j\ \sigma_{ij}$$

The risk (variance) of the n assets portfolio is written as:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i\ w_j\ \sigma_{ij} = \sum_{i=1}^{n} w_i^2\ \sigma_i^2 + 2\sum_{i=1}^{2}\sum_{j=i+1}^{3} w_i\ w_j\ \sigma_{ij}$$

Diversification allows financier or trader to minimize the risk measure of the stock portfolio, regardless of risk levels, without considering of the stock held. Portfolio diversification consists of uncorrelated stocks that can achieve the maximum return with the lowest standard deviation (SD).

The mathematical formulation of the issue in optimizing the stock portfolio is written by:

$$\text{Min } (\lambda.\ \sigma_p - (1-\lambda).E\ (R_p)) = \text{Min } (\lambda \sum_{i=1}^{n}\sum_{j=1}^{n} w_i\ w_j\ \sigma_{ij} - (1-\lambda)\sum_{i=1}^{n} w_i\ \ E\ (R_i))$$

Whereas $\lambda \in [0, 1]$ is the factor of risk aversion,

n: The portfolio size with weights w_i for asset i

$E\ (R_p)$: The Expected return of the portfolio

$E\ (R_i)$: The weighted average for the expected return of the independent assets

σ_i : The SD of stock i

ρij : The correlation coefficient between two assets i and j

σij : The covariance between two assets i and j.

3.2. Modeling for Stock Portfolio Management

In this research, a new model for the stock management system is designed by using SPEA, ANFIS and APT to more accurately forecast the stock prices and achieve higher returns.

3.2.1. Strength Pareto Evolutionary Algorithm

Zitzler and Thiele (Zitzler and Thiele, 1999) offered an elitist evolutionary algorithm known as the SPEA. The algorithm maintains an exterior population for each generation that reserves all the aforementioned unspecified answers. For every generation, the exterior population is blended with the present population. All of the non-nominated answers in the blended population are assigned a physical form by the number of dominated answers. Dominated answers are worse than the worst physical form of all non-nominated answers. A deterministic clustering approach is utilized to guarantee diversity between non-nominated answers (Jiang and Yang, 2017).

In the offered model, we have regarded the following financial indicators which have a significant role in portfolio selection. A set of technical indicators have been mentioned as follows:

I. Trend indicators: These types of technical indicators assess the direction and power of a trend by comparing prices to a reputable baseline

    I1: Moving average convergence-divergence (MACD): Employed to determine variations in the power, path, momentum, as well as length of a trend in a stock's price

    I_2: *Parabolic Stop and Reverse (Parabolic SAR):* Used to discover potency reversals in the market price path.

II. Momentum indicators: These technical indicators could recognize the velocity of price motion by comparing the present closing price to prior closes.

    I3: Commodity Channel Index (CCI): An oscillator that assists to determine price reversals, price climax, and trend power.

I4: Relative Strength Index (RSI): Calculates current trading power, the speed of variation in the trend, and size of the shift.

III. Volatility Indicators: These types of technical indicators calculate the rate of price motion, irrespective of the path.

I5: Average True Range (ATR): Demonstrates level of price fluctuation.

I6: Bollinger Band (BBANDS): Calculates the “highness” or “lowness” of price, by previous deals.

IV. Volume Indicators: These types of technical indicators calculate the power of a trend by volume of stocks exchanged

I7: On-Balance Volume (OBV): Efforts to calculate the degree of accumulation or distribution, by evaluating volume to price.

I8: Volume Rate of Change (VRC): Emphasizes raises in volume. These typically occur mainly at market tops, bottoms, or breakouts.

3.2.1.1. Procedure

The Step-By-Step procedures for the implementation of SPEA are cited below:

Step 1 (Initialization): The first population is created and a blank Pareto-optimal exterior collection is established

Step 2 (Update of the External set): The exterior Pareto-optimal collection is upgraded

Step 3 (Fitness Assignment): The fitness values of the individuals in the Pareto collection and the population are computed

Step 4 (Selection): The population and individuals of the exterior collection are merged

Step 5 (Crossing and Merging): Carry out the crosses and mutations based on their chances of generating the new population.

Step 6 (Completion): The criteria are examined to cease. The lookup is ceased when the iteration counter surpasses the highest number. The flowchart of SPEA is shown in Fig. A9.

3.2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a type of adaptive networks containing both neural networks and fuzzy logic rules.

Neural networks are monitored by learning algorithms that use a range of historical data to predict future values. In fuzzy logic, the control signal is made by dragging on the control foundation. This rule base is founded on historical data and is accidental which means that the controller's output is accidental too, which can barricade from optimal results.(Jang, 1993)

The utilization of ANFIS causes it to be easier to reconcile the rule base choice to the status. Within this approach, the control base is chosen using neural network approaches using the reverse propagation algorithm. To improve the capabilities and functionality, the fuzzy logic characteristics, ex the approximation of a nonlinear system by adapting the IF-THEN regulations, are adopted in such a modeling approach. This unified method creates ANFIS a global estimator.(Jang and Sun, 1995)

3.2.2.1. Fuzzy Inference System (FIS)

A FIS has been constructed on the three principal ingredients, that is to say, the fundamental principles, which contain the choice of the fuzzy logic principles "if-then" (Cheng et al., 2009). Depending on the affiliation of a fuzzy collection; and inference of fuzzy inference approaches from principles to obtain the output. Fig. A10 demonstrates the precise construction of the FIS. FIS works while the input including the real value is transformed into fuzzy values utilizing the fuzzification procedure by way of its subscription function, the fuzzy value to be between 0 and 1. The fundamental principles, as well as the databases, are known as the knowledge foundation, both of which are important components of decision making. Improving a database generally involves the description of a world, specifying the number of linguistic values to utilize for every linguistic variable, and also specifying a membership function (Cheng et al., 2005a; Cheng et al., 2005b).

3.2.2.2. Adaptive Network

The adaptive network is an instance of a multilayered feedforward neuronal network. In the learning process, these types of networks mostly utilize a controlled learning algorithm. Moreover, the adaptive network has architectural characteristics that comprise some adaptive nodes that are straightly attached to one other without having weight value in between. Any node of the network has various functions and duties, as well as the output relies on the inbound signals and parameters accessible in the node (See Fig. A11). A learning principle that was utilized can influence the parameters of the node and decrease the incidence of errors on the adaptive network output (Jang, 1993).

3.2.2.3. ANFIS Structure

The ANFIS structure is an adaptive network that utilizes intra-algorithm-supervised learning which has an analogous performance to the Takagi-Sugeno fuzzy inference system model.

Fig.4 demonstrates the fuzzy argumentation mechanism of the plan for the Takagi-Sugeno model and the ANFIS structure. For the sake of ease, presume which there are two x and y inputs and one f output. Two equations were utilized in the If-Then technique for the Takagi-Sugeno strategy, are cited below:

Equation 1 = If x is A_1 and y is B_1 Then $f1 = p_1x + q_1x + r_1$

Equation 2 = If x is A_2 and y is B_2 Then $f2 = p_2y + q_2y + r_2$

Wherein:

A_1, B_1, A_2, B_2: membership functions of each input x and y

p_1, p_2, q_1, q_2, r_1, r_2: linear parameters in part-Then (consequent part)

In accordance with Fig. A12, the ANFIS structure has five layers. The first and fourth layers include an adaptive node whereas the other layers include a fixed node. The formula for every layer is cited below:

Layer 1:

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x-c_i}{2a_i}\right)^2\right]$$

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}}$$

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1,2$$

$$O_{1,i} = \mu_{Bi-2}(y), \quad i = 3,4$$

Layer 2:

$$O_{2,i} = \mu_{Ai}(x) * \mu_{Bi}(y) \quad i = 1,2$$

Where w_i is the output that signifies the firing power of every equation.

Layer 3:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_i w_i}$$

Layer 4:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i\,(p_i x + q_i y + r_i)$$

Wherein wi is the normalized firing power from the former layer, and $(p_i x + q_i y + r_i)$ is a parameter in the node.

Layer 5: In this layer, a circle node is labeled as $\sum$.

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

3.2.3. Arbitrage Pricing Theory (APT)

The APT was introduced in 1976 by Stephen Ross (Roll and Ross, 1984). APT is a substitute form of the CAPM that offers investors an estimated return on risky securities such as CAPM. The APT discuss the group of factors determined to the risk premium together with the correlation of the price of the asset with the expected excess return of the market portfolio

APT is a multi-factor model by the nexus between the expected return on a financial asset and its risk. The model aims to obtain the sensibility of asset performance to alterations in some macroeconomic parameters. The belief that discounted securities can provide short-term, the risk-free profit opportunities is inherent in arbitrage pricing theory. APT varies from classic CAPM, which employs just one factor. Nonetheless considers that a factor model can efficiently explain the correlation between risk and reward. The APT model seeks to remove the constraints of a one-factor-model, where diverse stocks have various sensitivities to different market factors that could be completely distinctive from all other observed measures. It can be claimed in layman's terms that it cannot always be presumed that all actions always respond to one and the same parameter and thus to the necessity of multifactorial detection and its sensitivities. The APT formula as follows:

$$E(x) = R_f + b_1 \times (f_1) + b_2 \times (f_2) + \ldots + b_n \times (f_n)$$

Wherein:

E(x): The expected return of the risky asset

R_f: The risk-free interest rate which expected from a risk-free asset

b: Stock sensitivity with regards to the factor; also mentioned as beta factor 1, 2 …

n: Risk premium related to specific factor

f: factor

Considering that the formula demonstrates, the expected return on the asset is a type of linear regression considering numerous factors which could impact the price of the asset, in other words, the level of asset sensitivity to those factors. Recent empirical evidence reveals that the APT functions were more desirable than CAPM in explaining the expected return on risky assets.

3.3. Proposed Model

Figure 1 demonstrates the scheme of the proposed model for the stock portfolio management strategy. The diagram utilizes SPEA and ANFIS module to generate exchanging signals for the purchase or sale of stocks. The APT module is utilized to compile and diversify the portfolio with the ANFIS module. The effectiveness of the offered model can also be assessed by examining the portfolio that created by the planned model in comparison with different portfolio techniques.

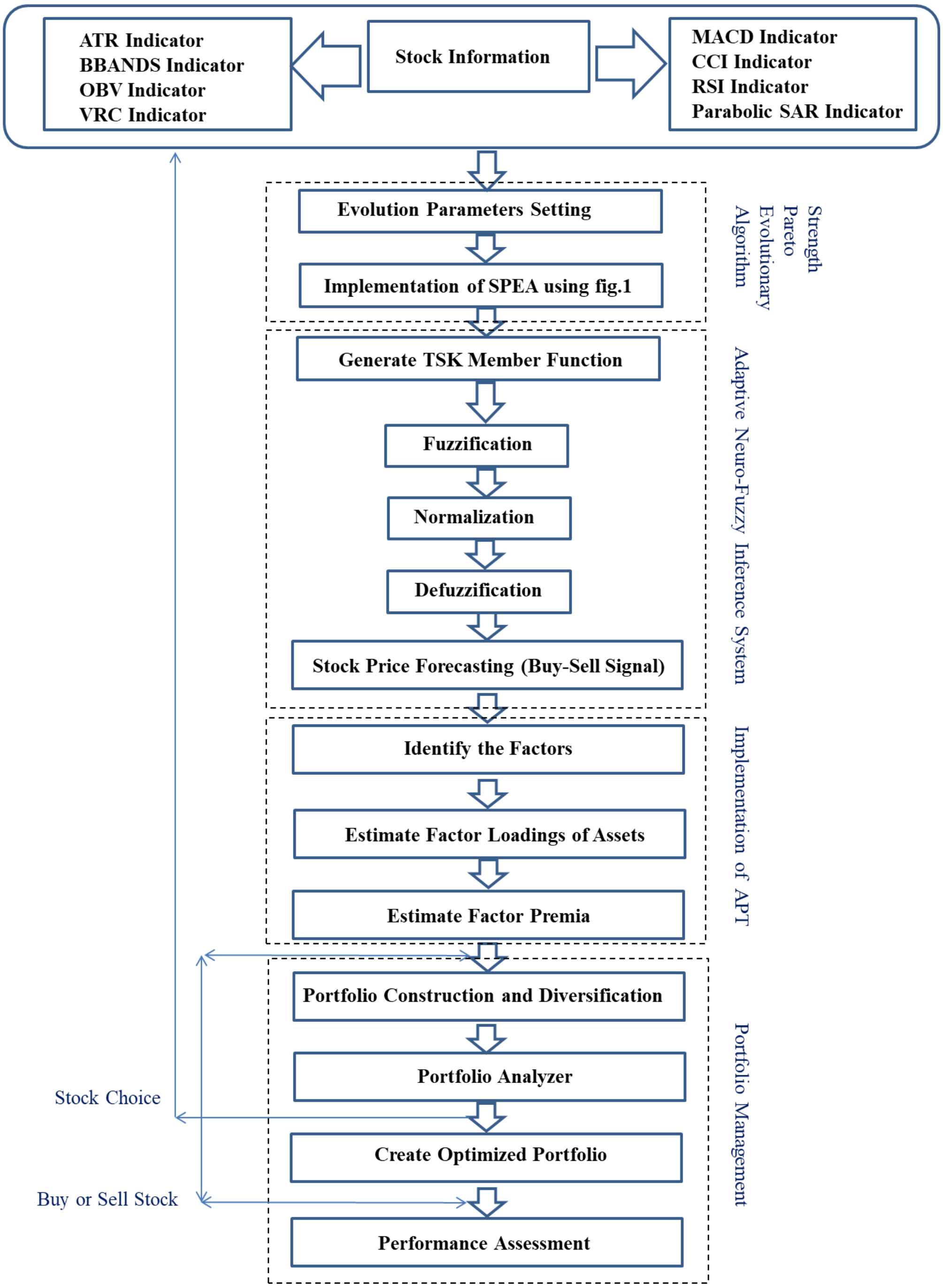

Fig.5. Proposed Model

4. Results

4.1. Data Sources and Experimental Setup

The offered model has been assessed by utilizing stocks in TSE TEPIX and TSE TEDIX indices to assessment the performance of the presented method. The model is evaluated employing stock information from 2007 to 2017. And accordingly, Training and testing information of TSE are acquired from www.tsetmc.com & www.codal.ir so they are indicated in Table 1.

Table 1. Training/Testing Data

Indices	Training Data		Testing Data	
	From	To	From	To
TSE TEPIX TSE TEDIX	21/03/2006	22/03/2007	23/03/2007	20 March 2017

When choosing the portfolio, it is essential to contemplate the real constraints. We observe the real constraints of the Tehran Stock Exchange, including Limitations of price fluctuation and Volume of the Transaction.

During this research Trapezoidal fuzzy form is employed for Membership Functions of input variables and the number of fuzzy regulations in the system is linked to the number of fuzzy collections for every input variable that shown in Table A.2.

4.2. Investment Strategy

In the financial world, an investment strategy consists of methods or techniques that serve as guidelines for the choice of an investment portfolio by an investor. Investors have different profit targets and their abilities make various techniques suitable. Many decisions include a compromise between risk and return. The majority of traders are someplace in between, accepting some risk while expecting for greater returns. (Chan, 2013)

The investment strategies that are considered in this article are as follows:

Momentum Investing: a share purchase or other high yielding securities in the last three to twelve months and a low-interest stock sale during the same period

Buy and Hold: This strategy includes buying and holding stocks of the company for a long time. That is a long-term investment strategy in accordance with the concept that stock exchanges deliver good long-term returns despite intervals of fluctuation or decrease. This position also believes that the timing of the market, that the market can go down and sell the highest, does not operate or does not operate for tiny traders. As a result, it' is better to buy and hold.

Value vs. Growth: A value-oriented investment strategy explores the intrinsic value of a company, and worth investors look for stocks from corporations which they opine are undervalued. The Final Results of Model and Discussion investment strategy examines a company's progress capability so when it anticipates a corporation to grow more rapid than corporations in a similar industry, or across the market, it will entice growing investors trying to increase their wealth.

Pairs Trading: Pairs trading is a neutral trading strategy in the market that corresponds to the long position with a short position in some highly correlated instruments such as two stocks or options. Pair traders expect a low correlation and then stay underperforming for a long time while short selling for outperformers and closing positions when the relationship returns to statistical standards. The profit of the strategy results from the difference of the price changes between the two instruments and not from the direction in which each movement follows.

4.3. Portfolio Performance Assessment Index

Portfolio performance assessment is an instrument for evaluating the efficiency of a portfolio over a time period. The principal assessment methodologies comprise of two classical and modern categories. The most important approaches utilized are the Sharpe Ratio, the Treynor Ratio, and the Jensen Alpha. Within this study, risk-adjusted procedures are preferred over classical methods.

4.3.1. Sharpe Criterion

The Sharpe Index assesses the overall risk by computing the SD. The approach utilized by Sharpe is to rank all of the portfolios in accordance with assessment metrics. The reward is within the counter as a risk premium.(Sharpe, 1966, 1994)

The overall risk is the denominator as the SD of the yield. The formula for computing Sharp's ratio is as follows:

$$\mathrm{SI} = \frac{R_t - R_f}{\sigma_f}$$

Wherein,

SI: The Sharpe's Index

R_t: The average return on portfolio

R_f: The risk-free return

σ_f: The standard deviation of the portfolio return.

4.3.2. Treynor Criterion

Treynor's action has been correlated with the surplus return of a portfolio of non-diversifiable or systematic risks (Treynor and Black, 1973). The Treynor (Treynor, 2011) founded his method on the concept of the characteristic line. It is the standard deviation risk metric, i.e., the portfolio's overall risk is substituted by the beta. The formula for computing Treynor's ratio is as follows:

$$T_n = \frac{R_n - R_f}{\beta_m}$$

Wherein,

T_n: The Treynor's measure of performance
R_n: The Return on the portfolio
R_f: The risk-free rate of return
β_m: The Portfolio Beta

4.3.3. Jensen Criterion

Jensen (Jensen, 1968) tries to establish an overall performance standard based upon the risk. This metric is founded on the CAPM. It assesses the predictive skill of the portfolio administrator to attain outperformance expected for the accepted risk area. The ability to generate a return by effectively forecasting security prices on a standard assessment.
The formula for computing Jensen's ratio is as follows:

$$R_p = R_f + \beta(R_n - R_f)$$

Wherein,

R_p: Portfolio return
R_{MI}: Return on market index
R_f: The risk-free rate of return

4.4. Final Results of Model

To accredit the utilization of the offered portfolio model, the empirical outcomes are available in Table 3 to 5. From the outcomes in Tables 3 to 5, we have discovered that the annualized yield on our SPEA-ANFIS-APT portfolio provides a greater yield than other portfolio models.

The planned technique is evaluated in comparison with other portfolio strategies and reconfirmed by two recognized indicators TSE TEPIX and TEDIX. Also, the beta systematic risk indicator is a key factor to assess performance. Our presented portfolio model ($\beta = 0.76$) is less than 1, meaning that the stocks are considerably less volatile than the TSE TEPIX and TSE TEDIX indicators.

Fig. 5 to 9 indicates the outcomes of assessments for the return of all portfolios with the TSE and TSE TEPIX TEDIX. It implies that the investment performance of the incorporated portfolio model is greater than other active portfolio approaches for all years.

Fig. 10 to 12 indicates the outcomes model testing that they ensures the proposed model has high strength and accuracy. From experimental assessments, each ratio of the suggested model portfolio is certainly more than other portfolio models for indicators. It is clear that the experimental outcomes corroborate that the novel technique considerably strengthens the anticipated values of the portfolio yield.

1) Return on Asset
2) Return on Investment
3) Sharpe Performance Index (reward-to-variability ratio)
4) Jensen Performance Index (ex-post alpha)
5) Treynor Performance Index (reward-to-volatility ratio)

Table 3 indicates performance comparisons of portfolio strategies with Tehran Exchange Price Index.
Table 4 indicates performance comparisons of portfolio strategies with Tehran Exchange Cash Dividend Index.
Table 5 indicates performance comparisons of portfolio strategies with Tehran Exchange Dividend & Price "total return" Index

Table 3. Model results in comparison with TSE TEPIX

Strategy	[1]ROA(%)	[2]ROI (%)	[3]SPI(%)	[4]JPI (%)	[5]TPI (%)
TSE TEPIX	22.41	65.55	29.31	NA	NA
SPEA-ANFIS-APT	48.31	89.15	86.52	35.12	22.71
Momentum Investing	15.72	39.24	38.23	6.03	−3.39
Buy and Hold	22.39	84.11	59.17	8.72	−1.25
Value vs. Growth	39.17	83.22	75.45	20.49	14.61
Pairs Trading	31.72	71.45	50.71	22.36	7.33

Table 4. Model results in comparison with TSE TEDIX

Strategy	[1]ROA(%)	[2]ROI (%)	[3]SPI(%)	[4]JPI (%)	[5]TPI (%)
TSE TEDIX	27.76	99.68	41.56	NA	NA
SPEA-ANFIS-APT	59.82	172.05	105.12	47.16	25.81
Momentum Investing	28.63	118.12	53.22	12. 91	−5.33
Buy and Hold	18.62	83.48	29.85	8.82	−10.07
Value vs. Growth	50.18	167.44	88.36	32.59	17.81
Pairs Trading	40.19	141.52	72.39	25.17	15.35

Table 5. Model results in comparison with TSE TEDPIX

Strategy	[1]ROA(%)	[2]ROI (%)	[3]SPI(%)	[4]JPI (%)	[5]TPI (%)
TSE TEDPIX	24.68	77.32	34.09	NA	NA
SPEA-ANFIS-APT	55.07	149.50	89.95	49.82	22.43
Momentum Investing	19.73	134.72	42.81	13.58	−4.26
Buy and Hold	23.34	70.43	44.37	7.19	−7.64
Value vs. Growth	42.71	125.27	80.25	30.64	14.17
Pairs Trading	36.52	130.91	66.17	25.67	6.25

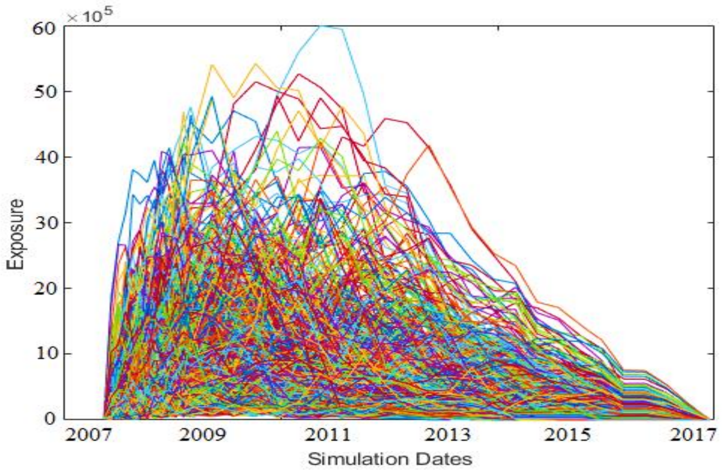

Fig.6. Portfolio Exposure for All Strategies

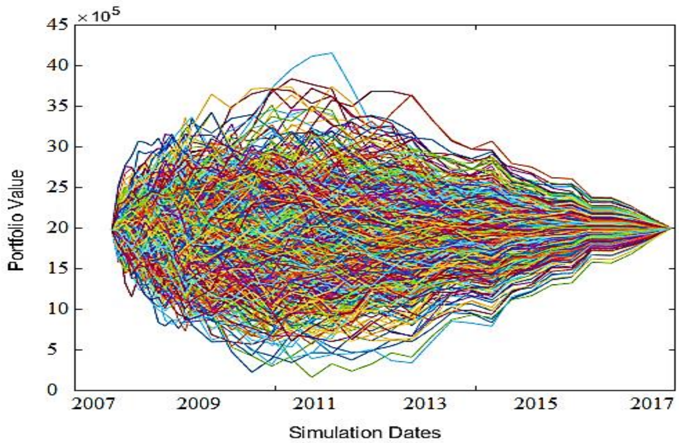

Fig.7. Total Portfolio Values for All Strategies

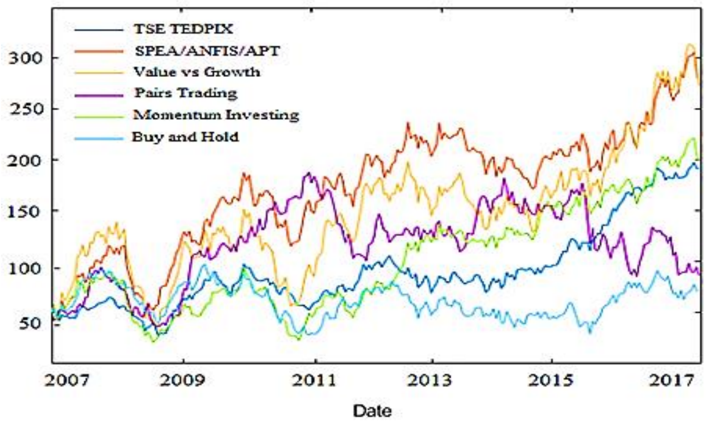

Fig.8. Comparison of Portfolios Values

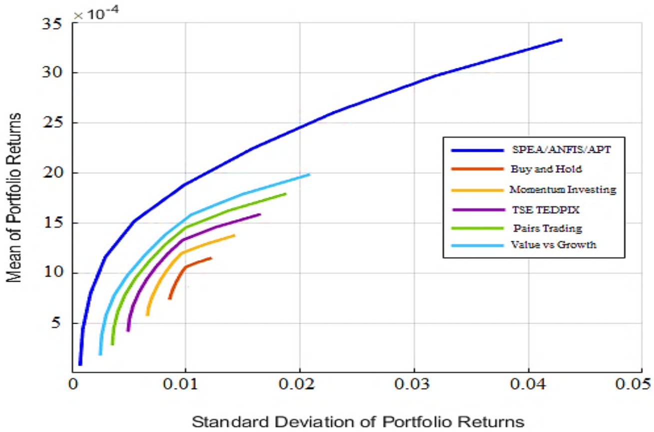

Fig.9. Comparison of Portfolios Returns

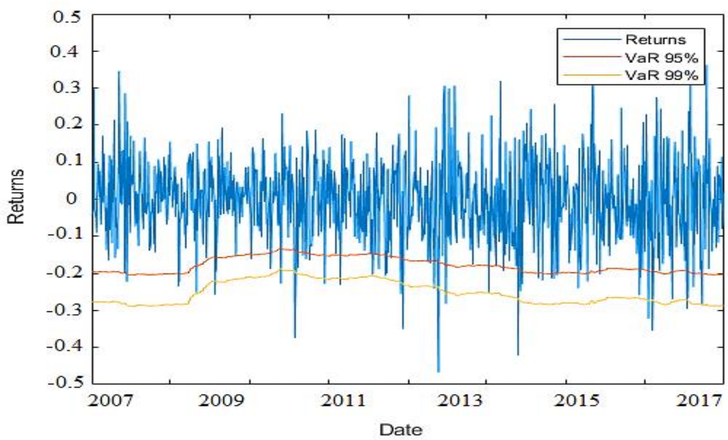

Fig.10. Model Testing by VAR

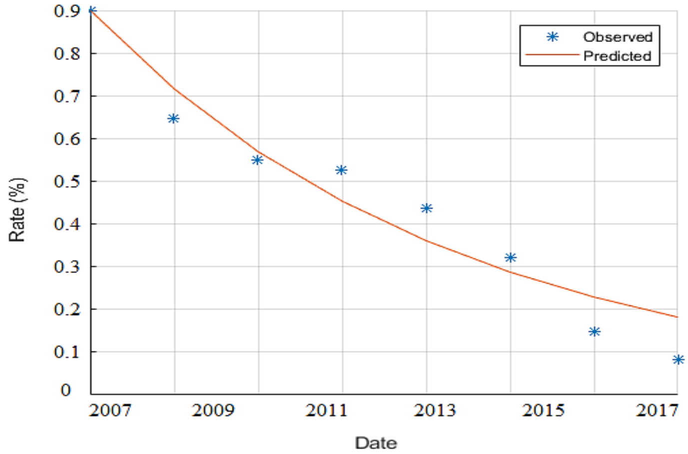

Fig.11. Model Fit (Training Data)

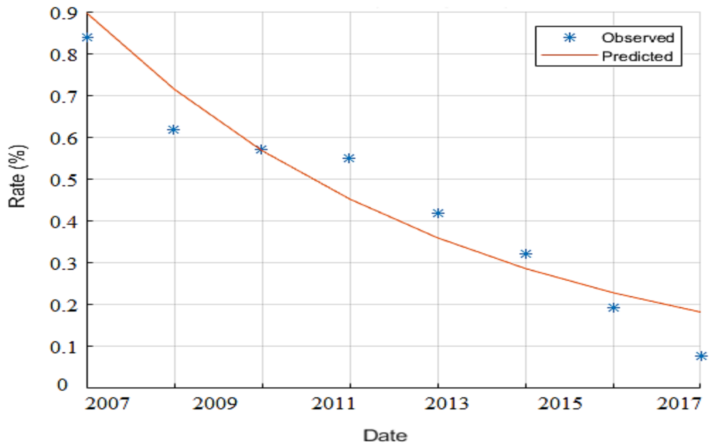

Fig.12. Model Fit (Testing Data)

5. Discussion and Conclusions

In this investigation, we incorporate the SPEA-ANFIS prognosticating tool into the portfolio optimization model to solve the APT portfolio optimization issue.

To our knowledge, our method is the first metaheuristic method that merges three modules SPEA & APT & ANFIS together with portfolio performance evaluation under real limitations that are derived from this model. Within this research, we have unified APT portfolio model into SPEA-ANFIS forecasting model for optimizing the exchange between portfolio's risk and return. By the experimental outcomes, we plainly have realized that offered method are prepared for simulating the active unpredictable stock exchanges conveniently which make more desirable predictive results in comparison with traditional linear models.

Moreover, it fairly minimized the SD of stocks' allocation which implies that the envisaging becomes fewer uncertain

The SPEA-ANFIS-APT has produced maximum return values that could entirely describe the nonlinear nexus between the stock returns. As future work, we are planning to utilize the PESA rather than the SPEA.

References

1) Abbondante, P., 2010. Trading volume and stock indices: A test of technical analysis. American Journal of Economics and Business Administration 2, 287.

2) Aranha, C., Iba, H., 2007. Modelling cost into a genetic algorithm-based portfolio optimization system by seeding and objective sharing, Evolutionary Computation, 2007. CEC 2007. IEEE Congress on: IEEE, pp. 196-203.
3) Ardia, D., Boudt, K., Carl, P., Mullen, K.M., Peterson, B., 2010. Differential evolution (deoptim) for non-convex portfolio optimization.
4) Bermúdez, J.D., Segura, J.V., Vercher, E., 2012. A multi-objective genetic algorithm for cardinality constrained fuzzy portfolio selection. Fuzzy Sets and Systems 188, 16-26.
5) Björk, T., Murgoci, A., Zhou, X.Y., 2014. Mean–variance portfolio optimization with state-dependent risk aversion. Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics 24, 1-24.
6) Briza, A.C., Naval Jr, P.C., 2011. Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data. Applied Soft Computing 11, 1191-1201.
7) Chan, E., 2013. Algorithmic trading: winning strategies and their rationale: John Wiley & Sons.
8) Chan, M.-C., Wong, C.-C., Cheung, B.K., Tang, G.Y., 2002. Genetic algorithms in multi-stage portfolio optimization system, proceedings of the eighth international conference of the Society for Computational Economics, Computing in Economics and Finance, Aix-en-Provence, France.
9) Chang, T.-J., Meade, N., Beasley, J.E., Sharaiha, Y.M., 2000. Heuristics for cardinality constrained portfolio optimisation. Computers & Operations Research 27, 1271-1302.
10) Chang, T.-J., Yang, S.-C., Chang, K.-J., 2009. Portfolio optimization problems in different risk measures using genetic algorithm. Expert Systems with Applications 36, 10529-10537.
11) Chen, W., Zhang, R.-t., Cai, Y.-m., Xu, F.-s., 2006. Particle swarm optimization for constrained portfolio selection problems, Machine Learning and Cybernetics, 2006 International Conference on: IEEE, pp. 2425-2429.
12) Cheng, C.-H., Hsu, J.-W., Huang, S.-F., 2009. Forecasting electronic industry EPS using an integrated ANFIS model, Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on: IEEE, pp. 3467-3472.
13) Cheng, C.-T., Lin, J.-Y., Sun, Y.-G., Chau, K., 2005a. Long-term prediction of discharges in Manwan Hydropower using adaptive-network-based fuzzy inference systems models, International Conference on Natural Computation: Springer, pp. 1152-1161.
14) Cheng, C., Chau, K., Sun, Y., Lin, J., 2005b. Long-term prediction of discharges in Manwan Reservoir using artificial neural network models, International Symposium on Neural Networks: Springer, pp. 1040-1045.
15) Crama, Y., Schyns, M., 2003. Simulated annealing for complex portfolio selection problems. European Journal of operational research 150, 546-571.
16) Eddelbüttel, D., 1996. A hybrid genetic algorithm for passive management, Working Paper presented at the Second conference on computing in economics and Finance, Society of computational economics, Geneves, Suisse.
17) Gunasekaran, M., Ramaswami, K., Karthik, S., 2013. Integration of SRA, ANFIS and CAPM for stock portfolio management. CSI transactions on ICT 1, 291-300.
18) Hochreiter, R., 2008. Evolutionary stochastic portfolio optimization, Natural Computing in Computational Finance: Springer, pp. 67-87.
19) Jang, J.-S., 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE transactions on systems, man, and cybernetics 23, 665-685.
20) Jang, J.-S., Sun, C.-T., 1995. Neuro-fuzzy modeling and control. Proceedings of the IEEE 83, 378-406.
21) Jensen, M.C., 1968. The performance of mutual funds in the period 1945–1964. The Journal of finance 23, 389-416.
22) Jiang, S., Yang, S., 2017. A strength Pareto evolutionary algorithm based on reference direction for multiobjective and many-objective optimization. IEEE Transactions on Evolutionary Computation 21, 329-346.
23) Krink, T., Paterlini, S., 2011. Multiobjective optimization using differential evolution for real-world portfolio optimization. Computational Management Science 8, 157-179.
24) Li, J., Xu, J., 2013. Multi-objective portfolio selection model with fuzzy random returns and a compromise approach-based genetic algorithm. Information Sciences 220, 507-521.
25) Lin, D., Li, X., Li, M., 2005. A genetic algorithm for solving portfolio optimization problems with transaction costs and minimum transaction lots, International Conference on Natural Computation: Springer, pp. 808-811.
26) Lwin, K., Qu, R., Kendall, G., 2014. A learning-guided multi-objective evolutionary algorithm for constrained portfolio optimization. Applied Soft Computing 24, 757-772.
27) Markowitz, H., 1952. Portfolio selection. The journal of finance 7, 77-91.
28) Markowitz, H.M., 1999. The early history of portfolio theory: 1600-1960. Financial analysts journal, 5-16.

29) Qu, B., Zhou, Q., Xiao, J., Liang, J., Suganthan, P.N., 2017. Large-Scale Portfolio Optimization Using Multiobjective Evolutionary Algorithms and Preselection Methods. Mathematical Problems in Engineering 2017.
30) Roll, R., Ross, S.A., 1984. The arbitrage pricing theory approach to strategic portfolio planning. Financial analysts journal, 14-26.
31) Ross, S.A., 2013. The arbitrage theory of capital asset pricing, HANDBOOK OF THE FUNDAMENTALS OF FINANCIAL DECISION MAKING: Part I: World Scientific, pp. 11-30.
32) Ruiz-Torrubiano, R., Suárez, A., 2007. Use of heuristic rules in evolutionary methods for the selection of optimal investment portfolios, Evolutionary Computation, 2007. CEC 2007. IEEE Congress on: IEEE, pp. 212-219.
33) Ruiz-Torrubiano, R., Suárez, A., 2010. Hybrid approaches and dimensionality reduction for portfolio selection with cardinality constraints. IEEE Computational Intelligence Magazine 5, 92-107.
34) Saborido, R., Ruiz, A.B., Bermúdez, J.D., Vercher, E., Luque, M., 2016. Evolutionary multi-objective optimization algorithms for fuzzy portfolio selection. Applied Soft Computing 39, 48-63.
35) Shalan, S.A.B., Ykhlef, M., 2015. Solving multi-objective portfolio optimization problem for Saudi Arabia stock market using hybrid clonal selection and particle swarm optimization. Arabian Journal for Science and Engineering 40, 2407-2421.
36) Sharpe, W.F., 1966. Mutual fund performance. The Journal of business 39, 119-138.
37) Sharpe, W.F., 1994. The sharpe ratio. Journal of portfolio management 21, 49-58.
38) Thong, V., 2007. Constrained Markowitz Portfolio Selection Using Ant Colony Optimization: Erasmus Universiteit.
39) Treynor, J.L., 2011. Treynor on institutional investing: John Wiley & Sons.
40) Treynor, J.L., Black, F., 1973. How to use security analysis to improve portfolio selection. The Journal of Business 46, 66-86.
41) Yu, T.-Y., Tsai, C., Huang, H.-T., 2010. Applying simulation optimization to the asset allocation of a property–casualty insurer. European Journal of Operational Research 207, 499-507.
42) Zitzler, E., Thiele, L., 1999. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. IEEE transactions on Evolutionary Computation 3, 257-271.