



Stock market prediction and Portfolio selection models: a survey

Akhter Mohiuddin Rather¹ · V. N. Sastry² ·
Arun Agarwal¹

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Abstract Stock data is known to be chaotic in nature and it is a challenging task to predict the non-linear patterns of such data. Forming an optimal portfolio of stocks is yet another challenging task and limitations do exist in every portfolio model in some form or the other. In order to resolve such problems, many artificial intelligence models have appeared in literature which are also known as intelligent models. Prediction of stocks as well as investing in appropriate stocks has remained in focus among investors, industrialists as well as among academicians. This paper surveys important published articles in the related area available in literature. This survey highlights traditional mathematical models available in articles which have appeared decades back till artificial intelligence based models available in recent articles.

Keywords Stock returns · Portfolio selection models · Artificial intelligence based models · Time series prediction

✉ Akhter Mohiuddin Rather
akhter@uohyd.ac.in

V. N. Sastry
vnsastry@idrft.ac.in

Arun Agarwal
aruncs@uohud.ernet.in

¹ School of Computer and Information Sciences, University of Hyderabad, Hyderabad 500046, India

² Institute for Development and Research in Banking Technology, Castle Hills, Masab Tank, Hyderabad 500057, India

1 Introduction

Stocks and portfolio of stocks are directly linked with each other. In stock market numerous stocks are available to invest in, and an investor can choose number of stocks for investment and this becomes his/her portfolio. Prediction of stocks has gained lot of attention among investors and this has led researchers to propose various models. These models include time series based linear models such as autoregressive integrated moving average (ARIMA) models [20] and other linear models such as exponential smoothing [21], generalized autoregressive conditional heteroskedasticity as well as stochastic volatility model [48]. Prediction of stock returns is known as challenging task because the data is non-stationary or non-linear in nature whose patterns are difficult to be captured by these linear models. These linear models are also known as statistical models; in order to overcome the limitations of statistical models, artificial intelligence (AI) based models have evolved. AI-based models include artificial neural networks (ANN) which also includes multilayer perceptron (MLP) and radial basis function (RBF) [27], support vector machines (SVM), support vector regression (SVR) [22, 67], genetic algorithms (GA), particle swarm optimization (PSO) [99], artificial fish swarm (AFS) and general regression neural network (GRNN). AI-based models such as ANNs contain some non-linear functions which are able to detect non-linear patterns in data thus improving prediction performance. On the other hand GA and PSO are population based search techniques which are able to solve those optimization problems where traditional models are unable to produce desired results.

Once the stocks are selected, it is time for investing in those stocks so as to form a portfolio of stocks. The foundation of portfolio theory was laid by Markowitz [101] with his famous mean–variance model. Mean–variance model has often been criticized by various researchers that it invests in few stocks thus increasing risk in investment. Following Markowitz, various researchers proposed enhanced models but the goal is always common, i.e. to maximize expected return and at the same time to minimize risk of a portfolio. These models include traditional linear models as well as AI-based computationally intelligent models.

The rest of the paper is organized as follows: Sect. 2 presents classification of articles, literature survey on prediction of stocks is presented in Sects. 3, 4 presents literature survey on portfolio selection models, Sect. 5 presents key takeaway from this survey and finally Sect. 6 presents conclusions.

2 Classification of articles

This study includes literature survey of more than 140 articles on 'prediction of stocks' as well as on 'portfolio selection of stocks'. Figure 1 Shows various published articles on stock prediction using a tree. Important articles, which have made significant contributions are shown in the figure in chronological order. Decades old published articles are shown on top and as we scroll down, recent

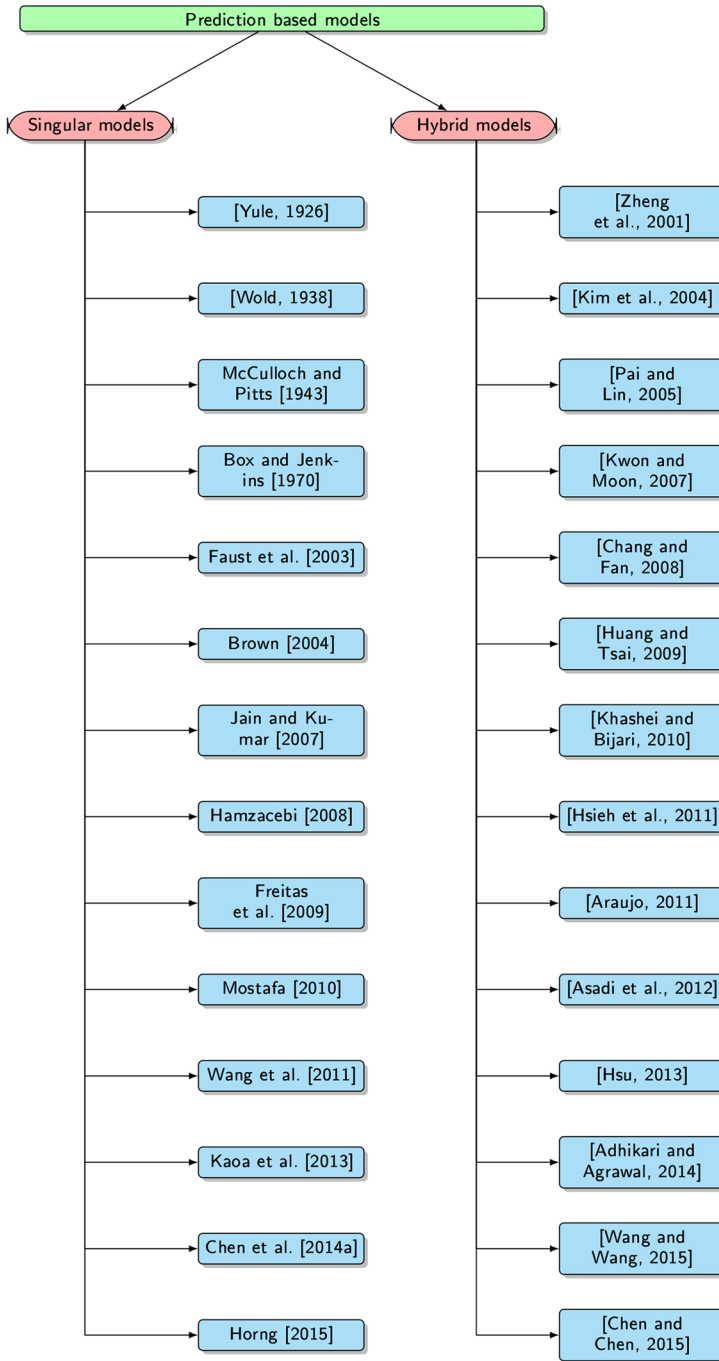


Fig. 1 Tree diagram showing various articles on prediction based models

articles are shown. We have distinguished the articles in two groups: the first group contains “Singular models” which are based on linear models such as ARIMA and non-linear models such as ANN, SVM, PSO etc. Last one decade has seen a trend of combined prediction, which includes integration of various prediction based models so as to form a robust model, such models are popularly known as hybrid models. The second group (“Hybrid models”), shows important articles on hybrid prediction models evolved over time. Similarly Fig. 2 shows important published articles on “portfolio selection models” using a tree. The tree shows articles in chronological order which have certainly made tremendous contributions in this field. It is expected that this survey proves to be useful for those researchers who tend to enhance or improve already existing models in related research.

3 Literature survey on stock prediction

Linear prediction based models have appeared in literature for long and they are still used in practice. Some of well known early contributions are: linear-trend prediction model [6] and exponential smoothing model which assigns exponentially decreasing weights for time series prediction [21]. However ARIMA models proposed by Box and Jenkins [20] gained momentum and is still known as one of the important contribution in time series prediction. Similarly random walk model predicts next value based on past value [100].

3.1 Autoregressive moving average models

The work of Box and Jenkins [20] is considered as an important contribution in prediction theory by means of famous autoregressive moving average (ARMA) model. The work of Box and Jenkins is actually inspired on the early work of Yule [136] and Wold [130]. ARMA models represent the time series data using the time lags of past observations, so as to predict its future movements. Shumway and Stoffer [123] suggest that in time series data, it is acceptable to let the dependent variable to be affected by the past observations of the independent variables.

3.1.1 Autoregressive model of order p , $AR(p)$

The idea behind autoregressive models is that the current value of the series, r_t , can be expressed as a function of p past observations, $r_{t-1}, r_{t-2}, \dots, r_{t-p}$. A process r_t is said to be an autoregressive process of order p , denoted by $AR(p)$ if the following equation is satisfied.

$$r_t = c + \sum_{i=1}^p \phi_i r_{t-i} + \varepsilon_t \quad (1)$$

where:

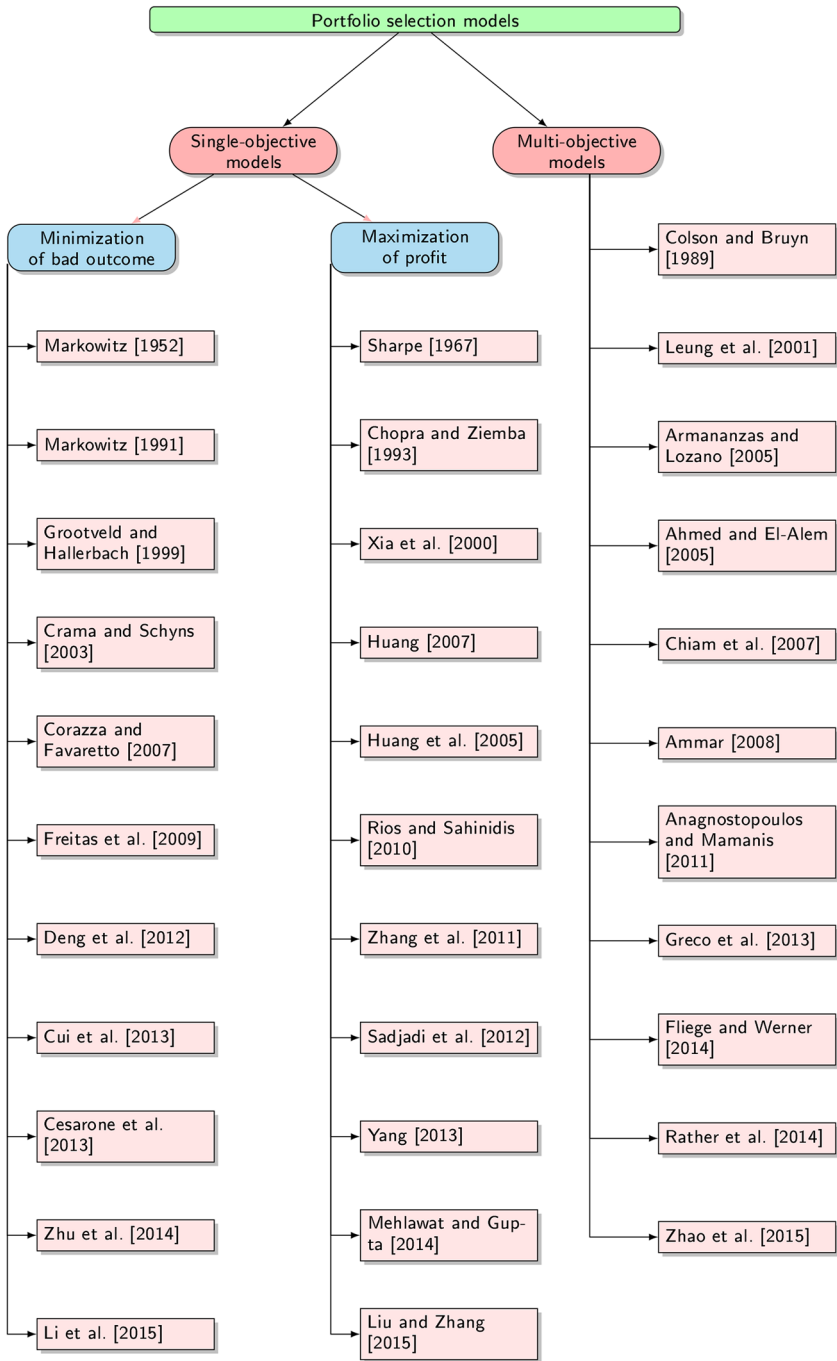


Fig. 2 Tree diagram showing various portfolio selection models

r_t is dependent variable value at time t and is a linear function of the previous p values.

r_{t-i} , ($i = 1, \dots, p$) are independent variable values at time t , or past lagged values.

p is an integer, referred as order of AR model.

c is constant intercept.

ϕ_i , ($i = 1, \dots, p$) are constants which are coefficients of the lagged terms.

ε_t is an error term, also known as white noise sequence with 0 mean and variance σ_ε^2 .

3.1.2 Moving average model of order q , $MA(q)$

In moving average model, the time series depends only on q past random terms and a present random term ε_t . There are q lags in the moving average model.

A moving average process of order q denoted by $MA(q)$ is given by the following equation.

$$r_t = \mu + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

where:

μ is the mean of the series.

q is an integer, referred as order of MA model.

θ_j ($j = 1, \dots, q$) are constants which are coefficients of the lagged terms.

ε_t is an error term or white noise sequence with 0 mean and variance σ_ε^2 .

3.1.3 Autoregressive moving average model, $ARMA(p, q)$

Autoregressive moving average model integrates both autoregressive model, $AR(p)$, as well as moving average model, $MA(q)$, thus the model is referred as $ARMA(p, q)$ model. The autoregressive moving average model is thus defined as:

$$r_t = c + \sum_{i=1}^p \phi_i r_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{3}$$

There are p past values of itself on which the model depends, the model also depends upon q past random terms ε_t . Equation 3 possesses several important cases of the $ARMA$ family of models. If $q = 0$, then the equation becomes an AR model of order p . If $p = 0$, the model reduces to MA model of order q .

In prediction based models, AI-based approach is gaining momentum very rapidly. AI-based approach using ANNs was earlier started decades back [27, 85, 104]. Konno and Yamazaki [87] used traditional statistical methods along with ANN. SVM was also used as AI-based prediction method for stocks [37, 67]. Time series prediction using ANN has also gained momentum in related research

[26, 75]. As a significant development, [129] proposed autoregressive neural network in which linear time series based prediction models and could be implemented on ANN. Later on [54] proposed autoregressive moving reference regression system for time series data and the same regression model was later on implemented on four different ANNs [112, 113].

In very recent articles it has been observed that ANNs still continue to dominate this area. For instance, these articles report the use of ANNs including RBF and MLP for prediction purpose: Cheng et al. [26], Gomes et al. [40], Dai et al. [41], Hafezi et al. [57], Jian and Kumar [75], Kim and Ahn [83], Liao and Wang [96], Patel et al. [109], Rather [112, 113], Shen et al. [122], Wang et al. [128], and Xia et al. [132]. Other AI techniques include GA, PSO, SVM, SVR, GRNN and AFS which have gained momentum in stock prediction. The articles which report the use of such AI techniques for stock prediction include: Armano et al. [13], Cortes and Vapnik [37], Horng [60], Huang et al. [67], Koa et al. [79], Kim and Han [82], Majhi and Panda [99], Mostafa [106].

3.2 Singular models

This section presents survey of articles which report the use of independent or singular models for prediction. In a latest research, [57] proposed an intelligent model in a multi-agent framework called bat-neural network multi-agent system. Dash et al. [42] proposed an exponential generalized autoregressive conditional heteroskedasticity model. Patel et al. [109] compared four prediction models, ANNs, SVM, random forest and naive-Bayes model. Krasnozhon and Levendis [88] aggregated information via market process so as to solve Hayekian knowledge problem. Prediction of earnings per share four- and eight-quarters ahead for 30 Dow firms was shown by Bansal et al. [15]. An algorithm combining artificial bee colony and ordinal optimization theory was proposed by Horng [60]. Zhanga et al. [140] applied observational data-based causal analysis in stock prediction problem. Scholars are using some methods which were not common earlier, for instance text-mining was also used in stock prediction problem [43]. Chen et al. [30] did prediction of implied volatility index, similarly [79] built prediction model using SVR. A simulation-based method for computing point and density predictions was shown by Lannea et al. [92]. A global optimization approach of ANN was shown by Kim and Ahn [83] and Dai et al. [41] showed combination of non-linear component analysis and ANN.

RBF and AFS was also used for prediction purpose [122]. Wang et al. [128] developed an algorithm using wavelet de-noising-based ANN. Gomes et al. [40] suggested the use of three simple functions in ANN in place of activation functions. Wave-let de-noising-based backpropagation ANN was shown by Wang et al. [128]. Liao and Wang [96] measured fluctuations of stocks using ANN. MLP and GRNN were used by Mostafa [106] so as to predict Kuwait stock exchange. Kato and Konno [80] suggested a bridge between discriminant analysis and MLP. Hamzacebi [58] showed a method to determine the number of input and output neurons in ANN. Xia et al. [132] combined arbitrage pricing theory and ANN for stock prediction. Beside ANN, GA and PSO are also being used in the related research

[1, 13, 52, 82, 99, 107]. Faust et al. [51] verified prediction performance of standard exchange rate models, using different vintages of data. Using AI techniques, [34] maintained link between stock prediction and portfolio selection.

3.3 Hybrid models

It has been observed that non-linear models also do not guarantee desirable prediction of stocks, therefore many scholars have attempted to improve the prediction performance of stocks. This includes integration or hybridization of various mathematical model into a single model. Hybrid prediction model can be formed of different linear prediction models, non-linear models or combination of both linear and non-linear models [91, 127, 137]. The aim of forming a hybrid model is that it should outperform other individual models.

In a very recent work, hybridization of ARIMA, exponential smoothing and autoregressive moving reference recurrent neural network was carried out by Rather et al. [115]; the experiments were carried out on stock data and the results showed that the proposed model of authors was able to detect the non-linear patterns of data very well. In another recent work [9] proposed a model called increasing decreasing linear neuron for high-frequency stock market prediction. Chen and Chen [28] proposed a time series model which integrates fuzzy time series with granular computing techniques. Wang and Wang [126] showed a stochastic time effective function neural network with principal component analysis for time series prediction. A fuzzy time series models based on fitting functions to forecast weighted indexes of the stock market was proposed by Chen et al. [31]. Hsu [62], Khashei and Bijari [81] integrated ARIMA and ANN; in a similar work [108] integrated ARIMA and SVM and thus hybrid model was formed. Integration of exponential smoothing model, ANN and ARIMA was performed by Wang et al. [127]. Hybrid morphological perceptrons, called dilationerosion perceptron was presented to overcome the random walk dilemma in the time series prediction [11].

Adhikari and Agrawal [2] formed a hybrid model for prediction purpose by integrating random walk model, ANN and Elman ANN. Kao et al. [78] integrated wavelet transform, multivariate adaptive regression splines and SVR. Integration of non-linear independent component analysis, PSO and SVR was also performed [98]. Hsu [62] integrated ANN, feature selection and genetic programming. Hybrid prediction model based on adaptive network-based fuzzy inference system was shown by Chen et al. [29]. Asadi et al. [14] proposed a hybrid model by hybridizing data preprocessing methods, GA and Levenberg Marquardt algorithm for learning ANN. Hsieh et al. [61] integrated artificial bee colony algorithm, wavelet transforms and recurrent neural network. A hybrid intelligent model composed of a modular morphological neural network and a modified GA was shown by Araujo [10].

Integration of SVR with self-organizing feature map and a filter-based feature selection to reduce the cost of training time and to improve prediction accuracies was also shown [64]. Kwon and Moon [91] proposed a hybrid neurogenetic system using recurrent ANN and GA was also used to optimize weights of ANN. Integration mechanism using fuzzy GA for the optimized integration of knowledge from several sources such as machine knowledge, expert knowledge and user

knowledge was shown by Kim et al. [84]. Zheng et al. [142] discussed about state-dependent vector hybrid linear and non-linear autoregressive moving average.

Based on this literature survey on hybrid prediction models for stock market prediction, it is observed that this field has received attention from researchers from past one and half decades only. It is also observed that last one decade has witnessed a rapid momentum in the field of AI techniques being integrated in hybrid prediction models.

4 Literature survey on portfolio selection models

This section presents literature survey on portfolio selection models evolved over time. Important articles in this field have been surveyed. Much work has been done so as to improve mean–variance model proposed by Markowitz [101] both computationally and theoretically. After mean–variance model, several other models of portfolio selection emerged using the basic assumptions of mean–variance model. Since [101], mathematical analysis on portfolio management has received great attention especially in mathematical analysis.

4.1 Mean–variance portfolio model

Variance is known as most popular definition of risk for portfolio selection introduced by Markowitz [101]. since then, variance has become the most popular mathematical definition of risk for portfolio selection. In mean–variance model a common assumption is that an investor is risk averse and that either, the stock returns follow normal distribution and the investor's utility is a quadratic function of the rate of return. However both the cases do not hold in real world. It is widely accepted that in practice, portfolios hardly follow normal distribution. Since mean–variance model has remained a fundamental model in portfolio theory, it would be appropriate to discuss in brief about the model.

Consider a portfolio with N stocks, with each stock having T returns at successive time periods, such that $i = 1, \dots, N$ and $t = 1, \dots, T$ and return at particular period is given as r_{it} . Markowitz mean–variance model is given as:

$$\text{Minimize} \quad \sum_{i=1}^N \sum_{j=1}^N X_i X_j \sigma_{ij} \quad (4)$$

Subject to

$$\sum_{i=1}^N X_i \mu_i \geq \beta \quad (5)$$

$$0 \leq X_i \leq 1 \quad (6)$$

$$\sum_{i=1}^N X_i = 1, i = 1, \dots, N \quad (7)$$

where: Equation 4 is an objective function to minimize risk of the portfolio represented by variance of a portfolio.

Equation 5 guarantees desired return β of a portfolio.

Equation 6 conveys that the model is for purchase trades only.

Equation 7 guarantees total resource allocation.

X_i are portfolio weights or investment proportions.

μ_i is the expected return of stock i .

4.2 Limitations of mean–variance model

When mean–variance model is used to construct a portfolio, the first stage involves calculating mean of each asset or stock and covariance between each pair of stocks. This can be done easily from series of historical data. In order to estimate the mean and covariance matrix between stocks, there are some factors such as sample size which influence such estimation. Research has revealed that if sample size is too small, it may result into large estimation errors in mean and covariance. These statistical errors result into a portfolio having weights concentrated on fewer stocks, which is considered as one of the limitation in mean–variance model [77]. Since higher returns also contribute to the extreme of variance as lower returns, thus mean–variance model treats higher returns as equally undesirable as low returns [69]; this is also known as another limitation of mean–variance model. The sensitivity of mean–variance efficient portfolios to changes in the means of individual assets was discussed by Best and Grauer [18]. It has been found that there are estimation errors in means, variances as well as in covariance; the impact of such errors on portfolio selection was discussed by Chopra and Zeieba [34].

5 Classification of portfolio selection models

According to Fig. 2, portfolio selection models have been categorized into two groups: 'Single-objective models' and 'Multi-objective' models. Single-objective models are again categorized into two sub-groups: 'Minimization of bad outcome' (portfolio selection models which have objective function as minimization of bad outcome such as risk) and 'Maximization of profit', (portfolio selection models which have objective function as to maximize expected return or profit). 'Multi-objective' models have more than one objective function, such as minimization of risk or maximization of profit.

5.1 Single-objective portfolio models

As per our categorization, this sections discusses portfolio models having single objective function, which is further categorized into two sub categories, i.e. “Minimization of risk” and “Maximization of profit”.

5.1.1 Minimization of risk

As per Fig. 2, we have listed 11 articles under this subcategory which are briefly discussed below.

- (a) Markowitz [101] Fundamental model also known as foundation to portfolio theory. The model has objective function to minimize variance (risk) of a portfolio at given level of expected return.
- (b) Markowitz et al. [103] Extended model of mean–variance model, known as mean-semivariance model, the model is discussed in detail in next section.
- (c) Grootveld and Hallerbach [56] Variance and downside risk measure; the model is discussed in next section.
- (d) Crama and Schyns [38] Simulated annealing approach, the model is discussed in next section.
- (e) Corazza and Favaretto [36] In portfolio selection, quadratic mixed-integer programming problem has been used. Further discussion is given in next section.
- (f) Freitas et al. [54] Proposed prediction based portfolio model using ANN, This is first of such kind of work in literature.
- (g) Deng et al. [44] For the sake of identifying efficient frontier in portfolio optimization problem, a mathematical model using particle swarm optimization was developed.
- (h) Cui et al. [39] A Portfolio model with value at risk as a measure of risk was proposed.
- (i) Cesarone et al. [25] Modified mean–variance model with limited stocks; named as “Limited Asset Markowitz” model was solved as standard quadratic program.
- (j) Zhu et al. [144] A portfolio selection model with dual features, i.e. return distribution and prediction was proposed.
- (k) Li et al. [94] A fuzzy portfolio selection model proposed by authors which is based on the theory of possibilistic return.

5.1.2 Maximization of profit

As per Fig. 2, we have listed 11 articles under this subcategory which are briefly discussed below.

- (a) Sharpe [121] A popular model known as Sharpe index or Sharpe ratio is discussed in detail in next section.

- (b) Chopra and Ziemba [34] Discussed how errors in mean, variance and covariance can affect the final portfolio. The paper has been discussed in detail in next section.
- (c) Xia et al. [132] A new model for portfolio selection was proposed in which expected returns of securities are considered as variables rather than as the arithmetic means of stocks. Further discussion about the model is given in next section.
- (d) Huang [68] Two new models for portfolio selection were proposed in which stock returns are stochastic variables with fuzzy information. The same author has proposed a new definition of risk in portfolio selection by means of a curve named as risk curve [70].
- (e) Huang [70] Mean-risk model was proposed for measuring portfolio risk, which also shows the risk using a graph. The model has been discussed in great detail in [63] of this thesis.
- (f) Rios and Sahinidis [116] Dynamic portfolio selection was also considered using ANN. The authors consider portfolio selection problem with an indefinite quadratic utility function.
- (g) Zhang et al. [139] Proposed a portfolio model using sequential minimal optimization algorithm. The model is based on possibilistic mean–variance theory.
- (h) Sadjadi et al. [120] Proposed a portfolio model with uncertain data; the model has been solved using GA. The authors have focused on maintaining limited number of assets from the market.
- (i) Yang [135] Multi-account investment decision problem has been considered. Based on the requirements of trading, each account’s portfolio has been considered separately.
- (j) Mehlawat and Gupta [105] A portfolio model has been proposed as a chance constrained model.
- (k) Liu and Zhang [97] The authors showed possibility theory for a multi-period fuzzy portfolio optimization problem with minimum transaction lots.

5.1.3 Multi-objective models

In Fig. 2, we have listed 11 articles under this subcategory which are briefly discussed below.

- (a) Colson and Bruyn [35] Authors have proposed integrated system for three phases involved in portfolio management. These phases are: the information phase, decision phase and control phase.
- (b) Leung et al. [93] The authors have proposed a goal programming approach for portfolio selection problem. The model combines various forecasts which are obtained from past history of returns.
- (c) Armananzas and Lozano [12] Three popular optimization techniques, greedy search, simulated annealing and ant colony optimization have been used in the multi-objective framework of the portfolio optimization problem.

- (d) Ahmed and El-Alem [3] After discussing several multi-objective models, the authors have selected lexicographic model in portfolio selection problem. Several pareto optimal solutions are obtained by the method.
- (e) Chiam et al. [32] An evolutionary approach for multi-objective portfolio optimization; the authors have proposed an order-based representation.
- (f) Ammar [7] A fuzzy based multi-objective model has been proposed which has fuzzy random coefficients in objective function as well as in constraints.
- (f) Anagnostopoulos and Mamanis [8] A multi-objective evolutionary portfolio model has been proposed which has been solved using GA. The model is bi-objective and aimed to solve complex portfolio optimization problem.
- (g) Greco et al. [55] Mean–variance model has been modified under uncertainty leading to a multi-objective model with generic convex approach. The authors claim that it's fist such robust approach in which uncertainty has been taken care of. This approach involves uncertainty in portfolio selection. The model has been solved using multi-criteria decision aiding. Rough set approach has also been used in the work.
- (h) Rather et al. [114] A new multi-objective portfolio model has been proposed in which one objective is to maximize entropy so that well diversified portfolio is obtained. Another objective is to maximize gain loss spread of a portfolio.
- (i) Zhao et al. [141] Based on asymmetric laplace distribution, mean-conditional value at risk-skewness portfolio optimization model has been proposed.

5.2 Portfolio theory: recent trends and historical models

After the pioneer work of Markowitz [101], some other portfolio models were proposed by scholars which are known as very important contribution in portfolio theory. One such model was proposed by Sharpe [121], which is a reward to risk criterion model, and also known as Sharpe ratio or Sharpe index. Another model was proposed by Roy [118] which is also known as ‘Safety first principle’, later updated by Roy [119], Hanssmann [59] and Bawa [16].

Based on asymmetric laplace distribution, mean-conditional value at risk-skewness portfolio optimization model has been proposed [141]. A chance constrained multiobjective portfolio selection model was proposed by Mehlawat and Gupta [105]. A portfolio selection model with dual features, i.e. return distribution and prediction appeared in literature [144]. Cui et al. [39] proposed a portfolio selection model with value at risk as a measure of risk. As extension to their previous work [24, 25] introduced quantity and cardinality constraints, so that the stocks are limited in the modified model.

In another work, [46] proposed a method called equal weight portfolio investment model. Kumar and Bhattacharya [90] proposed an agent based portfolio model which restricts the number of assets or stocks in it. Using possibilistic mean, possibilistic variance and possibilistic covariance a portfolio model has been proposed with borrowing constraint [45]. Reformulation of mean–variance model, and several approaches to overcome limitations of existing models have been

discussed [125]. Huang and Qiao [73] proposed a multi-period portfolio selection model when stock returns are given by expert's evaluations. Inspired from Kruskal [89], mean–variance model has been updated using the concept of minimum spanning tree [65]. A portfolio selection model came up wherein uncertainty was taken care of Huang [72]. Inspired from Chiu and Liu [33], Li and Shu [95] applied Markovian regime switching geometric brownian motion so as to represent the prices of risky stocks.

Downside risk measure has also gained interest among many researchers which was earlier shown by Markowitz [102] wherein semivariance was used instead of variance as portfolio risk measure. Akcay and Yalcin [4] used downside risk measure for portfolio selection problem having shortfall probability as constraint. Inspired from Elliott et al. [49, 50] modified mean–variance model using the concept of hidden Markovian regime-switching Black-Scholes-Merton economy. Xiang and Fei [133] proposed a portfolio model which takes care of borrowing and lending rates and also uses value at risk as risk measure. For higher order moments of a portfolio, global optimization model has been proposed [138]. Markowitz et al. [103] used downside risk measure which has some advantages over variance as it counts deviations below mean.

5.3 Artificial intelligence based approach

Scholars have focused on using AI techniques in portfolio management [34]. Since the number of stocks to be analysed are usually very large, thus it requires heavy computational time. An innovative approach was proposed by Xia et al. [132]. In another research [52] show a model of portfolio which is based on coherent market hypothesis where ANN was used. Dynamic portfolio selection was also considered using ANN [116]. According to Vaclavik and Jablonsky [125], GA is a stochastic optimization technique as well as a search algorithm based on survival of the fittest theory. In order to support portfolio optimization process using GA, [131] proposed the index fund management. Using GA, a decision making process was presented [76] which results into a state dependent dynamic portfolio optimization. GA technique was implemented to obtain solutions for portfolio selection problem having minimum transaction lots [74].

In a very recent work [97] proposed a portfolio model based on possibility theory. In this model a multi-period fuzzy portfolio optimization problem with minimum transaction lots has been considered. Li et al. [94] proposed a fuzzy portfolio selection model based on possibilistic return and possibilistic risk. A multiobjective portfolio model which diversifies portfolio and also maximizes spread between gain and loss returns appeared in literature [114]. Adopting AI technique, [44] solved portfolio model using PSO. Duan and Stahlecker [47] proposed a portfolio selection model which treats future return of a stock as fuzzy set.

Using the concept of autoregressive neural network proposed by White [129], Freitas et al. [54] formed a prediction based mean–variance portfolio model. However with this survey it was observed that the field of prediction based portfolio has received very little attention from researchers. Huang [71] showed fuzzy based

portfolio model with diversification as a risk measure achieved using entropy. Fernandez and Gomez [53] used ANN and GA for portfolio selection with an approach of large scale optimization. A multiobjective portfolio model which uses three different optimization techniques: greedy search, simulated annealing and ant colony optimization [12].

5.4 Related research

Huang [70] proposed new measure of risk using normal distribution; the author shows this risk measure in a portfolio by calculating probability of likely losses. Thereby a risk curve is drawn which shows how much risk is involved in an investment. In order to distribute or minimize risk, [17] used cross-entropy as an objective function so as to diversify portfolio among multiple assets. Popkov [111] has done similar work using entropy but computation time is also taken care of. Zhong et al. [143] proposed an algorithm for mean–variance model which takes care of short selling. Celikyurt and Ozekici [23] showed multi period portfolio model which takes care of risky as well as of risk less assets. Huang [68] treated stock returns as stochastic variables with fuzzy knowledge. Using branch and bound algorithm, mean–variance model has been modified and solved as a quadratic-linear programming problem [36]. Inspired from Rockafellar and Uryasev [117], “Value at risk” and “conditional value at risk” has been considered along with mean–variance model [5].

Kato and Konno [80] integrated stock-bond relationship in a portfolio optimization model, which is actually revised model of Konno and Wijayanayake [86]. Inspired from Konno and Wijayanayake [86], Xue et al. [134] modified mean–variance model so that it takes care of concave transaction costs. Asymmetrical possibilistic regression and Mellin transformation has been used for portfolio selection [66]. Crama and Schyns [38] modified mean–variance model by including simulated annealing metaheuristic technique, the work is inspired from Perold [110]. A multi-objective model appeared in literature which takes care of financial trading wherein goal programming approach has been used [93].

Konno and Wijayanayake [86] developed mean absolute deviation portfolio model which takes care of concave transaction cost of portfolio. Best and Hlouskova [19] modified mean–variance model by taking care of uncorrelated and bounded assets. Grootveld and Hallerbach [56] discussed differences and similarities between using variance and semivariance in portfolio management. Cardinality constraints, minimum transaction lots and market capitalization have been included in the extended mean–variance model [124]. A multi-objective model considering three phases of portfolio management: information phase, decision phase and control phase was proposed by Colson and Bruyn [35]. Perold [110] developed an algorithm for large scale mean–variance portfolio optimization.

6 Problems identified

This survey has lead to extract useful information from two main research areas: prediction of stocks and portfolio selection of stocks. One common observation in both the areas is that traditional models are being dominated by AI based models. The area of multi-objective portfolio models and hybrid modeling for prediction purposes are being of keen interest among researchers. Based on this study, it was observed that traditional portfolio selection models possess several limitations. These models of portfolio selection which use mean returns of stocks as an estimator of the expected return are unable to take advantage of opportunities for short term investment. This makes way for researchers to develop new portfolio selection models.

However linear or traditional mathematical models, whether meant for prediction or for optimization cannot be treated as inferior as in many cases they work well wherein AI-based models are not required. It is always expected that hybrid prediction based models produce efficient results; it is important to mention that beside AI-based models, linear mathematical models also contribute in such performance of hybrid models.

One of the biggest limitation of AI-based models is their slow convergence and optimal solutions are not always guaranteed. Many authors including the authors of some of the articles surveyed here have reported about this common limitation. For instance PSO and GA are population based AI techniques in which optimal solution may or may not be obtained in the first pass. A common practice is to restart GA or PSO with new set of population and wait for the final output. Many scholars have reported about the slow convergence of ANNs. For instance, it is a trial and error method to select optimal number of neurons in hidden layer(s).

Based on this literature survey on stock prediction, it is observed that the field of hybrid prediction has received lot of attention from researchers during past one and half decades. It is also observed that last one decade has witnessed a rapid momentum in the field of AI-based models being integrated in hybrid prediction models.

7 Conclusions

This study has surveyed articles on prediction of stocks and portfolio selection of stocks. Important articles in related research have been listed in chronological order year wise. Useful information from each article has been extracted and highlighted. The aim of this study is to extract important information from each of the surveyed article which can be useful for researchers, scholars, academicians as well as for practitioners.

From this study it is observed that latest AI-based models as mentioned earlier as well as some other AI-based models such as deep belief networks, extreme learning machines can help produce more accurate predictions for stocks. When it comes for portfolio selection of stocks, prediction based portfolio models can be an interesting

area for future research which has received very little attention from researchers. These are certainly important avenues for future research.

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