International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2017, 7(3), 602-608.

A Hybrid Model for Portfolio Optimization Based on Stock Clustering and Different Investment Strategies

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ABSTRACT

In today's dynamic business environment, in order to compete in the market, financial institutes are trying to find the best portfolio policy that in turn leads to an increase in the return and a decrease in the risk for the investors. The objective of this study is to develop a portfolio considering the behavior of investors in risk taking. This research aims to support investors, experts and intermediate managers in establishing optimized portfolio of stocks according to investment strategy. The proposed model has used the five indexes of risk, return, skewness, liquidity and current ratio of 66 companies that enlisted in Tehran stock exchange market and then clustered different companies using the hybrid method of clustering algorithm. After that, the clusters ranked using Topsis method. Ultimately, using genetic algorithm, the portfolio is established for different classes of investors with respect to their risk-taking level. The results show that the proposed model in comparison to general index, the industry index and the index of 50 more active companies are better in Tehran stock exchange.

Keywords: Portfolio Optimization, Clustering, Neural Network, Genetic Algorithm
JEL Classifications: C880, C610

1. INTRODUCTION

Portfolio selection problem is a well-studied topic in finance and it is concerned with the optimal allocation of a limited capital among a finite number of available risky assets, such as stocks, bonds, and derivatives in order to gain the possible highest future wealth (Lwin et al., 2014).

This case of research is highly contingent upon reliable prediction of future performance of company stocks and successful portfolio construction (Huang, 2012b). The portfolio selection problem, which involves computing the proportion of the initial budget that should be allocated in the available assets, is at the core of financial management. A fundamental answer to this problem was given by Markowitz who proposed the mean-variance model that laid the basis of modern portfolio theory (MPT).

Markowitz's portfolio theory is based on a mean-variance optimization process that searches for efficient portfolios. An efficient portfolio means one that provides minimum risk for a given level of return or maximum return for a given level of risk (Joro and Na, 2006). It must be done by another basic assumption that rational risk-averse investors select their portfolios using only mean-variance criteria.

Many of these attacks on Markowitz and MPT result from the misapplication of basic concepts. To the extent these attacks are made by practitioners and portfolio managers, it likely reflects poor performance as a result of broken assumptions behind said MPT misapplication. In fact, it is difficult to find places where some assumption is not broken by the actual application of mean-variance optimization. Many fixes that are applied to solving mean-variance optimization issues further break the assumptions behind the basic theory, making it less useful and certainly less useful under stressful situations. Thus, from a practical application of MPT in creating efficient portfolios one must be absolutely cognizant of the basic assumptions of the theory, not just the mathematical models of optimization (Wilford, 2012).

Most of the reasonable works on portfolio selection have been done based on only the first two moments of return distributions.

However, there is a controversy over the issue of whether higher moments should be considered in portfolio selection. Many researchers argued that the higher moments cannot be neglected unless there are reasons to trust that the returns are symmetrically distributed (e.g. normal) or that higher moments are irrelevant to the investor's decisions (Li et al., 2010).

With respect to the successful performance of neural networks and genetic algorithm (GA) in solving optimization problem, those algorithms could provide investors with suitable method to achieve optimized portfolio (Soureh and Amanollahi, 2017). Classification is a supervised process in which new data instances with multiple attributes are grouped into relevant categories based on their class information.

Among ANN algorithms, the back-propagation neural network is the most popular method in many applications such as classification, forecasting and pattern recognition.

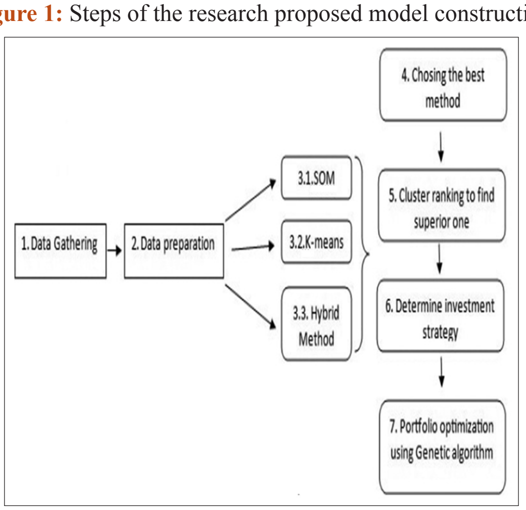
This research looks for a model in assessing the performance of portfolio that seems able to overcome the present problems and overcome the weak points of previous models. This model consists of following stages are shown in Figure 1.

2. LITERATURE REVIEW

The literature contains some classifiers for automatic classification purposes, including self-organizing map (SOM), K-means, GA, a hybrid method of SOM and K-means. In light of Markowitz and Sharp theories, the approach of investment in their framework has taken an evolution process and has increased the application of mathematical planning and the precision of investment decision making in portfolio.

Fu et al. (2013) examined two different applications of the GA in portfolio management. They found GA was adopted again to obtain the distribution of stock weighting in the portfolio which totally affects the risk, return and the Sharpe ratio of portfolio. Their result also shows that using multiple indicators is better than a single indicator to find optimal portfolio.

Figure 1: Steps of the research proposed model construction



Vazhayil and Balasubramanian (2014) used a variant of portfolio optimization technique to Generate India's 12th 5 year plan electricity generation portfolio taking into account the carbon costs. This optimization methodology proposed offers a comprehensive approach for generation planning in the context of a developing country which can take care of multiple relevant factors while incorporating various constraints.

Chang et al. (2009) believed that using mathematical programming is the best option in solving portfolio optimization with different risk models, particularly portfolios that considering the restrictions of proper numbers as well. They used the GA with different portfolio risks which have already been calculated in various methods. Using different models of risk calculation, which was used in this GA method, investors will be able to obtain their efficiency border for a fixed amount of their capital. They found the fact that the portfolio with a smaller size has higher efficiency than its larger size.

Boyacioglu and Avci (2010) predicted stock market using ANFIS method. The goal of the research was to study the ANFIS algorithm power for careful prediction of stock market. They tried to model and predicted stock index return in Istanbul stock exchange market. They used six macro-economic variables and three parameters as input variables. The empirical results showed that the model successfully predicted the monthly output of 100 national ISE index with 98.3% precision. ANFIS is a suitable tool for economists and stock brokers by predicting the stock price index output. Huang (2012a) established a methodology to select effective portfolio using support vector regression (SVR) and GA. In the beginning, they used SVR method to establish representatives of actual portfolio return that are used for valid ranking of stocks and selected higher ranking stocks. Eventually, GA was used for desirability of model parameters and specific selection for following business was the desirable complex of input variables in SVR model.

That capital return which is prepared for proposed methodology has bench-mark. Based on the desirable results that were obtained, it is claimed that the twin GA-SVR methodology causes an expansion of the research and provides an effective solution in selecting stocks by presenting simple calculations for financing.

One of the solutions in optimized formation of portfolio is to select the portfolio from stocks of companies that do not have behavioral similarity in financial terms and somehow variable. Using this method, the existing risk reduces significantly and one could high return for the investment which is made.

Since in ordinary methods, no other criteria than risk and return is considered and the companies are not ranked and clustered prior to portfolio formation, and also, no effect of skewness and liquidity in their calculations for forming portfolio was considered, the method which is used in present re-search can be an effective contribution in selecting the portfolio and gaining profit for investors.

Our contribution in this paper is to compare between three clustering methods to find suitable one for grouping companies with similar characteristics in one group and considering investor policy characteristics of individuals in stock exchange. In addition, we ranked the clusters based on three criteria named risk, return and skewness.

3. RESEARCH METHODOLOGY

The model proposed in this research provides a flexible and realistic support to the investors, experts and intermediate managers in their decision making in the assessment and making portfolio. The stages of the proposed model of the research are shown in Figure 1. This study develops a model of portfolio optimization based on data mining clustering algorithms. The model consists of seven parts (Figure 1).

3.1. Data Gathering and Preparation

To perform this research information of return, risk, skewness, liquidity and the current ratio of all existing stock company's data were gathered from Tehran's stock exchange with appropriate Turnover. There were some companies with the lake of turnover in a time period which were emitted and finally 66 number of companies were chosen to be analyzed and constructing the research's model in order to consider the valuable portfolio for investors.

3.1.1. Data normalization

The data of the companies enlisted in Tehran's stock exchange. In some companies there were lacked historical data and therefore, the data of those companies were deleted as well.

In addition, companies with low transaction in 1 month or those with no activities in some part of time intervals concerned by the research were deleted.

Furthermore, stocks with loss were deleted. In some among all companies enlisted in Tehran's stock exchange, with respect to conditions mentioned above, 66 companies were selected for the research. Concerned data is for a period of 2 years.

To perform more detailed processing, we normalized data before starting the calculation. This was done using variance functions (1).

$$X = (x - mean(x))/STD(x) \tag{1}$$

3.2. Data Clustering using Data Mining Algorithm

Clustering is among data-mining classification algorithm. The clustering algorithm places information with close and similar characteristics in separate groups, called clusters.

3.2.1. K-means clustering

K-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the closest mean. K-means starts with a single cluster with its center as the mean of the data.

In this stage, K-means algorithm used to cluster data to K incompatible mutual clusters. For the objective of data clustering, the return, risk, and skewness indexes, the current and liquidity ratios are used. To do so, the 24-month historical data for 66 companies that are enlisted in stock exchange market were used.

Due to the importance of the number of clusters in this algorithm, to specify the number of suitable clusters, the Davis-Bouldin criteria and sum of squares errors (SSE) were used and the number of optimized clusters was assessed accordingly. The Davis- Bouldin in fact calculates the ratio of intra-cluster dispersion to the inter-cluster distances from following Equations (2 and 3):

$$I_{DB} = \frac{1}{c}\sum_{k=1}^{c} \overset{\max}{L^1 k}\left\{\frac{S_c(Q_k)+S_c(Q_l)}{d_{ce}(Q_k,Q_l)}\right\} \tag{2}$$

$$Sc(Qk) = \frac{\Sigma_i \parallel X_i - C_k \parallel^2}{|Q_k|} \tag{3}$$

In which, *C* is the number of cluster; S_c is the intra-clusters spread, dcl is the distance between the centers of the two clusters *k* and *l*. The small values of Davis-Bouldin index relate to the compressed clusters with fully separated centers. As a result, the numbers of clusters that minimize Davis-Bouldin indexes are considered as the optimized number of clusters. In this part, the k-means algorithm was executed by the number of clusters from 2 to 10 by using MATLAB. This algorithm was executed by 160 execute repetitions on data and the most optimized value after 18 times of repetition for Davis-Bouldin indexes and SSE is as follows in Table 1. The results obtained show that the most appropriate number of clusters is 7; as in Davis-Bouldin and SSE have lower values in this state.

3.2.2. SOM clustering

In the past years, SOM neural network has been recognized as the most favorable analysis device in business area. SOM provides a powerful and attractive device for multi-dimensional data in spaces with lower dimension. On the other hand, this algorithm is a method for clustering and pre-processing of information. In this study, SOM and the data of the filtered companies are built using the return, risk and skewness indexes. The model which is used in this study is developed using SOM algorithm and a network in different dimensions and Hexagon neurons. Each one of the neural cells is adjusted through synapse weights that are connected to the input vector in the periods of learning. The first phase of SOM is the unsmooth estimation which is used for producing gross data models. The second phase is the adjustment which is used for adjusting the network map to the model of good data characteristics. As it is shown in Table 2, the 5 × 5 network dimensions has the least amount of Davis-Bouldin and SSE value that shows it will have the best performance. According to Table 1, the most optimized result in using SOM for clustering concerned companies is when the network has 5 × 5 dimensions and the number of clusters-12 is taken as seven (Table 2). The values of Davis-Bouldin and SSE indexes for each one of the aforesaid dimensions are in accordance with Table 2.

3.2.3. A combination of SOM and K-means clustering

In this stage, first, with respect to SOM clustering algorithm the optimized number of clusters and centers of each cluster was determined. After determining the optimized number of clusters and cluster centers, they were used as an input for K-means. We tracked down for a hierarchical clustering method such as SOM with better performance in efficient number of clusters, cluster centers and initial point determination and at the same time with a good performance in cluster member's determination using a nonhierarchical algorithm such as K-means. The results of executing SOM and K-means hybrid algorithm for 5 × 5 network dimensions and 1000 frequencies of train and the distance between neighboring neurons from each other are shown in Figure 2. A greater distance shown with darker colore.as the following picture shows, the neurons with closer distance could be considered as a cluster. With respect to Table 2 and what is mentioned above, we could use the SOM and K-means combined methods with 7 clusters in clustering the concerned data. The cluster labels for each neuron are shown in Figure 2.

Eventually, Davis-Bouldin and SSE indexes were calculated in clustering results. As the Table 3 shows, hybrid method, the most optimized results are when the number of cluster is considered as seven.

Table 1: Davis-Bouldin parameter rate and SSE in K-means

Number of clusters	Davis-Bouldin	SSE
2	2.370	7782.92
3	2.289	7249.48
4	1.916	6741.876
5	1.889	6524.555
6	2.205	6239.272
7	1.638	5841.7
8	1.972	5869.368
9	2.115	5901.755
10	2.607	6087.181

SSE: Sum of errors squares

Table 2: Dimensions of network and Davis-Bouldin parameter rate and SSE in SOM

Network dimensions	Number of clusters	Davis-Bouldin	SSE
5×5	2	0.845	305.536
	3	0.706	205.355
	4	0.794	129.402
	5	0.745	99.262
	6	0.778	79.755
	7	0.653	64.955
	8	0.711	69.197
	9	0.806	70.520
	10	0.767	71.233

SSE: Sum of errors squares, SOM: Self-organizing map

Table 3: Davis-Bouldin parameter rate and SSE in hybrid model

Number of cluster	Davis-Bouldin	SSE
2	0.898	292.604
3	1.043	205.045
4	0.768	124.123
5	0.811	101.841
6	0.816	82.426
7	0.667	51.533
8	0.697	56.194
9	0.727	69.478
10	0.710	72.321

SSE: Sum of errors squares

3.2.4. Comparison between clustering methods

A simple comparison between three clustering methods says the best mode of the number of clusters was the 7 clusters, showing that the companies are grouped in suitable number. To welfare analyzing the results more accurate the Davis-Bouldin and SSE indexed values were compared, then three methods in the most optimized states were considered. As shown in Table 4, the third method, which is a combination of SOM and K-means has less SSE and Davis-Bouldin value and the main focus of this research is on this method (Table 4).

3.3. Clusters Ranking

In this section, to identify the superior clusters based on 3 parameters of the 5 parameters concerned in this research and to establish a place for investors in selecting companies that the investors plan to purchase their stocks for investment, the existing clusters are ranked based on their amount of profit, return and skewness.

Topsis method ranks clusters in to six stages. The mean indexes as an input present per cluster calculated and the results are listed in Table 5. Then the ranked clusters were listed in Table 6.

3.4. Classifying Individuals in Risk-taking Terms Based on Investment Strategies

Investors should assess their risk taking capability or failure. An investor expects to receive more return as a reward for the risk he has incurred as per the amount of higher risk he takes. Investors have different risk taking, some of them are venture and some are more risk aversion and some are risk-neutral.

Figure 2: Clusters obtained

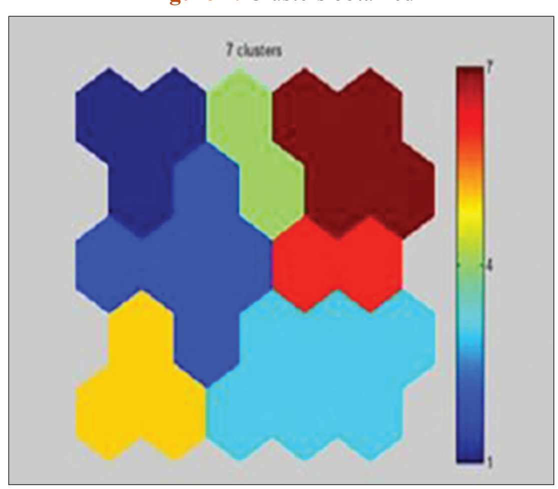


Table 4: Values of Davis-Bouldin parameters and optimized SSE in three clustring methods

Methods used	K-means	SOM hybrid	Methods
Amount of Davis-Bouldin index	1.892	0.697	0.653
Amount of SSE index	3687.601	64.955	56.194

SSE: Sum of errors squares, SOM: Self-organizing map

Table 5: Amount of mean indexes for clusters

Clusters	First	Second	Third	Fourth	Fifth	Sixth	Seventh
Return mean	3.427	5.234	1.353	1.325	4.678	7.493	0.323
Risk mean	3.608	3.894	2.437	3.224	5.629	6.897	1.765
Skewness mean	0.056	0.205	0.171	0.155	0.146	0.096	0.045

Table 6: Cluster's rank

Sixth cluster	Second cluster	Fifth cluster	First cluster	Seventh cluster	Third cluster	Fourth cluster
0.254	0.195	0.180	0.150	0.830	0.069	0.065

Risk aversion could be denied, as investors do not take venture plans unless the expected return of the plan is very high.

In terms of venture, investors could be divided into three groups:

- Risk-aversion: These individuals follow a very conservative approach. A risk-aversion individual prefers a safe return and does not participate in the situations when chance and is involved.
- Venture: These individuals have rivalry strategy and the individual in this situation asks for risk acceptance and likes to take his chance.
- Risk-neutral: Third group consists of people that are called risk-neutral. These individuals believe that the value of money is only the nominal value. Risk-neutral behavior is seen mostly in wealthy people.

3.5. Portfolio Optimization using GA

In this part of the research, to form portfolio based on clustering individuals into different classes, as mentioned using the GA, three different portfolios for individuals with different risk-taking are discussed.

To optimize the portfolio selection by GA, each chromosome is a possible solution that considered as an array of real numbers. So that each member of the array is the value of each company's outstanding shares in portfolio revealed. Due to the random variables and parameters of the GA and to Find the best GA operator in order to solve the optimal portfolio selection problem Several operators of GA selection includes roulette wheel selection, tournament selection and tournament selection and Scaling with crossover, discrete, two point and Mid-Point crossover was considered. Eventually the results were obtained by running the genetic algorithm 14 times.

Scaling with crossover, discrete, two points and mid-point crossover was considered. Eventually the results were obtained by running the GA 14 times.

With respect to the clustering performed and ranking the clusters (Table 7), the first three clusters; that is, the sixth, second and fifth clusters were used as superior clusters and other clusters were deleted. Those clusters are outstanding clusters that contain companies with higher profitability. The mentioned clusters are as follows in Table 7.

Table 7: Sixth cluster

Sixth cluster	Cluster number	Output mean	Risk mean	Skewness mean
Iran building head	6	2.977	5.083	0.104
Isfahan Sugar	6	9.745	6.734	0.040
Khorasan Shirin Sugar	6	6.647	7.831	0.238
Neyshabour Sugar	6	10.605	7.942	0.081
Pars Switch	2	1.505	3.455	0.066
Shiraz Petrochemical	2	5.300	3.207	0.370
Farabi Petrochemical	2	8.897	5.019	0.180
Azarab	5	2.345	5.450	0.030
Iran Yasa	5	5.528	4.639	0.172
Behseram	5	2.130	6.547	0.183
Paxan	5	3.741	6.247	0.139
Iran Porcelain	5	3.163	4.379	0.191
Petrochemical	5	3.065	5.365	0.152
Ardakan Ceramic	5	9.484	6.480	0.233
Doroud Cement	5	4.906	4.723	0.420
Sadi Tile	5	3.761	4.829	0.162
Sina Tile	5	4.753	4.740	0.194
Piazar Agro-industry	5	8.218	8.519	0.190

Table 8: Percent of investment in companies stocks for risk-aversion individuals with 8% risk

Company	Cluster	Investment percentage	Portfolio output
Iran Yasa	Fifth	0.023	8.31%
Pars Switch	Second	0.166	
Shiraz Petrochemical	Second	0.118	
Farabi Petrochemical	Second	0.167	
Ser. Petrochemical	Fifth	0.214	
Khorasan Shirin Sugar	Sixth	0.25	
Piazar Agro-industry	Fifth	0.058	

Table 9: Percent of investment in companies stocks for venture individuals

Company	Cluster	Investment percentage	Portfolio return
Isfahan Sugar	Sixth	0.257	12.29%
Khorasan Shirin Sugar	Sixth	0.013	
Neyshabour Sugar	Sixth	0.25	
Farabi Petrochemical	Second	0.25	
Ardakan Ceramic	Fifth	0.236	

Table 10: Percent of investment in companies stocks for risk-natural individuals

Company	Cluster	Investment percentage	Portfolio return
Isfahan Sugar	Sixth	0.25	12.25%
Neyshabour Sugar	Sixth	0.25	
Farabi Petrochemical	Second	0.25	
Ardakan Ceramic	Fifth	0.24	

Table 11: Portfolio of risk-aversion individuals for both historical and case study data

Companies	Cluster	Historical investment percent	Portfolio return	Investment percent	Portfolio return
Iran Yasa	Fifth	0.232	8.31%	0.023	8.97%
Pars Switch	Second	0.166		0.166	
Shiraz Petrochemical	Second	0.118		0.1887	
Farabi Petrochemical	Second	0.167		0.167	
Ser. Petrochemical	Fifth	0.214		0.214	
Khorasan Shirin Sugar	Sixth	0.25		0.25	
Piazar Agro-industry	Fifth	0.058		0.058	

Table 12: Portfolio of venture people

Companies	Cluster	Historical investment percent	Portfolio return	Investment percent	Portfolio return
Isfahan Sugar	Sixth	0.25	12.29%	5.547	17.54%
Neyshabour Sugar	Sixth	0.25		5.915	
Farabi Petrochemical	Second	0.25		4.367	
Ardakan Ceramic	Fifth	2.236		1.717	

Table 13: The portfolio formation of venture individual for both historical and case studies data

Companies	Cluster	Historical investment percent	Portfolio return	Investment percent	Portfolio return
Isfahan Sugar	Sixth	0.25	12.25%	5.547	17.64%
Neyshabour Sugar	Sixth	0.25		5.915	
Farabi Petrochemical	Second	0.25		4.367	
Ardakan Ceramic	Fifth	0.249		1.814	

Table 14: Values of main indexes of stock exchange of Tehran

Index	General index	Industry index	Index of 50 more active company
Start	38602.6	33420.3	1643.2
End	40550.8	35172.8	1681.2
Index group	5.04	5.24	2.31

Table 15: Return of portfolio

Model	Risk-aversion individuals	Venture individuals	Risk-neutral individuals
Return	8.31%	17.54%	17.64%

Calculation was performed by MATLAB software and due to the limitations in using MATLAB, specialized cod was written for those operations.

The first class of risk-aversion individuals:

In this stage, all 18 companies in the three superior clusters were used as the inputs of GA. The algorithms limitation was accepting the risk of the portfolio up to 8% the output of the algorithm used to form the portfolio and the list of the companies with mentioned specifications are as follows in Table 8.

The second group in which there are venture individuals and accepts a reasonable risk against suitable return, companies with returns higher than or equal to the mean return of superior clusters companies and the risk of acceptable portfolio which used as the input of GA to form the portfolio is up to 15% ceiling, the output results are in Table 9. In the third group in which there are individuals who called risk-neutral that are prepared to take higher risk against receiving higher return.

In this stage, return of higher than 50% than mean-return average of superior cluster companies were used as GA input. In the companies with this specification were selected. The description had listed in Table 10.

4. CONCLUSIONS

Based on the results obtained from the previous stages, results obtained from the model suggested in the research and the actual results and the superior indexes of Tehran Stock Exchange are compared for validation of the model.

4.1. Comparing the Optimized Portfolio Formed for Venture Individuals based on the Research Model and Tehran Stock Exchange Portfolio

In this stage, the entire 18 companies that are in the three superior clusters were used for forming the portfolio and the risk for acceptable portfolio is up to 8% ceiling. The results of investment in each company with historical data and those with Tehran stock exchange data with their return of portfolio are as follows in Table 11.

As it could be observed, the return of portfolio optimized is 8.97% that in comparison with the total indexes, the 50 superior companies and industries, which are discussed below, provides better return.

4.2. Comparing the portfolio optimized for venture individuals based on the research model and the actual portfolio

Research model and the actual portfolio risk taking individuals accept reasonable risk against suitable return. In this stage, the historical data, which included companies with, return higher than or equal to the mean return of superior cluster companies are selected and the risk of acceptable portfolio is up to 15% ceiling the return of portfolio for the next month Tehran stock exchange data based on the 24-month information for this class was 12.29% and the percentage of investment in each company is specified as well. The results of investment in each company and the return of portfolio are as follows in Table 12.

As it could be observed, the output of the portfolio is 17.54% that in comparison with the total indexes, the 50 superior and industrial companies that are discussed in following parts, it provides better output.

4.3. Comparing Portfolio Formed for High Risk Individuals Based on the Research Model and the Real Portfolio

There are individuals ready to take higher risk against receiving higher return. In this stage, with historical data were selected with the return of 50% more than the mean-return of superior cluster companies and the risk of acceptable portfolio was considered up to 22% ceiling, using Tehran stock exchange data based on the 24-month data for this class was 12.25% and the percentage of investment in each company is specified as well. For the above-mentioned companies, following results were obtained in Table 13.

As it could be observed, the return of the portfolio is 17.64% that yield is better return compared to the total indexes, the 50 more active and industrial companies that are listed as follows. The total index of the market in the same month grew 54% and the index of the more active 50 companies during that month increased 5.24% and the industry index; too, showed 2.31% growth. At the same time, the portfolios formed for different risk-taking individuals by the suggested model, with respect to limitations and deleting the effects of companies such as Fars, Jam and etc. From those indexes showed more return than the growth of market index of the 50 more active companies and industry index companies Tables 14 and 15.

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