International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:3, No:12, 2009

A New Fuzzy DSS/ES for Stock Portfolio Selection using Technical and Fundamental Approaches in Parallel

H. Zarei[1], M. H. Fazel Zarandi[2], M. Karbasian[3]

Abstract—A Decision Support System/Expert System for stock portfolio selection presented where at first step, both technical and fundamental data used to estimate technical and fundamental return and risk (1st phase); Then, the estimated values are aggregated with the investor preferences (2nd phase) to produce convenient stock portfolio.

In the 1st phase, there are two expert systems, each of which is responsible for technical or fundamental estimation. In the technical expert system, for each stock, twenty seven candidates are identified and with using rough sets-based clustering method (RC) the effective variables have been selected. Next, for each stock two fuzzy rule-bases are developed with fuzzy C-Mean method and Takai-Sugeno-Kang (TSK) approach; one for return estimation and the other for risk. Thereafter, the parameters of the rule-bases are tuned with back-propagation method. In parallel, for fundamental expert systems, fuzzy rule-bases have been identified in the form of "IF-THEN" rules through brainstorming with the stock market experts and the input data have been derived from financial statements; as a result two fuzzy rule-bases have been generated for all the stocks, one for return and the other for risk.

In the 2nd phase, user preferences represented by four criteria and are obtained by questionnaire. Using an expert system, four estimated values of return and risk have been aggregated with the respective values of user preference. At last, a fuzzy rule base having four rules, treats these values and produce a ranking score for each stock which will lead to a satisfactory portfolio for the user.

The stocks of six manufacturing companies and the period of 2003-2006 selected for data gathering.

Keywords—Stock Portfolio Selection, Fuzzy Rule-Base Expert Systems, Financial Decision Support Systems, Technical Analysis, Fundamental Analysis.

I. INTRODUCTION

TODAY Stock market is an important pillar of each economy. In between, portfolio selection is concerned with an individual who is trying to allocate one's wealth among alternative securities such that the investment goal can be achieved. Having many companies to select, portfolio selection becomes more and more sophisticated.

In the real world problems, stock portfolio selection is usually a complex problem. While by employing many criteria solution area could be explored and categorized, in many cases some criteria are missing or the weights of them are not realistic. From another point of view, it can be observed that all the investors in stock market are interested in gaining more but not everybody is completely satisfied. Obviously, if there was a model that can select portfolio which could guarantee the best result, what would happen if all investors use it! Therefore, the goal in this area is not to find the best but rather a rational solution. It is assumed that the investor has a certain set of attitudes toward the desirability of various levels of wealth. In some circumstances, securities could be categorized into classes, and ask how the investor allocates among them, [1], [2].

Harry Markowitz (1952) paced a big step on portfolio selection by presenting a mean-variance model, [3]. The model is still recognized as a debut for modern portfolio selection theory and states that the key information of a portfolio can be derived from three measurements: expected returns (taken as the arithmetic mean), standard deviations, and correlations among those returns, [4].

Quantifying investment return as the mean of returns of the securities, and investment risk as the variance from the mean, Markowitz formulated his models mathematically in two ways: minimizing variance for a given expected value, or maximizing expected value for a given variance. The model gives one an exact solution when s/he have covariance matrix between all stock prices and return estimations. While it has risk and return in parallel, it can reach to a solution frontier by changing risk tolerance of the investor.

Whereas Markowitz model bring a modern structure for portfolio selection thanks to its ability to diversify stocks for risk mitigation and also its ability to consider investor tolerance in risk, but there are many problems which cause some uselessness in portfolio selection by his model today, [1].

The experience shows that many investors select other portfolios below efficient frontier even when they have Markowitz solutions [5]. It could be because of:

- The required covariance matrix estimation which is very difficult task and there is no guarantee that the estimation would be effective.
- The required return estimation which could fail.
- Consider not all user preferences and suffice to risk tolerance solely.

From a practical point of view, however, the Markowitz model may often be considered too basic, but it ignores many

1 Hamzeh Zarei is with Pars LNG project, National Iranian Gas Export Company, Tehran, Iran. hzarei@ucalgary.ca
2 Mohammad Hossein Fazel Zarandi is with department of industrial engineering, Amirkabir University of Technology, Tehran, Iran. zarandi@aut.ac.ir
3 Masood Karbasian is the Deputy of Tehran's Mayor in urban services, Iran. m.karbasian@gmail.com

of the constraints faced by real-world investors: trading limitations, size of the portfolio, etc. All the above problems urge the scientists to propose more relevant models in this regards and present some alternative models. A very popular one is Sharp model, [6], who proposed Capital Asset Market Pricing Model, [7].

The model reduces the number of estimation but not a progress on user preference consideration, [8].

Portfolio theory has been greatly improved since Markowitz and Sharp, but still there is a lack of an integrated framework that can organize the choice and implementation of these methodologies and models to support portfolio selection logically. Other attempts to develop a framework for portfolio selection have failed at important issues such as flexibility, and a managerially oriented decision support for portfolio selection which means that still there is a big gap between satisfactory portfolio and the results of the models, [4]. It is the reason that investors still could not rely on traditional or new evolved models and just use them on beside. The focus of this paper is to propose a model which can help investors by emulating their behavior considering:

- Both technical and fundamental approach for portfolio selection.
- User preferences

In this case fuzzy rule base expert systems are used to mimic expert behavior in portfolio selection. The rest of the paper is organized as follows: next section presents the background by discussion of major approaches to Portfolio Selection. In the 3rd section, the proposed model is described in detail. In the 4th section, the results of running the model in each part and in total are shown. Finally, the conclusion and further words are presented in the 5th section.

II. Background

A. Technical Analysis

In technical analysis, investors intend to gain from change of price which could happen on a daily basis. In technical analysis the assumptions are:

1. Everything is summarized in the price.
2. Price moves based on the trends.
3. History repeats.

Based on the above assumptions, each technical analyst tries to make money through buying the stocks in the lowest price and selling them in the highest. Major input data include price and volume (volume of stock value, transacted) while there are many other indexes which are mainly derived from Price, Volume, Earnings per Share (EPS) or Dividends per Share (DPS) [9].

Risk in the view of a technical analyst means price fluctuation which could jeopardize expected return from the bought stock.

B. Fundamental Analysis

Whereas in technical analysis emphasis is on price and the vision is short-term, in fundamental analysis intrinsic value is desired and the investor view is long-term. Investor tries to find the real value of the stocks, it would be easy to decide buy or sell when the intrinsic value of them are known; The stock would be bought when the price is lower than the intrinsic value and vice versa, [10].

In contrast to technical analysis which uses price and other similar daily input data, the fundamental analysts use fundamental data which are normally published on an annual basis or in the most optimistic case quarterly. The data could be categorized as follows:

a. External Variables
b. Internal Variables

External variables are those variables which could not been changed because they exist in the economy of a country, namely:

- Treasury Bill Rate
- Inflation Rate
- Gross Domestic Production
- Unemployment Rate
- Political Situation
- Oil Price (Energy Price)
- Economical Vision
- And many explored or non-explored variables that each company sense their effects.

Internal variables are those variables that belong to a company itself. The risk of them could be avoided by not-choosing the stock, [11]. They are also numerous but some of the majors are:

- Financial History
    - Financial Statements
    - Financial Ratios
- Shareholder Earnings History
    - Average Price of stock
    - Returns (Cash flow)
    - Planned and Actual EPS
    - Planned and Actual DPS
- Operational History
    - Production and Capacity
    - Human Resource and Management
    - Innovation and Creativity
    - Development Plan
    - Legislation Consistency
    - Environmental Consistency

Among the above elements, the history of financial activities and shareholder earnings are used in our research. Using financial statement to predict future position of a company has been exercised by the other researchers as well, [12].

III. Proposed Model For Portfolio Selection

Since the traditional models for portfolio selection have problems either in mathematical capabilities or investor preferences, proposing a model with most possible consideration of financial variables (the effecting variable in

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:3, No:12, 2009

stock market are infinitive so our research is limited to the achievable and scientifically studied ones) and also user preferences are tried. Technical and fundamental approaches are used in parallel to estimate short-term and long-term return and risk. In addition, Tehran Stock Exchange data are used for testing the model and the manufacturing companies are focused because of specific intrinsic of their financial statements. This is the reason that all of the achieved rules are based on the manufacturing company's financial statements.

The period of 2003-2006 is selected to have full range of data records for testing. Technical data was gathered on a daily basis while Fundamental data was gathered on an annual basis. The model was tested in two periods, 2003 and 2006.

A. 1st Phase: Technical estimation

In technical part of this research, using technical input data, the return and risk are estimated. in order to obtain each output, one fuzzy rule base is generated. Fuzzy C-Mean clustering method is used which can assign a membership function to elements in different clusters. 70% percent of the training data is used to produce model and the remaining 30% is used for tuning with back-propagation method.

1) Input Data

Considering the literature, twenty seven technical inputs are identified. The types of technical inputs in this part of the model are as follows:

1. Change in Price (Daily)
2. Change in Price (Weekly)
3. Change in Price (Fortnight)
4. Change in Price (Monthly)
5. Change in Volume (Daily)
6. Change in Volume (Weekly)
7. Change in Volume (Fortnight)
8. Change in Volume (Monthly)
9. Change in Market Value (Daily)
10. Change in Market Value (Weekly)
11. Change in Market Value (Fortnight)
12. Change in Market Value (Monthly)
13. Date(Month)
14. Date (Day)
15. Weekday
16. Change in P|E (Daily)
17. Change in P|E (Weekly)
18. Change in P|E (Fortnight)
19. Change in P|E (Monthly)
20. Price Variation in last Week
21. Change in Value index (Daily)
22. Change in Value index (Weekly)
23. Change in Value index (Fortnight)
24. Change in Value index (Monthly)
25. Daily Fluctuation
26. Daily Fluctuation(Yesterday)
27. Change in EPS

2) Model Structure

For each stock, two fuzzy rule bases are generated: One for return estimation and the other for risk; each of them has MISO structure with TSK type.

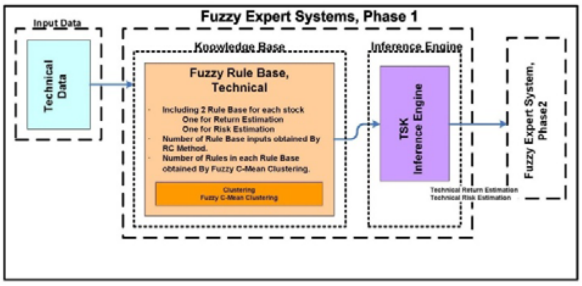

Fig. 1 First Phase, Technical Expert System

In Fig. 1, structure of Technical Expert system is illustrated. Fuzzy C-Mean clustering method is used for rule base generation while daily technical data construct the inputs. For each period of testing and each stock, one fuzzy rule base is created.

B. 1st Phase: Fundamental estimation

Parallel to technical estimation which emphasizes on short-term, fundamental estimation emphasizes on long-term return and risk.

1) Input Data

According to general references of accountings, there are elements in any financial statement which could be used for further inferences, [13]. Some more important of them are as follows:

- Total Asset
- Current Asset
- Inventory
- Current Liability
- P|E
- Net Profit
- Sales
- Shareholder Equity
- Cost of Sales
- Earnings Per Share
- Dividend Per Share
- Number of Dealt Share
- Total Number of Share
- Operating Profit
- Gross Profit
- Interest cost
- Financial Facilities
- Return on Investment
- Earnings before Tax

The rules have been requested from experts by reviewing the above elements of financial statements. Final rules which are result of many meetings with experts could be found in chapter IV, section D.

2) Model Structure

For each period of testing, two fuzzy rule bases (MISO) are generated for all stocks; one for Long-Term Return estimation and the other for Long-Term Risk estimation. Rule generation is done in brainstorming sessions and interviews attending by the experts and senior managers of Iranian Investment firms. Both rule bases are in accordance with TSK type.

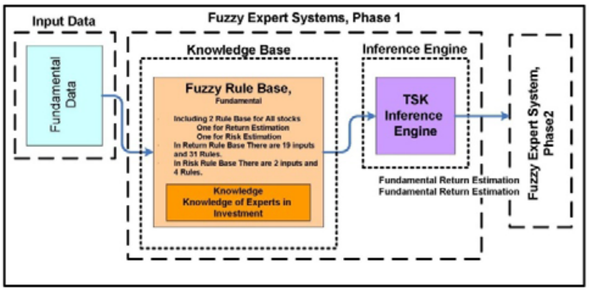

Fig. 2 First Phase, Fundamental Expert System

The outputs of this part of the model are Long-Term Return and Risk estimations. In Fig. 2, the structure of fundamental expert system is illustrated.

C. 2nd Phase: First phase outputs aggregate with user preferences

In the 2nd Phase, the outputs from the 1st Phase are aggregated with user preferences. In the last expert system there is a fuzzy rule base which calculates weight of each stock in portfolio. The final portfolio is obtained through normalizing the weights.

1) Input Data

There are eight inputs in this fuzzy rule base, four of them come from the 1st Phase expert systems and the others come from user (investor) when s/he uses the system. The 1st phase outputs which become the 2nd Phase input are:

- 1st input: Long-Term Return Estimation, which indicate the return of each stock in future.
- 2nd input: Short-Term Return Estimation, which indicate the return of each stock in near future.
- 3rd input: Long-Term Risk Estimation, which indicate the risk of each stock in future.
- 4th input: Short-Term Risk Estimation, which indicate the risk of each stock in near future.

The user preferences which are other inputs encompass:

- 1st input: Long-Term return priority, which represent the priority of future return in user opinion.
- 2nd input: Short-Term return priority, which represent the priority of near future return in user opinion.
- 3rd input: Long-Term risk tolerance, which represent the priority of future risk in user opinion.
- 4th input: Short-Term risk tolerance, which represent the priority of near future risk in user opinion.

2) Model Structure

Fig. 3, shows structure of the 2nd Phase. As it can be observed, the outputs from the 1st Phase plus four inputs from Investor become the inputs for the 2nd Phase.

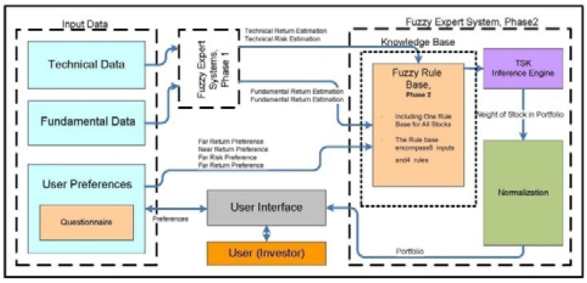

Fig. 3 Second Phase, Aggregating user preferences

D. Total Scheme of the proposed model

The entire proposed model is consolidated and demonstrated in Fig. 4.

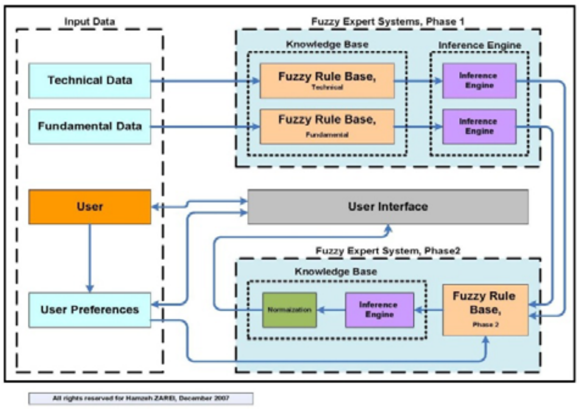

Fig. 4 Proposed model, Total Scheme

In this figure, it can be observed that the model consist of two main phases; in the first phase, the risk and return for technical and fundamental data are estimated. Then in phase two, the results of this estimation are aggregated with user preferences and produce satisfactory portfolio.

IV. Result of Running the Model

In accordance with the proposed model in previous chapter, input data are gathered from:

- Stock market public published data including website and formal books and Journals.
- Published books of Companies data.
- Financial Statement of each company.

Since the implication of financial statement differs between productive and investment companies, six manufacturing companies are selected in two different industries:

The companies are:

- “Iran Tire”, “Dena” and “Sahand” in rubber and tiring industry.
- “Traktor Sazi”, “Absal” and “SarmaAfarin” in equipment making industry.

Technical data are gathered on a daily basis from 2000 to 2006. For fundamental data, data are collected on an annual basis for six years starting 2000. Note that Iranian companies use Persian solar year as fiscal calendar which begin in 20th or

21th March each year of Gregorian calendar; so year 1382-1385 in Persian calendar which was used in following figures is almost equivalent to 2003-2006.

A. Selecting effective elements by RC Method

By using rough set-based clustering (RC) method, RCs are calculated for return and risk and the candidates were selected until the RC value increases. In

Table , the selected elements which are used for making fuzzy rule bases in technical expert system are summarized, [14].

TABLE I
SELECTED CANDIDATES OF TECHNICAL FUZZY RULE BASES

Company	Type of Rule Base	Selected candidates of first Period	Selected candidates of second Period
Iran Tire	**Return**	**16-17-24-12-22**	**3-21-5-12-23-6-26-24-9**
	Risk	**3-23-16-2-5-24-19-8-9-27**	**3-23-19-14-1**
Dena	**Return**	**2-23-15-4-19-3-22-21**	**26-14-19**
	Risk	**2-23-26-5-9-4-17-3-24-15-21-14**	**4-9-27-21-15-13-26-19-5-16-17-6-25-14-2**
Sahand	**Return**	**2-17-22-10-21-26-4-6**	**22-2-3-21-9-23-15-24**
	Risk	**1-23-26-5-19-15-9-25**	**3-14-24-5-21-7-23-1-13-15-22-20-6-16-19-10**
Traktor Sazi	**Return**	**2-26-17-25**	**22-8**
	Risk	**2-24-9-26-23-3-20-5-1**	**1-20-10-2-3-4-6-9**
Absal	**Return**	**2-23-16-15-24-27**	**3-22-1-15-13-12-18-17**
	Risk	**2-17-1-11-13**	**3-7-20-8-2-23-1-9-22-24-19-6-21-17**
Sarma Afarin	**Return**	**2-23-16-19-10-20-3-17-6**	**24-9-10-2-23-20-12-5**
	Risk	**1-23-26-17-11**	**2-25-3-23-12-5-19-9-11-14-17-6-7-18**

In table 1, the selected candidates have been shown for two period of testing. Here the numbers are from the list of inputs which was stated in chapter III, section A. According to RC algorithm, the process of selecting candidates has been stopped as when as the RC values start to grow. For each stock two sets of candidates have been chosen; one for return estimation and the other for risk. By considering chosen candidates as input data, the rest of research is carried out.

B. Tuning technical fuzzy rule bases

After selecting the effective elements in technical part using RC method, TSK fuzzy rule bases are developed by clustering with Fuzzy C-Mean method. In each period of test for each stock, two fuzzy rule bases are generated; one for return and the other for risk. Here, twenty four fuzzy rule bases have been built as there are six companies and two period of testing; just one of them depicted in Fig. 5 that shows a fuzzy rule base for one of the companies.

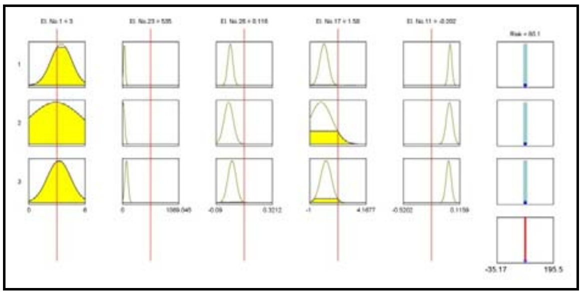

Fig. 5 One of the Fuzzy Rule Bases in 1st Phase, Technical; Before Tuning. (SarmaAfarin Co., Technical Risk in year 1382; which is equivalent to 21th March 2003 to 19th March 2004)

In the next step the parameters of rule bases are tuned with remaining 30% of data. In Fig. 6, a tuned fuzzy rule base demonstrating the changes in membership functions is shown. The process of tuning is done by back-propagation method, [15].

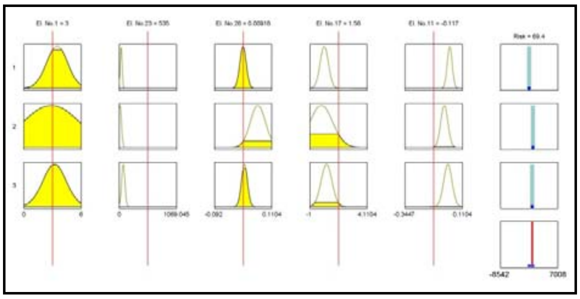

Fig. 6 One of the Fuzzy Rule Bases in 1st Phase, Technical; After Tuning. (SarmaAfarin Co., Technical Risk in year 1382; which is equivalent to 21th March 2003 to 19th March 2004)

C. Testing 1st Phase: Technical estimation

In this research, the model is tested on each period of testing base on daily data. The estimation process is done with daily tuning using past two weeks. In Fig. 7, one of the results of technical expert systems is shown which is belonging to return estimation of SarmaAfarin Company in year 1382 (equivalent to 21th March 2003 to 19th March 2004). There are two periods of testing, since there are six companies to be tested and for each company technical return and risk should be estimated, twenty four figures similar to Fig. 7 are produced to show model performance in technical part of the model.

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:3, No:12, 2009

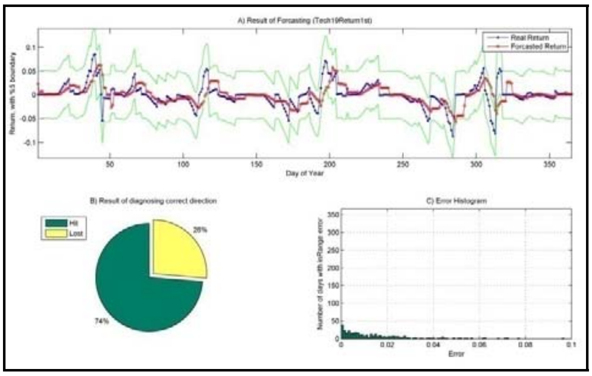

Fig. 7 One of the test results in 1st Phase (Technical). (SarmaAfarin Co., Technical Returns in year 1382; which is equivalent to 21th March 2003 to 19th March 2004). In this figure there are three sections, in above (a) comparison of estimated and real amounts depicted. Below left (b) the percentage of hit rate which in them model could estimate the correct direction, up or down. Below right (c) there is histogram that distributes error amounts.

As shown in Fig. 7, the estimation is reasonable since there is no outrage in the Fig. 7(a) except in some rare days that stock had an unpredictable behavior or sudden huge fluctuation. The summarized test result of all days of all stocks is presented in section G.

D. Fundamental fuzzy rule bases

By having many meetings (with Brainstorming method) with market experts and asking them to describe the rules, prevailing relation between financial statements, ratio and future return and risk of the company, the rules in Table are concluded in the format of “IF-THEN” rules.

TABLE II
FUNDAMENTAL EXPERT SYSTEM FOR RETURN ESTIMATION, "IF-THEN" RULES

Rule No.	Input No.	IF	THEN
1	1	Quick Ratio is more than average of Industry	Return would be high
2		Quick Ratio is less than average of Industry	Return would be low
3	2	Quick Ratio is more than average of past 3 years	Return would be high
4		Quick Ratio is less than average of past 3 years	Return would be low
5	3	Current Ratio is more than average of Industry	Return would be high
6		Current Ratio is less than average of Industry	Return would be low
7	4	Current Ratio is more than average of past 3 years	Return would be high
8		Current Ratio is less than average of past 3 years	Return would be low
9	5	Asset is less than industry’s average	Return would be high
10	6,7	P|E Ratio is less than industry average And Profit margin in more than industry average	Return would be high
11		P|E Ratio is more than industry average And Profit margin in less than industry average	Return would be low
12	8	ROI is more than Industry average	Return would be high
13		ROI is less than Industry average	Return would be low
14	9	Sales/assets had a stable growing in past 3 years	Return would be high
15	10	Profit/assets had a stable growing in past 3 years	Return would be high
16	11	Profit/Equity had a stable growing in past 3 years	Return would be high
17	12	Profit Margin had a stable growing in past 3 years	Return would be high
18	13	Turnover is more than industry average	Return would be high
19		Turnover is less than industry average	Return would be low
20	14	Turnover had a stable growing in past 3 years	Return would be high
21		Turnover didn’t have a stable growing in past 3 years	Return would be low
22	15	DPS/EPS is more than industry average	Return would be high
23		DPS/EPS is less than industry average	Return would be low
24	16	DPS/EPS is more than 50%	Return would be high
25		DPS/EPS is less than 50%	Return would be low
26	17	Growth of sales is more than growth of cost of sales	Return would be very high
27		Growth of sales is less than growth of cost of sales	Return would be very low
28	18	Operational Profit/EBT more than industry average	Return would be high
29		Operational Profit/EBT less than industry average	Return would be low
30	19	Interest/Financial facilities is less than ROA	Return would be very high
31		Interest/Financial facilities is more than ROA	Return would be very low

Fuzzy rule bases for return estimation are generated by Gaussian membership function and with TSK method. Here, there are 31 rules with 19 inputs. The output is estimated Long-Term Return. Since the importance of the rule is not similar to experts’ opinion, (rules number 26, 27, 30 and 31 are more important), two different membership functions are used to represent them.

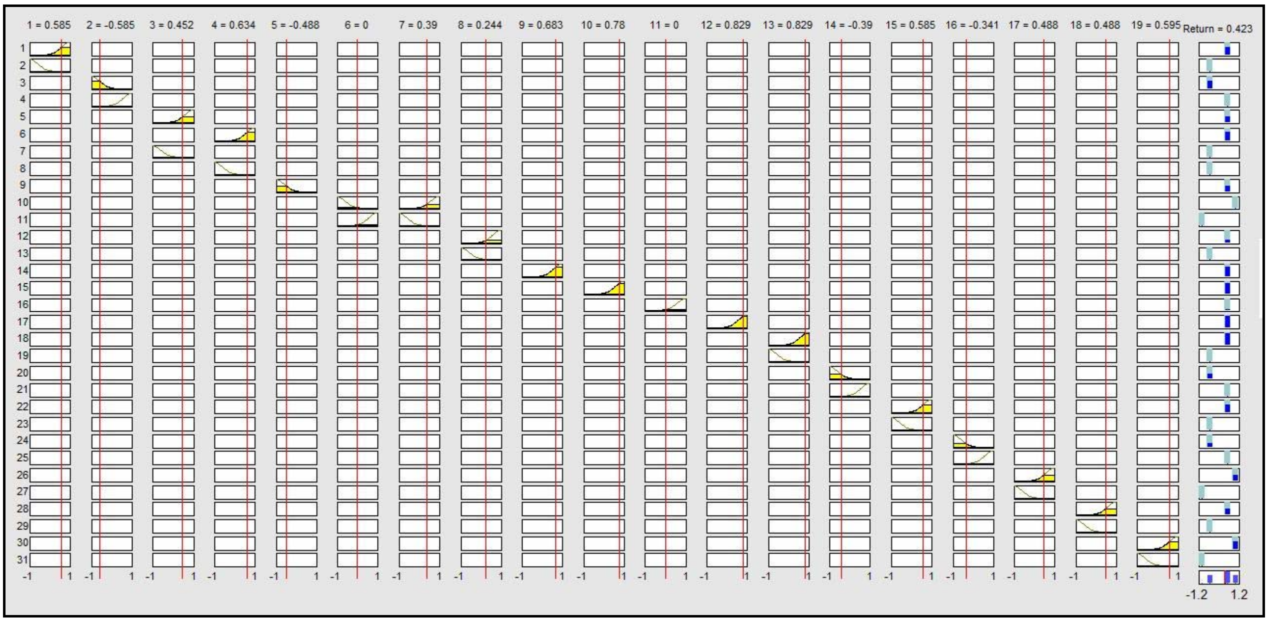

Fig. 8 Fuzzy Rule Base; 1st Phase (Fundamental). Return estimation

For Long-Term Risk same procedure has been adopted. Four rules have been concluded which can be observed in Table .

TABLE III
FUNDAMENTAL EXPERT SYSTEM FOR RISK ESTIMATION, "IF-THEN" RULES

Rule No.	Input No.	IF	THEN
1	1	Asset is more that industry average	Risk would be high
2		Asset is less that industry average	Risk would be low
3	2	Liquidity is more than industry average	Risk would be high
4		Liquidity is less than industry average	Risk would be low

The fuzzy rule base for the 1st phase (fundamental risk estimation is shown in Fig. 9.

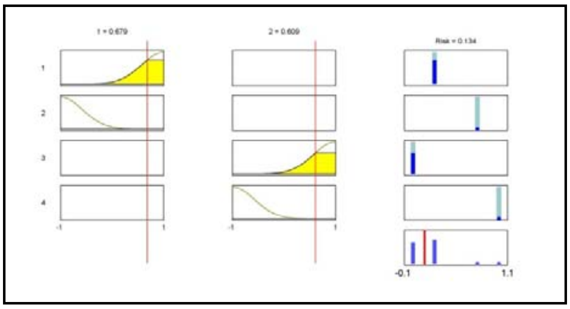

Fig. 9 Fuzzy Rule Base; 1st Phase (Fundamental). Risk Estimating

E. Testing 1st Phase Fundamental

In Fig. 10, the result of the model in fundamental part has been illustrated which encompasses Long-Term return estimation. Again please note that Iranian companies use Persian solar year as fiscal calendar which begin in 20th or 21th March each year of Gregorian calendar; so year 1382-1385 in Persian calendar which was used in following figures is almost equivalent to 2003-2006.

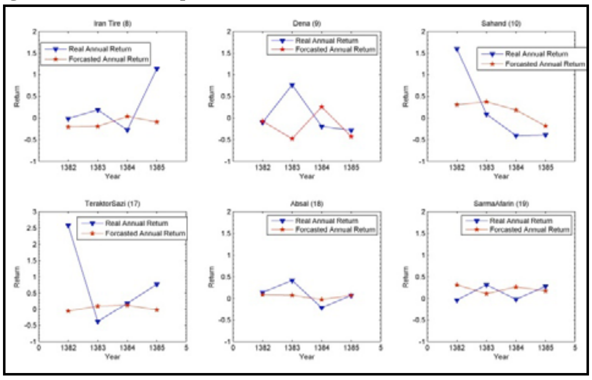

Fig. 10 First Phase (Fundamental). Return Test Result.
Note that Persian calendar is used for veracity of data (equivalent to 2003-2006).

In Fig. 11, the result of the model in fundamental part has been illustrated which encompasses Long-Term risk estimation.

The result of the model in fundamental part is summarized in Table , as it can be seen, the model could estimate well in most cases. In some cases, the model didn't estimate as expected which could be attributed to unexpected result of company in some years.

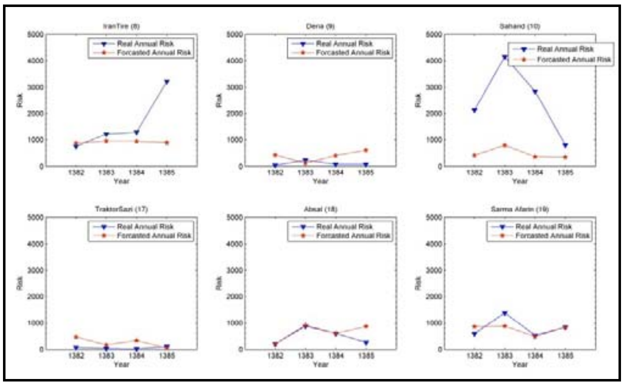

Fig. 11 First Phase (Fundamental). Risk Test Result.

Note that Persian calendar is used for veracity of data (equivalent to 2003-2006).

TABLE IV
FUNDAMENTAL RESULT

Fundamental Results		Iran Tire	Dena	Sahand	Traktor sazi	Absal	Sarma Afarin
1382 (2003)	Return	Ok	Ok	Error	Error	Ok	Ok
	Risk	Ok	Ok		Ok	Ok	Ok
1383 (2004)	Return	Ok	Error	Ok	Ok	Ok	Ok
	Risk	Ok	Ok	Error	Ok	Ok	Ok
1384 (2005)	Return	Ok	Ok	Error	Ok	Ok	Ok
	Risk	Ok	Ok		Ok	Ok	Ok
1385 (2006)	Return	Error	Ok	Ok	Error	Ok	Ok
	Risk		Ok	Ok	Ok	Ok	Ok

F. 2nd Phase fuzzy rule bases

In the 2nd Phase, the user preferences have been aggregated with estimated values. Long-Term and Short-Term return and risk was estimated in the 1st Phase. The user preferences are received using questionnaire via four criteria which have been discussed in chapter III, section C. Four rules have been generated for obtaining weight of each stock in the portfolio. One of the main advantages of our model is to calculate a unique portfolio for each investor based on her/his preferences.

In Table , the rules are illustrated which finally produce a value for each stock and then the weight of stock in portfolio could be calculated based on that, proportionally.

TABLE V
SECOND PHASE EXPERT SYSTEM FOR AGGREGATING USER PREFERENCES; "IF-THEN" RULES

Rule No.	IF			THEN
1	Long-Term Return Estimation is high	and	Long-Term Return Priority is high	Weight is high
2	Short-Term Return Estimation is high	and	Short-Term Return Priority is high	Weight is high
3	Long-Term Risk Estimation is high	and	Long-Term Risk importance is high	Weight is high
4	Short-Term Risk Estimation is high	and	Short-Term Risk importance is high	Weight is high

In Fig. 12, Fig. 13 and Fig. 14, the used MF of risk, return and user Preferences are demonstrated, respectively.

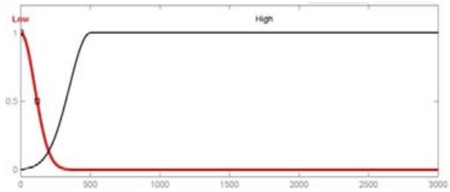

Fig. 12 Risk Membership Function, 2nd Phase

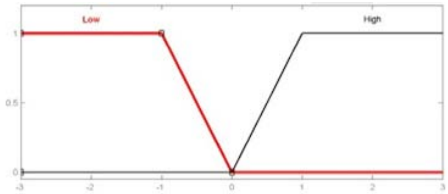

Fig. 13 Return Membership Function, 2nd Phase

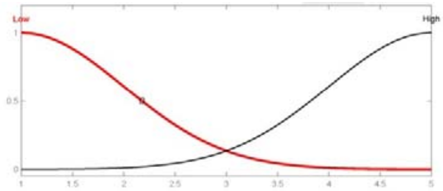

Fig. 14 User Preferences Membership Function, 2nd Phase

By using Table , and the above MF, fuzzy rule base could be generated. It has been illustrated in Fig. 15.

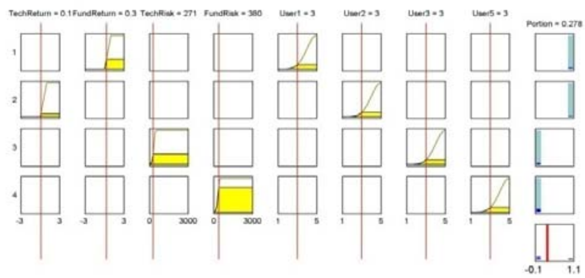

Fig. 15 Fuzzy Rule Base, 2nd Phase.

G. Testing and Validation

To test the proposed model, it is assumed that there exist six different investors having different preferences. In Table , the values of inputs for these six investors have been shown. Although for testing, the preferences of these six investors are considered but the model's ability doesn't limit to them; any combination of values (from 1 to 5) could be formed as values for preferences. Value "1" shows no priority of the criterion while number "5" shows most important ones.

TABLE VI
SAMPLE GENERATED USER PREFERENCES FOR TESTING

Sample Users	1st Input	2nd Input	3rd Input	4th Input
	Long-Term Return Priority	Short-Term Return Priority	Long-Term Risk Tolerance	Short-Term Risk Tolerance
Normal Investor	3	3	3	3

Sample Users	1st Input	2nd Input	3rd Input	4th Input
	Long-Term Return Priority	Short-Term Return Priority	Long-Term Risk Tolerance	Short-Term Risk Tolerance
Future Return Emphasis	5	1	1	1
Capital Gain	1	5	1	1
Avoid Future Risk	1	1	5	1
Avoid Price Fluctuation	1	1	1	5
Risky Investor	5	5	1	1

Fig. 16 shows the results of testing model on a random day of a period of testing. For each investor a portfolio has been selected.

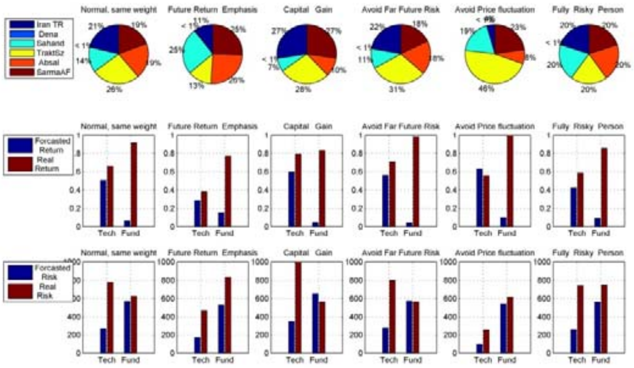

Fig. 16 Portfolio selection for each Preferences on a sample day(31th day of year 1382 equivalnt to 20th April, 2003). The bar charts below the figures show the estimated and real return and risk of the portfolios.

To have a complete and general measurement of model performance, the model is ran for all days in 1382 (equivalent to days between 21th March 2003 and 19th March 2004) and select portfolio of two investors; first, the investor with Long-Term return priority and second, the investor with Short-Term Priority. They are compared with random generated portfolios. The comprehensive results are shown in Fig. 17.

As it is demonstrated, the model has suitable performance especially in technical estimation and user satisfaction. In Fig. 18, similar to Fig. 17, the test was performed for year 1385 (equivalent to days between 21th March 2006 and 19th March 2007) and the results are depicted.

In Table , all achieved results are summarized. It shows the model has good performance in considering user preference. When unpredictable circumstances in the area of stock market are considered in that period, estimation performance is considerable.

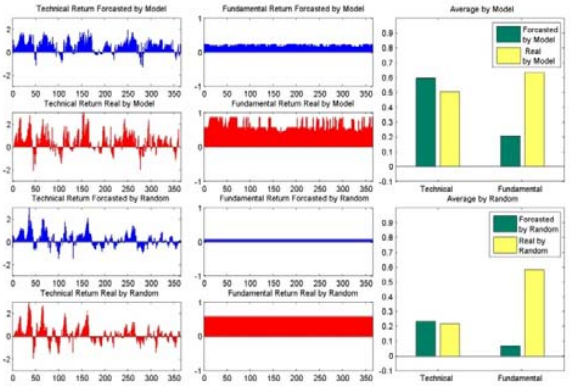

Fig. 17 Final Testing Result, comparison with Random Generated Portfolio; Year 1382 (equivalent to days between 21th March 2003 and 19th March 2004).

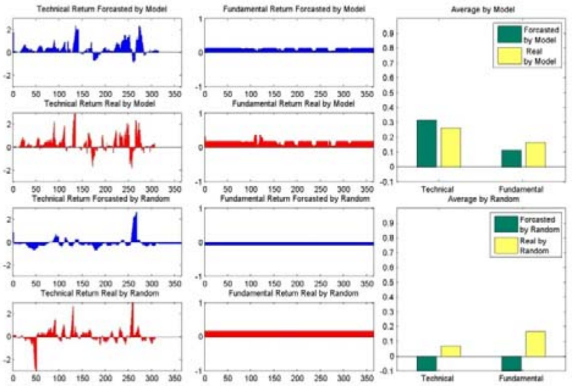

Fig. 18 Final Testing Result, comparison with Random Generated Portfolio; Year 1385 (equivalent to days between 21th March 2006 and 19th March 2007)

TABLE VII
FINAL TESTING RESULT, COMPARISON WITH RANDOM GENERATED PORTFOLIO

Final Testing Result			Model	Random
1382 (2003)	Near Return	Estimated	60%	24%
		Real	50%	21%
	Far Return	Estimated	20%	7%
		Real	65%	58%
1385 (2006)	Near Return	Estimated	31%	-10%
		Real	27%	7%
	Far Return	Estimated	12%	-10%
		Real	18%	18%

V. CONCLUSION

A model for portfolio selection has been proposed which uses two kinds of data in parallel, Technical and Fundamental data. By generating expert system for each kind of the data, return and risk estimated for each stock for each scope of short-term and long-term. Thereafter user preferences were received and with aggregating with estimated values, a unique portfolio which could satisfy user preferences was produced. Model performance in each Phase has been illustrated in figures and tables. Comparison of the model performance and random generated portfolio were depicted and described as well. The model had satisfying performance but there are some unexpected results of some companies which show us that there could be some other affecting elements.

Acknowledgment

It is necessary to thank the experts who helped gathering and extracting rules and spent their priceless time to find relation between financial statements and companies' future. Also the data received by data providers were very helpful and made the research feasible.

References

[1] W. Breen, "Specific versus General Models of Portfolio Selection" *Oxford Economic Papers*, November 1968, New Series ed., pp. 361-368.
[2] F. J. Travers, *Investment Manager Analysis: A Comprehensive Guide to Portfolio Selection, Monitoring, and Optimization*. John Wiley & Sons, Inc., 2004.
[3] H. Markowitz, "Portfolio Selection." *The Journal of Finance* (Cowles Foundation), vol. VII, no. 1, pp. 77-91, March 1952.
[4] J. Dong, H. S. Du, S. Wang, K. Chen, X. Deng. "A framework of Web-based Decision Support Systems for portfolio selection with OLAP and PVM." *Decision Support Systems*, no. 37, pp. 367– 376, 2004.
[5] H. Markowitz, *Portfolio Selection, Efficient diversification of Investment*. New York: John Wiley & Sons, Inc., 1959.
[6] W. F. Sharp, "A simplified model for portfolio analysis" *Management Science*, pp. 277-293, January 1963.
[7] G. M. Frankfurter, E. P. Herbert, J. P. Seagle, "Performance of the Sharpe Portfolio Selection Model: A Comparison." *The Journal of Financial and Quantitative Analysis* (University of Washington School of Business administration) 11, no. 2, pp. 195-204, June 1976.
[8] W. F. Sharpe, "Portfolio Analysis" *The Journal of Financial and Quantitative Analysis* (University of Washington School of Business Administration), vol. 2, no. 2, pp. 76-84, June 1976.
[9] L. Stevens, *Essential Technical Analysis, Tools and Techniques to Spot Market Trends*. John Wiley & Sons, Inc., 2002.
[10] P. Chang, L. Chen-Hao, "A TSK type fuzzy rule based system for stock price prediction." *Expert Systems with Applications*, no. 34, pp. 135–144, 2008.
[11] E. Helfert, *Financial Analysis: Tools and Techniques, a Guide for Managers*, McGraw-Hill, 2001.
[12] K. G. Palepu, P. M. Healy, V. L. Bernard. *Business analysis & valuation: using financial statements: text & cases.* Thomson Learning, 2004.
[13] A. Groppelli, E. Nikbakht, *Finance. 4th edition,* Barron's Educational Series Inc., 2000.
[14] M. Sugeno, T. Yasukawa, "A Fuzzy-Logic-Based Approach to Qualitative Modeling" *lEEE Transactions on Fuzzy Systems*, pp. 7-31, February 1993.
[15] J.-S. R. Jang, "ANFIS: Adaptive-Network-based Fuzzy Inference", *IEEE Transactions on Systems, Man, and Cybernetics*, vol.27, no. 3, pp. 665-685, May 1993

Hamzeh Zarei (IEEE: S'06, M'08) received his B.Sc. from IUST in Industrial Engineering, 2004. In 2008, He graduated in M.Sc. in Financial Engineering from Amirkabir University of Technology (AUT). Concurrent with his education, he has been involved in many industrial and research projects since 2003.

He is pursuing his education in the field of "Project Management" in University of Calgary and Sharif University of Technology.