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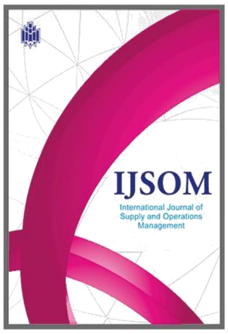


# Modeling Portfolio Optimization based on Fundamental Analysis using an Expert System in the Real Estate Industry

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**Abstract**
Models of decision making optimization in the stock market have been challenged and evaluated by researchers in recent years. Financial and economic knowledge alone will not allow to analyze and facilitate decision making and to determine the appropriate strategy and one of the most important obstacles in this regard is the complexity of tools and methods of analysis and modeling. The multiplicity of indicators and financial ratios on the one hand and the breadth of data on the other hand are the most important obstacles in the behavioral analysis of financial markets. Accordingly, the present study aims to model the decision-making process in financial markets. In this research, a different approach is presented in conceptual modeling by combining methods and tools of artificial intelligence with financial issues. Based on this, the portfolio will be optimized by extracting appropriate financial ratios considering the effect of time, and then modeling them in a technical expert system assuming a neutral risk investor. In addition to trying to conclude and analyze based on the realities of the stock market fundamental analysis, the system rules and the classification of companies are also distinguished from similar studies based on the dynamics of the stock market. The proposed model has been implemented using the data of companies in the real estate industry during 2007-2018. The results indicate the proper performance of the proposed model and it has the appropriate flexibility to decide and select a portfolio.

**Keywords:** Portfolio optimization; Rule-based expert system; Fundamental analysis.

## 1. Introduction

Today, decision-making models have received increasing importance along with the development of tools and financial markets to maximize the efficiency of investors' decision making process. Selection of the probable alternatives in the stock market and creation of the related portfolio are dependent on multiple factors of decision making process complicated for the analyzers (Falah Shams et al., 2016). An efficient investment does not only increase the wealth of shareholders, but can also improve the economic growth of countries. The market will be much more efficient by entering the stock market and using new investment tools. A large body of literature has been devoted to prioritizing the stock selection criteria and making an efficient portfolio by considering different criteria using modern models interacting with each other. The major issue of this research is, therefore, it valuate the stock and create a portfolio using a rule-based expert system that takes the fundamental indexes into account in the long term. The expert systems as one of the artificial intelligence branches can simulate the expert's behavior. These systems have been computerized in order to achieve the highest wisdom level of various expert experiences. The most important reasons are to speed up the process, increase the precision, and reduce the risk and cost (Rouzbahani et al., 2007). Expert systems are used to solve problems that, 1) there is no specific algorithm for solving the problems, and 2) there is explicit knowledge to solve the problems. The shells, which are some computer programs in information system field, are suitable tools to mechanizing the expert systems (Rouzbahani et al., 2007). The FOOPES[1] used in this essay has features such as fuzzy logic, object orientation, probability theory (under uncertainty), Windows-based utility, multilingual capabilities, and intractability with database software (Rouzbahani et al., 2007). The main components of an expert system are shown in Figure1.

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[1] Fuzzy Object Oriented Probabilistic Expert System

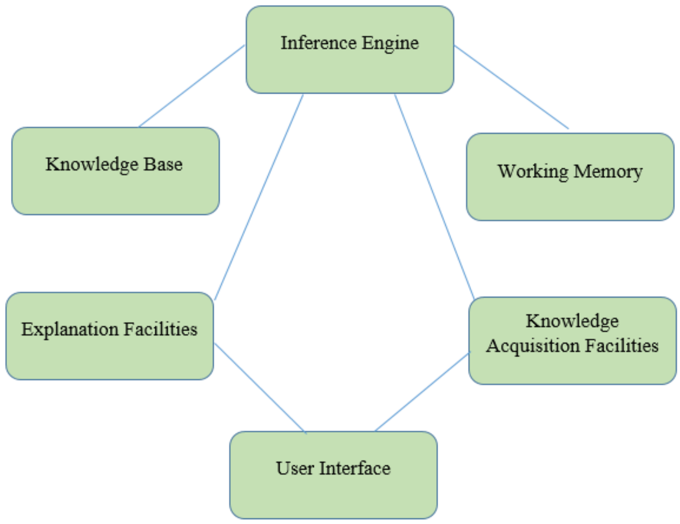


**Figure1.** Main components of an expert system

One of the important components of expert systems is the knowledge base where the expert knowledge is coded to be understandable for the system. In general, knowledge is saved as conditional expressions and rules in the knowledge base, and the inference engine uses the rules of logic and knowledge available in the knowledge base to deliver the results to the user. The current research aims to model the optimum portfolio selection in the stock market environment, which has received the highest attention from the investors as it is the main source of all other markets. It is, therefore, of paramount importance to develop a system that is able to not only predict and analyze the market conditions but also to make spotless decisions. In the present paper, therefore, it is tried to provide an appropriate method for optimizing the decision-making process of stock purchasing by using artificial intelligence methods and focusing on the expert system model. The main question of this research is how to make an optimal portfolio based on an expert system using the indicators of fundamental analysis in the stock market environment. In this research, a particular industry is considered as a case study conducted using actual industry data and analyzing the financial statements of companies under consideration. The period of study falls between 2007 and 2017, a 10-year period data for making portfolio in 2017 and 2018 in order to compare the data with real returns of industry and total market.
The financial experts try to make an image of companies' current and future conditions using their financial information and financial statements, which is known as fundamental analysis in financial terms. The fundamental analysis in the extraction and conclusion parts needs a huge amount of data. For this reason, financial experts with a wide range of information and mastery can take advantage of this approach (Raghu, 1994).

A new and different approach in conceptual modeling has been made in this research by combining methods and tools of artificial intelligence. Based on this, the information analysis process and portfolio optimization are facilitated by extracting appropriate financial ratios and then modeling them in a technical knowledge system. It should be noted that the combination of rules and indexes used here in addition to the conclusion logic followed by ranking companies and using a realistic case study can be considered as the distinguished aspect of this research. The proposed framework of this study is actually a two-level model that is distinguished from conventional portfolio optimization models in determining the optimal portfolio with the possibility of using other financial indicators, besides return and risk.
Financial ratios that are not available in conventional optimization models are used for ranking in the first part. This section allows the investor to use corporate financial data published in alternate periods and contains valuable information in fundamental analysis and decision making. In single-level optimization, however, which used commonly and traditionally, the majority of the firm's financial data will not be taken into consideration, and thus no fundamental and a priori analysis will be possible for the analyst. The structure of the present research is shown as a flowchart in Figure 2.

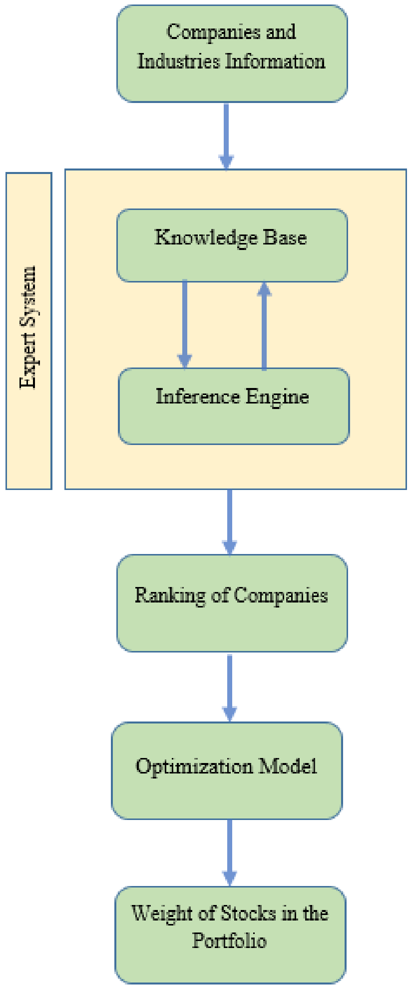


**Figure2.** Structure of the present research

This article is presented as follows:
The theoretical ideas and a review on the existing studies in this field is presented in the second section in order to highlight the most important studies that are within the scope of this study. The third section describes the proposed expert system. Then, the research model is run followed by a conclusion and the research outcomes.

## 2. Literature review

Over the past 100 years, a lot of efforts and many models were presented to encourage the investors to utilize the new ways of investment. The optimization concepts of portfolio and also diversification in the investigation process can be considered as great tools to have a more thorough understanding of financial issues. The publication of Harry Markowitz's portfolio selection was the greatest achievement in this field (Fabozzi et al., 2007). Since its publication, it has experienced a lot of improvements and changes in people's ideas about portfolio and has been used as a useful tool in order to optimize the portfolio (Lai et al., 2006). He suggested that investors should consider both risk and return together and should also select the allocation of investment among all investing opportunities using the trade-off between the two factors (Fabozzi et al., 2007). However, Markowitz's portfolio theory can only offer a solution for the capital allocation. In the real investment market, there are a lot of investing opportunities that can confuse the investors due to the huge amount of data (Garkaz et al., 2011). These complexities and uncertainties in this issue have led to interest in the use of artificial intelligence techniques, one of which is the expert system.

Most of achievements in artificial intelligence have been problem solving and decision making approaches that cover the main features of the expert systems. Expert systems are referred to those types of artificial intelligence applications that reach a level of expertise to decide instead of an expert on a particular field. These systems are programs whose knowledge base is accumulated of the information by which humans make decisions on a specific issue.
The application history of the expert system in financial management can be divided into several major categories, namely selection of investment portfolio, financial planning, financial analysis, credit granting, rating of bonds, investment, and evaluation of bankruptcy risk. Here are some examples of research done in the field of portfolio selection using the expert system.

Xidonas et al. (2009) devised a financial analysis system to support decision-making on the selection of portfolios. This system chooses a portfolio by assessing the overall performance of a company, and commercial enterprises are categorized according to their respective industry. This system only uses the fundamental technique based criteria. The thresholds for financial ratios have been devised by experts. There are a total of 1406 production rules. The system was evaluated using its application in Athens Stock Exchange. Zarei et al. (2009) presented a two-phase skilled system. The first phase makes use of both technical and fundamental data to estimate the risk and return. The investors' preferences are combined with the estimated values to produce an appropriate portfolio in the second phase. The first phase consists of two expert systems, each of which is responsible for fundamental or technical evaluation. In the technical expert system, 27 candidates have been identified for each stock, and variables have been selected using clustering methods based on rough clusters (RCs). Then, two fuzzy base rules were fostered for each stock by the fuzzy C-Mean method and the TSK[2] approach. The estimated risk and return values are combined with the investors' preferences in the second ohase and it will finally offer a fuzzy basic rule to rank the processed data. Hadavandi et al. (2010) presented an expert system based on fuzzy genetic systems and artificial neural networks in order to predict stock prices. In their model, the initial price, the final price, the highest price, and the lowest daily price are considered as independent variables and the prediction of the final price of the next day as the dependent variable of the model.
Fasanghari and Montazer (2010) offered an expert system focusing over Tehran Stock Exchange evaluation in order to create a portfolio and suggest it to targeted customers in Tehran stock market. This system ranks stocks based on the fundamental analysis ratios and qualitative criteria of Tehran Stock Exchange. The system inputs are modeled by the triangular membership function using the up, mid, and low linguistic variables. The membership function parameters and the number of production rules in the knowledge base are determined by the fuzzy Delphi method, which aggregates the knowledge of several experts. The incurred risk is also mixed with the ranking process to offer a portfolio based on the preferences of investors. The results are verified by a survey of the experts. In this system, factors selected for proposing an investment basket are stock market, sale rules, earning per share, projects, shareholders, and floating stocks.

Yunusoglu et al. (2013) introduced a rule-based fuzzy expert system for medium-term decision makers and evaluated the system using the data of 61 stocks in Istanbul Stock Exchange. The proposed system performance was analyzed compared to a benchmark index at different levels of investor's risk aversion and various time periods of investment. Their results indicated that the performance of the proposed system was better in all circumstances, especially in the case of investor's risk aversion and in the midterm. Masehian et al. (2015) designed an expert system to identify the most proper PSO for solving different optimization problems using a comprehensive survey and taxonomy on different types of PSO. Algorithms are classified according to aspects such as particle, variable, process, and swarm. After integrating different acquirable information, the knowledge base of the expert system is formed consisting of 100 rules. Then, the system is able to logically evaluate all the algorithms and report the most appropriate PSO-based approach based on interactions with users, referral to knowledge base, and necessary inferences via user interface. In order to examine the validity and efficiency of the system, a comparison is made between the system outputs against the algorithms proposed by newly published articles. Accordingly, they concluded that the proposed expert system could be considered as a proper tool for finding an appropriate PSO variant matched with the application under consideration. Kamley et al. (2015) provided a rule-based expert system with forward chaining for the Mumbai Stock Exchange. The system comprises such variables as initial price, final price, and the highest and the lowest price.
In their further study, Kamli et al. (2015) compared the forward and backward chain in an expert system to optimize the stock portfolio in the National Stock Exchange of India, and reported a better performance of the back chain.
Dymova et al. (2016) used the technical analysis methods in the Forex[3] market. They tried to utilize the Forex skilled system mixed with technical analysis in order to obtain the new approach of Rule-based evidential reasoning (RBER). They claimed that traditional fuzzy logic rules could lead to undesirable results when subjected to collisional fuzzy classes such as low and medium. The proposed fuzzy system was implemented on real market data for four currency pairs at intervals of 15 minutes, 30 minutes, and 1 and 4 hours.

The rapid pace of globalization has made it easier for investors to invest in global stock markets. Thus, there is an inevitable need for logical decision-making by the psychology of shareholders' behavior. Under this behavioral economy, traditional financial theory, which emphasizes financial, logical, and computational decision-making, is inconsistent with a new behavioral financial theory. Accordingly, Velumoni and Rau (2016) presented a new system by combining financial factors, investor sentiment, and information technology using perspective theory. Stocks of leading Indian banks were selected as real data and the authors reported relatively good results. Zamani et al. (2015) presented an expert system based on fuzzy neural network for predicting stock prices. The predictions were used to solve the mean-variance and mean-variance-skewness models using the genetic algorithm. In order to measure the performance of the model, its efficiency was compared with the traditional mean-variance and mean-variance-skewness models as well as with the market index.

[2] Takagi–Sugeno–Kang
[3] Foreign Exchange Market

Falah Shams et al. (2016) developed a rule-based fuzzy expert system to facilitate the portfolio selection. It was attempted to select the portfolio with the consideration of investors' risk appetite based on both fundamental and technical indicators. The model was found to perform well in midterm for risk-averse investors. Abadian et al. (2017) used the fundamental analysis as an effective measure to select an appropriate portfolio. The importance of individual criteria was measured by the Shannon entropy method. Then, the surveyed society comprising member companies of Petrochemicals was ranked by the SAW and TOPSIS ELECTRE techniques. They concluded that using the multi-index approaches for ranking led to different outcomes, and ultimately decisions could be made using average ranking method. Slimani et al. (2017) applied neural networks to demand forecasting in a simple supply chain composed of a single retailer and his supplier with a game theoretic approach. This work analyses the problem from the supplier's point of view. Various attempts were made in order to optimize the total network error and the findings indicated that different neural net structures such as Adaline, Multi-Layer Perceptron (MLP), or Radial Basis Function (RBF) Network could be used to forecast demand. However, the most adequate one with optimal error was the MLP architecture.

Almahdi and Yang (2019) have recently extended a recurrent reinforcement portfolio allocation and rebalancing management system with complex portfolio constraints using particle swarm algorithms. In particular, they propose to use a combination of recurrent reinforcement learning (RRL) and particle swarm algorithm (PSO) with Calmar ratio for both asset allocation and constraint optimization. Using S & P100 index stocks, they show that such a system with a Calmar ratio based objective function yields a better efficient frontier than the Sharpe ratio and mean-variance based portfolios. By comparing with multiple PSO based long only constrained portfolios, they propose an optimal portfolio trading system that is capable of generating both long and short signals and handling the common portfolio constraints. They further develop an adaptive RRL-PSO portfolio rebalancing decision system with a market condition stop-loss retraining mechanism, and show that their proposed portfolio trading system outperforms the benchmarks consistently especially under high transaction cost conditions. The paper of Dou et al. (2019) employs a baseline-based method to decide whether to select a redundant system. First, the problem is analyzed in depth to demonstrate the connotation of baseline and related concepts are defined. Then, based on the definition of the redundancy system, baseline system, and baseline value, the weapon system portfolio selection approaches are proposed with regard to a baseline value. Starting from the two core parts of the approach, i.e. selection strategy analysis and weapon systems ranking, the strategy of weapon system selection was analyzed under a single objective and multiple objectives. Subsequently, the interval number theory was employed to extend the VIKOR method to the E-VIKOR method, with a linear programming model as the weighting method under uncertainties to rank the candidate weapon systems. Finally, a case with three different ranking results of candidate weapon systems was studied under different weighting schemes. The weapon system portfolio refining was developed based on the ranking results, baseline value, and selection strategy. Garcia-Galicia et al. (2019) consider the problem of policy optimization in the context of continuous-time Reinforcement Learning (RL), a branch of artificial intelligence, for financial portfolio management purposes. The underlying asset portfolio process is assumed to possess a continuous-time discrete-state Markov chain structure involving the simplex and ergodicity constraints. They provide a RL solution based on an actor/critic architecture in which the market is characterized by a restriction, called transaction cost, involving time penalization. The portfolio problem in Markov chains is determined by solving a convex quadratic minimization problem with linear constraints. Any Markov chain is generated by stochastic transition matrices and the mathematical expectations of the rewards. They estimate the elements of the transition rate matrices and the mathematical expectations of the rewards. This method learns the optimal strategy in order to make a decision on what portfolio weight to be taken for a single period. With this strategy, the agent is able to choose the state with maximum utility and select its respective action. The optimal policy computation is solved by employing a proximal optimization novel approach, which involves time penalization in the transaction costs and the rewards. They employ the Lagrange multipliers approach to include the restrictions of the market and those that are imposed by the continuous time frame. Moreover, a specific numerical example in baking, which fits into the general framework of portfolio, validates the effectiveness and usefulness of the proposed method.

## 3. The proposed expert system

It is known that expert systems are based on the knowledge base of expert people, along with the inputs a user introduces to the system. In this research, an expert system has been designed to select the optimal portfolio based on the experts' viewpoints and previous studies. An expert system is designed to be able to select the optimal portfolio. The design of this expert system, inspired by Fallah Shams (2015), is described below. The inputs of the expert system are fundamental data taken from financial statements of companies. Fundamental inputs reflect the management performance, competitive advantage, and financial health of companies. Before any investing decisions, the investor has to make comparison between the values and financial indexes of companies. However, the performance of a company cannot actually be measured solely with the data of the same year, and judge the overall performance of that company according to the financial ratios of one year. Thus, considering the long term performance of a company can reflect more facts about its stock price changes and profit and loss. This research seeks to enable the investor to study both short term and long term activities of a company in the stock market, thereby, choosing the best alternative to invest. To achieve this objective, the proposed system computes the indicators selected for companies from the past period and a final index is calculated from their weighted average. Considering that recent developments of a company's interior and exterior could have a greater impact on its current performance, the latest periods are given higher weight and lower weight will be assigned to the importance of these data for farther periods. Another point that can cause confusion in investment is the fact that high or low numerical values of the indexes alone cannot indicate the strong or weak performance of a company. In order to solve this problem, the system compares the numerical values of the each stock indices with the industry average. Thus, those indicators are considered to be better that are higher than the average. To work with an expert system, the first step is to understand the rules in that system. Suppose that there are M stocks to choose from. Required indicators (N indicators) are selected as system inputs according to the studied industries, market conditions, and investor's opinion. At first, all the indicators (for different companies at different times) are scored according to the average of that period. The indicators are scored +1, −1, and 0 if they are higher, lower, and equal to the average. The rules established in this section are in the form of relationships (1), (2) and (3):

$$IF \quad X_{ij}^t < \bar{X}_{Ij}^t \quad THEN \quad k_{ij}^t = -1 \tag{1}$$

$$IF \quad X_{ij}^t = \bar{X}_{Ij}^t \quad THEN \quad k_{ij}^t = 0 \tag{2}$$

$$IF \quad X_{ij}^t > \bar{X}_{Ij}^t \quad THEN \quad k_{ij}^t = +1 \tag{3}$$

$i = 1, \dots, M \qquad j = 1, \dots, N$
$t = 1, \dots, T \qquad I = 1, \dots, Z \quad (Z \le M)$[4]

Where "i" shows the stock counter, "j" represents the index counter, "t" indicates the time period, and I stands for the industry counter. X indicates the index and $\bar{X}$ represents the simple average of the index.
Therefore, $X_{ij}^t$ is a variable that contains the numerical value of the jth index from the ith stock in period t. $\bar{X}_{Ij}^t$ shows the average number of jth index in industry I in period t (company i belongs to industry I). k is also a scoring variable for each index. The total number of rules for this step is M × N × T.
Considering the above rules, stocks can be evaluated and rated regardless of the industry they belong to.
In the next step, rules are used to check the scores of the indicators and calculate the average rating of a company in each period:

$$IF \tag{4}$$
$$-1 \le k_{i1}^t \le 1 \ and \ -1 \le k_{i2}^t \le 1 \ and \dots and \ -1 \le k_{iN}^t \le 1$$

$$THEN$$

$$K_i^t = \frac{\sum_{j=1}^N k_{ij}^t}{N}$$

The number of these rules is M × T.
Expected outcome of this system is the ranking of companies. Eq. (5) shows the final rank. As discussed at the beginning of this section, the ranking of stocks is determined by taking into account the coefficient of past performance of the companies.

$$R_i = \frac{\sum_{t=1}^T u_t K_i^t}{\sum_{t=1}^T u_t} \tag{5}$$

Where $u_t$ is the weight of different years shown as $u_t = t$ to consider more effectiveness of recent years, and $R_i$ is the rank of ith company and the final output of the system.
The proposed expert system allows users to apply their own restrictions. For example, stocks in which the ratio of a company's stock price to the company's earnings per share (P/E), market value to book value (MV/BV), and return on equity (ROE) are negative in the past year, can be eliminated in the beginning by defining the rules as follows (6):

$$X_{i1} = \frac{P}{E} \qquad X_{i2} = \frac{MV}{BV} \qquad X_{i3} = \text{ROE}$$

[4] It is possible a few stocks be for an industry.

$$IF \quad X_{i1} < 0 \quad or \quad X_{i2} < 0 \quad or \quad X_{i3} < 0 \quad THEN \quad k_{i1} = k_{i2} = k_{i3} = 2 \tag{6}$$

These shares are eliminated in the next stages due to the presence of the condition $-1 \leq k_{ij} \leq 1$ for all indices of a share (expressed in relation (4)).

## 4. Problem modeling

The rankings obtained from the proposed expert system at this stage are used to model the problem and find the weight of each share in the portfolio. The model used in this study is inspired by the Markowitz's modern portfolio theory as presented below:

$$\max Z = \sum_{i=1}^{M} w_i \ R_i \tag{7}$$

$$\sum_{i=1}^{M} w_i = 1 \tag{8}$$

$$LB \leq \sum_{i=1}^{M} y_i \leq UB \tag{9}$$

$$w_i - UBWy_i \leq 0 \tag{10}$$

$$w_i - LBWy_i \geq 0 \tag{11}$$

$$0 \leq w_i \leq 1 \tag{12}$$
$$y_i \in \{0,1\} \tag{13}$$

The model objective function maximizes the rank of the stocks included in the portfolio. Limitation (8) ensures that all existing capital is invested. Limitation (9) is the restriction of diversity, limiting the upper and lower thresholds for the number of shares in the portfolio. In this limitation, $y_i$ is a binary variable with a value of 1 if the stock is included in the portfolio, otherwise its value is 0. UB and LB are the upper and lower thresholds for the number of stocks present in the portfolio, respectively. Limits (10) and (11) indicate the upper (UBW) and lower (LBW) thresholds for the weight of the shares in the portfolio, which are set by the investor. Obviously, the constraints of the designed model are adjustable according to the characteristics of the investor. One of the points taken into account in financial modeling is the investor risk aversion. In this study, the investor is considered to be risk neutral. This feature can easily be used based on market indicators and investor behavior as a model constraint. Therefore, it is important to note that the limitations of an optimization model are one of the most important tools for determining the framework of a well-known and generalizable model.

## 5. Results of the model implementation

### 5.1. Data used in the implementation of the model

To illustrate the application of the model presented in this research, a portfolio was selected among the companies of the mass production and real estate industry that were active during the years under review (Table 1). The needed data was taken from the companies' financial statements from the Codal website and and Rahavard software in a 10-year period from 2007 to 2018.

**Table1.** Company names

| Company symbol | Company name |
|---|---|
| VSAKHT | Iran Construction Investment |
| VTOOS | Toos Gostar Urban Development |
| SFARS | Construction and Development of Fars |
| SHAHED | Shahed Investment |
| SNOOSA | Tehran Renovation and Building |
| SAJAN | Sakht Ajand |
| SMASKAN | Housing Investment Group |

### 5.2 Execution of the expert system

Six core indicators were used as inputs for the proposed expert system. Several financial ratios are considered and used to fundamentally analyze the stock. Considering the goal of modeling the choice of portfolios in this study, the choice of index is not prioritized and not considered as an important principle. In other words, the number and variety of indicators had no effect on the totality of the model, and each analysis generally considered some of the indicators based on the characteristics of the industry and market conditions. Therefore, the most well-known financial indicators and, on the other hand, the most important ones were considered as representatives in this study. Table 2 provides the relevant description.

**Table2.** The indicators used in this study

| Ratio | | Application |
|---|---|---|
| Liquidity ratio | Current | The company's ability to pay short-term debts |
| Leverage ratio (capital structure) | Times interest earned | The company's ability to pay midterm and long-term debts |
| | Debt (%) | |
| Profitability ratio | Net profit margin (%) | Evaluation of company profit making ability |
| | Return on equity (%) | |
| | Return on asset (%) | |

**Liquidity ratios:** Liquidity ratios are a set of financial metrics that are used to determine the ability of a company to pay off its short-term debt. Generally, the higher these ratios, the larger the security margin the company will cover for its short-term debt. In this research, the "current ratio" is used as the most well-known indicator of various types of liquidity ratios. To calculate that "current assets" are divided by the "current liabilities ".

$$LI = \frac{Current\ assets}{Current\ liabilities}$$

**Times interest earned:** The times interest earned (TIE) ratio is a measure of a company's ability to meet its debt obligations based on its current income. The formula for a company's TIE number is earnings before interest and taxes (EBIT) divided by the total interest payable on bonds and other debts. The result is a number that shows how many times a company could cover its interest charges with its pretax earnings.

**Debt ratio:** This ratio is obtained by dividing the sum of debt by assets. In general, lenders prefer a relatively low debt ratio. A high debt ratio usually means that the company has been forced to use more facilities to provide needed resources.

**Net profit margin:** a proportion that calculates the profitability of each Rial from sales:

$$Net\ profit\ margin = \frac{Profit\ (after\ tax)}{net\ sales}$$

The net profit of a company is the first criterion that most investors consider in relation to company profits, but pure attention to net profits does not provide accurate information about the firm's performance.

**Return on equity:** Return on equity represents the net profit generated for each Rial of equity (sources provided to the company by the shareholders). An increase in the ratio will increase the shareholder's profits.

$$Return\ on\ equity = \frac{Profit\ (after\ tax)}{equity}$$

**Return on asset**: This ratio is obtained via dividing the company's net income by the sum of assets. Some analysts consider this ratio to be the final indicator for determining the adequacy and efficiency of management.

The ratio is the return that the company has earned for all investors and creditors. This ratio is also important for the efficiency of the company.

Indicators are chosen to be applied to individuals with different goals. For example, those who intend to invest in short-term can ignore the leverage ratios and consider only rating other indicators.

Indicators for selected companies and the industry are calculated over 10 years, and these values are given as input to the expert system. The values of indicators for the industry and for companies are presented in Table 3 and Appendix 1, respectively. The parameters T and N representing the number of indices take 10 and 6, respectively. M shows the number of companies and is equal to 7. Since this study considers only one industry, then I = 1.

**Table3.** Industry indicators over 10 years

| Real estate industry | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|
| Current | 2.793 | 2.427 | 2.014 | 1.821 | 1.895 | 2.056 | 3.493 | 2.391 | 2.396 | 2.008 |
| Times interest earned | 3152.4 | 672.1 | 1272.8 | 666.4 | 1905.9 | 2823.3 | 4040.8 | 1359.2 | 2975 | 10896.2 |
| Debt (%) | 37.3 | 37.9 | 44.4 | 48.1 | 48 | 46.1 | 43.2 | 44.5 | 40.7 | 45.1 |
| Net profit margin (%) | 45.2 | 30.4 | 29.7 | 26.5 | 24.3 | 19.9 | 31.8 | 36.5 | 32.3 | 20.4 |
| Return on equity (%) | 25 | 20.7 | 20.5 | 22.9 | 17.6 | 21.1 | 23.5 | 22.2 | 11.9 | 5.5 |
| Return on asset (%) | 15.4 | 12.9 | 10.9 | 11.5 | 9.2 | 10 | 12.9 | 11.4 | 7.1 | 3.7 |

The values of the obtained indexes are given as inputs to the expert system and the program is executed in FOOPES software. The outputs of this expert system are the corporate ratings, which are presented with the definition of the used variables (Table 4):

**Table4.** Ranking the companies

| Company symbol | SFARS | SHAHED | SAJAN | SNOOSA | SMASKAN | VSAKHT | VTOOS |
|---|---|---|---|---|---|---|---|
| Rank variable (Final rating) | 0.5556 | 0.5259 | 0.2963 | 0.1407 | 0.1185 | -0.126 | -0.126 |
| | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ |
| Weight variable | $w_1$ | $w_2$ | $w_3$ | $w_4$ | $w_5$ | $w_6$ | $w_7$ |
| Variable of the presence or absence of a stock | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ | $y_6$ | $y_7$ |

### 5.3 Implementation of the model

The expert system rates obtained by FOOPES software are now used as model inputs, as discussed in Section 4. This optimization problem is solved by GAMS software and the results are presented in Table 5. By solving this problem, the investor can find the optimal weights of each share in his portfolio.

**Table5.** Results from the model implementation

| Weight of stocks | The existence or absence of a stock in a portfolio |
|---|---|
| $w_1 = 0.3$ | $y_1 = 1$ |
| $w_2 = 0.3$ | $y_2 = 1$ |
| $w_3 = 0.3$ | $y_3 = 1$ |
| $w_4 = 0.1$ | $y_4 = 1$ |
| $w_5 = 0$ | $y_5 = 0$ |
| $w_6 = 0$ | $y_6 = 0$ |
| $w_7 = 0$ | $y_7 = 0$ |

In solving this model, the maximum and minimum numbers of stocks in the portfolio are 6 and 3, and the upper and lower limits of the weight of each share are 0.3 and 0.02, respectively. The opinion of the investor is important in choosing these values. According to the results, the proposed portfolio includes only the stocks SFARS, SHAHED, SAJAN, and SNOOSA, and the weight of the first three stocks are 0.3 and 0.1 for SNOOSA, respectively. As suggested, the proposed approach to portfolio decision making in this paper differs from traditional approaches in this field. The proposed approach does not merely take into account the current situation of companies but also considers the companies' present and past structure and function. Due to these conditions and the fact that the opinion of financial experts in the construction of the rules and thus the overall result is strongly influenced in this method, the results of the implementation of this method are quite different from other methods and it is not possible to make a direct comparison due to this inherent difference. In general, one cannot ignore the fact that a company's performance is a result of its past performance, and even if decision making under the current conditions of stock prices can be beneficial in the short run, exploring a company's fundamental conditions is the prerequisite for an intelligent investment.

To evaluate the effectiveness of the proposed method, the portfolio return measure is used in this section. For this purpose, the average portfolio return of the proposed method (using the weights obtained from the model) over the two years were compared with the average return of the market index[5]. The average return on portfolio is 35.18 and is slightly lower than the average return of the market index (47.20). Nevertheless, it is important to note that all industries with different structures and conditions are involved in the average return of the market index. Thus, to ensure more confidence in the performance of the proposed method, portfolio returns were compared with average return of the real estate industry over the years 2017 and 2018, indicating a better performance of the proposed method (Table 6).

**Table6.** Comparison of returns in years 2017 and 2018

| Average of total return (%) | Average of industry return (%) | Average of portfolio return (%) |
|---|---|---|
| 47.20 | 12.73 | 35.18 |

### 6. Summary and conclusion

There are wide types of methods to optimize the portfolio. In general, most of the critics point out that the optimization models cannot be real and flexible enough to be used in the applied space. In the present study, some of the criticisms were resolved using the appropriate technical techniques. The model with complete flexibility showed to be capable of predicting market trends and, consequently, the optimal selection of assets. This study first introduced an expert system that is able to rank companies according to fundamental criteria. After the companies were fundamentally scrutinized and each one was awarded a rank, these results were considered as inputs of the proposed model and optimal stock weights in the portfolio were identified by solving the model. Proposed procedures were implemented for the real estate industries during the years 2007-2017 and the portfolio was selected for the years 2017 and 2018. Considering the returns as a benchmark, the average return on portfolio was then compared with those of the industry and the

[5] Market Index Returns are obtained from Tehran Securities Exchange Technology Management Company.

market index. The results showed a higher return on portfolio than the whole industry and a slight difference with the market index, which indicates the proper performance of the proposed method.
The most important points in this research are as follow:

- The system inputs and data are based on the fundamental analysis and the most important share analysis in the market.
- The model can be flexible enough facing different industrial conditions.
- The modeling is based on the data and the financial statements of the existing companies in Tehran stock exchange, therefore, it is possible to develop this work and use it in a practical and realistic space.
- The proposed approach was done at two levels. The companies were ranked by an expert system in the first step and the portfolio was optimized in the second step. It is possible to optimize the second stage based on minimizing portfolio risk or maximizing returns.
- The model has both high flexibility and functionality in the optimization process. Thus, there is the possibility to optimize the model regarding the analysis features and the industry.

In other words, the multiplicity of indicators and financial ratios on the one hand, and the wide variety of data on the other hand are the most important obstacles in order to have a behavioral analysis of the financial markets. Therefore, analysts try to overcome these limitations by using different methods and tools and gaining an effective way of analyzing market events. Based on the expert system, the proposed model is distinct in terms of modeling and the remarkable numbers of rules making it clear that it is possible to evaluate and analyze on a wide scale in spite of the inherent complexity and behavior of various phenomena.

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**Appendix 1**

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Iran Construction Investment | Current | 2.793 | 2.427 | 2.014 | 1.821 | 1.895 | 2.056 | 3.493 | 2.391 | 2.396 | 2.008 |
| | Times interest earned | 3152.4 | 672.1 | 1272.8 | 666.4 | 1905.9 | 2823.3 | 4040.8 | 1359.2 | 2975 | 10896.2 |
| | Debt (%) | 45.3 | 46.2 | 54.3 | 54 | 53.9 | 56.2 | 56.8 | 48.4 | 52.2 | 54.4 |
| | Net profit margin (%) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 83 | 14 | -28 |
| | Return on equity (%) | 21.5 | 21.2 | 16.2 | 12.9 | 11.2 | 6.8 | 8 | 24 | 3 | -4.3 |
| | Return on asset (%) | 11.7 | 11.4 | 7.4 | 5.9 | 5.2 | 3.1 | 3.5 | 12.4 | 1.4 | -2 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Toos Gostar Urban Development | Current | 1.85 | 1.044 | 1.274 | 1.689 | 1.662 | 1.962 | 6.185 | 6.245 | 3.654 | 2.966 |
| | Times interest earned | 1725.6 | 286.7 | -450 | 139.6 | -53.4 | 285.2 | 835.3 | 13718 | 28608.9 | 264400 |
| | Debt (%) | 46.9 | 43.7 | 41.9 | 33 | 36.1 | 30.4 | 13.7 | 13.6 | 23.2 | 29 |
| | Net profit margin (%) | 43.4 | 23.3 | -10.7 | 48.2 | 23.1 | 61.9 | 79.9 | 49.3 | 37.9 | 59.9 |
| | Return on equity (%) | 27 | 32.9 | -3.3 | 13.5 | 5.6 | 8 | 17.6 | 10.9 | 6.5 | 2.5 |
| | Return on asset (%) | 14.3 | 18.5 | -1.9 | 9.1 | 3.6 | 5.5 | 15.2 | 9.4 | 5 | 1.8 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Construction and Development of Fars | Current | 4.65 | 2.797 | 5 | 1.87 | 4.609 | 3.978 | 3.589 | 3.181 | 5.353 | 3.922 |
| | Times interest earned | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Debt (%) | 56.4 | 46.3 | 33.7 | 40.2 | 37.1 | 37.8 | 34.9 | 41.6 | 27.8 | 30.1 |
| | Net profit margin (%) | 75.3 | 41.7 | 43.6 | 49.6 | 2.1 | 21.1 | 82.1 | 85 | 59.9 | 49.1 |
| | Return on equity (%) | 15 | 19 | 15 | 6.2 | 15.1 | 14.9 | 14.1 | 22.3 | 25.3 | 26.1 |
| | Return on asset (%) | 9.4 | 10.2 | 9.9 | 3.7 | 9.5 | 9.3 | 9.2 | 13 | 18.3 | 18.2 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Shahed Investment | Current | 4.128 | 3.658 | 2.696 | 4.092 | 2.098 | 3.009 | 3.777 | 3.185 | 3.874 | 3.764 |
| | Times interest earned | 7863.4 | 5547.4 | 10231.8 | 592.8 | 518.7 | 268.9 | 544.9 | 118.3 | 170.8 | 0 |
| | Debt (%) | 17.7 | 18.6 | 23.3 | 15.3 | 26.9 | 23.2 | 18.8 | 20.3 | 13.9 | 13.1 |
| | Net profit margin (%) | 165.8 | 103.6 | 89.3 | 31.4 | 62 | 23 | 68.8 | 59.9 | 56.8 | 91.3 |
| | Return on equity (%) | 18.8 | 35.4 | 37.2 | 27.7 | 21.3 | 20.7 | 19.4 | 18.7 | 12.3 | 11.2 |
| | Return on asset (%) | 15.4 | 28.8 | 28.5 | 23.5 | 15.6 | 15.9 | 15.8 | 14.9 | 10.6 | 9.8 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Tehran Renovation and Building | Current | 0.543 | 1.138 | 1.089 | 0.933 | 0.98 | 0.748 | 0.675 | 0.958 | 1.595 | 1.105 |
| | Times interest earned | 17.4 | 245.8 | 134.3 | 10.6 | 8.7 | 18.1 | 21.6 | 5.8 | 11.6 | 9.5 |
| | Debt (%) | 87 | 68 | 73 | 80 | 67.2 | 81 | 91 | 91 | 71 | 79 |
| | Net profit margin (%) | 21 | 40 | 38.2 | 10.4 | 3.9 | -11 | 29.1 | 10.2 | 23.8 | 70.2 |
| | Return on equity (%) | 6.7 | 25.01 | 24 | 22.9 | 11.8 | 4 | 5.6 | 7.8 | -5.5 | -50 |
| | Return on asset (%) | 3.4 | 8 | 6.5 | 2.8 | 2.4 | 0.8 | 0.6 | 0.8 | -1.6 | -10 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sakht Ajand | Current | 2.321 | 2.807 | 2.012 | 1.583 | 1.248 | 1.143 | 2.283 | 0.335 | 0.731 | 1.668 |
| | Times interest earned | 108.9 | 77.2 | -16.3 | 11.7 | -30.7 | -34.4 | -2.66 | 137.9 | 6838.8 | 2370.6 |
| | Debt (%) | 39.8 | 32.1 | 45 | 56.4 | 72 | 83.4 | 40.5 | 78 | 64.1 | 59.9 |
| | Net profit margin (%) | 41.2 | 47.8 | 44.7 | 33.1 | 22.8 | 22.1 | 63.1 | 65.4 | 64.6 | 47.1 |
| | Return on equity (%) | 8.1 | 21.4 | -14.4 | 13.7 | 11.8 | 28.9 | 55 | 23.6 | 16.5 | 17.4 |
| | Return on asset (%) | 4.9 | 14.5 | -7.9 | -9.8 | -19 | 4.8 | 32.8 | 5.2 | 5.9 | 7 |

| Company Name | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Housing Investment Group | Current | 1.979 | 2.131 | 2.419 | 1.821 | 1.904 | 2.45 | 11.842 | 4.239 | 6.2 | 3.321 |
| | Times interest earned | 1087.9 | 0 | 0 | 1 | 1 | 0 | 1223.1 | 1743.1 | 1752 | 1178.4 |
| | Debt (%) | 51.6 | 43.1 | 37.6 | 39 | 32.3 | 25.7 | 9.4 | 18.1 | 7.2 | 11.4 |
| | Net profit margin (%) | 76 | 54 | 32 | 0 | 0 | 0 | 0 | 96 | 87 | 72 |
| | Return on equity (%) | 24.6 | 30.3 | 21.2 | 20.5 | 22.5 | 25.1 | 24 | 24.3 | 19.5 | 6.6 |
| | Return on asset (%) | 11.9 | 17.2 | 13.2 | 12.4 | 15.2 | 18.7 | 21.8 | 19.9 | 18.1 | 5.9 |

| | Financial Ratio | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Industry | Current | 2.793 | 2.427 | 2.014 | 1.821 | 1.895 | 2.056 | 3.493 | 2.391 | 2.396 | 2.008 |
| | Times interest earned | 3152.4 | 672.1 | 1272.8 | 666.4 | 1905.9 | 2823.3 | 4040.8 | 1359.2 | 2975 | 10896.2 |
| | Debt (%) | 37.3 | 37.9 | 44.4 | 48.1 | 48 | 46.1 | 43.2 | 44.5 | 40.7 | 45.1 |
| | Net profit margin (%) | 45.2 | 30.4 | 29.7 | 26.5 | 24.3 | 19.9 | 31.8 | 36.5 | 32.3 | 20.4 |
| | Return on equity (%) | 25 | 20.7 | 20.5 | 22.9 | 17.6 | 21.1 | 23.5 | 22.2 | 11.9 | 5.5 |
| | Return on asset (%) | 15.4 | 12.9 | 10.9 | 11.5 | 9.2 | 10 | 12.9 | 11.4 | 7.1 | 3.7 |