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A MCDM-based Approach Using UTA-STAR Method to Discover Behavioral Aspects in Stock Selection Problem

Zahra Touni, Ahmad Makui & Emran Mohammadi*

Zahra Touni, *Department of Industrial Engineering, Iran University of Science & Technology, Tehran, Iran*
Ahmad Makui*, *Department of Industrial Engineering, Iran University of Science & Technology, Tehran, Iran*
Emran Mohammadi, *Department of Industrial Engineering, Iran University of Science & Technology, Tehran, Iran*

KEYWORDS

UTA-Star method;
Multiple criteria decision aiding (MCDA);
Utility functions;
Stock selection.

ABSTRACT

Financial decision-making is a principal part of any decisions; hence, great efforts are made to improve the methods to assess and analyze the stocks in financial markets as an important part of the financial decisions. This paper addresses the stock selection by discovering the investor's utility function. Investors in the Stock Exchange consider diverse criteria to buy securities and bonds. Due to the criteria development in stock selection, understanding the investor's behavior by a consultant is a prominent issue. Recognizing an exclusive utility function, according to the characteristics of the investors, facilitates acquiring each share's value for the decision-maker (DM). In this study, UTASTAR method is used to estimate the marginal value function by using 3 appropriate criteria (risk, return, and liquidity) and, finally, fit the total utility function. It provides an opportunity to make a rational decision adjustable to the investor's mentality that considers their ranking, prioritization, selection, or classification. The ranking of the options is as compatible as possible to the original one. The method is applied to an example from Iran Stock Exchange.

1. Introduction

Financial decision-making is involved in a plethora of important issues for individual and institutional investors, managers of firms and organizations, as well as policy makers (Zopounidis & Doumpos, 2013). Financial markets play an important role in modern society related to the economic and social organization. Financial activities exert an influence over the economic developments of several countries worldwide (Lin, Chiu & Lin, 2012). Information authenticity to support the decision-making and how fast one is able to make decisions are two key factors for success in these competitive markets. By and large, there are two conventional approaches to analyzing and predicting financial market behaviors: (i) the fundamental analysis and (ii) the technical analysis. The former approach that harmonizes with long-term predictions is connected to economic factors. On the other hand, technicians believe that all the changes and fundamental criteria are shown in the price fluctuations. That is why the technicians usually use time series to model the historical behavior of an asset, believing that history tends to repeat itself (Murphy, 1999). Many researchers study price patterns to predict the future prices of instruments (stocks, futures, options, etc.) based on historical data to deal with stock selection problem, while there is a conflict between scientists. Before the 1980s, most researchers were doubtful about the ability to predict prices

* Corresponding author: *Emran Mohammadi*
Email: e_mohammadi@iust.ac.ir
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and preferred the buy-hold strategy (Alexander, 1961; Fama, 1970; Jensen & Benington, 1970). However, later studies illustrate just the opposite (Bessembinder & Chan, 1998; Brock, Lakonishok, & LeBaron, 1992; Lo, Mamaysky, & Wang, 2000). Technical analysis goes through historical prices to forecast future stock prices; it is based on the premise that history repeats itself and all information is reflected in stock prices. Two major classes of work that are trying to predict financial time series include the statistical models and machine learning approaches (J.-Z. Wang, Wang, Zhang & Guo, 2011). Generating data in a linear process is assumed in the case of traditional statistical methods. However, financial time series are complex, dynamic and nonlinear in nature (Si & Yin, 2013). Artificial neural networks (ANN) as a machine-learning technique have been widely used in forecasting time series and achieving relative success in modeling and predicting financial time series. The popularity of these methods is for the ability to capture nonlinear behaviors of time series without any statistical assumptions about the data (Lu, Lee, & Chiu, 2009; Tay & Cao, 2001). Investigating price patterns, such as charts formations and candlestick patterns, could be advantageous, too. Lee & Jo, 1999 presented an expert system for foretelling stock market timing using candlestick charts. In contrast, in their paper, Marshall, Young & Rose, 2006 found that candlestick technical analysis was of no worthiness on U.S. Dow Jones Industrial Average stocks during 1992–2002. Book-to-market equity (B/M) or earnings-to-price (E/P) ratios are usually two favorable factors of financial researchers that categorize stocks with the high amount of them (Fama & French, 1998). A study involving the combination of fundamental and technical variables in the ANN model was carried out by Lam (2004) to forecast how a financial asset performs. Price forecasting lends considerable assistance in such decisions, and there is a wide range of studies on this particular issue. Some recent works are as follows. Using a stock selection algorithm, Goumatianos, Christou & Lindgren (2013) proposed the architecture of a whole intraday trading management system for building long or short portfolios. Barak, Dahooie & Tichý (2015) presented a model in the estimation function via neuro-fuzzy models. The definition of fuzzy time series (FTS) was proposed by Song & Chissom (1993, 1994), when they intended to predict the University of Alabama's number of enrollments. Since then, FTS has been considered as a subject in forecasting, especially when dealing with imprecise and unidentifiable data trend. For instance, shipping index (Duru, 2010), pollution (Domańska & Wojtylak, 2012), rice production (Singh, 2007), electricity load demand (Efendi, Ismail, & Deris, 2015; J. Wang, Liu, Song, & Zhao, 2016), and stock exchange (Huarng, Yu, & Hsu, 2007; Wei, 2016) are merely few examples to present. The work presented by Chourmouziadis & Chatzoglou (2016) proposed a fuzzy system for portfolio management by accentuating an intelligent short-term stock trading in which a combination of soft computing techniques and technical indicators for asset selection is used. Many studies have been conducted on financial markets. A bunch of these studies examines the relationship between financial variables. In a recent study (Ebrahimi, Abdollahi & Farmani, 2016), the inter-relationship between a firm's profitability and growth inthe Iranian manufacturing industry consisting of Tehran Stock Market was investigated. Most studies attempt to consider real-world constraints in financial optimization models. Transaction cost is one of these constraints. Seyedhosseini et al. presented a multi-period portfolio selection model where the rates of borrowing are greater than the lending rates, and transaction costs are considered as an important constraint for portfolio manager (Sadjadi, Seyedhosseini & Hassanlou, 2010). In addition, portfolio selection includes several criteria. Risk and profit are the most popular criteria, and various methods have been introduced to the literature to calculate these two criteria. In one of the recent works, DCC-Copula-GARCH model was hired that considered the dynamic correlation structure of assets for calculating Value at Risk (Ebrahimi & Emadi, 2016). Due to the nature of decision-making that always involves various factors, multi-criteria decision methods present effective contributions in this context, backing up financial DMs in modeling, analyzing, and evaluating, under all decision criteria relating to a special decision instance. In recent decades, MCDA has improved and is becoming a significant issue in the science relating to management and operation research. In order to facilitate decision-making in ill-structured problems that include conflicting multiple criteria, goals, objectives, and points of view, the field of MCDA is devoted to the development and implementation of decision support tools and methodologies. Financial decisions as other decisions vary among different persons, and it can be claimed that it is a unique decision. Offering all the financial market investors a group of special stocks does not strike them as an interesting investment. Using a mechanism that can offer investors some suitable stock by considering how much risk they can stand against asset price fluctuations is a significant issue. To assess the value (utility) of diverse options, according to the DM's preferences, there are several multi-criteria decision-making (MCDM) methods that use the concept of utility. There are many different methods of multi-criteria analysis, which can be recommended based on the circumstances of decision-making. Utility theory has played a central role in the field of decision analysis, since its principles are expressed by von Neumann and Morgenstern 1944 (Von Neumann & Morgenstern, 2007). Utility functions can be applied to transform raw performance values of the alternatives against diverse criteria, both factual (objective, quantitative) and judgmental (subjective, qualitative), to a common, dimensionless scale. Utilities are used to convert the raw performance values so that a more preferred performance obtains a higher utility value. The UTA method initially proposed by Jacquet-Lagrèze & Siskos (1978, 1982) has several interesting features. UTA is a well-known method for inferring additive utility functions from a set of representative, past decision data. The initial UTA algorithm has been improved and extended for various applications resulting in a family of UTA methods. Over the past two decades, UTA-based methods have been applied to several real-world decision-making problems from the fields of financial management, marketing, environmental management, and human resources management. For a survey on UTA history, principles, and variants, see Siskos, Grigoroudis & Matsatsinis (2005). UTA methodology uses linear programming techniques in order to optimally infer additive value/utility functions so that these functions are as consistent as possible with the global decision-maker’s preferences. The utility function can subsequently be used to estimate the utilities of the options that are not included in the reference set based on the given scores. Utilities can then be used to rank the alternative options from the best to the worst, or pick the top-K most efficient alternative, or classify options into groups of similar utility (value), thus reducing the cognitive effort of DM. This study applies UTASTAR method, which is an improved version of the original UTA model. UTA methods are regression-based approaches that have been developed as an alternative to multi-attribute utility theory (MAUT) and to adopt the aggregation-disaggregation principles, which are more compatible with stock selection problem. Disaggregation-aggregation approach decomposes the decision problem in two phases. In the disaggregation phase, a preference model is constructed from the DMs’ judgments on a small set of reference candidate locations. The aggregation phase, based on the information induced from the disaggregation phase, constructs value or utility functions (Demesouka, Vavatsikos, & Anagnostopoulos, 2013). For stock valuation and selection, the first step is identifying appropriate indicators and criteria. Risk and Expected return are two necessary and important factors for selecting a stock. Many studies carried out the stock selection attempt to develop price forecasting methods on the basis of fundamental criteria or technical assess. There are a few pieces of research that are done on extracting DM's utility functions in financial application, especially in stock Exchange. In the next part, the UTASTAR method is reviewed; then, a numerical example is proposed to clarify the use of this method in financial issues. Finally, at the end of the article, the conclusion is expressed.

2. UTASTAR Method

The UTA method (Jacquet-Lagrèze & Siskos, 1982) intends to assess decision models from a priori known decision or preference data in the form of ranked lists of options. This approach is called preference disaggregation in the literature. We commence the process by explaining and modeling the decision problem into a set of criteria with non-decreasing, exhaustive and non-redundant utility functions. It proceeds with inferring one global and several partial additive utility functions from a given ranking of the reference set options by using special linear programming techniques (Patiniotakis, Apostolou, & Mentzas, 2011).

2-1. Concepts, assumptions, definitions, and notations

The main concepts, assumptions, definitions, and notations used in UTA literature are presented in the following:

* The set of criteria is denoted as (Fama, 1970gN), where N is the number of criteria.

* The reference set is denoted as AR and a ∈ AR is a single option in A_R.

* The evaluation (score) scale of the i^{th} criterion is [g_{i*}, g^*_i], where g_{i*} is the worst score and g^*_i is the best score on the scale.
* The utility function for the i^{th} criterion is denoted as u_i, and the global utility function is denoted as U. The criteria utility functions are usually referred to as marginal utility functions in the literature.

$$u_i : [g_{i*}, g_i^*] \to [0,1] \tag{1}$$

* The global utility function is assumed to be an additive function with the following form

$$u\left[\bar{g}(\alpha)\right] = \sum_{i=1}^{N} u_i\left[g_i(\alpha)\right] \tag{2}$$

subject to the following constraints:

$$\begin{cases} \sum_{i=1}^{N} u_i\left[g_i^*\right] = 1, \\ u_i\left[g_{i*}\right] = 0, \forall i = 1,2,\ldots,N . \end{cases} \tag{3}$$

* Each marginal utility function is assumed to be continuous and piecewise linear, meaning that it is comprised of linear segments linking each segment to the next one (Fig. 1). Furthermore, the evaluation scale [g_{i*}; g^*_i] of the i^{th} criterion is assumed to be divided into (ai -1) equal intervals. The endpoints of intervals are denoted as gij for the i^{th} criterion and the j^{th} interval and are given from the following formula:

$$g_i^j = g_{i*} + \frac{j-1}{a_i - 1}\left[g_i^* - g_{i*}\right], \forall i = 1,2,\ldots,N. \tag{4}$$

$\forall \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{N}$

* In UTASTAR, the global utility of an option α is approximated with

$$u'\left[g(\alpha)\right] = \sum_{i=1}^{N} u_i\left[g_i(\alpha)\right] - \sigma^+(\alpha) + \sigma^-(\alpha), \tag{5}$$

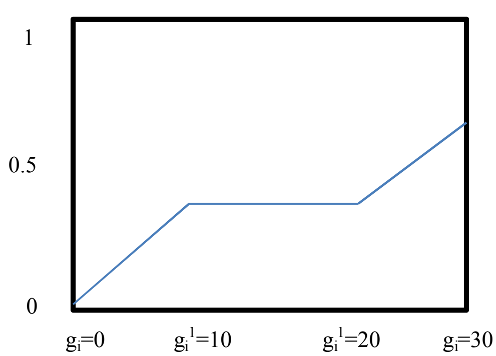

Fig.1. Example of the piecewise linear utility function.

where $\sigma^+(\alpha)$ and $\sigma^-(\alpha)$ are the overestimation and underestimation errors, respectively. An example of the piecewise linear utility function is presented in Fig.1.
* Suppose that reference set options are ordered from the most preferred to the least preferred, i.e., α_1 is the best option and α_m is the worst. The utility differences of two successive options are defined as follows:

$$\Delta(\alpha_k, \alpha_{k+1}) = u'\left[g(a_k)\right] - u'\left[g(a_{k+1})\right], \forall k = 1,2,\ldots,m. \tag{6}$$

* Eventually, the utility differences of successive interval endpoints are defined as follows:

$$w_{ij} = u\left[g_i^{j+1}\right] - u\left[g_i^j\right] \geq 0, \forall i = 1,2,\ldots,N \text{ and } \forall j = 1,2,\ldots,a_i \text{ (7)}1.$$

$\forall \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{N}$ ***and*** $\forall \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{a_i} - \mathbf{1}$

By definition, it holds

$$\begin{cases} u_i(g_i^1) = 0 \quad \forall i = 1,2,\ldots,N, \\ u_i(g_i^j) = \sum_{i=1}^{j-1} w_{ij} \quad \forall i = 1,2,\ldots,N \text{ and } j = 2,3,\ldots,a_i - 1 \end{cases} \tag{8}$$

2-2. UTASTAR algorithm

The UTASTAR algorithm (Siskos & Yannacopoulos, 1985) is an improvement of the original UTA method. Next, the steps of the algorithm are presented.
Step 1. Reorder the reference set options from the best to the worst, i.e., $\alpha_1 > \alpha_2 > \ldots > \alpha_m$. It is acceptable for some consecutive options to be equivalent, meaning that $a_k \sim a_{k+1}$ (indifference); however, too many of such cases can deteriorate the quality of the results.
Step 2. Express the global utilities of the options first in terms of marginal utilities and, then, as functions of w_{ij}., i.e.,

$$u_i\left[g_i(\alpha)\right] = \sum_{k=1}^{q-1} w_{ik} + \frac{g_i(\alpha) - g_i^j}{g_i^{j+1} - g_i^j} w_{iq}, \quad \forall i = 1,2,\ldots,N \tag{9}$$

Step 3. Introduce the utility differences $\Delta(\alpha_k, \alpha_{k+1})$ for each pair of consecutive options and their errors $\sigma^+(\alpha)$ and $\sigma^-(\alpha)$:

$$\Delta(\alpha_k, \alpha_{k+1}) = u'\left[g(a_k)\right] - u'\left[g(a_{k+1})\right] = \tag{10}$$

$$\alpha_k)\big]-u'\big[g(a_{k+1})\big]=u\big[g(a_k)\big]-\sigma^+(\alpha_k)+\sigma^-(\alpha_k)-u\big[g(a_{k+1})\big]+\sigma^+(\alpha_{k+1})-\sigma^-(\alpha_{k+1})$$

Step 4. For solving the LP problem, use the well-known SIMPLEX (Dantzig & Cottle, 1963) method:

$$\begin{cases} [\min] z = \sum_{k=1}^{m}\left(\sigma^+(a_k)+\sigma^-(a_k)\right) \\ \text{subject to} \\ \left.\begin{array}{l}\Delta(\alpha_k,\alpha_{k+1}) \ge \delta \quad \text{if } \alpha_k \succ \alpha_{k+1} \\ \Delta(\alpha_k,\alpha_{k+1}) = 0 \quad \text{if } \alpha_k \sim \alpha_{k+1}\end{array}\right\} \forall \text{k} \\ \text{u}_i(\text{g}_i^{j+1}) - \text{u}_i(\text{g}_i^{j}) \ge 0 \ \forall \text{i and j} \\ \sum_{i=1}^{N}\sum_{j=1}^{a_i-1} w_{ij} = 1 \\ w_{ij} \ge 0,\ \sigma^+(\text{a}_k) \ge 0,\ \sigma^-(\text{a}_k) \ge 0,\ \forall \text{i,j and k} \end{cases} \tag{11}$$

Step 5. Test the existence of multiple or near-optimal solutions (stability analysis). If more than one optimal solution is found, then the mean optimal utility function is chosen. The stability analysis involves checking the optimal solutions that maximize

$$u_i\left[g_i^*\right] = \sum_{k=1}^{a_i-1} w_{ik},\quad \forall \text{i=1,2,...,N} \tag{12}$$

with an extra constraint of

$$\sum_{k=1}^{m}\left[\sigma^+(\alpha_k)+\sigma^-(\alpha_k)\right] \le z^* + \varepsilon, \tag{13}$$

where z* is the optimal value of LP problem of Step 4, and e > 0 is a small positive number. For more information on UTASTAR and UTA family of methods, see Siskos & Grigoroudis (2010), Siskos et al. (2005).

3. A Numerical Example

An example of Iran Stock Exchange is adopted to illustrate the proposed method. This study considers some of the stocks from Iran Stock Exchange in the last year to generalize the acquired utility to other stocks. Some of the stocks are deleted because of data scarcity. Finally, 114 stocks are assessed with 3 criteria Beta, Return, and Liquidity. Risk is very challenging and inherently a probabilistic or statistical concept. There are various and, sometimes conflicting, notions and measures of risk. Beta is a measure of the volatility, or systematic risk of a security or a portfolio in comparison to the market as a whole. Beta is used in the capital asset pricing model (CAPM), which calculates the expected return of an asset based on its beta and expected market returns. Beta is calculated by

$$\frac{\text{cov}(r_i, r_{market})}{\sigma^2_{market}} \tag{14}$$

The more transferring of the shares, the more liquidity we have, as illustrated by the number of +. Liquidity risk is the risk that a company or a bank may be unable to meet short-term financial demands. This usually occurs due to the inability to convert security or hard asset to cash without the loss of capital and/or income in the process. The amount of stock Return is the average amount of stock return over the last year. The preference order of the DM is shown at column ranking, where 1 is the most preferred alternative. Of note, ties are allowed, yet not favored since several ties can deteriorate the quality of the results.

For each of the criteria, some breakpoints are considered, and the utility of the other points is determined by the linear interpolation method. Finally, the utility of each stock is written according to the proportion of breakpoints utility. It is clear that the utility of the first point is zero. The first two criteria (Return, Beta) include objective measurements, whereas the third one (Liquidity) includes subjective evaluations. Of note, the utility of Beta increase (s) as its value decreases (i.e. the less the better), whereas return and liquidity utilities increase as their value increases or more '+' is given (i.e., the more, the better). Table 1 illustrates some of the data that are needed for applying the UTA method. The following ranking is done by an expert investor (Tab.1):

Tab. 1. Raw data and DM ranking

Stock	Liquidity	Beta	Return	DM Ranking
Mobin	12+	0.01024	24.0646	1
Shkharak	1+	0.00026	62.1609	2
Kroy	4+	0.02004	24.1212	3
Hsina	1+	-0.27064	23.2374	4
Khmehr	2+	0.00476	0.0327	5
Dsina	1+	0.11461	33.8748	6

The alternatives are reordered from the most preferred to the least preferred. To start the UTASTAR, as the primarily stage presented in the preceding part, the utilities of the six alternatives are defined. Therefore, the following scales have been selected:

$[G_{1*},g_1^*]$ = [0.0327, 15.56475, 31.0968, 46.62885, 62.1609]
$[G_{2*},g_2^*]$ =[0.11461, 0.018298, -0.07802, -0.17433, -0.27064]
$[G_{3*},g_3^*]$=[1+,4+,7+,10+,12+]

By operating the linear interpolation for the criterion according to the formula for the marginal value of an option, the utility of each stock may be explicated as:

$$
\begin{aligned}
&U(mobin)=0.45U_1(15.56475)+0.54U_1(31.0968)+0.91U_2(0.018298)+0.09U_2(-0.07802)+U_3(12+)\\
&U(shkhark)=U_1(62.1609)+0.81\,U_2(0.018298)+0.19U_2(-0.07802)+U_3(1+)\\
&U(kroy)=0.44U_1(15.56475)+0.56\,U_1(31.0968)+0.02\,U_2(0.11461)+0.98\,U_2(0.018298)+U_3(4+)\\
&U(hsina)=0.5U_1(15.56475)+0.5U_1(31.0968)+U_2(-0.27064)+U_3(1+)\\
&U(khmehr)=U_1(0.0327)+0.86\,U_2(0.018298)+0.14U_2(-0.07802)+0.67U_3(1+)+0.33\,U_3(4+)\\
&U(dsina)=0.82\,U_1(31.0968)+0.18\,U_1(46.62885)+U_2(0.11461)+U_3(1+)
\end{aligned}
\tag{15}
$$

where the following normalization conditions for the marginal value functions have been used: $U_1(0.0327)= U_2(0.11461)= U_3(1+)=0$; stock's total value may be indicated in terms of variables W_{ij}:

$$
\begin{aligned}
&U(mobin)=w_{11}+0.54w_{12}+w_{21+}0.09w_{22}+w_{31}+w_{32}+w_{33}+w_{34}\\
&U(shkhark)=w_{11}+w_{12}+w_{13}+w_{14}+w_{21}+0.19w_{22}\\
&U(kroy)=w_{11}+0.56w_{12}+0.98w_{21}+w_{31}\\
&U(hsina)=w_{11}+0.5w_{12}+w_{21}+w_{22}+w_{23}+w_{24}\\
&U(khmehr)=w_{21}+0.14\,w_{22}+0.33\,w_{31}\\
&U(dsina)=w_{11}+w_{12}+0.18w_{13}
\end{aligned}
\tag{16}
$$

To apply the UTA model (step 4), it is necessary to write utility difference for each pair of sequential actions in the ranking process to be considered in the linear model as a constraint.

The UTA model (step 4) results in: $z^*=0 \Leftrightarrow \sigma^+(a_k)=\sigma^-(a_k)=0\ \forall k$. For this reason, another model formulated as in the following is used, which maximizes the utility of each criterion. Table 2 presents the formulation of the LP that needs be solved in the second step.

Tab. 2. Linear programming formulation

W11	W12	W13	W14	W21	W22	W23	W24	W31	W32	W33	W34	RHS
0	-0.46	-1	-1	0	-0.1	0	0	1	1	1	1	>0.05
0	0.44	1	1	0.02	0.19	0	0	-1	0	0	0	>0.05
0	0.06	0	0	-0.02	-1	-1	-1	1	0	0	0	>0.05
1	0.5	0	0	0	0.86	1	1	-0.33	0	0	0	>0.05
-1	-1	-0.18	0	1	0.14	0	0	0.33	0	0	0	>0.05
1	1	1	1	1	1	1	1	1	1	1	1	=1
1	1	1	1	0	0	0	0	0	0	0	0	[Max]$u_1(g_1^*)$
0	0	0	0	1	1	1	1	0	0	0	0	[Max]$u_2(g_2^*)$
0	0	0	0	0	0	0	0	1	1	1	1	[Max]$u_3(g_3^*)$

By computing the average of these three solutions, the utilities for each alternative are calculated as follows:

U(mobin)=0.90, U(shkhark)=0.48, U(kroy)=0.43, U(hsina)=0.38, U(dsina)=0.33,U(khmehr)=0.09,

It is completely compatible with the primary DM's ranking.

The application of this method to the stock selection problem helps one understand the DM's behavior towards changes that occur in the various ranges of criteria. It is vital for a consultant to know how much risk an individual can experience. After reconditioning DM's characteristics, proportionate stocks favorable to DM's personality are presented. The marginal value function is illustrated in the table 3.

Tab. 3. Final solution

Return	Beta	Liquidity
$U_1(0.0327)=0$	$U_2(0.11461)=0$	$U_3(1+)=0$
$U_1(15.56475)=0.04467$	$U_2(0.018298)=0.31367$	$U_3(4+)=0.054$
$U_1(31.0968)=0.09034$	$U_2(-0.07802)= 0.31367$	$U_3(7+)=0.054$
$U_1(46.62885)= 0.09034$	$U_2(-0.17433)= 0.31367$	$U_3(9+)=0.054$
$U_1(62.1609)=0.16764$	$U_2(-0.27064)= 0.31367$	$U_3(12+)=0.519$

By using curve fitting for extracting criteria's utility function related to investor's behavior obtained from the breakpoints assistances to reach the total utility function, the investor is intensively risk averse against liquidity (Fig.2) and risk-seeker against Beta (Fig.3). However, the reaction of the investor to return profit was variable (Fig.4). Companies with high liquidity and low risk from the viewpoint of an investor are more reliable.

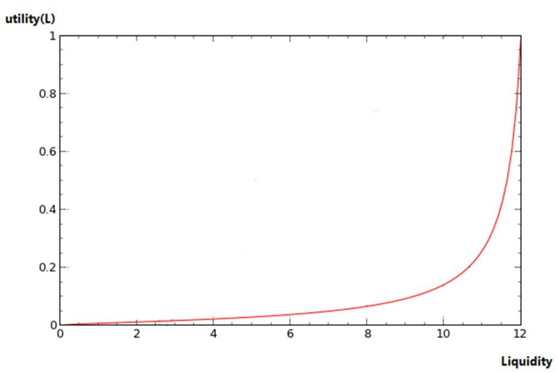

Fig.2. Illustrate DM's Liquidity utility

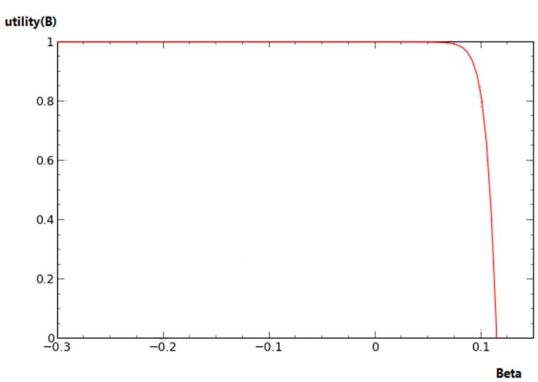

Fig.3. Illustrate DM's Risk utility (Beta)

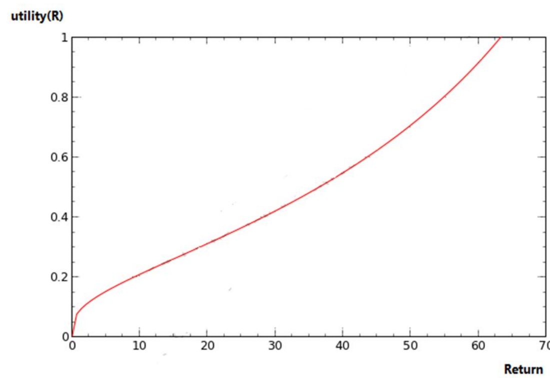

Fig. 4. Illustrate DM's Return utility

The related utility functions for the investor is as follows:

$$\text{Utility(R)} = 1/(-8.52+20.14R^{-0.18})$$
$$\text{Utility(B)} = -3.19+(4.19/e^{-16.22+131.4B}) \quad (17)$$
$$\text{Utility(L)} = 1/(-93.5+219.76L)$$

A general utility function for the investor is determined as follows:

$$\text{Total utility} = 1/(-8.52+20.14R^{-0.18}) -3.19+ (4.19/e^{-16.22+131.4B})+ 1/(-93.5+219.76L) \quad (18)$$

4. Case Study

This research is trying to consider the stock selection problem as a challenging issue. Something that makes the stock selection issue challenging is the difference between the preferences of the investors and their financial behaviors. As a case study for identifying investor's utility, the known UTASTAR method has been used for 113 members of Iran Stock Exchange to understand DM's behavior related to financial issues as a multi-criteria decision problem.

By applying total utility function, companies in the Stock Exchange can be ranked according to DM's characteristics. Table 4 presents the top ten stocks more favorable to investor and defines the place of six companies ranked by the DM. Forming a suitable portfolio involving DM's preferable shares and considering the limitation besides his/her demands can develop investor's satisfaction. According to the conventional theory of finance, maximizing return with minimum risk should be a milestone of every rational investor. However, the existence of other variables is more realistic. Moreover, behavioral aspects, such as the investor's attitude towards solvency or liquidity, are not taken into consideration. The problem of selecting an attractive portfolio is a multi-criteria issue, which should be tackled by an appropriate technique. The chosen method could well identify the investor's preferences. The utility of companies was determined precisely in accordance with the initial ranking of the investor from 6 companies that were given to him in the sample. By the correct identification of the investor's rankings, the validity of this method is proved. The investor ranked the sample companies from one to six. The UTASTAR was able to find the utility function of the investor so that none of his rankings would change. Since the results are visible, by approximating the utility functions, the position of initial companies did not change; it can be seen that other companies are ranked according to their criteria values.

Tab. 4. The place of some stocks according to DM's leaning

symbol	liquidity	beta	R	u(l)	u(beta)	u(return)	u(total)	rank
Mobin	12+	0.01024	24.0646	0.996813	0.999999	0.35511545	2.351927	1
Khzamia	12+	-0.00245	1.648	0.996813	1	0.10119638	2.098009	2
Shkhark	1+	0.00026	62.1609	0.00792	1	0.97117389	1.979093	3
Zmagsa	1+	-0.16264	54.573	0.00792	1	0.79555111	1.803471	4
Shormoz	1+	-0.00665	52.509	0.00792	1	0.75452336	1.762443	5
Etela	2+	0.00002	50.1541	0.012474	1	0.71057714	1.72305	6
Shamla	1+	0.01318	49.9129	0.00792	0.999998	0.70623564	1.714153	7
Vghadir	6+	-0.00662	44.153	0.038334	1	0.61029237	1.648626	8
Khodkafa	1+	-0.00945	44.1321	0.00792	1	0.60996883	1.617889	9
Kgol	10+	0.00926	31.2819	0.142049	0.999999	0.43644338	1.578491	10
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Kroy	4+	0.02004	24.1212	0.022861	0.999995	0.35572319	1.378579	37
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Hsina	1+	-0.27064	23.2374	0.00792	1	0.34627712	1.354197	42
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Khmehr	2+	0.00476	0.0327	0.012474	0.999999	0.03466788	1.047141	112
Dsina	1+	0.11461	33.8748	0.00792	8.38E-07	0.46798943	0.47591	113

The total utility function computes the amount of all of the stock's utilities involved in the Stock Exchange, according to the criteria. By considering the UTASTAR method for quantifying investor's utility, an effortless comparison can be made. Table 4 arranges the position of the top ten companies and the six primarily ones ranked by the DM who intensively endeavors to accept risky stocks, unlike being quite risk averse of liquidity and approximately neutral (low degree of risk aversion) in terms of stock's profitability. According to Figs. 2,3,4, the investor is strict against the liquidity; only a stock with the high volume of sales can convince him/her. However, to face beta, which is a representative of stock's risk, is so courageous; in addition, the amount of utility to encountering return increases gradually. It is determined that DM's preferable stocks have a place in two categories: 1. Stocks containing the high level of liquidity and normal profit simultaneously; 2. Companies with a great deal of return besides less than average turnover. In both groups, the investor is risk-loving. It is not fair to consider ranking as the main purpose of applying the UTASTAR method, while MCDM has a considerable reputation for including a variety of ranking methods such as SAW, AHP, TOPSIS, VIKOR, DEA, TAXONOMY, etc., which can sort alternatives through different criteria; conflict in results is very common. Significant differences result in uncertainty and vagueness of DM or a consultant intending to clarify investor's preferable shares. This ranking approach is different from other similar approaches in terms of its ability to extract, lean, and rank the alternatives.

5. Conclusion

This paper used the known UTASTAR method to understand the DM's behavior towards financial issues such as a multi-criteria decision problem. Multi-criteria decision-making had different tools to solve problems with different criteria. However, the application of these methods for MCDA makes it more effective to extract preferences and mentality of the individual person so as to offer him a less risky option with a certain outcome or consult on a risky stock with a huge amount of return. For applying the UTASTAR method, a sample of six shares in Iran Stock Exchange was considered and ranked by an expert with 3 evaluation criteria. Utility function was employed to find behavioral aspects and preferences of DM in the position of a company manager, individual, or institutional investors. Modeling, analyzing, and evaluating multiple financial problems could be done with a great degree of accuracy. Stock selection is a prerequisite action of portfolio selection, which can be done to reduce the size of the problem and ensure purposeful portfolio optimization.

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