FUZZY GOAL PROGRAMMING APPROACH TO DECISION MAKING: CASE OF MOLDOVA STOCK EXCHANGE

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SUMMARY
This paper is focused on the problem and practical application of fuzzy mathematical programming to investment decision making process. Fuzzy logic uses vaguely characterized expert knowledge and allows the inclusion of subjective or intuitive characteristics of the expert in select models. Fuzzy logic is applied to investment instrument listed on the Moldova stock market. The fuzzy model contains two input variables and one output variable that determines whether the investment in a particular instrument is appropriate.

Keywords: fuzzy logic, fuzzy mathematical programming, investment instrument, stock market.

Introduction. In the past few decades, most stock market analyzes have been derived using statistical time series models, but these models, as Kashpruk [2016] points out, are not suitable for researching nonlinear data. In addition, the stock market is a complex and dynamic system. To solve this problem, artificial intelligence models have been proposed, including artificial neural networks, genetic algorithms, and fuzzy logic. And the latter makes it possible to examine the imperfect knowledge of asset returns and the uncertainty associated with the behaviour of financial markets.

Fuzzy models are tolerant of inaccuracy, uncertainty and approximation. As a result, fuzzy logic has become popular among the academic community. Fuzzy logic allows you to cover inaccuracies and work with the meanings of natural language words in a relatively simple way. The reason why fuzzy logic works is quite surprising, because it uses vaguely characterized expert knowledge. It is the relationship between relevance and accuracy of information, the principle that the main representative of fuzzy logic Lotfi A. Zadeh [1978] called the principle of incompatibility. The potential of fuzzy logic to improve forecasting models can be found in various applications due to its known ability to bridge the gap between numerical data (quantitative information) and language expression (qualitative information).

As reported by Grupta et al. [2008] investment decisions need to be made with limited information because people do not have sufficient knowledge of the issue and generally cannot even determine the reasonable probability of alternative outcomes, so they must make decisions under uncertainty conditions. As Sheen [2005] points out, investors mostly have information that is characterized by language descriptions such as high risk, low profits, high interest rates, etc. Dostál [2018] states that the values of stock prices, commodities, currency rates, etc. are influenced by complex economic and psychological phenomena that contain
a high proportion of chaos. Artificial intelligence is the best that currently exists to process and evaluate economic and financial information and data. Similarly, Bao and Yang [2008] and Chang et al. [2011] add that it is reasonable to assume that because stock prices are influenced by deterministic and random factors, stock market forecasts can only be successful using tools and techniques that can overcome the problem of uncertainty, noise, and price non-linearity.

**Theoretical Background.** Watada [1997], in his paper, explores the vague targets for the expected return and risk to consider the problem of choosing a fuzzy portfolio. Carlsson et al. [2002] presented a possible approach to portfolio selection, provided that return of investment instrument are described by trapezoidal fuzzy numbers. Setnes and van Drempt [1999] examine the application of Takagi-Sugeno fuzzy models to the problem of stock market analysis. Different model structures are evaluated in a case study by modeling the Dutch Dutch AEX-price index. Simutis [2000] dealt with the analysis of a fuzzy expert system to support decision making with stock-based skills. Knowledge and stock data were formulated in terms of fuzzy variables and translated into a set of rules. Hiemstr [1994] concluded that fuzzy logic retains knowledge of stock market prediction and allows modelling of uncertainty and imperfect knowledge.

Dourra et al. [2002] use fuzzy information technology in their work through technical analysis. They simulate human behaviour in stock trading. The authors recommend fuzzy logic as a suitable method to solve the complexity of the stock market. Vercher et al. [2007] proposed two models of fuzzy portfolio selection, where they minimize the downside risk that is limited by the expected return. Othman and Schneider [2010] consider fuzzy logic to be easier and more beneficial for investors, based on a study conducted. Rao et al. [2017] argues that investment decisions based on a fuzzy model can be particularly useful for investors looking to minimize risk in solving their long-term investment portfolio. Brzeszczyński and Ibrahim [2019] design and evaluate a trading system that is conceptually close to fuzzy logic systems based on the «IF-THEN» rule. More specifically, it examines the extent to which foreign and domestic stock markets return signals of varying size and direction, helping to predict the performance of domestic capital markets. The reason for this is that if overnight foreign information is dependent on the direction and size of the domestic market’s return on the next day, then foreign signals of different strengths should be expected to have a different impact.

**Research Methods.** Process of fuzzy logic includes three basic steps: fuzzification, fuzzy inference and defuzzification:

**Fig. 1.** Process of fuzzy logic.

![Diagram showing the process of fuzzy logic: Fuzzification, Fuzzy inference, Defuzzification](Source: Dostál, 2015.)

Fuzzification inputs and outputs represents the three necessary steps. The first step is to transform the numeric variables into language variables. Each language variable represents a membership function for one input or output. The second step requires determining the number of membership functions. Choosing a low number of membership functions leads to fast convergence in near non-optimal solutions. Conversely, choosing a high number of membership functions leads to model overload. Some fuzzy modelling empirical studies such as Hachich et al. [2011] report that the number of membership functions usually ranges...
from three to five. The final fuzzification step is to select the form of inputs and outputs. Input membership functions are represented by trapezoidal membership functions, as in Carlsson et al. [2002]. The trapezoidal function is shown in Figure 2.

**Fig. 2.** Trapezoidal membership function.

![Trapezoidal membership function](image)


Fuzzy rules allow to derive knowledge of the system state according to the language variables obtained by the fuzzification. This knowledge also has a language qualification. Usually, fuzzy rules are derived from experience gained by experts. This information is translated into simple rules to be used in the fuzzy inference process. There are several forms of rules and several associated operators. Usually, a rule of type *<IF>, <THEN>* is used. The purpose is to study and analyze the impact of each variable on the dynamics of investment instrument prices.

The last step is defuzzification. Each function is considered if the relevant state has a positive degree of membership or truth. This stage is the result of various factors of membership of input fuzzy sets that deal with the rule condition. The final value of the output is calculated as a weighted average of all linear functions and is weighted by the degree of truth. The article uses the Sugeno model.

**Research results.**

**Financial Indicators.** The first problem of fuzzy modeling is to set the number of inputs and combinations between them. It is a common practice for different researchers to use many indicators and combine them in an effort to achieve good performance by having different ways of analyzing price movements. The model includes the revenue and risk of the companies under review.

Return provided by a given investment is a key stock investment indicator. Return can be understood as investor’s reward for the risk taken.

$$r = \frac{\text{market price}_t - \text{market price}_{t-1}}{\text{market price}_{t-1}}$$

Risk may be characterized as the possibility of the expected return deviating from the real return. It is a certain degree of uncertainty related to the expected return.

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T} (\bar{r}_{it} - \bar{r}_{it})^2}{T - 1}}$$
Examined Set. The Moldova Stock Exchange acts as a market indicator and provides a place where supply and demand clash. The result is the best price for buyers and sellers, with the transaction being securities. The Stock Exchange of Moldova (MSE) was established in 1994. The first transactions on the stock exchange took place on June 26, 1995. Stock titles were selected on the official MSE website to enter the fuzzy model. Monthly stock price rates for 2018-2016 are used. A sample of the correct data is shown in Table 1.


<table>
<thead>
<tr>
<th>Year</th>
<th>Script</th>
<th>Return</th>
<th>Risk</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>1</td>
<td>3.03%</td>
<td>26.39%</td>
<td>0.5</td>
</tr>
<tr>
<td>2017</td>
<td>1</td>
<td>21.06%</td>
<td>3.97%</td>
<td>1</td>
</tr>
<tr>
<td>2016</td>
<td>1</td>
<td>-2.91%</td>
<td>0.64%</td>
<td>0.25</td>
</tr>
<tr>
<td>2018</td>
<td>2</td>
<td>-10.00%</td>
<td>5.00%</td>
<td>0</td>
</tr>
<tr>
<td>2017</td>
<td>2</td>
<td>-12.50%</td>
<td>3.31%</td>
<td>0</td>
</tr>
<tr>
<td>2016</td>
<td>2</td>
<td>8.89%</td>
<td>9.44%</td>
<td>0.75</td>
</tr>
<tr>
<td>2018</td>
<td>3</td>
<td>41.82%</td>
<td>36.96%</td>
<td>1</td>
</tr>
<tr>
<td>2017</td>
<td>3</td>
<td>-24.65%</td>
<td>27.87%</td>
<td>0</td>
</tr>
<tr>
<td>2016</td>
<td>3</td>
<td>-0.61%</td>
<td>11.63%</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Source. MSE, 2018.

Proposed Model. The created fuzzy model for investment decision making on MSE contains two input variables and one output variable. The Sugeno type fuzzy model is used. The fuzzy inference structure generated is shown in Figure 3. Figure 4 shows a graphical representation of the FIS surface.

Fig. 3. Fuzzy inference system for model.

The return and risk of membership functions are shown in Figure 5 and Figure 6. Trapezoidal membership functions are used. The fuzzy inference model is divided into five fuzzy sets (very high, high, medium, low, very low).
In the proposed model with 2 inputs and 1 output, IF-THEN rules are used and their exemplary formulation is shown in Table 2. The ANFIS generated a total of 25 rules. The verbal interpretation of the rules is as follows: IF the return is very high and the risk is very low THEN it is recommended to invest in the investment instrument.
Tab. 2. Example of Fuzzy System Rules.

<table>
<thead>
<tr>
<th>Rule</th>
<th>IF (input1 is m1f1) and (input2 is m2f1) then (output is outf1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>IF (input1 is m1f1) and (input2 is m2f1) then (output is outf1)</td>
</tr>
<tr>
<td>2</td>
<td>IF (input1 is m1f2) and (input2 is m2f2) then (output is outf2)</td>
</tr>
<tr>
<td>3</td>
<td>IF (input1 is m1f3) and (input2 is m2f3) then (output is outf3)</td>
</tr>
<tr>
<td>4</td>
<td>IF (input1 is m1f4) and (input2 is m2f4) then (output is outf4)</td>
</tr>
<tr>
<td>5</td>
<td>IF (input1 is m1f5) and (input2 is m2f5) then (output is outf5)</td>
</tr>
<tr>
<td>6</td>
<td>IF (input1 is m1f6) and (input2 is m2f6) then (output is outf6)</td>
</tr>
<tr>
<td>7</td>
<td>IF (input1 is m1f7) and (input2 is m2f7) then (output is outf7)</td>
</tr>
<tr>
<td>8</td>
<td>IF (input1 is m1f8) and (input2 is m2f8) then (output is outf8)</td>
</tr>
<tr>
<td>9</td>
<td>IF (input1 is m1f9) and (input2 is m2f9) then (output is outf9)</td>
</tr>
<tr>
<td>10</td>
<td>IF (input1 is m1f10) and (input2 is m2f10) then (output is outf10)</td>
</tr>
<tr>
<td>11</td>
<td>IF (input1 is m1f11) and (input2 is m2f11) then (output is outf11)</td>
</tr>
<tr>
<td>12</td>
<td>IF (input1 is m1f12) and (input2 is m2f12) then (output is outf12)</td>
</tr>
</tbody>
</table>

Case study. The case study is represented by investment instrument with a return of 19.2%, a risk of 25.5%. The result of evaluating the decision-making process on investing in an investment instrument is 0.892, which is a value very close to 1 and therefore a recommendation for potential investors to buy an instrument in Moldova Stock Exchange. The recommendation to buy is mainly due to the high return, which is a key indicator for investors. The high return is accompanied by the corresponding risk.

Fig. 7. Fuzzy logic controller.

Conclusion. The paper focuses on the use of fuzzy mathematical programming as an effective tool for investment decisions. Fuzzy logic allows you to insert uncertainty into historical data, but also to include subjective or intuitive characteristics in portfolio selection models. The indisputable advantage of a fuzzy model is the fact that if an investor can create more fuzzy models not only with different values but also with different membership functions.

Because of the uncertainty of future investment instrument data boundaries and the associated inaccuracies, uncertainties, and decision-making preferences, fuzzy logic seems appropriate to address investment decision-making.

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BIBLIOGRAPHY