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# Stock Market Volatility Analysis using Fuzzy Logic: Fuzzy AHP and TOPSIS

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***Abstract*— Accurately measuring stock market volatility is essential for making well-informed decisions in the field of financial analysis. By combining fuzzy logic with the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), this study offers a novel method for analyzing stock market volatility. To deal with the inherent imprecision and uncertainty related to volatility assessments, fuzzy logic is used. Fuzzy membership functions, which quantify the degree of membership in preset categories like Low, Medium, and High, are used to represent each volatility level. Economic indicators, market trends, historical data, and other factors that affect stock market volatility are all methodically ranked and evaluated using the AHP technique. AHP offers a formal framework for evaluating the relative importance of these criteria by creating pairwise comparison matrices and determining priority weights. After that, stocks are ranked and chosen according to how well they perform in comparison to ideal and non-ideal solutions using the TOPSIS approach. With this approach, one may determine which stocks are most suitable and least ideal, as well as get a thorough evaluation of their volatility. This method takes into account the intricacies of financial markets while simultaneously improving the accuracy of volatility analysis by fusing fuzzy logic with AHP and TOPSIS. The suggested methodology provides analysts and investors with a strong tool that helps them control risk and make better stock market investments.**

***Index Terms*— Stock market, Fuzzy AHP, Fuzzy TOPSIS.**

## I. INTRODUCTION

In today's world, enhancing risk management systems has become a crucial concern for financial institutions. Risk management revolves around estimating and controlling the amount of risk within a limited risk buffer. Risk assets, including stocks, bonds, and loans, are exposed to unpredictable fluctuations that are not independent but rather correlated. Statistical methods such as Value-at-Risk (VaR) are used to measure the amount of risk associated with these assets. Financial institutions must set aside capital based on the estimated risk to compensate for potential losses.

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This allocation of the risk buffer and the control of the total risk amount become important issues due to the limited capital.

Portfolio theory offers a framework to address these issues. Value-at-Risk (VaR), a standard tool in risk management endorsed by BIS regulations, estimates the maximum expected loss over t days at a given confidence level c, implying a (1 – c) % chance of exceeding that loss. Common methods for calculating VaR include the variance-covariance and Monte Carlo approaches. The variance-covariance method (VC) estimates VaR assuming Gaussian distributed returns and relies on the variance- covariance matrix of assets. While it allows for intuitive analysis and easy risk calculation based on the portfolio theory, VC underestimates risk by ignoring volatility fluctuations and the resulting fat-tailed return distributions observed in actual markets. On the other hand, the Monte Carlo method (MC) evaluates VaR through a simulation based on a time series model such as the GARCH model. MC is flexible in terms of models but requires substantial computational resources and faces analytical challenges. Therefore, there is a need for a method that can manage the characteristics of markets, such as fat-tallness, while also allowing for theoretical analysis. Say the future trend (i.e., grow, fall, or remain stable) of a stock is a difficult task since stock market data are exact time-variant and typically follow a different pattern [2]. Forecasts of the behavior of prices have been made in tandem with analysis and forecasts of the behavior of the stock market. Some of the approaches use charts of prices and volumes as well as visual human interpretation of these diagrammatic representations to predict future behavior. Some others compute technical indicators by tampering with the time series' previous values. Before proceeding, it is important to clarify why predicting the stock market trend (i.e., price direction) is more practical than forecasting exact price values. Given the stock market's memory-less nature, daily price levels are highly unpredictable. However, studies suggest that with the right indicators and training, trends — whether upward, downward, or stable — can still be forecasted with reasonable accuracy using historical data. The paper's outline is structured as follows: Section 2 examines the relevant literature. An overview of the Probability Fuzzy Logic (PFL) approach for stock price prediction under uncertainty is presented in Section 3. The experimental setup, simulation findings, and performance analysis are covered in Section 4. Section 5 contains the paper's conclusion.

## II. Literature Survey

These days, a lot of research articles have addressed the problem of stock price prediction due to the difficulty of making decisions in the stock market and developing a real-time strategy for purchasing and selling stocks through portfolio selection and management. Many people use AI to guess if stock prices will go up or down—some for a few days, others for months or years. Most of these AI tools use stock charts and past numbers (like averages or trading volume) to make their predictions, instead of looking at news or company details. In stock trading, decisions are made through a complicated procedure. or analyzing stock market behavior. In [1], a probabilistic approach is employed to manage the large influx of stock market data. In recent years, there has been growing interest in exploring machine learning algorithms as potential tools to improve market forecasting, surpassing the capabilities of traditional methods [2]. The present study seeks to analyze current research trends and identify future directions in the field of stock market prediction using machine learning (ML), through a comprehensive review of existing literature [3]. A methodical approach to literature review is employed to locate pertinent, peer-reviewed journal papers from the previous two decades and group studies with comparable approaches and settings. Studies using artificial neural networks (ANNs), support vector machines (SVMs), hybrid or other artificial intelligence (AI) methodologies, and studies combining genetic algorithms with other methods fall into four areas [4-6]. Akshitha et al. [11] used fuzzy methods such as Fuzzy TOPSIS and AHP for ranking cybercrime. Khushi et al. [12] used ML models for detecting fraud in online transactions. Akshitha et al. [13] employed ML and DL approaches for analysing stock market. Kumar et al. [14] used fuzzy methods for Enhancing Password Security. Singh et al. [15] employed ML and DL approaches for estimating stock price and visualizations were done in Tableau.

## III. Methodology

### *A. AHP*

Step 1:

- ➢ Describe the problem and Criteria
- ➢ Define the alternatives
- ➢ Priority among the criteria and alternatives using pair wise comparison
- ➢ Check the fuzzy consistency

- Calculate the relative weights from the pair-wise comparison
- Perform the sensitivity

The matrix is reciprocal, meaning aij=1/(aji).

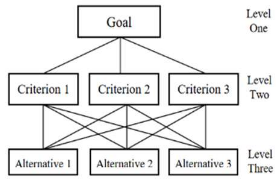


Fig 1. Sample Hierarchical Tree

Step 2: Normalizing the Matrix

The subsequent step entails normalizing the pairwise comparison matrix to guarantee that the values are on a uniform scale. This is achieved by dividing each element aij in the matrix by the total of its column:

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{1}$$

This normalization process produces a matrix $R=[r_{ij}]$ where each column sums to 1.

Step 3: Calculating Criteria Weights

Following normalization, the weights of the criteria are determined. These weights indicate the relative significance of each criterion. The weight $w_i$ for every criterion is calculated by averaging the normalized values for each row:

$$w_i = \frac{1}{n}\sum_{j=1}^{n} r_{ij} \tag{2}$$

The resulting vector $W=[w_1,w_2,\ldots,w_n]$ contains the weights for each criterion, where the sum of the weights equals 1.

Step 4: Ranking the Alternatives

Ultimately, the various alternatives (distinct sets of environmental conditions) are prioritized. This is achieved by computing a weighted sum for each alternative:

$$\text{Alternative Score}_j = \sum_{i=1}^{n} w_i \times x_{ij} \tag{3}$$

Here, $x_{ij}$ represents the value of alternative criterion j. Alternatives are then ranked based on their scores and with higher scores indicating better viability.

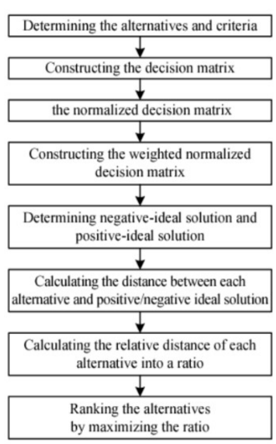


Figure 2. Flowchart

TABLE I. DATASET

| | | | | | |
|---|---|---|---|---|---|
| High | Low | Volume | Close | Open | |
| High | 1 | 2 | 0.5 | 1 | 0.5 |
| low | 0.5 | 1 | 0.33 | 0.5 | 0.25 |
| Volume | 2 | 3 | 1 | 2 | 1 |
| Close | 1 | 3 | 0.5 | 1 | 0.5 |
| Open | 2 | 2 | 1 | 2 | 1 |

### *B. TOPSIS*

An examination of stock market volatility analysis using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method should cover the following important aspects:

STEP 1: Introduction to Stock Market Volatility

Definition: The degree of fluctuation in stock prices during a specific time frame is what stock market volatility means. This is an important factor in financial markets because it impacts investment choices, risk evaluation, and overall market steadiness. Construct the Decision Matrix (DM) Initially, a decision matrix D is created, in which each element xij denotes the performance of alternative i concerning criterion j. The structure of the DM is as follows:

$$D = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} \tag{4}$$

where m is the number of alternatives and n is the number of criteria.

Step 2: Normalize the Decision Matrix (DM)

The decision matrix is later normalized in order to remove the effects of various units of measurement. The normalized value rij is determined as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{5}$$

This step produces a normalized matrix R where each element rij is dimensionless.

Step 3: Calculate the Weighted Normalized Matrix

After normalization, the weighted normalized matrix V is got by multiplying every element to the corresponding weight:

vij=wj×rij (6)

Step 4: Find the Ideal and Negative-Ideal Solutions

The subsequent step involves determining the optimal solution (A+) and the suboptimal solution (A−). The optimal solution signifies the most favorable values, whereas the suboptimal solution denotes the least favorable:

A+=(max(vij)|benefit criteria,min(vij)|j∈cost criteria)

A−=(min(vij)|j∈benefit criteria,max(vij)|j∈cost criteria)

Step 5: Calculate the Separation Measures

The separation measures for each alternative from the ideal and negative-ideal solutions are determined by using the Euclidean distance (ED) as follows:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2} \qquad S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2} \tag{7}$$

Step 6:

Determine the Relative Closeness to the Ideal Solution

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{8}$$

Step 7: Rank the Alternatives

Ultimately, the options are prioritized according to their relative proximity Ci∗, where greater values signify more advantageous circumstances for crop sustainability. And… that's all. We obtained a ranked set of alternatives based on specified criteria.

TABLE II. COEFFICIENTS

| | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| Si* | 1.471 | 2.151 | 1.465 | 1.453 | 2.118 |
| Si- | 4.165 | 4.172 | 4.699 | 4.129 | 3.726 |
| CCi | 0.261 | 0.341 | 0.237 | 0.261 | 0.362 |

## IV. RESULTS

AHP- Analytical hierarchy process is a good method for determining the weight of processes related to certain goals. In this case, the evaluation model consists of five attributes that are considered to be relevant, high, low, volume, class and open and the rank have seen.

TABLE III. TOPSIS-RANK THE ALTERNATIVES

| Alternatives | Scores | Ranks |
|---|---|---|
| Open | 0.263 | 3 |
| High | 0.341 | 2 |
| Low | 0.237 | 5 |
| Close | 0.261 | 4 |
| Volume | 0.362 | 1 |

TABLE IV: THE ALTERNATIVES

| Alternatives | AHP | TOPSIS |
|---|---|---|
| High | 2 | 3 |
| Low | 4 | 2 |
| Volume | 1 | 5 |
| Close | 3 | 4 |
| Open | 5 | 1 |

## V. CONCLUSION

Fuzzy AHP enhances the Analytic Hierarchy Process (AHP) by integrating fuzzy logic, making the decision-making model better equipped to handle uncertainties and subjective judgments. When analyzing stock market volatility, Fuzzy AHP enables a more thorough assessment of criteria like historical volatility, market sentiment, economic indicators, and company performance. It helps in transforming qualitative evaluations into quantitative metrics, effectively addressing the inherent uncertainty in financial markets. The TOPSIS method, short for Technique for Order of Preference by Similarity to Ideal Solution, works alongside Fuzzy AHP by ranking options according to their proximity to an ideal solution. When analyzing stock market volatility, TOPSIS assesses different stocks or investment choices by comparing them to both an ideal (best-case) and a worst-case scenario. This approach aids in pinpointing stocks that closely match the ideal investment profile, taking into account both positive and negative factors. Analysing stock market volatility with a combination of Fuzzy AHP and TOPSIS presents a robust solution for managing uncertainty and enhancing investment decision-making. These techniques tackle the intricacies and uncertainties in financial data, offering a methodical way to assess and prioritize stock options, thereby facilitating more knowledgeable and deliberate investment decisions

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