



Multi-Valued Neutrosophic Sets for Forecasting Cryptocurrency Volatility

Noura Metawa^{1,2}, Rhada Boujlil³, Maha Metawea⁴

¹ College of Business Administration, University of Sharjah, UAE

² Faculty of Commerce, Mansoura University, Egypt

³ College of Business Administration, Prince Sultan University, KSA

⁴ College of Business Administration, Delta University for Science and Technology, Egypt

Emails: nmetawa@sharjah.ac.ae; rboujlil@psu.edu.sa; dr.mahasaad@hotmail.com

Abstract

The media, legislators, investors, scholars, and regulatory agencies have all shown increased interest in the Cryptocurrency sector recently. Using different criteria in furthermore to return and risk in the cryptocurrency issue utilizing the multi-criteria decision-making (MCDM) methodologies makes it more practical in the real world. A model for predicting the volatility of cryptocurrencies is proposed in this study, and it is based on the TOPSIS approach. The model uses five criteria and six cryptocurrencies. Using a multi-valued neutrosophic set, also known as MVNS, helps to reduce the amount of uncertainty associated with the problem. MVNS was used to express the criteria and alternatives, and the model might possibly represent the Cryptocurrency with varying degrees of truth, indeterminacy, and falsity values.

Keywords: TOPSIS; Multi-valued neutrosophic sets; Forecasting cryptocurrency volatility; MCDM

1. Introduction:

Rising investments in the cryptocurrency market as a category of emerging products leads to a more equitable distribution of both wealth and earnings. The volatile nature of the cryptocurrency market necessitates the creation of a diversified portfolio to ensure that the income and wealth that can be attained through cryptocurrency investments can be maintained over time. This contributes to the overall effort of obtaining sustainable development objectives[1]–[3].

Alternative types of investments, as opposed to conventional ones, are what investors turn to when they want to hedge against threats to the purchasing power of their money posed by elements such as increasing inflation and low-interest rates. An activity is considered to be an investment if, after careful consideration, it is shown to guarantee both the preservation of the initial capital and a reasonable rate of return. Cryptocurrencies are a new asset class that takes the form of a specialized kind of digital money that is produced and stored via electrical means. The exchange of these currencies takes occur only inside a digital setting as well. As a result, their availability is not restricted to a particular period or area, and the fact that they are only available in limited quantities ensures that their worth does not decline with time. As a result, as a new category of assets, they guarantee investors larger returns while maintaining the same degree of risk in order to preserve the value of their money[4]–[6].

To help companies and arbitragers minimize risks through asset allocation and create suitable hedging positions, and to help decision-makers in constructing regulatory frameworks by perfecting the asset values volatility forecasting for risk assessment, it may be crucial to examine and suggest even further insights into aspects of volatility modeling

techniques and cryptocurrency market forecasting. This would allow investors and hedgers to minimize risks through asset allocation and create suitable hedging positions[7]–[9].

Several scholars have, for a significant amount of time, held the view that it is standard practice to base their forecasts on historical values. Yet, forecasting based only on historical values might lead to unavoidable overcomplication and ambiguity owing to the ambiguities within the data as well as the random effect from the outside. As a consequence of this, one of the most active areas of study for a very long time has been the process of removing disturbances from a time series while maintaining the integrity of the relevant features. Thus, the multi-valued neutrosophic sets (MVNSs) are the finest framework to use when trying to uncover the fluctuation patterns and regulations of a time series prediction in the commercial world. The framework could reflect the fluctuation trend of up, equal, and bottom with degree courses of truth, indeterminacy, and falsity that substantially preserve details of the previous data by using MVNS to define the fluctuation patterns of a time series. This allowed the design to significantly retain the specifics of the previous data.

In the procedures of analysis forecasting Cryptocurrency volatility, MVNSs is an ideal method for representing the fuzzy information that is required. For instance, when experts in a business analysis evaluate the criteria for forecasting Cryptocurrency volatility, there is much uncertainty. It's possible that they feel more comfortable representing this sort of uncertain information with many real numbers between 0 and 1, rather than a single real number, such as "0.6,0.7,0.8," than with a single real number.

In addition, there is some uncertainty about the evaluation process; for example, the criterion may characterize the degree of falsity-membership as falling somewhere between 0.1 and 0.2. In addition, the degree to which the criterion is unsure as to whether the measurement is represented by a set of multiple real values that fall within the range [0,1], such as [0.2,0.3]. An example of a forecasting Cryptocurrency volatility problem is shown above, and it may involve degrees of truth, indeterminacy, and falsity all at the same time. Each of these three degrees of membership may be represented by a set of several different real numbers that fall between 0 and 1, as shown. As a result, MVNSs are more successful at expressing hazy and uncertain facts in relation to forecasting Cryptocurrency volatility issues.

The following outline provides an outline of the structure of this work. In Part 2, various interconnected ideas pertaining to MVNSs are discussed. In Section 3, we discuss the definition of a MVNSs. Section 4 presents forecasting Cryptocurrency volatility. In Section 5, a numerical example of the selection process for forecasting Cryptocurrency volatility is used to show how the suggested technique might be used in practice. The study is brought to a close in Section 6 when we outline several potential avenues for further investigation.

2. Related Work

Using MVNSs and probability distribution, Peng et al. [10] developed the concept of probability multi-valued neutrosophic sets (PMVNSs). PMVNS has the potential to function as a dependable instrument for depicting unclear, partial, conflicting, and reluctant decision-making data and for reflecting the distribution features of all specific criteria that are presented. They focused on the development of an innovative approach to discuss MCDM problems in which the weight data is totally unknown and the evaluation values take the form of PMVNSs. Juan-juan Peng and his colleagues [11] developed MVNS, which makes it possible for the truth value, the indeterminacy value, and the falsity value to each have a range of crisp values ranging from zero to one, accordingly. Then, the processes of MVNSs predicated on Einstein processes are described, and a comparison method for MVNSs is established using the related studies of HFSs and Atanassov's intuitionistic fuzzy sets. This technique for comparing MVNSs is dependent on the development of HFSs and Atanassov's intuitionistic fuzzy sets (IFSs). The PMVNSs have the ability to provide a more detailed description of material that is both complicated and unclear. So, lie et al. [12] adapted the PROMETHEE approach so that it could be used in a PMVNSs setting so that they could combine the benefits of the PROMETHEE method with PMVNSs. In the beginning, a few fundamental preliminary topics are discussed, including MVNSs, PMVNSs, and the traditional PROMETHEE approach. After that, they presented the operational laws of PMVNSs depending on the project rules of MVNSs and probability distributions. These laws were derived from the previous laws that governed MVNSs. In the meanwhile, both the score function and the accuracy function of PMVNSs have been provided in order to make it easier to compare any two PMVNSs. Liu and Cheng[13] developed a three-phase MCDM approach in addition to improving the MABAC method while it was operating in a PMVNS setting. In the beginning, some principles of PMVNS, the classic MABAC technique, and regret theory (RT) are discussed again. Next, the clustering method for PMVNSs is created, and it is used to determine the crucial degree of DMs. Moreover,

the probability of preference relations stated by the PMVNNs is first provided, and it is employed to substitute the distance variance in the standard MABAC technique. Peide Liu and Cheng have created an expanded version of the ARAS approach for MCDM. In the first place, they suggested using a probability multi-valued neutrosophic normalized weighted Bonferroni distance (PMVNNWBD) in order to quantify how near-weighted PMVNNs are to one another. An entropy metric for PMVNSs is then given as a means of describing the degree of inaccuracy that may be expected from PMVNSs and of deriving the weights of DMs.

As a more broad idea, NMVSs, which also include SVNMs and MVNSs, were presented by Ye et al. [14]The authors then suggest a technique that converts NMVSs into consistent single-valued neutrosophic sets (CSVNSs) by using the mean scores and conformance degrees (complement of standard deviations) of the truth, indeterminacy, and falsity multi-valued sequences found in NMVSs as the basis for the transformation. It was necessary for Jun Ye et al. [15]to present single- and interval-valued hybrid neutrosophic multi-valued sets (SIVHNMVSs), correlation coefficients of consistency interval-valued neutrosophic sets (CIVNSs), as well as their MCDM approach in the context of SIVHNMVSs. Initially, they suggested SIVHNMVSs and a technique for transforming SIVHNMVSs into CIVNSs depending on the average and consistent degree of truth, falsity, and indeterminacy sequences. This encoding method was used to transform SIVHNMVSs into CIVNSs. Then, we presented two correlation coefficients among CIVNSs relying on the multiplying of both the correlation coefficient of interval-valued neutrosophic sets and the correlation coefficient of neutrosophic consistency sets as well as two weighted correlation coefficients of CIVNSs. Guan et al. [16]came up with an innovative model for predicting that was founded on MVNSs. The goal of this model was to discover the fluctuation patterns and regulations of a time series. They suggested a method that would make use of an MVNS in order to describe the fluctuation patterns of a time series. The framework would be capable of capturing the fluctuation trend of up, equal, and down with varying degrees of truth, indeterminacy, and falsity, which would significantly maintain specifics of the historical values. The DEMATEL technique and the TOPSIS method were combined in order to create a novel multi-valued interval neutrosophic fuzzy multiple attribute decision making approach. This approach was devised by Wei Yang and colleagues[17]. The evaluation values are presented in the form of multi-valued interval neutrosophic fuzzy numbers. Both the relationships between characteristics and their weights may be represented using DEMATEL. Attribute weights can also be calculated. Juan-juan Peng and his colleagues [18]explored MCDM difficulties using the qualitative flexible multiple criteria approach (QUALIFLEX). This is a technique in which the scores of the criterion are stated using MVNSs. They studied the possibility of using an enhanced version of the QUALIFLEX technique, which is based on probability, to solve MCDM situations in which the evaluations of options are in the form of MVNNs.

With the original data being expressed in terms of a multi-valued m-polar neutrosophic soft set, Mahmood et al. [19]aimed to achieve optimal fuzzy soft constants by using Bonferroni mean and TOPSIS. It is defined that a multi-valued m-polar neutrosophic soft set is a generalization of the m-polar neutrosophic soft set, which is achieved by merging it with the multi-valued neutrosophic soft set. This is the generalization of the m-polar neutrosophic soft set. Yang and Li [20]presented the idea of multi-valued neutrosophic linguistic sets (MVNLSs), and they defined the operational laws of multi-valued neutrosophic linguistic numbers (MVNLNs) based on algebraic operations and the distance measure for MVNLNs. This work was published in the journal Proceedings of the National Academy of Sciences. After that, the MVNLPWA operator and the MVNLPWG operator are proposed to group the multi-valued neutrosophic linguistic information. Additionally, some desirable properties of the two operators are investigated. Juan-juan Peng and his colleagues [21]developed an adaptation of the ELECTRE technique to deal with MVNSs MCDM issues. Many outranking relations for MVNNs based on classic ELECTRE techniques are established, and numerous features are investigated. These relations are based on the fact that MVNNs have multiple values. Xu Libo and colleagues[22] came up with an innovative strategy and methodology for MCDM MVNSs that was built on the interval-dependent degree and probability distribution. Initially, a reduced dependent function and distribution function are supplied, and then they are combined into a compact formula. This formula is named the interval-dependent function, and it comprises information about interval computing as well as probability distribution inside an interval. After that, a conversion operator is developed, and the process of converting MVNSs into interval sets is shown. The researchers Jun Ye et al. [23]introduced some algebraic operations among neutrosophic enthalpy values. Moreover, they provided certain aggregation operators with the assistance of generic t-norms and t-conorms, which resulted in a novel theoretical ground in the fuzzy environment. For the purpose of making decisions based on several criteria in MVNSs environments, they used algebraic and Einstein weighted operators of neutrosophic enthalpy values.

3. Multi-Valued Neutrosophic Sets

Let there be a non-empty fixed set denoted by $X = x_1, x_2, \dots, x_n$. One definition of an MVNS is as follows:

$$A = \{x_t, (t_A(x_t), i_A(x_t), f_A(x_t))\},$$

Where $t_A(x_t), i_A(x_t), f_A(x_t)$ are three sets, every of which is made of distinct values in the range [0,1], and where $x \in X$ is a superset of the other two sets. Where $t_A(x_t) = t_{A1}(x_t), t_{A2}(x_t), \dots, t_{Al}(x_t)$, $i_A(x_t) = i_{A1}(x_t), i_{A2}(x_t), \dots, i_{Alt}(x_t)$, and $f_A(x_t) = f_{A1}(x_t), f_{A2}(x_t), \dots, f_{Alt}(x_t)$.

be an MVNN with the parameters t, I, and f. It is possible to define the scoring function of b as follows:

$$s(b) = \frac{\frac{1}{l} \sum_{k=1}^l Bk + \frac{1}{l} \sum_{g=1}^l (1-iBg) + \frac{1}{l} \sum_{r=1}^l (1-fBg)}{3}$$

A common tactic used while dealing with MCDM is known as TOPSIS.

In the following, we will outline the phases of the TOPSIS method:

- Build a decision matrix,
- Establish a standard for the choice matrix.
- Determine the weighted normalized decision matrix.
- Identify the optimum remedies for both the good and the negative aspects of the problem.
- Determine the relative distances of each potential solution to the ideal solutions, both positive and negative.
- Determine the relative proximity coefficients by utilizing distance measurements to do your calculations.
- Place the available options in order.

4. Forecasting Cryptocurrency Volatility

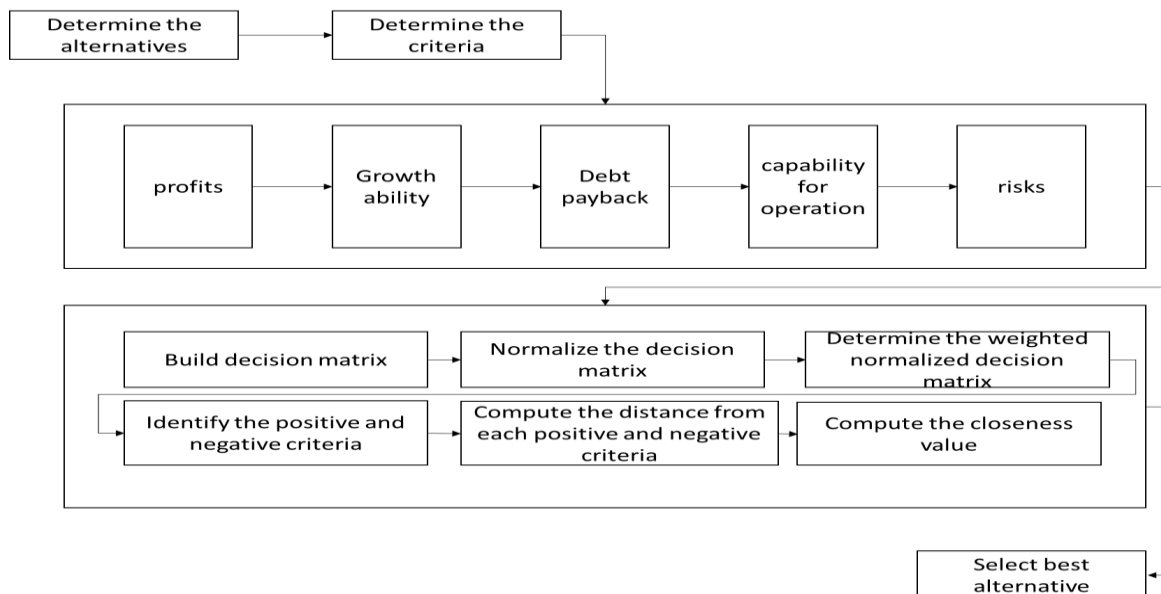


Figure 1: The framework of cryptocurrency methodology.

As a result of advances in technology, digital currencies are increasingly being acknowledged as a viable alternative to more conventional investing strategies. The rise in popularity of this category of assets may be attributed to their transnational character, the ability to trade them round-the-clock, their cheap transaction costs, and the fact that it is not possible to manipulate the transactions involving them. The fact that cryptocurrencies are used all around the world has piqued the interest of several investors from various parts of the world. Investors in this asset class diversify their bitcoin holdings because of the significant volatility of the cryptocurrency market.

Even though there have been a lot of studies done on the subject, many academics are still interested in optimizing portfolios that only include conventional assets. In recent times, there has also been a rise in the number of studies conducted on the topic of cryptocurrency portfolios. A methodology for the allocation of bitcoin portfolios is presented here. A significant number of scholars have underlined the modest number of assets that are held in the portfolios of individual investors because of their simpler administration requirements.

Figure 1 shows the steps of the cryptocurrency methodology. Start with five criteria and six alternatives. Then first compute the weights of five criteria the evaluation of five criteria by the decision-makers. Then build the decision matrix between criteria and alternatives. Then apply the TOPSIS method to rank and select the best option.

5. Results and Discussion

This section provides the application of the MVNs TOPSIS method. Accepting larger degrees of risk is necessary to increase the possible return on investment, and conversely, lower risk levels are connected with an increased likelihood of earning less money. Investors in the financial markets are continually seeking methods to find a balance between the risks they take and the returns they get. This approach, which is being presented, is comprised of the following five kinds of criteria: Revenues and profits, Growthability, Debt payback, capability for operation, and risks. And there are six cryptocurrencies. Let three experts evaluate the criteria and alternatives. Then build the decision matrix as shown in tables 1-3. Then compute the weights of the criteria. The weights of criteria are organized as follows: $w_1 = 0.157894737$, $w_2 = 0.118421053$, $w_3 = 0.184210526$, $w_4 = 0.263157895$, $w_5 = 0.276315789$.

Table 1: The decision matrix 1 by the TOPSIS method.

	Crypto _{C1}	Crypto _{C2}	Crypto _{C3}	Crypto _{C4}	Crypto _{C5}
Crypto _{A1}	0.6	0.8	0.9	0.3	0.2
Crypto _{A2}	0.3	0.2	0.4	0.9	0.6
Crypto _{A3}	0.8	0.3	0.6	0.7	0.8
Crypto _{A4}	0.7	0.4	0.8	0.6	0.9
Crypto _{A5}	0.7	0.6	0.9	0.8	0.3
Crypto _{A6}	0.6	0.6	0.3	0.2	0.3

Table 2: The decision matrix 2 by the TOPSIS method.

	Crypto _{C1}	Crypto _{C2}	Crypto _{C3}	Crypto _{C4}	Crypto _{C5}
Crypto _{A1}	0.2	0.8	0.2	0.2	0.3
Crypto _{A2}	0.3	0.2	0.4	0.9	0.6
Crypto _{A3}	0.3	0.3	0.2	0.2	0.3
Crypto _{A4}	0.3	0.2	0.8	0.6	0.9
Crypto _{A5}	0.7	0.6	0.2	0.8	0.3
Crypto _{A6}	0.9	0.9	0.3	0.9	0.9

Table 3: The decision matrix 3 by the TOPSIS method.

	Crypto _{C1}	Crypto _{C2}	Crypto _{C3}	Crypto _{C4}	Crypto _{C5}
Crypto _{A1}	0.6	0.8	0.7	0.3	0.7
Crypto _{A2}	0.7	0.7	0.4	0.7	0.7
Crypto _{A3}	0.8	0.3	0.6	0.7	0.9

Crypto _{A4}	0.7	0.4	0.7	0.6	0.9
Crypto _{A5}	0.9	0.7	0.9	0.8	0.2
Crypto _{A6}	0.6	0.6	0.7	0.2	0.7

Then combined the three decision matrices into one matrix. Then normalize the decision matrix as shown in table 4.

Table 4: The normalization 4 by the TOPSIS method.

	Crypto _{C1}	Crypto _{C2}	Crypto _{C3}	Crypto _{C4}	Crypto _{C5}
Crypto _{A1}	0.31423	0.58554	0.428815	0.178263	0.264456
Crypto _{A2}	0.291785	0.268373	0.285876	0.557071	0.418722
Crypto _{A3}	0.426455	0.219578	0.333522	0.356525	0.44076
Crypto _{A4}	0.381565	0.243975	0.54793	0.401091	0.595026
Crypto _{A5}	0.516235	0.463553	0.476461	0.534788	0.176304
Crypto _{A6}	0.471345	0.512348	0.309699	0.289677	0.418722

Then multiply the weights of criteria by the normalization matrix to compute the weighted normalized decision matrix. Then rank the alternatives as shown in figure 2. Cryptocurrency 4 is the best option and Cryptocurrency 1 is the worst option.

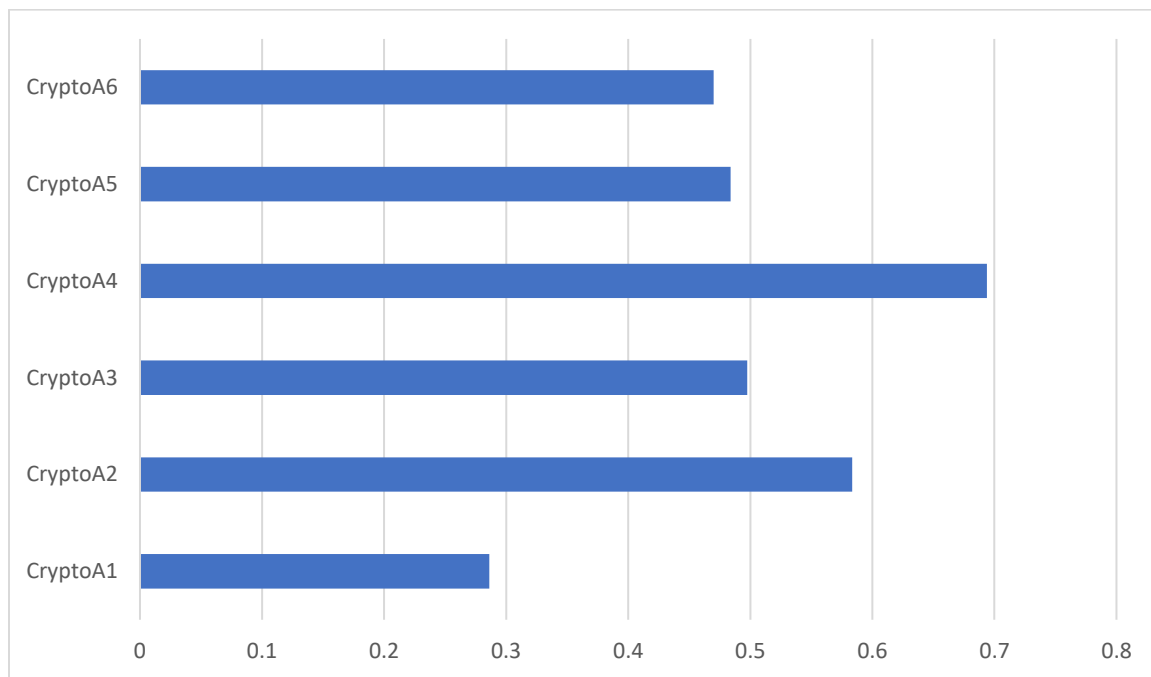


Figure 2: The order of six cryptocurrencies.

6- Conclusion

Despite recent price volatility, cryptocurrency holdings have lately found their way into the portfolios of investors. Yet, owing to the significant volatility of this asset class in comparison to other conventional asset classes, it is vital to pay greater attention to the forecasting models for bitcoin volatility. In this light, this piece of research provides a multi-criteria decision model that they name asymmetric TOPSIS. The model consists of five criteria and six different forecasting options for bitcoin volatility. On the one hand, the usage of the MVNS helps to lower the amount of uncertainty associated with the model. MVNSs, which are combinations of SNSs and HFSs, provide the added capacity of dealing with ambiguity, missing information, and imprecise data.

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