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Rule-Based Neutrosophic Triplet Refined Interval-Valued Data Partition Analyzing The Movement of Stock Market Price

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Abstract:

This study introduces an innovative approach to analysing stock market index movements through a Rule-Based Neutrosophic Triplet Refined Interval-Valued Data Partition (NTRIVDP) model. This method segments data into intervals and applies Neutrosophic statistical measures to convert it into Neutrosophic triplets. These triplets are then processed through a defined rule-base, calculating the Neutrosophic triplet count to derive the average predicted output. The stock market poses significant challenges for accurate prediction, as traditional methods often fall short in capturing the intricacies of market behaviour. The proposed NTRIVDP model leverages Neutrosophic logic, effectively handling uncertain and vague information to offer a more nuanced understanding of market dynamics. This provides valuable insights for investors and financial analysts aiming to analyse stock market index behaviour more accurately. To assess the efficacy of the proposed model, performance metrics such as Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE) are utilized. For the parameter 'α = 0.1, 0.2, 0.3', the model yields promising results, with an MSE of 25,969.68 and a MAPE of 6.570417. These findings indicate that the proposed model surpasses existing methods, demonstrating its effectiveness in forecasting stock market movements. This research highlights the potential of Neutrosophic logic in enhancing the accuracy of stock market predictions, presenting a significant advancement in financial forecasting methodologies.

Keywords: Neutrosophic Triplet, Rule-base, interval valued data partition, Mean Absolute Percent Error, Mean Squared Error.

1. Introduction

In the constantly evolving and volatile financial markets, accurate prediction and analysis of stock market indices are crucial for investors, financial analysts, and policymakers. Traditional forecasting methods often fall short in capturing the intricate, dynamic, and uncertain nature of market behaviour. This shortcoming has spurred the development of advanced computational models capable of managing uncertainty and delivering more reliable predictions. A notable advancement in this regard is the application of Neutrosophic Set Theory, developed by Florentin Smarandache in 1995. This theory extends fuzzy logic, intuitionistic fuzzy logic, and paraconsistent logic to address uncertainty and enhance forecasting accuracy.

Neutrosophic Set Theory is a powerful extension of fuzzy set theory, incorporating three-valued logic to manage indeterminate and inconsistent information. This theory is well-suited for tackling real-world problems characterized by uncertainty, incompleteness, and contradiction. In the realm of stock market analysis, Neutrosophic logic provides a more nuanced and comprehensive framework for understanding market dynamics compared to traditional methods.

Fuzzy set theory was initially introduced in [1], and its application across various domains was detailed in [2]. The foundational concepts of fuzzy set theory, introduced by Zadeh in 1965, have seen widespread application. Fuzzy set theory represents uncertain and vague information by assigning membership grades to elements, offering a more flexible approach than classical binary logic. Researchers have explored its application in time series forecasting, developing fuzzy relations on time series data with linguistic values to predict future values [3], and refining these methods with simplified computational approaches based on the highest membership grade [4]. Despite these advancements, fuzzy set theory has limitations in handling the full spectrum of uncertainties in stock market analysis.

To overcome these limitations, researchers have turned to Neutrosophic logic. For instance, [5] introduced a method utilizing a Neutrosophic environment and a Fuzzy CETD matrix to assess stock market fluctuations. Comprehensive discussions on Neutrosophic logic, defining propositional connectives and examining relationships with other uncertainty reasoning frameworks like intuitionistic fuzzy logic, were provided by [6]. The potential of Neutrosophic logic in forecasting stock index trends for investment decisions was demonstrated by [7]. Moreover, [8] highlighted Neutrosophic logic's superiority over Interval Statistics in handling various indeterminacies, offering a detailed probability framework. The concepts of Neutrosophic measure, Neutrosophic integral, and Neutrosophic probability were introduced by [9], while [10] extended classical statistics to handle set values instead of crisp values.

The objective of this study is to address the challenges in stock market forecasting by proposing a Rule-Based Neutrosophic Triplet Refined Interval-Valued Data Partition (NTRIVDP) model. This innovative approach segments data into intervals and applies Neutrosophic statistical measures to convert the data into Neutrosophic triplets. These triplets are processed through a defined rule-base, calculating the Neutrosophic triplet count to derive the average predicted output. The proposed NTRIVDP model leverages the strengths of Neutrosophic logic to handle the inherent uncertainty and vagueness in stock market data. By converting data into Neutrosophic triplets, the model provides a more nuanced representation of market behavior, capturing the indeterminate and inconsistent aspects that traditional methods often overlook. This enhanced representation allows for more accurate and reliable predictions, offering valuable insights for investors and financial analysts.

To evaluate the efficacy of the proposed NTRIVDP model, performance metrics such as Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE) were utilized. The experimental results demonstrate that the proposed model is more effective and reliable in forecasting stock market movements compared to existing methods, making it a valuable tool for financial forecasting.

The main significance of the NTRIVDP model lies in its ability to effectively handle the uncertainty and vagueness inherent in stock market data. By leveraging Neutrosophic logic, the model provides a more comprehensive representation of market behaviour, capturing the subtle nuances that traditional methods often miss. This enhanced representation allows for more accurate predictions, offering valuable insights for investors and financial analysts. The proposed methodology also highlights the potential of Neutrosophic logic in advancing the field of financial forecasting. By incorporating three-valued logic to handle indeterminate and inconsistent information, Neutrosophic logic provides a powerful framework for dealing with the complexities of real-world problems. The success of the NTRIVDP model demonstrates the effectiveness of this approach in addressing the challenges of stock market forecasting, paving the way for further research and development in this area.

The proposed methodology is detailed in section 3, with experimental results and discussions presented in section 4. Finally, a brief conclusion is provided in section 5, summarizing the findings and implications of the study. This structured approach underscores the objective of the study and highlights the potential of Neutrosophic logic in advancing financial forecasting methodologies.

2. Basic concepts

2.1 Definition of Neutrosophic set: [9]

Let U be a universe of discourse, and M a subset of U. An element x from U is characterized with respect to the set M as $x(T, I, F)$, where it is t% true in the set, i% indeterminate in the set, and f% false. Here, t varies in T, i varies in I, and f varies in F.

2.2 Definition of Neutrosophic Logic triplet:[9]

The Neutrosophic Logic (NL) truth value of a proposition P is represented as NL(P) = (T, I, F), where T is the degree of truth, I is the indeterminate degree (the extent to which it is unknown whether P is true or false), and F is the degree of falsehood of the proposition P.

Consider <A> as a notion, attribute, idea, proposition, theorem, theory, etc. Let <antiA> be the opposite of <A>, and <neutA> be neither <A> nor <antiA>, but the neutral (indeterminate or unknown) aspect related to <A>.

For example:

- If <A> = positive, then <antiA> = negative, and <neutA> = zero.
- If <A> = win, then <antiA> = lose, and <neutA> = tie-game.

2.3 Definition of Neutrosophic Statistics: [10]

Neutrosophic statistics encompasses the handling of indeterminate data, characterized by varying degrees of ambiguity, vagueness, partial knowledge, contradictions, and incompleteness. While classic statistics uses crisp data represented through charts, diagrams, and algorithms, Neutrosophic statistics accommodate the inherent uncertainty and imprecision found in real-world data. This approach provides a more comprehensive and flexible framework for analyzing and interpreting data with inherent uncertainties.

3. Methodology:

The step-by-step procedure for the proposed Rule-Based Neutrosophic Triplet Refined Interval-Valued Data Partition (NTRIVDP) model is meticulously designed to handle the uncertainties inherent in stock market data. The block diagram of the proposed model is shown in Figure 1. The detailed steps are as follows:

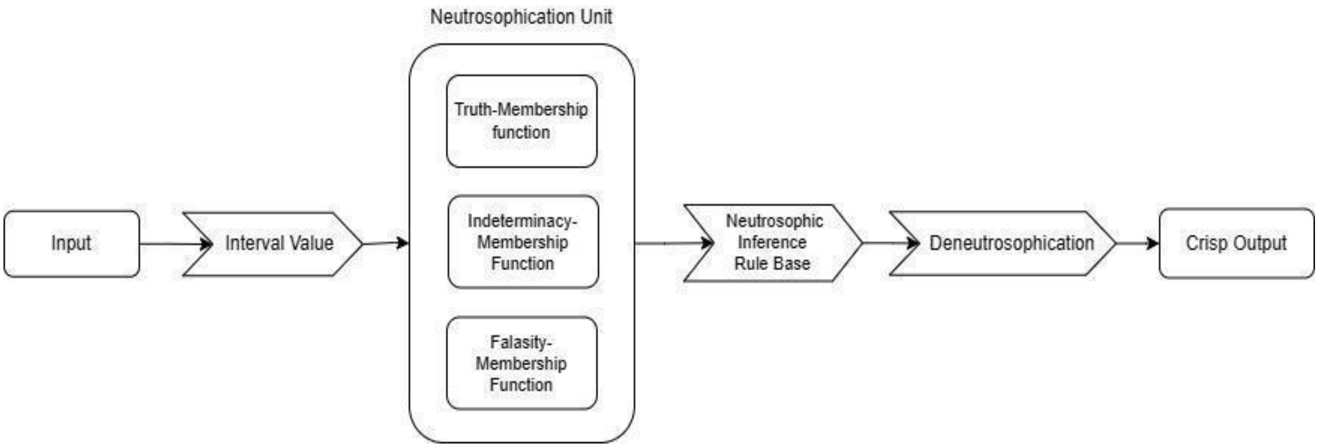


Figure 1: Block diagram of NTRIVDP

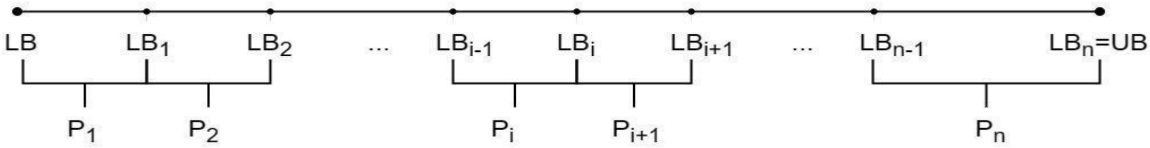
Step1: Define the Universe of Discourse

- **Universe Definition**: Define the universe of discourse 'U' in a column vector as, U = $\begin{pmatrix} a_{11} \\ a_{21} \\ a_{31} \\ \vdots \\ a_{ij} \end{pmatrix}$

- **Bounds and Increment Calculation**: Choose the lower bound 'LB' and upper bound 'UB' for the column vector. Calculate the incremental value 'h' using the formula: h = $\frac{UB-LB}{n}$, where 'n' is the number of data points in the column vector.

- **Data Conversion**: Convert the data into Actual Value Interval-Valued Data Partition ($AV_{\mathbf{IVDP}}$) as illustrated in Figure 2 and the Actual Value of Interval-Valued Data Partition ($AV_{\mathbf{IVDP}}$) is given by,

$$AV_{\mathbf{IVDP}} = \begin{pmatrix} a_{11}\,, b_{11} \\ a_{21}\,, b_{21} \\ a_{31}\,, b_{31} \\ \vdots \\ a_{ij}\,, b_{ij} \end{pmatrix}$$



$$where\ \ LB_1 = LB + h,\ \ LB_2 = LB_1 + h\,, \ldots\ldots, LB_{i-1} + h\,, \ldots\ldots, UB = LB_n = LB_{n-1} + h$$

Figure 2: Data partitioning

Step 2: Neutrosophic Statistical Computations

- **Average and Standard Deviation**: Compute the average and standard deviation within the Neutrosophic Statistical environment using the following formulas:

$$\left(\mu_1, \mu_2\right)_{IVDP} = \left(\sum_{i=1}^{n} \frac{a_{ij}}{n}, \sum_{i=1}^{n} \frac{b_{ij}}{n}\right), where\ j\ is\ fixed$$

$$(\sigma_1, \sigma_2)_{IVDP} = \left(\sqrt{\frac{\sum\left(a_{ij} - \mu_1\right)^2}{n}}\ , \sqrt{\frac{\sum\left(b_{ij} - \mu_2\right)^2}{n}}\right), where\ j\ is\ fixed$$

Here, $\left(\mu_1, \mu_2\right)_{IVDP}$ denotes the average, and $(\sigma_1, \sigma_2)_{IVDP}$ denotes the standard deviation of interval-valued data partition.

Step 3: Neutrosophic Triplet Conversion

- **Conversion to Neutrosophic Triplets**: Transform the statistical measurements such as average and standard deviation into an appropriate Neutrosophic triplet refined interval valued data partitions denoted as <A>, <antiA>, <neutA> using the IF-THEN Neutrosophic refined rule-base outlined below.

If $(a_{ij}, b_{ij})_{IVDP} < [\left(\mu_1, \mu_2\right)_{IVDP} - \alpha\,(\sigma_1, \sigma_2)_{IVDP}]$ then (-1,-1) i.e., <antiA, antiA>

If $(a_{ij}, b_{ij})_{IVDP} = [\left(\mu_1, \mu_2\right)_{IVDP} - \alpha\,(\sigma_1, \sigma_2)_{IVDP}]$ then (0,0) i.e., <neutA, neutA>

If $(a_{ij}, b_{ij})_{IVDP} > [\left(\mu_1, \mu_2\right)_{IVDP} - \alpha\,(\sigma_1, \sigma_2)_{IVDP}]$ then (1,1) i.e., <A, A>

This step, known as Neutrosophication, involves the parameter ‘α’ which is in the range [0,1].

Step 4: Average Predicted Value Calculation

- **Neutrosophic Inference Engine**: To compute the average predicted value of AV_{IVDP} for the Neutrosophic triplets, denoted as ‘AP_{IVDP}’, the Neutrosophic inference engine is used. This computation can be performed in Excel using COUNTIF, SUMIF, and AVERAGEIF functions as given below.

- **COUNTIF Rule Syntax**:

= COUNTIF (range, "criteria")

- **SUMIF Rule Syntax**:

= SUMIF (range, criteria, [sum range])

- **AVERAGEIF Rule Syntax**:

= AVERAGEIF (range, criteria, [average range])

This step produces a crisp output, a process known as Deneutrosophication, which provides a definitive value for the average predicted output.

Step 5: Error Calculation

- **Error Calculation**: The error, denoted by $Error_{IVDP}$, is calculated as the difference between the actual value of interval- valued data partition (AV_{IVDP}) and the average predicted value of the interval-valued data partition (AP_{IVDP}). The formula is given by:

$$Error_{IVDP} = AV_{IVDP} - AP_{IVDP}$$

Step 6: Midpoint Error Computation

- **Midpoint Error (MPE)**: To convert the data partition into a single value, compute the Midpoint Error (MPE), denoted as MPE. This is calculated using the following formula:

$$MPE = \frac{\text{Error}_{IVDP}}{2}$$

This step helps in simplifying the error measurement by providing a single representative value.

Step 7: Sum of Squared Errors (SSE)

- **SSE Calculation**: Compute the Sum of Squared Errors (SSE) by summing the squares of the Midpoint Errors (MPE):

$$SSE = \sum(MPE)^2$$

This step aggregates the squared errors, providing a comprehensive measure of the total deviation.

Step 8: Average Predicted Value Representation

- **Average Predicted Value (AP)**: Find the average of the lower bound and upper bound in the interval of the average predicted value (AVIVDP). This is represented as the average predicted value (AP).

Step 9: Performance Error Measures

- **Performance Metrics**: Measure the forecasting accuracy using performance error metrics such as Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE). These are defined as follows:
  - **Mean Squared Error (MSE)**:

$$MSE = \frac{\sum_{i=1}^{n}((AV_{IVDP})_i - (AP_{IVDP})_i)^{\,2}}{n}$$

  - **Mean Absolute Percent Error (MAPE)**:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(AP_{IVDP})_i - (AV_{IVDP})_i}{(AV_{IVDP})_i}\ X\ 100$$

4. Results and discussion:

In this section, the proposed method is applied to predict the share price of the State Bank of India (SBI) at the Bombay Stock Exchange (BSE). For the experimental study, the annual report of SBI for the fiscal year 2009–2010 is utilized. Specifically, share price data for SBI at BSE from April 2009 to March 2010 is analysed, as detailed in Table 1.

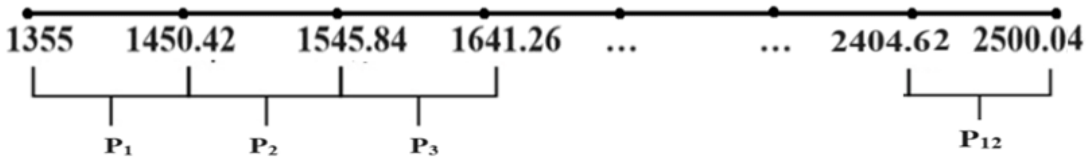
Table 1: Actual value of SBI shares at BSE.

Months	Actual Value
Apr-2009	1355.00
May-2009	1891.00
Jun-2009	1935.00
Jul-2009	1840.00
Aug-2009	1886.90
Sep-2009	2235.00
Oct-2009	2500.00
Nov-2009	2394.00
Dec-2009	2374.75
Jan-2010	2315.25
Feb-2010	2059.95
Mar-2010	2120.05

The Experiments results are discussed in the following steps:

Step 1: Based on the data in Table 1, the universe of discourse U is defined as a column vector for the dataset under consideration: U = $\begin{pmatrix} 1355.00 \\ 1891.00 \\ 1935.00 \\ \vdots \\ 2120.05 \end{pmatrix}$

Here, we choose a lower bound 'LB' = 1355 and an upper bound 'UB' = 2500. With n=12 (for instance), the incremental height is computed for the column vector as h = 95.42. The data partitioning for the dataset is performed accordingly.



The actual value interval-valued data partition (AV_{IVDP}) is subsequently obtained and presented in Table 2.

Table 2: Conversion of Actual Value to Actual Value Interval Valued Data partition (AV_{IVDP}).

Actual value	**Actual value Interval valued Data partition (AV_{IVDP})**	**Data Partition**
1355.00	(1355, 1450.42)	P_1
1891.00	(1832.1, 1927.52)	P_6
1935.00	(1927.52, 2022.94)	P_7
1840.00	(1832.1, 1927.52)	P_6
1886.90	(1832.1, 1927.52)	P_6
2235.00	(2213.78, 2309.2)	P_{10}
2500.00	(2404.62, 2500.04)	P_{12}
2394.00	(2309.2, 2404.62)	P_{11}
2374.75	(2309.2, 2404.62)	P_{11}
2315.25	(2309.2, 2404.62)	P_{11}
2059.95	(2022.94, 2118.36)	P_8
2120.05	(2118.36, 2213.78)	P_9

Step 2: Calculating the average and standard deviation of 'AV_{IVDP}' using the formulas within the Neutrosophic statistical environment, we obtain:

$$(\mu_1, \mu_2)_{IVDP} = \left(\frac{1355+1832.1+\cdots+2118.36}{12}, \frac{1450.42+1927.52+\cdots+2213.78}{12}\right) = (2038.843, 2134.263)$$

$$(\sigma_1, \sigma_2)_{IVDP} = \left(\sqrt{\left(\frac{(1355-2038.843)^2+(1832.1-2038.843)^2+\ldots+(2118.36-2038.843)^2}{12}\right)}, \sqrt{\left(\frac{(1450.42-2134.263)^2+(1927.52-2134.263)^2+\cdots+(2213.78-2134.263)^2}{12}\right)}\right) = (288.460, 288.460)$$

The results obtained are summarized in Table 3.

Table 3: Average and standard Deviation of AV_{IVDP}

Average '$(\mu_1, \mu_2)'_{IVDP}$	(2038.8433, 2134.263)
Standard Deviation '$(\sigma_1, \sigma_2)_{IVDP}$'	(288.460, 288.460)

Step 3: The statistical measurements obtained in Step 2 are then transformed into Neutrosophic triplet refined interval-valued data partitions, denoted as <A>, <antiA>, and <neutA>. This conversion is performed using the IF-THEN Neutrosophic rule base for values of α ranging from 0.1 to 0.9. The results are detailed in Table 4.

Table 4: NTRIVDP for α = 0.1, 0.2 ,0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9.

AV_{IVDP}	NTRIVDP for α= 0.1, 0.2, 0.3	NTRIVDP for α= 0.4, 0.5, 0.6, 0.7	NTRIVDP for α= 0.8,0.9
(1355, 1450.42)	<antiA, antiA>	<antiA, antiA>	<antiA,antiA>
(1832.1, 1927.52)	<antiA, antiA>	<antiA, antiA>	<A, A>
(1927.52, 2022.94)	<antiA, antiA>	<A, A>	<A, A>
(1832.1, 1927.52)	<antiA, antiA>	<antiA, antiA>	<A, A>
(1832.1, 1927.52)	<antiA, antiA>	<antiA, antiA>	<A, A>
(2213.78, 2309.2)	<A, A>	<A, A>	<A, A>
(2404.62, 2500.04)	<A, A>	<A, A>	<A ,A>
(2309.2, 2404.62)	<A, A>	<A, A>	<A, A>
(2309.2, 2404.62)	<A, A>	<A, A>	<A, A>
(2309.2, 2404.62)	<A, A>	<A, A>	<A, A>
(2022.94, 2118.36)	<A, A>	<A, A>	<A, A>
(2118.36, 2213.78)	<A, A>	<A, A>	<A, A>

Step 4: For α values of 0.1, 0.2, and 0.3, the COUNTIF function is used to determine the number of cells categorized as <antiA, antiA> and <A, A> across the columns of the Neutrosophic Triplet Refined Interval-Valued Data Partition (NTRIVDP). The results are depicted in Figure 3.

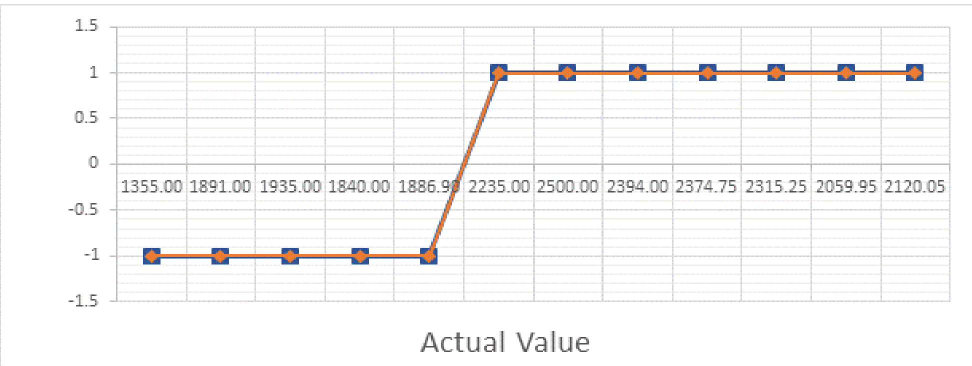


Figure 3: NTRIVDP for (α= 0.1, 0.2, 0.3)

Figure 3 shows that the share prices (1355.00, 1891.00, 1935.00, 1840.00, 1886.90), which fall into the <antiA, antiA> category, yield a count of 5. Conversely, the share prices (2235.00, 2500.00, 2394.00, 2374.75, 2315.25, 2059.95, 2120.05) that fall into the <A, A> category result in a count of 7.

Similarly, for α values of 0.4, 0.5, 0.6, and 0.7, the results from the COUNTIF function are illustrated in Figure 4.

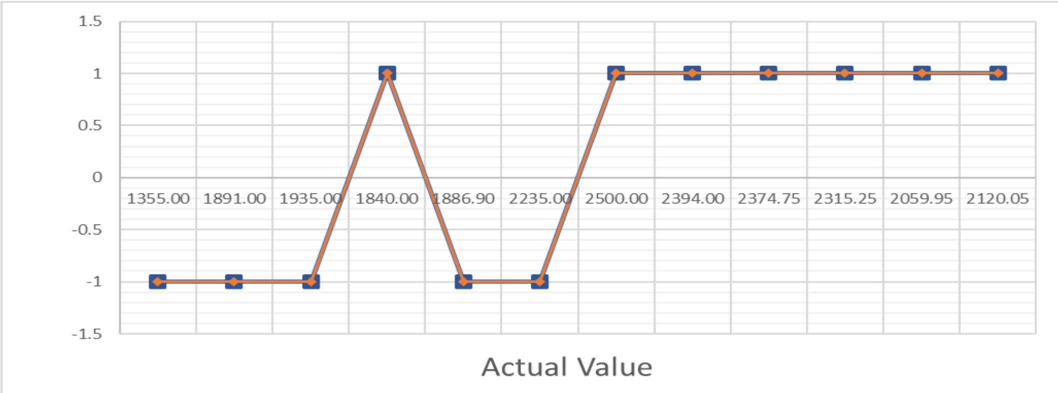


Figure 4: NTRIVDP for (α = 0.4, 0.5, 0.6, 0.7)

Figure 4 reveals that the first three share prices fall into the <antiA, antiA> category, the fourth share price is categorized as <A, A>, the fifth and sixth share prices are again in the <antiA, antiA> category, while the remaining six share prices are classified as <A, A>. This results in a count of 5 for <antiA, antiA> and 7 for <A, A>.

Also, for α values of 0.8 and 0.9, the COUNTIF results are depicted in Figure 5.

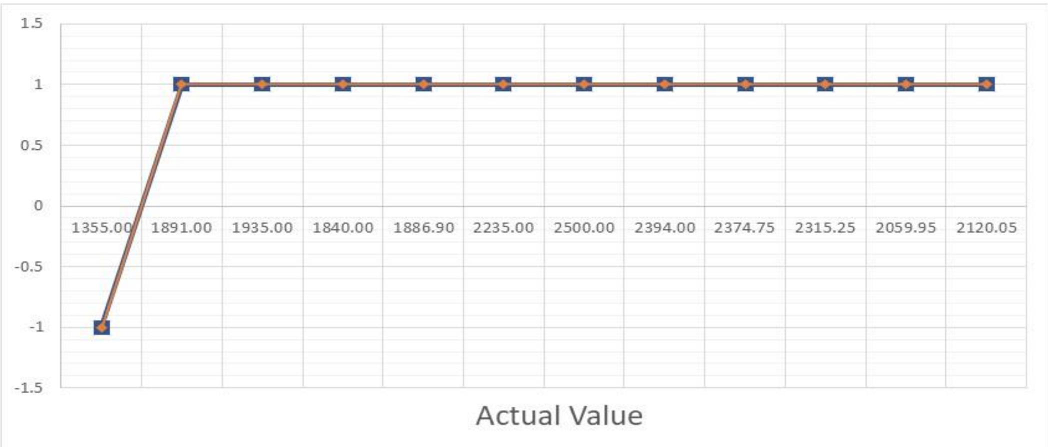


Figure 5: NTRIVDP for (α = 0.8, 0.9)

Figure 5 demonstrates that the first share price falls into the <antiA, antiA> category, resulting in a count of 1, while the remaining share prices are classified as <A, A>, yielding a count of 11.

- The SUMIF results for α values of 0.1, 0.2, and 0.3, computed in Excel, are displayed below.

$$\text{SUMIF } of\ AV_{IVDP}\ for\ < antiA, antiA > = (1355{,}1450.42) + (1832.1{,}1927.52) + (1927.52{,}2022.94) + (1832.1.1927.52) + (1832.1{,}1927.52)$$

$$\text{SUMIF } of\ AV_{IVDP}\ for\ < A, A > = (2213.78{,}2309.18) + (2404.62{,}2500.04) + (2309.20{,}2404.62) + (2309.20{,}2404.62) + (2309.20{,}2404.62) + 2022.94{,}2118.36) + (2118.36{,}2213.78)$$

- The AVERAGEIF results for α values of 0.1, 0.2, and 0.3, computed in Excel, are presented below.

AVERAGEIF of AV_{IVDP} for <antiA, antiA> = (8778.82, 9255.92) / (5,5)

AVERAGEIF of AV_{IVDP} for <A, A> = (15687.22, 16355.14) / (7,7)

- The computed COUNTIF, SUMIF, and AVERAGEIF values of AV_{IVDP} for α = 0.1, 0.2 and 0.3 are shown in Table 5.

Table 5: Actual value and predicted value for α = 0.1, 0.2, 0.3

NTR_{IVDP}	COUNTIF of AV_{IVDP}	SUMIF of AV_{IVDP}	AVERAGEIF of AV_{IVDP} (AP_{IVDP})
<antiA,antiA>	5	(8778.82, 9255.92)	(1755.764,1851.184)
<A,A>	7	(15687.30, 16355.24)	(2241.043, 2336.463)

- Similarly, the computed COUNTIF, SUMIF, and AVERAGEIF values of AVIVDP for α = 0.4, 0.5, 0.6, and 0.7 are shown in Table 6.

Table 6: Actual value and predicted value for α = 04, 0.5, 0.6, 0.7

NTR_{IVDP}	COUNTIF of AV_{IVDP}	SUMIF of AV_{IVDP}	AVERAGEIF of AV_{IVDP} (AP_{IVDP})
<antiA,antiA>	4	(6851.3,7239.98)	(1712.825, 1808,245)
<A,A>	8	(17614.7418378.08)	(2201.8425,2297.26)

- Additionally, the computed COUNTIF, SUMIF, and AVERAGEIF values of AVIVDP for α = 0.8 and 0.9 are presented in Table 7.

Table 7: Actual value and predicted value for α = 0.8, 0.9

NTR_{IVDP}	COUNTIF of AV_{IVDP}	SUMIF of AV_{IVDP}	AVERAGEIF of AV_{IVDP} (AP_{IVDP})
<antiA,antiA>	1	(1355,145042)	(1355,1450,42)
<A,A>	11	(23111.04,24160.64002)	(2101.003636,2196.42182)

Step 5: The values of AP_{IVDP}, AP, $Error_{IVDP}$, MPE, (MPE)^2, and SSE are calculated and detailed in Table 8 for α=0.1 ,0.2, and 0.3.

Table 8: The result of AP $_{IVDP}$, AP, Error $_{IVDP}$, MPE ,(MPE)^2 , for α = 0.1 ,0.2, 0.3.

AV $_{IVDP}$	AP $_{IVDP}$	AP	Error $_{IVDP}$	MPE	(MPE)^2
(1355, 1450.42)	(1755.764,1851.184)	1803.47	(-400.764, -400.764)	-400.764	160611.7837
(1832.1, 1927.52)	(1755.764,1851.184)	1803.47	(76.336 , 76.366)	76.336	5857.184896
(1927.52, 2022.94)	(1755.764,1851.184)	1803.47	(171.756 , 171.756)	171.756	29397.06994
(1832.1, 1927.52)	(1755.764,1851.184)	1803.47	(76.336 , 76.366)	76.336	5857.184896
(1832.1, 1927.52)	(1755.764,1851.184)	1803.47	(76.336 , 76.366)	76.336	5857.184896
(2213.78, 2309.2)	(2241.0314285714, 2336.4485714285)	2288.74	(-27.251, -27.268)	-27.2595	743.0803403
(2404.62, 2500.04)	(2241.0314285714, 2336.4485714285)	2288.74	(163.569, 163.572)	163.5705	26755.30847
(2309.2, 2404.62)	(2241.0314285714, 2336.4485714285)	2288.74	(68.149, 68.152)	68.1505	4644.49065
(2309.2, 2404.62)	(2241.0314285714, 2336.4485714285)	2288.74	(68.149, 68.152)	68.1505	4644.49065
(2309.2, 2404.62)	(2241.0314285714, 2336.4485714285)	2288.74	(68.149, 68.152)	68.1505	4644.49065
(2022.94, 2118.36)	(2241.0314285714, 2336.4485714285)	2288.74	(-218.091, -218.088)	-218.0895	47563.03001
(2118.36, 2213.78)	(2241.0314285714, 2336.4485714285)	2288.74	(-122.671, -122.668)	-122.6695	15047.80623
					SSE = 31163.15888575

Similarly, the values of AP_{IVDP}, AP, Error $_{IVDP}$, MPE, (MPE)^2, and SSE are calculated and presented in Table 9 for α = 0.4 , 0.5, 0.6, and 0.7

Table 9: The result of AP $_{IVDP}$, AP, Error $_{IVDP}$, MPE ,(MPE)^2 , for α = 0.4 , 0.5, 0.6, 0.7

AV $_{IVDP}$	AP $_{IVDP}$	AP	Error $_{IVDP}$	MPE	(MPE)^2
(1355, 1450.42)	(1712.825, 1808.245)	1760.535	(-357.825, -357.825)	-357.825	128,038.730625
(1832.1, 1927.52)	(1712.825, 1808245)	1760.535	(119.275, 119.275)	119.275	14226.525625
(1927.52, 2022.94)	(2201.8425, 2297.26)	2249.55125	(- 274.3225, -274.3225)	- 274.3225	75251.4624
(1832.1, 1927.52)	(1712.825, 1808.245)	1760.535	(119.275, 119.275)	119.275	14226.525625
(1832.1, 1927.52)	(1712.825, 1808.245)	1760.535	(119.275, 119.275)	119.275	14226.525625
(2213.78, 2309.2)	(2201.8425, 2297.26)	2249.55125	(119.275, 119.275)	119.275	14226.525625
(2404.62, 2500.04)	(1712.825, 1808.245)	2249.55125	(202.7575, 202.7575)	202.7575	41111.6176

AV IVDP	AP IVDP	AP	Error IVDP	MPE	$(MPE)^2$
(2309.2, 2404.62)	(1712.825, 1808245)	2249.55125	(107.34, 107.34)	107.34	11521.8756
(2309.2, 2404.62)	(2201.8425, 2297.26)	2249.55125	(107.34, 107.34)	107.34	11521.8756
(2309.2, 2404.62)	(1712.825, 1808.245)	2249.55125	(107.34, 107.34)	107.34	11521.8756
(2022.94, 2118.36)	(1712.825, 1808.245)	2249.55125	(-178.9, 178.9)	-178.9	32005.21
(2118.36, 2213.78)	(2201.8425, 2297.26)	2249.55125	(83.48, 83.48)	83.48	6968.9104
					SSE = 360,763.2211

Additionally, the values of AP_{IVDP}, AP, $\text{Error}_{\text{IVDP}}$, MPE, $(MPE)^2$, and SSE are calculated and presented in Table 10 for α = 0.8 and 0.9

Table 10: The result of AP IVDP, AP, $\text{Error}_{\text{IVDP}}$, MPE, $(MPE)^2$, for α = 0.8, 0.9

AV IVDP	AP IVDP	AP	Error IVDP	MPE	$(MPE)^2$
(1355, 1450.42)	(1355, 1450.42)	1402.71	(0,0)	0	0
(1832.1, 1927.52)	(2101.0036, 2196.42182)	2148.72171	(-268.9036, -268.9018)	268.9027	72308.662067
(1927.52, 2022.94)	(2101.0036, 2196.42182)	2148.72171	(-173.4836, -173.5118)	173.4977	30101.4519
(1832.1, 1927.52)	(2101.0036, 2196.42182)	2148.72171	(-268.9036, -268.9018)	268.9027	72308.662067
(1832.1, 1927.52)	(2101.0036, 2196.42182)	2148.72171	(-268.9036, -268.9018)	268.9027	72308.662067
(2213.78, 2309.2)	(2101.0036, 2196.42182)	2148.72171	(112.7764, 112.75818)	112.76729	12716.4617
(2404.62, 2500.04)	(2101.0036, 2196.42182)	2118.746917	(303.5964, 303.59818)	303.59729	92171.31449
(2309.2, 2404.62)	(2101.0036, 2196.42182)	2148.72171	(208.1764, 208.17818)	208.17729	4337.7841
(2309.2, 2404.62)	(2101.0036, 2196.42182)	2148.72171	(208.1764, 208.17818)	208.17729	4337.7841
(2309.2, 2404.62)	(2101.0036, 2196.42182)	2148.72171	(208.1764, 208.17818)	208.17729	4337.7841
(2022.94, 2118.36)	(2101.0036, 2196.42182)	2148.72171	(-78.0636, -78.06182)	78.06271	6093.78669
(2118.36, 2213.78)	(2101.0036, 2196.42182)	2148.72171	(17.3564, 17.35818)	17.35729	301.2755161441
					SSE = 569329.69116258

Figure 6, shown below, illustrates the actual values and the average predicted values of the interval-valued data partition (IVDP).

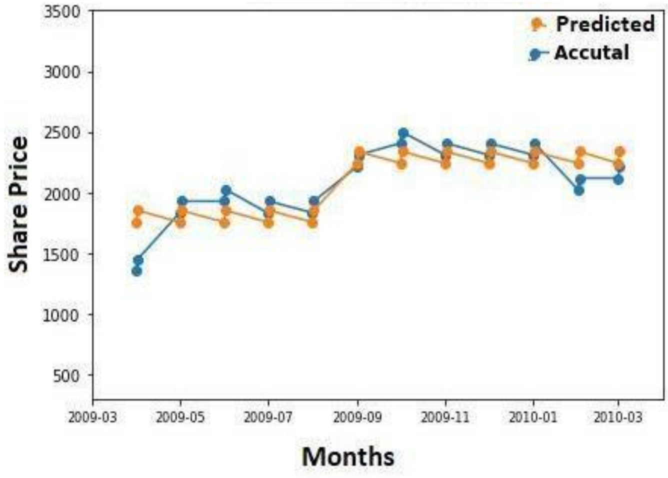


Figure 6: Actual and Average Predicted values of IVDP

Step 6: For α = 0.1, 0.2, 0.3, the performance error measures for the proposed method are calculated as follows: Mean Squared Error (MSE) = 25,969.68 and Mean Absolute Percent Error (MAPE) = 6.570417.

Table 11 and Figure 7 present a comparative analysis of the actual versus predicted values, contrasting the results of the proposed model with those obtained using existing methods, such as Singh's method and B.P. Joshi's method.

Table 11**:** Comparison of AP of the proposed model with the other existing models.

MONTHS	Singh's method	B.P.Joshi method	Average Predicted Value of 'AP' of NTRIVDP
Apr-2009	2000	1750	1803.47
May-2009	2000	1850	1803.47
Jun-2009	2000	1850	1803.47
Jul-2009	2000	1850	1803.47
Aug-2009	2000	1850	1803.47
Sep-2009	2400	2250	2288.74
Oct-2009	2000	2250	2288.74
Nov-2009	2000	2250	2288.74
Dec-2009	2000	2250	2288.74
Jan-2010	2000	2250	2288.74
Feb-2010	2000	2250	2288.74
Mar-2010	2000	2250	2288.74

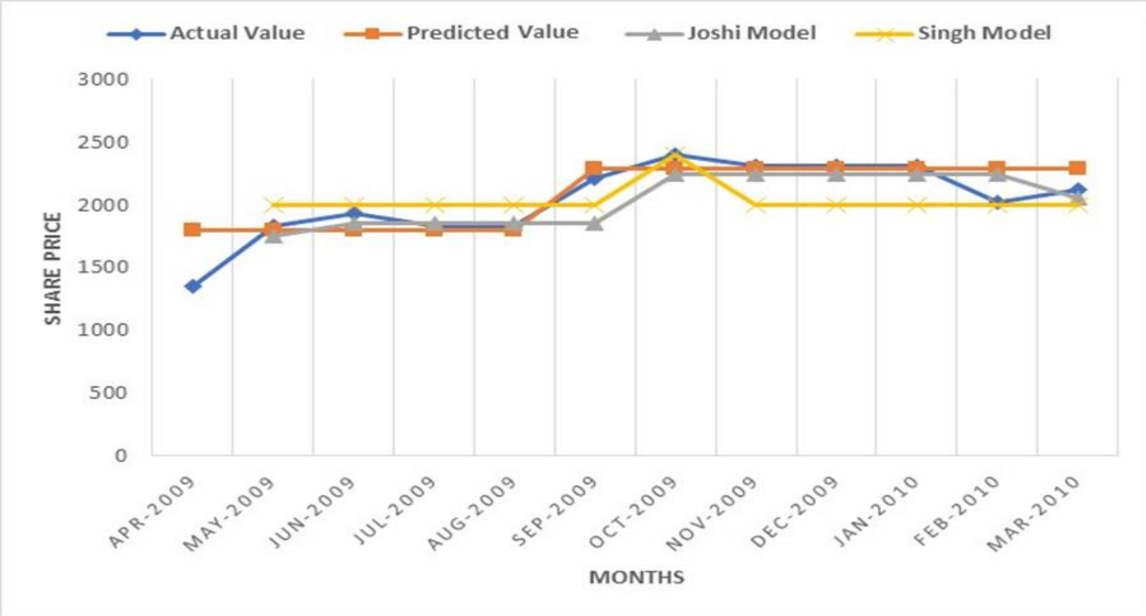


Figure 7: Comparison of proposed model with existing model.

Table 12 provides a comparative analysis of various performance measures, evaluating the proposed model against existing models.

Table 12. Comparison of MSE and MAPE 0f NTRIVDP with existing methods.

Performance Measure	B.P. Joshi Model	Singh Model	Proposed Model
Mean Square Error (MSE)	29170.43	48434.98	25,969.68
Mean Absolute percentage Error (MAPE)	6.199161	8.432273	6.570417

Table 13 presents the Mean Squared Error (MSE) for various values of α: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. The results indicate that α = 0.1, 0.2, and 0.3 yield the most favourable outcomes compared to the other α values.

Table 13: Neutrosophic triplet to average predicted share price.

Parameter 'α'	MSE
0.1, 0.2, 0.3	25,969.68
0.4, 0.5, 0.6, 0.7	33,711.02
0.8, 0.9	47,444.14

5. Conclusion:

This study introduces a novel approach to analyzing stock market index movements through a rule-based Neutrosophic Triplet Refined Interval-Valued Data Partition (NTRIVDP) model. The model has demonstrated notable efficacy, yielding a Mean Squared Error (MSE) of 25,969.68 and a Mean Absolute Percent

Error (MAPE) of 6.570417 when α = 0.1, 0.2, and 0.3. These performance metrics reflect the model's superior ability to predict stock market fluctuations with high accuracy. The NTRIVDP model effectively addresses the complexities and uncertainties inherent in stock market dynamics, leveraging Neutrosophic logic to capture subtle nuances that traditional methods often overlook. Its flexibility in adjusting α values enables fine-tuning to different market conditions, enhancing its adaptability and responsiveness in the ever-changing financial landscape. The study's results underscore the model's advancement over existing forecasting techniques, highlighting its potential to provide more precise predictions and better alignment with actual market movements. This improvement in accuracy facilitates more informed decision-making for investors and financial analysts, ultimately aiding in risk mitigation and return maximization. By pushing the boundaries of conventional forecasting methods, this research emphasizes the value of integrating innovative methodologies like the NTRIVDP in financial analysis. The promising outcomes not only validate the effectiveness of Neutrosophic-based approaches but also pave the way for further exploration of these techniques in broader financial forecasting applications. This advancement represents a significant step forward in developing robust and reliable frameworks for navigating the complexities of investment decision-making in a dynamic market environment.

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