Research Article

Neutrosophic D’Agostino Test of Normality: An Application to Water Data

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The D’Agostino test has been widely applied for testing the normality of the data. The existing D’Agostino test cannot be applied when the data have some indeterminate observations or observations which are obtained from the complex systems. In this paper, we present a D’Agostinotest underneutrosophicstatistics. WeproposetheD’Agostinotesttotestthenormalityofthedatahaving indeterminate observations. The design of the proposed test is given and implemented with the help of real data. From the comparison, it is concluded that the proposed test is effective, adequate, and suitable to be applied in the presence of indeterminacy.

1. Introduction

The data obtained from various fields such as medical, physiological, education, and chemical process are assumed to follow the approximately normal distribution. Therefore, before some estimation and forecasting, the normality of the data in hand is checked first. If the data follow the normal distribution, the statistical techniques based on normal distribution are used; otherwise, the nonparametric methods are applied for the analysis of the data. Among many statistical tests, the D’Agostino test has been widely applied for testing the normality of the data. This test is used to test the null hypothesis that the data do not significantly differ from the normal distribution versus the alternative hypothesis that the data significantly differ from the normality. D’Agostino and Stephens [1] introduced statistical tests when the data follow the normal distribution. ¨Oztuna et al. [2] studied the power of the test and type-I error rate for various tests under normality assumptions. Yap and Sim [3] discussed various statistical tests and showed that the D’Agostino test has better power. Chen and Xia [4] presented tests when data are nonnormal. Mishra et al. [5] presented the descriptive statistic for the test. More details on the statistical test for normality can be seen in [6–9].

The traditional statistical tests are applied to test the hypothesis that the data follow approximately normal distribution with exact mean and variance. In some situations, such as the measure of the water level, a lifetime of a product and melting of a material cannot be expressed in the exact form and have approximate mean and variances. In this case, the statistical test using the fuzzy logic is preferable to apply for the analysis of the data [10]. Hesamian and Akbari [11] presented the tests using fuzzy logic. Chachi and Taheri [12] worked on the optimal test using the fuzzy approach. Haktanır and Kahraman [13] discussed the role of tests in decision-making issues. For details, the reader may refer to [14–24].

The neutrosophic logic which is more efficient than the fuzzy logic and interval-based analysis was proposed by Smarandache [25]. This logic estimates the measures of truth, falsehood, and indeterminacy, while the fuzzy logic is unable to estimate the measure of indeterminacy. More applications of neutrosophic logic can be read in [26–36]. Based on the idea of neutrosophic logic, Smarandache [37] introduced the descriptive neutrosophic statistics which are applied for the analysis of the data having indeterminate observations. Kan dasamy and Smarandache [38] introduced the neutrosophic numbers for the first time. Chen et al. [39] applied the
neutrosophic numbers in rock measuring. Aslam [40] introduced a new branch of statistical quality control under neutrosophic statistics. Kolmogorov-Smirnov tests and Bartlett and Hartley tests using neutrosophic statistics were developed by Aslam [41, 42], respectively. More details on the application of neutrosophic statistics can be seen in [43, 44].

Although the D’Agostino test under classical statistics is available in the literature, the existing D’Agostino test cannot be applied if observations are imprecise, vague, and indeterminate. By exploring the literature and according to the best of our knowledge, there is work on the D’Agostino test in indeterminacy. The operational process of the proposed test is explained. The application of the proposed test will be given with the help of data. We expect that the proposed test will be informative and adequate than the existing D’Agostino test under classical statistics in the indeterminate environment.

2. Preliminary

Suppose that $a_i$ and $b_i I_N; I_N \epsilon [I_L, I_U]$ are determinate and indeterminate parts of neutrosophic random variable $z_N = a_i + b_i I_N; I_N \epsilon [I_L, I_U], i = 1, 2, \ldots, n_N$, where $n_N$ denotes the neutrosophic sample size. The values of $z_N$ reduce to $a_i$ when $I_N = 0$. Based on this information, compute the neutrosophic average for variable $z_N \epsilon [z_L, z_U]$ as follows:

$$z_N = \bar{a} + \bar{b} I_n, \ I_n \epsilon [I_L, I_U],$$

(1)

where $\bar{a} = (1/n_N) \sum_{i=1}^{n_N} a_i$ and $\bar{b} = (1/n_N) \sum_{i=1}^{n_N} b_i$.

The neutrosophic sum of squares (NSS) by following [39] is computed as follows:

$$\sum_{i=1}^{n_N} (z_i - z_{NI})^2 = \sum_{i=1}^{n_N} \left[ \min \left( (a_i + b_i I_L)(\bar{a} + \bar{b} I_L), (a_i + b_i I_L)(\bar{a} + \bar{b} I_L) \right), (a_i + b_i I_U)(\bar{a} + \bar{b} I_U) \right] \right], \ I_n \epsilon [I_L, I_U].$$

(2)

3. Design of the Proposed D’Agostino Test under Neutrosophic Statistics

The main objective is to design D’Agostino test under neutrosophic statistics for testing the null hypothesis $H_{0N}$ that the neutrosophic data follow the neutrosophic normal distribution versus the alternative hypothesis $H_{1N}$ that the data do not belong to the neutrosophic normal distribution. The acceptance of the null hypothesis means that the data are not significantly away from the normal distribution. The operational procedure of the proposed test is stated as follows.

Step 1: Compute the neutrosophic averages of lower values $a_i (i = 1, 2, \ldots, n_N)$ and upper values $b_i (i = 1, 2, \ldots, n_U)$ as follows: $\bar{a} = (1/n_N) \sum_{i=1}^{n_N} a_i$ and $\bar{b} = (1/n_N) \sum_{i=1}^{n_N} b_i$.

Step 2: Find neutrosophic average as follows:

$$z_N = \bar{a} + \bar{b} I_n, \ I_n \epsilon [I_L, I_U].$$

(3)

Step 3: The neutrosophic sum of squares (NSS) by following [39] is calculated using the following expression:

$$\sum_{i=1}^{n_N} (z_i - z_{NI})^2 = \sum_{i=1}^{n_N} \left[ \min \left( (a_i - \bar{a})^2, ((a_i - \bar{a}) + 1 \times (b_i - \bar{b})), (a_i - \bar{a}) + 1 \times (b_i - \bar{b}) \right) \right], \ I_n \epsilon [I_L, I_U].$$

(4)

Step 4: Compute the neutrosophic numerator $T_N \epsilon [T_L, T_U]$ of the proposed test as follows:

$$T_N = \sum_{i=1}^{n_N} \left( \frac{n_N + 1}{2} \right) X_{NI} T_N \epsilon [T_L, T_U].$$

(5)

where $n_N$ denotes the rank of neutrosophic observations $X_{NI}$ for $a_i (i = 1, 2, \ldots, n_L)$ and $b_i (i = 1, 2, \ldots, n_U)$.

Step 5: Compute the neutrosophic test statistic $D_N \epsilon [D_L, D_U]$ of the proposed test as follows:

$$D_N = \frac{T_N}{\sqrt{n_N \sum_{i=1}^{n_N} (z_i - z_{NI})^2}} T_N \epsilon [T_L, T_U], D_N \epsilon [D_L, D_U].$$

(6)

Step 6: Decide the level of significance $\alpha$ and select the critical values from the D’Agostino table. The null hypothesis will be accepted if $D_N \epsilon [D_L, D_U]$ lies within the range of the tabulated values.
**4. Application for Portuguese Mineral Water**

In this section, we will give the application of the proposed test using the Portuguese mineral water (PMW) data. D’Urso and Giordani [45] used the same data and analyzed them using classical statistics. D’Urso and Giordani [45] considered six mineral concentrations such as six mineral concentrations of HCO$_3^-$, Cl$^-$, N$_2^+$, C$_{aq}^2+$, SiO$_2$, and pH. The PMW data are reported in Table 1. Table 1 clearly indicates that the data are reported in intervals. Before any prediction or estimation is given for the data, it is necessary to see that the data do not significantly differ from the normal distribution. Therefore, we will apply the proposed test on these data to test whether the six variables are from the neutrosophic normal distribution or not.

### Table 1: The PMW data.

| Portuguese mineral | n. 1 | n. 2 | n. 3 | n. 4 | n. 5 |
|-------------------|-----|-----|-----|-----|-----|
| HCO$_3^-$         | $a_i$ | $b_i$ | $a_i$ | $b_i$ | $a_i$ | $b_i$ |
| Cl$^-$            | 21   | 41   | 113  | 119  | 2.2  | 4.2  |
| N$_2^+$           | 7    | 9    | 16.5 | 17.5 | 3.6  | 4    |
| C$_{aq}^2+$       | 10   | 16   | 10.3 | 10.7 | 2.8  | 3.8  |
| SiO$_2$           | 3    | 4    | 15   | 21   | 0.01 | 1.01 |
| pH                | 23   | 29   | 13.7 | 14.9 | 1.01 | 7.8  |
|                   | 6.1  | 6.5  | 6.7  | 7.1  | 5.71 | 5.81 |

**The necessary computations for PMW data are given in the following steps.**

Step 1: The neutrosophic averages of lower values $a_i(i = 1, 2, \ldots, n_L)$ and upper values $b_i(i = 1, 2, \ldots, n_U)$ of PMW data of five different types of water are given in Table 2.

Step 2: The neutrosophic averages $\bar{z}_N$: $I_N(0, 1)$ for the water data are also shown in Table 2.

Step 3: The values of NSS are given in Table 3 by following [39]:

\[
\sum_{i=1}^{n_L} (z_i - \bar{z}_N)^2 = \sum_{i=1}^{n_U} \left[ \min \left( (a_i - \bar{a})^2, ((a_i - \bar{a}) + 1 \times (b_i - \bar{b})) \right), (a_i - \bar{a}) + 1 \times (b_i - \bar{b}) \right]^2 \]

\[
\sum_{i=1}^{n_L} (z_i - \bar{z}_N)^2 = \sum_{i=1}^{n_U} \left[ \max \left( (a_i - \bar{a})^2, ((a_i - \bar{a}) + 1 \times (b_i - \bar{b})) \right), (a_i - \bar{a}) + 1 \times (b_i - \bar{b}) \right]^2 \]

Step 4: The values $T_N \in [T_L, T_U]$ and $D_N \in [D_L, D_U]$ are also shown in Table 3.

Step 5: Let $\alpha = 0.05$; the range of the tabulated values is 0.2513, 0.2849. The null hypothesis that the data follow the normal distribution is accepted if $D_N \in [D_L, D_U]$ is within the range of the tabulated values. The acceptance or rejection of $H_{0N}$ is shown in Table 3. From Table 3, it is clear that the PMW data for all waters do not follow the neutrosophic normal distribution.

5. **Comparative Study and Discussion**

The proposed D’Agostino test under neutrosophic statistics is the extension of the D’Agostino test under classical statistics. The necessary computations for PMW data are given in the following steps.

| Water  | $\bar{a}_N$ | $\bar{b}_N$ | $\bar{z}_N$ |
|--------|-------------|-------------|-------------|
| n. 1   | 11.68       | 17.58       | [11.68, 29.26] |
| n. 2   | 29.2        | 31.7        | [29.2, 60.9]  |
| n. 3   | 2.55        | 4.43        | [2.55, 6.98]  |
| n. 4   | 4.75        | 5.93        | [4.75, 10.68] |
| n. 5   | 5.57        | 7.15        | [5.57, 12.72] |

The necessary computations for PMW data are given in the following steps.

Step 1: The neutrosophic averages of lower values $a_i(i = 1, 2, \ldots, n_L)$ and upper values $b_i(i = 1, 2, \ldots, n_U)$ of PMW data of five different types of water are given in Table 2.

Step 2: The neutrosophic averages $\bar{z}_N$: $I_N(0, 1)$ for the water data are also shown in Table 2.

Step 3: The values of NSS are given in Table 3 by following [39]:

\[
\sum_{i=1}^{n_L} (z_i - \bar{z}_N)^2 = \sum_{i=1}^{n_U} \left[ \min \left( (a_i - \bar{a})^2, ((a_i - \bar{a}) + 1 \times (b_i - \bar{b})) \right), (a_i - \bar{a}) + 1 \times (b_i - \bar{b}) \right]^2 \]

\[
\sum_{i=1}^{n_L} (z_i - \bar{z}_N)^2 = \sum_{i=1}^{n_U} \left[ \max \left( (a_i - \bar{a})^2, ((a_i - \bar{a}) + 1 \times (b_i - \bar{b})) \right), (a_i - \bar{a}) + 1 \times (b_i - \bar{b}) \right]^2 \]

Step 4: The values $T_N \in [T_L, T_U]$ and $D_N \in [D_L, D_U]$ are also shown in Table 3.

Step 5: Let $\alpha = 0.05$; the range of the tabulated values is 0.2513, 0.2849. The null hypothesis that the data follow the normal distribution is accepted if $D_N \in [D_L, D_U]$ is within the range of the tabulated values. The acceptance or rejection of $H_{0N}$ is shown in Table 3. From Table 3, it is clear that the PMW data for all waters do not follow the neutrosophic normal distribution.

The proposed D’Agostino test under neutrosophic statistics is the extension of the D’Agostino test under classical statistics.
6. Concluding Remarks

In this paper, we presented a D’Agostino test under neuropsychosomatic statistics. We proposed the D’Agostino test to test the normality of the data having indeterminate observations. The design of the proposed test was given and implemented with the help of real data. The proposed test was the extension of an existing D’Agostino test under classical statistics. From the comparison, it was concluded that the proposed test is effective, adequate, and suitable to be applied in the presence of indeterminacy. The development of software for the proposed test will be a fruitful area of research. The application of the proposed test for big datasets such as testing the normality of ocean data, Facebook user data, and rail data can be considered as future research.

Table 3: The values of NSS of five waters.

| Water | NSS | \( T_N \in [T_L, T_U] \) | \( D_N \in [D_L, D_U] \) | Decision |
|-------|-----|---------------------------|-----------------------------|----------|
| n. 1  | [811.01, 4915.23] | [73.85, 117.75] | [0.1764, 0.1142] | Do not accept \( H_{0_N} \) |
| n. 2  | [7858.36, 33176.61] | [274.2, 296.5] | [0.2104, 0.1107] | Do not accept \( H_{0_N} \) |
| n. 3  | [54.55, 268.79] | [18.43, 20.09] | [0.7847, 0.6489] | Do not accept \( H_{0_N} \) |
| n. 4  | [84.73, 521.31] | [20.75, 27.2] | [0.1533, 0.0810] | Do not accept \( H_{0_N} \) |
| n. 5  | [385.16, 1686.90] | [42.95, 47.35] | [0.1489, 0.0784] | Do not accept \( H_{0_N} \) |

Table 4: The comparison of two tests.

| Water | \( D_N \in [D_L, D_U] \) | The proposed test | The existing test |
|-------|---------------------------|-------------------|------------------|
| n. 1  | [0.1764, 0.1142] | 0.1764–0.1142 \( I_N \in [I_L, I_U] \) | \( 0 \) \( \rightarrow \) 0.1764 |
| n. 2  | [0.2104, 0.1107] | 0.2104–0.1107 \( I_N \in [I_L, I_U] \) | \( 0 \) \( \rightarrow \) 0.2104 |
| n. 3  | [0.7847, 0.6489] | 0.7847–0.6489 \( I_N \in [I_L, I_U] \) | \( 0 \) \( \rightarrow \) 0.7847 |
| n. 4  | [0.1533, 0.0810] | 0.1533–0.0810 \( I_N \in [I_L, I_U] \) | \( 0 \) \( \rightarrow \) 0.1533 |
| n. 5  | [0.1489, 0.0784] | 0.1489–0.0784 \( I_N \in [I_L, I_U] \) | \( 0 \) \( \rightarrow \) 0.1489 |

On the contrary, the existing test provides only the determined value which is not adequate when the data have interval, uncertain, and indeterminate values or the data are obtained from the complex system. From this comparison, it is concluded that the proposed test provides the values of statistic in the indeterminate interval, and this theory is the same as in [39]. Therefore, the use of the proposed test is adequate under an indeterminate environment.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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