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Presenting post hoc multiple comparison tests under neutrosophic statistics

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ABSTRACT

Objective: The existing post hoc tests under classical statistics have been applied for analyzing the data having all determined, precise and exact observations. In practice, the data recorded from the complex situations or under uncertainty does not contain all determined observations in the data.
Method: In this case, the data is recorded in the indeterminacy interval and can be analyzed using neutrosophic statistics.
Results: In this paper, we will modify the existing least significant difference Test, Bonferroni Test and Scheffe Test under the neutrosophic statistics. We will present some basic modified tests under neutrosophic statistical interval method (NSIM) and explained them with the help of real data. We will compare the performance of the proposed tests with the existing tests under uncertainty environment.
Conclusion: The proposed post hoc tests are flexible and informative than the post hoc tests under classical statistics.

1. Introduction

The statistical techniques and methods have been widely used in a variety of fields for testing, estimation, classification and forecasting of the data. Among many tests, the analysis of variance (ANONA) has been widely used in the design of the experiment. The ANONA has been widely applied for the analysis of the data in agricultural, medical and Chemometrics. The applications of ANOVA can be seen in Armstrong et al. (2002), Ulusoy (2008), Tarrío-Saavedra et al. (2011), Niedoba and Pięta (2016) and Borgonovo et al. (2018). Although, the ANOVA used for the testing of the null hypothesis that all population under-investigated has the same means Vs. the alternative hypothesis that at least two population has different means. The main issue in applying the ANOVA tests is that it does not tell the experimenter which pair of the population has different mean when the null hypothesis is rejected. To overcome this issue, the post hoc multiple comparison tests are applied to see which pair of the population has a different population mean. Among them, least significant difference Test, Bonferroni Test and Scheffe Test are very popular and commonly used for the pairwise testing of the population mean. Several authors applied these tests in a variety of fields for the testing of the pairwise mean. Dunnett (1964) presented some tables for post hoc tests. Hayter (1984) studied post hoc multiple comparison tests for unequal sample size. Shirley (1987) introduced the ranking method in post hoc test. Saville (1990) provided a practical solution. Patel et al. (2015) applied post hoc multiple comparison tests in medical research. Sauder and DeMars (2019) presented some updated suggestions about these tests. More details can be seen in Horrace and Schmidt (2000), Lee and Lee (2018), Ahmad (2019) and Sethuraman et al. (2019).

The post hoc multiple comparison tests designed under the assumption that all observations are determined. According to Mikhailov (2003) "However, in many cases, the preference model of the human decision-maker is uncertain and fuzzy and it is relatively difficult crisp numerical values of the comparison ratios to be provided. The decision-maker may be uncertain about his level of preference due to incomplete information or knowledge, inherent complexity and uncertainty within the decision environment, lack of an appropriate measure or scale". In these situations, the post hoc multiple comparison tests using the fuzzy approach are applied. Mikhailov (2003) presented these tests using alpha cut transformation. Izadikhah (2012) developed these tests using the

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nearest interval approximation method. For more details, the reader may refer to Mikhailov (2003) and Kulinskaya and Lewin (2009).

The fuzzy logic is based on the percentages of truth and falsehood while the neutrosophic logic which is the extension of fuzzy logic is additionally considered the percentage of indeterminacy. Therefore, the neutrosophic logic is the extension of fuzzy logic, see for example, Smarandache (1998) and Smarandache (2010). Smarandache (2019) presented the several generalizations of fuzzy logic. More applications of neutrosophic statistics can be seen in Abdel-Basset et al. (2018), Broumi et al. (2018) and Liu et al. (2018).

Based on neutrosophic logic, Smarandache (2014) introduced the neutrosophic statistics which deals with neutrosophic number and indeterminacy. The neutrosophic statistics is the generalization of classical statistics which is applied when data have uncertain, imprecise and indeterminate observations. The neutrosophic statistics provides the additional information about the measure of indeterminacy which classical statistics does not. Therefore, the neutrosophic statistics is more informative, effective and adequate to be applied in uncertainty than the classical statistics. Chen et al. (2017a,b) solved the rock measuring issues using neutrosophic numbers. Aslam (2018a,b, 2019b) introduced neutrosophic statistical quality control (NSQC) area using neutrosophic statistics. Aslam (2020) proposed the Dixon's test under neutrosophic statistics. Albassam et al. (2020) and Aslam et al. (2020) proposed the W/S test and diagnosis test under neutrosophic statistics.

Recently, Aslam (2019a) introduced the neutrosophic analysis of variance (NANONA) test. Aslam (2019a) NANONA test can be applied for the testing of the hypothesis of equality of means when data is recorded under uncertainty and have indeterminate observations. Aslam (2019a) did not study the post hoc tests under the neutrosophic statistics. In this paper, we will modify the existing least significant difference test, Bonferroni's test and Scheffe's test under the neutrosophic statistics. We will present some basic modified tests under neutrosophic statistical interval method (NSIM) and explained them with the help of real data. We will compare the performance of the proposed tests with the existing tests under uncertainty environment. We expect the proposed three tests can be used effectively for analysis of the data under uncertainty.

2. Preliminaries

Suppose that $X_N \epsilon [X_L, X_U]$ be an alternative form of neutrosophic random variable (nrv) follows the neutrosophic normal distribution (NND) with a neutrosophic population mean $\mu_N \epsilon [\mu_L, \mu_U]$ and neutrosophic population standard deviation $\sigma_N \epsilon [\sigma_L, \sigma_U]$, where X_L and X_U are smaller and larger values of indeterminacy interval. Let $X_N = X_L + X_U I_N$ be the neutrosophic form of nrv having determinate part X_L and indeterminate part $X_U I_N$; $I_N \epsilon [I_L, I_U]$, where $I_N \epsilon [I_L, I_U]$ is indeterminacy interval. Suppose $n_N \epsilon [n_L, n_U]$ be a neutrosophic random sample selected from a population of size N_N having indeterminate observations, for more details, see, (Smarandache, 2014; Aslam, 2018b). The neutrosophic population means and the standard deviation are defined as follows;

$$\mu_N \epsilon \left[\frac{\sum_{i=1}^{N_L} x_L}{N_L}, \frac{\sum_{i=1}^{N_U} x_U}{N_U} \right]; \mu_N \epsilon [\mu_L, \mu_U] \text{ and}$$

$$\sigma_N \epsilon \left[\sqrt{\frac{\sum_{i=1}^{N_L} (x_L - \mu_L)}{N_L - 1}}, \sqrt{\frac{\sum_{i=1}^{N_U} (x_U - \mu_U)}{N_U - 1}} \right]; \ \sigma_N \epsilon [\sigma_L, \sigma_U]$$

In practice, $\mu_N \epsilon [\mu_L, \mu_U]$ and $\sigma_N \epsilon [\sigma_L, \sigma_U]$ are unknown and can be estimated using the sample information. The neutrosophic sample mean and standard deviation is defined by;

$$\overline{X}_N \epsilon \left[\frac{\sum_{i=1}^{n_L} \overline{x}_L}{n_L}, \frac{\sum_{i=1}^{n_U} \overline{x}_U}{n_U} \right]; \mu_N \epsilon [\mu_L, \mu_U] \text{ and}$$

$$s_N \epsilon \left[\sqrt{\frac{\sum_{i=1}^{n_L} (x_L - \overline{x}_L)}{n_L - 1}}, \sqrt{\frac{\sum_{i=1}^{N_U} (x_U - \overline{x}_U)}{n_U - 1}} \right]; \ s_N \epsilon [s_L, s_U]$$

3. Neutrosophic LSD test

The least significant difference (LSD) test under classical statistics was originally developed by Fisher for testing the significance of the difference between pairwise populations. By following Fisher's method, we propose the neutrosophic least significant difference (NLSD) test for the pairwise testing of the population under uncertainty environment. The proposed NLSD test will be applied when some or all observations/parameters in a sample or population have neutrosophic numbers, imprecise observations and indeterminate observations. The NLSD test for testing the significance in difference means is given by

$$LSD_{(iN-jN)N} = \frac{\widehat{\mu}_{iN} - \widehat{\mu}_{jN}}{s_{N\left(\widehat{\mu}_{iN} - \widehat{\mu}_{jN}\right)}}; LSD_{(iN-jN)N} \epsilon \left[LSD_{(iL-jL)L}, LSD_{(iU-jU)U} \right] \quad (1)$$

where $\widehat{\mu}_{iN}$ and $\widehat{\mu}_{jN}$ are neutrosophic means of *ith* and *jth* groups, respectively and $s_{N\left(\widehat{\mu}_{iN} - \widehat{\mu}_{jN}\right)}$ be the neutrosophic standard error between *ith* and *jth* groups.

The proposed NLSD test in neutrosophic form can be written as

$$LSD_{(iN-jN)N} = A_N + BI_N; I_N \epsilon [I_L, I_U] \quad (2)$$

where A_N and BI_N are determinate and indeterminate parts of the proposed test. The proposed test reduces to test under classical statistic if $I_N = 0$. Note here that the statistic $LSD_{(i_N-j_N)N} \epsilon \left[LSD_{(i_N-j_N)N}, LSD_{(i_N-j_N)N} \right]$ has neutrosophic t-distribution with $(n_N - j_N)$ a neutrosophic degree of freedom (ndf). The proposed NLSD indicates that a pair has a significant difference in means if the actual difference is larger than the pairwise difference. Note here that the square Eq. (1) follows the neutrosophic F-distribution that can also be used for the testing of means difference alternately.

4. Neutrosophic Bonferroni test

The Bonferroni test is the extension of the LSD test under classical statistics. The optional process of the proposed neutrosophic Bonferroni test (NBT) is the same as under classical statistics. In this test, the significance level obtained in $LSD_{(iN-jN)N} \epsilon \left[LSD_{(iL-jL)L}, LSD_{(iU-jU)U} \right]$ is multiplied by the neutrosophic number of tests that are performed for the population under study. The neutrosophic Bonferroni test is defined as follows

$$BT_N = \text{minimum}\left(\frac{j_N \times (j_N - 1)}{2} \times LSD_{(i_N-j_N)N}, [1, 1] \right); BT_N \epsilon [BT_L, BT_U];$$
$$LSD_{(i_N-j_N)N} \epsilon \left[LSD_{(i_L-j_L)L}, LSD_{(i_U-j_U)U} \right] \quad (3)$$

The neutrosophic form of the proposed test can be written as

$$LSD_{(i_N-j_N)N} = C_N + DI_N; I_N \epsilon [I_L, I_U] \quad (4)$$

where C_N and DI_N are determinate and indeterminate parts of the proposed test. The proposed test reduces to test under classical statistic if $I_N = 0$.

Table 1
The ALT scores.

Method	Test score				Total
1	[80,81]	[92,92]	[87,88]	[83,83]	[342,344]
2	[70,70]	[81,82]	[78,78]	[74,75]	[303,305]
3	[63,64]	[76,76]	[70,71]	[80,81]	[289,292]
Total					[934,941]

5. Neutrosophic Scheffe test (NST)

In classical statistics, the Scheffe test (ST) is calculated using the LSD values. The proposed neutrosophic Scheffe Test (NST) is the generalization of the ST under classical statistics. The computational procedure of NST is based on the neutrosophic F-distribution. The NST is defined by

$$NST_N = \frac{\left(LSD_{(i_N - j_N)N}\right)^2}{j_N - 1}; LSD_{(i_N - j_N)N} \epsilon \left[LSD_{(i_L - j_L)L}, LSD_{(i_U - j_U)U}\right],$$
$$NST_N \epsilon [NST_L, NST_U] \tag{5}$$

The neutrosophic form of NST_N can be given by

$$NST_N = E_N + E_N I_N; I_N \epsilon [I_L, I_U] \tag{6}$$

where E_N and $E_N I_N$ are determinate and indeterminate parts of the proposed test. The proposed test reduces to test under classical statistic if I_N = 0.

6. Application

In this section, we will consider the same example in Aslam (2019a,b). According to Aslam (2019a,b) "To minimize the hostility levels among the university students, a clinical psychologist is interested to perform NANONA to compare three methods. He is interested to test either the population means of all groups are equal or not. He applied the HLT test to measure the data from various students and a high HLT score shows the great hostility levels. The twelve students are selected for this test. Four students are randomly selected and placed in a group and treated with method 1. Four students from eight students are again selected at random and treated with method 2. Four students from four students are again selected at random and treated with method 3. While measuring HLT scores, the clinical psychologist is uncertain in some scores. Under this situation, he recorded data in the neutrosophic interval". Aslam (2019a,b) applied NANONA for the testing the null hypothesis that all neutrosophic means Vs the alternative hypothesis that at least one mean is different. Aslam (2019a,b) concluded that means of all methods are not equal for this data. Now, we perform the post hoc multiple comparison tests on this data under neutrosophic statistics to see which pair of the population has different means. We will perform the three proposed tests under neutrosophic statistics for this data analysis. The data is borrowed from Aslam (2019a,b) and shown in Table 1 for variable indeterminacy interval $I_N \epsilon [I_L, I_U]$. The neutrosophic descriptive statistics for the data is shown in Table 2. The proposed neutrosophic post hoc tests are shown in Table 3.

Smarandache (2014) discussed the use of neutrosophic p-value for the testing of the null and alternative hypothesis. According to Smarandache (2014), the null hypothesis is rejected at significance level α if the maximum of neutrosophic P-value is greater than α. The null hypothesis is not rejected if a minimum of neutrosophic P-value is less than α. For more details, the reader may refer to Smarandache (2014). From Table 3, it can be noted that the neutrosophic populations [1, 1] and [3, 3] are significant as the maximum of neutrosophic P-value which is 0.029 is less than α = 0.05. In this case, the null hypothesis of equal means is rejected and we concluded that the means of these populations are not equal. Similarly, the other pair of population means can be interpreted.

7. Discussion and comparative study

In this section, we will discuss the results obtained from the real data and the advantages of the proposed neutrosophic post hoc tests over the existing post hoc tests under classical statistics. Chen et al. (2017a,b) suggested that a method in the presence of neutrosophic numbers is said to be more efficient if it provides the output of the analysis in the indeterminacy interval rather than the exact values. From Table 1, it can be seen that the ALT scores reduces to the data under classical statistics when there is no Neutrosophy in numbers. Table 2 shows the corresponding neutrosophic descriptive statistics for the neutrosophic data is given in Table 1. From Table 2, we note that the neutrosophic descriptive statistics is in the indeterminacy interval rather than the exact number. For an example, for population [1, 1], the neutrosophic mean indeterminacy interval and neutrosophic form is [85.50, 86.00] and $\mu_N = 85.50 + 86I_N$; $I_N \epsilon [0, 0.0058]$. In this neutrosophic mean interval, the first value which 85.50 is the determinate part and $86I_N$ is an indeterminate part. Therefore, under uncertainty, the experimenter can expect that the mean for the population [1, 1] will from 85.50 to 86.00. From Table 3, we note neutrosophic P-value for the populations [1, 1] and [3, 3] is [0.028, 0.029] for the proposed neutrosophic Tukey test. The first value in this interval indicates the determined part of P-value under classical statistics. The value 0.029 denotes the indeterminate part of the neutrosophic P-value. From this study, we can conclude that the proposed neutrosophic tests provide the neutrosophic P-value in an indeterminacy interval rather than the exact value which concurs with the theory of Chen et al. (2017a,b). Therefore, we can say that the use of the proposed neutrosophic tests under uncertainty will lead to an adequate analysis of the data than the existing tests under classical statistics.

Table 2
The neutrosophic descriptive statistics of the ALT scores.

	N	Neutrosophic Mean	Neutrosophic Std. Deviation	Neutrosophic Std. Error	95% neutrosophic Confidence Interval for Mean		Neutrosophic Minimum	Neutrosophic Maximum
					Lower Bound	Upper Bound		
1	[4,4]	[85.50,86.00]	[5.196,4.96]	[2.598,2.4]	[77.23,78.10]	[93.77,93.90]	[80,81]	[92,92]
2	[4,4]	[75.75,76.25]	[4.787,5.05]	[2.394,2.5]	[68.13,68.20]	[83.37,84.30]	[70,70]	[81,82]
3	[4,4]	[72.25,73]	[7.411,7.25]	[3.705,3.6]	[60.46,61.45]	[84.04,84.55]	[63,64]	[80,81]
Total	[12,12]	[77.83,78.42]	[7.930,7.83]	[2.289,2.2]	[72.80,73.11]	[82.87,83.39]	[63,64]	[92,92]

Table 3
Neutrosophic post hoc tests multiple comparisons.

	(I) groups	(J) groups	Neutrosophic Mean Difference (I-J)	Neutrosophic Std. Error	Sig.	95% Neutrosophic Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	[1,1]	[2,2]	[9.750,9.75]	[4.180,4.142]	[0.102,0.099]	[−1.92,−1.81]	[21.42,21.3]
		[3,3]	[13.250*,13.0]	[4.180,4.142]	[0.028,0.029]	[1.58,1.44]	[24.92,24.5]
	[2,2]	[1,1]	[−9.750,−9.75]	[4.180,4.142]	[0.102,0.099]	[21.42,21.31]	[1.92,1.81]
		[3,3]	[3.500,3.25]	[4.180,4.142]	[0.691,0.721]	[−8.17,−8.31]	[15.17,14.8]
	[3,3]	[1,1]	[−13.250*,−13.0*]	[4.180,4.142]	[0.028,0.029]	[24.92,24.56]	[−1.58,−1.44]
		[2,2]	[−3.500,−3.25]	[4.180,4.142]	[0.691,0.721]	[15.17,14.81]	[8.17,8.31]
Scheffe	[1,1]	[2,2]	[9.750,9.75]	[4.180,4.142]	[0.119,0.115]	[−2.45,−2.33]	[21.95,21.8]
		[3,3]	[13.250*,13.0*]	[4.180,4.142]	[0.034,0.036]	[1.05,0.92]	[25.45,25.0]
	[2,2]	[1,1]	[−9.750,−9.75]	[4.180,4.142]	[0.119,0.115]	[21.95,21.83]	[2.45,2.33]
		[3,3]	[3.500,3.25]	[4.180,4.142]	[0.714,0.742]	[−8.70,−8.83]	[15.70,15.3]
	[3,3]	[1,1]	[−13.250*,13.00*]	[4.180,4.142]	[0.034,0.036]	[25.45,25.08]	[−1.05,−0.92]
		[2,2]	[−3.500,−3.25]	[4.180,4.142]	[0.714,0.742]	[15.70,15.33]	[8.70,8.83]
LSD	[1,1]	[2,2]	[9.750*,9.75*]	[4.180,4.142]	[0.045,0.43]	[0.29,0.38]	[19.21,19.1]
		[3,3]	[13.250*,13.00*]	[4.180,4.142]	[0.011,0.12]	[3.79,3.63]	[22.71,22.3]
	[2,2]	[1,1]	[−9.750*,−9.750*]	[4.180,4.142]	[0.045,0.043]	[19.21,19.12]	[−0.29,−0.38]
		[3,3]	[3.500,3.25]	[4.180,4.142]	[0.424,0.453]	[−5.96,−6.12]	[12.96,12.6]
	[3,3]	[1,1]	[−13.250*,13.00*]	[4.180,4.142]	[0.011,0.12]	[22.71,22.37]	[−3.79,−3.63]
		[2,2]	[−3.500,−3.25]	[4.180,4.142]	[0.424,0.453]	[12.96,12.62]	[5.96,6.12]

* The mean difference is significant at the 0.05 level.

8. Conclusions

In this paper, we presented the design of the three neutrosophic post hoc tests for testing the null hypothesis of equal means. We presented some modified formulas of three post hoc tests under the neutrosophic statistics. The proposed neutrosophic post hoc tests are the generalization of post hoc tests under classical statistics. We discussed the advantages of the proposed tests and found that these are flexible, adequate and more information to be applied under uncertainty environment. We recommended the statisticians to apply this test in a verity of fields under uncertainty. The development of statistical software for the proposed tests can be considered as future research. Some more tests under neutrosophic statistics can be considered as future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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