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ROW-COLUMN DESIGNS: A NOVEL APPROACH FOR ANALYZING IMPRECISE AND UNCERTAIN OBSERVATIONS

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Abstract

Classical row-column designs cannot be applied when the underlying data set contains some imprecise, uncertain, or undetermined observations. In this paper, we discuss row-column design under a neutrosophic statistical framework. A significant contribution of our study is to propose a novel approach to analyzing row-column designs using neutrosophic data. This approach involves calculating the neutrosophic analysis of variance (NANOVA) table for the proposed design and using it to derive the F_N -test in an uncertain environment. Two numerical examples have been used to assess the proposed design's performance. Results from the study indicated that a row-column design under neutrosophic statistics was more efficient than a row-column design under classical statistics in the presence of uncertainty.

1. Introduction

Experimental design is crucial to the planning, analysis, and interpretation of experiments in order to produce accurate and objective results. The row-column design is one of the most widely used experimental designs in a variety of fields. These designs use two blocking factors, one representing the rows and the other representing the columns, in order to group the experimental units. Row-column designs were first introduced by Fisher [12]. Chang and Notz [10] discussed some optimal nested row-column designs through optimal designs for estimating treatment effects. Williams and John [23] used row-column factorial designs in agricultural field trials. A detailed discussion of row-column designs has been given by Shah and Sinha [20]. Several row-column designs are reviewed and illustrated in Dean and Voss [11]. We can find related articles and books about row-column design in John and Eccleston [13], Majumdar and Tamhane [14], Morgan and Parvu [15], and Morgan and Uddin [16].

The concept of neutrosophic statistics (NS) was introduced by Smarandache [21] for dealing with the problem of data which have some degree of indeterminacy. Neutrosophic statistics is more informative and flexible than classical statistics (Aslam [4]). The differences between fuzzy statistics, NS, and classical statistics are explained in a table (Aslam [6]). Aslam [5] has highlighted neutrosophic ANOVA. A more recent article of AlAita and Aslam [1] discussed the application of neutrosophic analysis of covariance to a variety of experimental designs. Besides, post hoc multiple comparison tests under NS have been proposed by Aslam and Albassam [8]. Aslam and Al-Marshadi [7] introduced the Watson-Williams test under NS for the analysis of circular and angular data that is uncertain, imprecise, and indeterminate. In another paper, diagnosis test under NS has been discussed by Aslam et al. [9]. Salama et al. [19] discussed neutrosophic correlation and simple linear regression. Nagarajan et al. [17] have proposed in their paper an analysis of neutrosophic multiple regression. Numerous statistical tests have been discussed under NS in Alvaracín Jarrín et al. [3], Smarandache [22], Alpaslan [2], Yazdani et al. [24] and Zolfani et al. [25].

A primary motivation for doing this research is to resolve problems caused by studies involving imprecise and uncertain data that require row-column designs. For example, in 5×3 row-column experiment, three different diets (treatments) were compared on the milk production of dairy cows (five rows) during three periods (three columns) for the purpose of determining whether they affect no protein nitrogen in rat colostrum. In order to analyze this example, under NS, we calculate the NANOVA table, and then derive the F_N-test in the neutrosophic form, which identifies the measure of indeterminacy. The row-column design under classical statistics cannot be used to analyze and interpret neutrosophic data that have some degree of indeterminacy. Accordingly, this type of research requires the proposed design.

According to our literature review, we are not aware of any work on row-column designs under NS. This paper introduces a neutrosophic row-column design. In addition, the F_N-test of row-column design is introduced under NS. Numerical examples are used to illustrate the hypothesis testing procedure. We anticipate that the proposed row-column design performs better than the existing design in the event of uncertainty.

The remaining portions of this paper are arranged as follows: The following section discusses some concepts related to neutrosophic statistics and classical row-column design. In Section 3, we present a statistical analysis of the neutrosophic row-column design. Detailed numerical examples are provided in Section 4. The discussion and comparative study are presented in Section 5. Finally, Section 6 presents the conclusion.

2. Preliminaries

This section discusses the ANOVA approach of row-column design and neutrosophic statistics in brief.

2.1. Model and ANOVA for a row-column design

A row-column design with a rows and b columns can be represented by the following statistical model:

$$y_{hqi} = \mu + \gamma_h + \delta_q + \tau_i + \varepsilon_{hqi}; \quad \begin{cases} h = 1, 2, ..., a, \\ q = 1, 2, ..., b, \\ i = 1, 2, ..., t, \end{cases} \tag{1}$$

where y_{hqi} represents the observation in the hth row and qth column for the ith treatment, μ represents an overall mean, γ_h represents the effect of the hth row, δ_q represents the effect of the qth column, τ_i represents the effect of the ith treatment, and ε_{hqi} represents the random error assumed to have mean of zero and variance σ^2. Let the total number of all plots in the blocks (rows and columns) be n. Then $n = ab$. Table 1 presents the ANOVA for row-column design.

Table 1. ANOVA table for row-column design

Source	SS	Df	MS	F
Rows (unadj)	SS_R	$a-1$	$MS_R = \frac{SS_R}{a-1}$	
Columns (unadj)	SS_C	$b-1$	$MS_C = \frac{SS_C}{b-1}$	
Treatments (adj)	$SS_{Tr(adj)}$	$t-1$	$MS_{Tr(adj)} = \frac{SS_{Tr(adj)}}{t-1}$	$\frac{MS_{Tr(adj)}}{MS_E}$
Error	SS_E	$ab-a-b-t+2$	$\frac{SS_E}{ab-a-b-t+2}$	
Total	SS_T	$n-1$		

The computing formulas for SSs can be expressed as follows:

$$SS_T = \sum_{h=1}^{a}\sum_{q=1}^{b}\sum_{i=1}^{t} n_{hqi}y_{hqi}^2 - \frac{y_{...}^2}{n},$$

$$SS_R = \frac{1}{b}\sum_{h=1}^{a} y_{h..}^2 - \frac{y_{...}^2}{n},$$

$$SS_C = \frac{1}{a}\sum_{q=1}^{b} y_{.q.}^2 - \frac{y_{...}^2}{n},$$

$$T_i = \sum_{h=1}^{a}\sum_{q=1}^{b} n_{hqi}y_{hqi},$$

$$Q_i = T_i - \frac{1}{b}\sum_{h=1}^{a} n_{h.i}y_{h.i} - \frac{1}{a}\sum_{q=1}^{b} n_{.qi}y_{.qi} + \frac{ry_{...}^2}{n},$$

$$SS_{Tr(adj)} = \sum_{i=1}^{t} Q_i\hat{\tau}_i,\ SS_E = SS_T - SS_R - SS_C - SS_{Tr(adj)},$$

where $y_{h..}$ represents the total number of observations in the hth row, $y_{.q.}$ represents the total number of observations in the qth column, and $y_{...}$ represents the total number of observations, $n_{h.i}$ stands for the number of times that treatment i appears in row h, and $n_{.qi}$ stands for the number of times that treatment i appears in column q.

2.2. Hypotheses and decision rule

Under classical statistics, a null hypothesis and an alternative hypothesis are presented as follows:

$$H_0 : \tau_1 = \tau_2 = \cdots = \tau_t = 0 \text{ vs } H_1 : \text{at least one } \tau_i \neq 0.$$

The null hypothesis is accepted if p-value $\geq \alpha$, where α is a level of significance. The null hypothesis is rejected if p-value $< \alpha$.

2.3. Neutrosophic statistics (NS)

It has been observed in recent years that many real-world examples have been applied under NS, which are generalizations of classical statistics. Furthermore, it is characterized by its flexibility and efficiency in uncertain environments, as well as its ability to calculate measure of indeterminacy resulting from the state of uncertainty. A brief introduction to some basic concepts related to NS is provided below.

Suppose that a neutrosophic random variable (NRV) $X_N \in [X_L, X_U]$ follows the neutrosophic normal distribution (NND) with a neutrosophic population mean $\mu_N \in [\mu_L, \mu_U]$ and a neutrosophic population variance $\sigma_N^2 \in [\sigma_L^2, \sigma_U^2]$, 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 $X_U I_N$; $I_N \in [I_L, I_U]$, where $I_N \in [I_L, I_U]$ is an indeterminate interval. (For more information, see (Aslam [5].)

3. Analysis of Neutrosophic Row-column Design

3.1. Model and NANOVA for a neutrosophic row-column design

The neutrosophic statistical model for a row-column design with a_N rows and b_N columns can be expressed as:

$$y_{Nhqi} = \mu_N + \gamma_{Nh} + \delta_{Nq} + \tau_{Ni} + \varepsilon_{Nhqi}; \quad \begin{cases} h = 1, 2, ..., a_N, \\ q = 1, 2, ..., b_N, \\ i = 1, 2, ..., t_N. \end{cases} \tag{2}$$

The neutrosophic form of y_{Nhqi} can be defined as

$$y_{Nhqi} = y_{Lhqi} + y_{Uhqi} I_N; \quad I_N \in [I_L, I_U], \tag{3}$$

where y_{Nhqi} represents the neutrosophic observation in the *h*th row and *q*th column for the *i*th treatment, μ_N represents a neutrosophic overall mean, γ_{Nh} represents the neutrosophic effect of the *h*th row, δ_{Nq} represents the neutrosophic effect of the *q*th column, τ_{Ni} represents the neutrosophic effect of the *i*th treatment, and ε_{Nhqi} represents the neutrosophic random error assumed to have mean of zero and variance $\sigma_N^2 \in [\sigma_L^2, \sigma_U^2]$. Let the total neutrosophic number of all plots in the blocks (rows and columns) be n_{NT}. Then $n_{NT} = a_N b_N$. Table 2 presents ANOVA of neutrosophic row-column design.

Table 2. NANOVA table for neutrosophic row-column design

Source	*NSS*	*Ndf*	*NMS* (neutrosophic mean squares)	F_N
Rows (unadj)	SS_{NR}	$a_N - 1$	$MS_{NR} = \frac{SS_{NR}}{a_N - 1}$	
Columns (unadj)	SS_{NC}	$b_N - 1$	$MS_{NC} = \frac{SS_{NC}}{b_N - 1}$	
Treatments (adj)	$SS_{NTr(adj)}$	$t_N - 1$	$MS_{NTr(adj)} = \frac{SS_{NTr(adj)}}{t_N - 1}$	$\frac{MS_{NTr(adj)}}{MS_{NE}}$
Error	SS_{NE}	$a_N b_N - a_N - b_N - t_N + 2$	$MS_{NE} = \frac{SS_{NE}}{a_N b_N - a_N - b_N - t_N + 2}$	
Total	SS_{NT}	$n_{NT} - 1$		

The computing formulas for NSSs can be expressed as follows:

$$SS_{NT} = \sum_{h=1}^{a_N}\sum_{q=1}^{b_N}\sum_{i=1}^{t_N} n_{Nhqi} y_{Nhqi}^2 - \frac{y_{N...}^2}{n_{NT}}; \;\; SS_{NT} \in [SS_{LT}, SS_{UT}],$$

$$SS_{NR} = \frac{1}{b_N}\sum_{h=1}^{a_N} y_{Nh..}^2 - \frac{y_{N...}^2}{n_{NT}}; \;\; SS_{NR} \in [SS_{LR}, SS_{UR}],$$

$$SS_{NC} = \frac{1}{a_N}\sum_{q=1}^{b_N} y_{N.q.}^2 - \frac{y_{N...}^2}{n_{NT}}; \;\; SS_{NC} \in [SS_{LC}, SS_{UC}],$$

$$T_{Ni} = \sum_{h=1}^{a_N}\sum_{q=1}^{b_N} n_{Nhqi} y_{Nhqi},$$

$$Q_{Ni} = T_{Ni} - \frac{1}{b_N}\sum_{h=1}^{a_N} n_{Nh.i} y_{Nh.i} - \frac{1}{a_N}\sum_{q=1}^{b_N} n_{N.qi} y_{N.qi} + \frac{r_N y_{N...}^2}{n_{NT}},$$

$$SS_{NTr(adj)} = \sum_{i=1}^{t_N} Q_{Ni}\hat{\tau}_{Ni}; \;\; SS_{NTr(adj)} \in [SS_{LTr(adj)}, SS_{UTr(adj)}],$$

$$SS_{NE} = SS_{NT} - SS_{NR} - SS_{NC} - SS_{NTr(adj)}; \;\; SS_{NE} \in [SS_{LE}, SS_{UE}],$$

where $y_{Nh..}$ represents the total number of the neutrosophic observations in the hth neutrosophic row, $y_{N.q.}$ represents the total number of the neutrosophic observations in the qth neutrosophic column, and $y_{N...}$ represents the total number of all the neutrosophic observations, $n_{Nh.i}$ represents the number of times that neutrosophic treatment i appears in neutrosophic row h, and $n_{N.qi}$ represents the number of times that neutrosophic treatment i appears in neutrosophic column q.

Neutrosophic mean squares are defined as:

$$MS_{NR} = \frac{SS_{NR}}{a_N - 1}; \;\; MS_{NR} \in [MS_{LR}, MS_{UR}],$$

$$MS_{NC} = \frac{SS_{NC}}{b_N - 1}; \;\; SS_{NT} \in [MS_{LC}, MS_{UC}],$$

$$MS_{NTr(adj)} = \frac{SS_{NTr(adj)}}{t_N - 1}; \; MS_{NTr(adj)} \in [MS_{LTr(adj)}, MS_{UTr(adj)}],$$

$$MS_{NE} = \frac{SS_{NE}}{a_N b_N - a_N - b_N - t_N + 2}; \; MS_{NE} \in [MS_{LE}, MS_{UE}].$$

The neutrosophic statistic F_N test becomes

$$F_N = \frac{MS_{NTr(adj)}}{MS_{NE}}; \quad F_N \in [F_L, F_U].$$

F_N can be expressed in the neutrosophic form as follows:

$$F_N = F_L + F_U I_{F_N}; \quad I_{F_N} \in [I_{F_L}, I_{F_U}],$$

where F_L and $F_U I_{F_N}$ are determinate and indeterminate parts of the proposed test. This test reduces to test under classical statistic if $I_{F_N} = 0$.

3.2. Neutrosophic hypotheses and decision rule

Under neutrosophic statistics, a null hypothesis and an alternative hypothesis are presented as follows:

$$H_{N0} : \tau_{N1} = \tau_{N2} = \cdots = \tau_{Ni} = 0 \text{ vs } H_{N1} : \text{at least one } \tau_{Ni} \neq 0.$$

The null hypothesis is accepted if $\min\{p_N\text{-value}\} \geq \alpha$, where α is a level of significance. The null hypothesis is rejected if $\max\{p_N\text{-value}\} < \alpha$.

4. Numerical Examples

Example 4.1. Following is a case study using yields (in kgs.) of paddy with imprecise observations from the article of Parthiban and Gajivaradhan [18]. The last line of data is generated randomly by the R program. The 5×4 neutrosophic row-column design is used. Table 3 illustrates the distribution of data.

Table 3. Data for the neutrosophic row-column design

	Columns			
Rows	1	2	3	4
1	$A_3[22, 27]$	$A_2[20, 25]$	$A_1[15, 20]$	$A_4[17, 22]$
2	$A_1[16, 21]$	$A_4[15, 19]$	$A_3[19, 24]$	$A_2[15, 20]$
3	$A_2[17, 22]$	$A_1[10, 15]$	$A_4[14, 19]$	$A_3[18, 24]$
4	$A_4[13, 17]$	$A_3[15, 20]$	$A_2[19, 24]$	$A_1[10, 16]$
5	$A_2[15, 16]$	$A_3[14, 18]$	$A_1[13, 15]$	$A_4[11, 14]$

Table 4. ANOVA table for the neutrosophic row-column design

Source	*NSS*	*ndf*	*NMS*	F_N	Neutrosophic form F_N	p_N -value
Rows (unadj)	[66.80, 127.30]	[4, 4]	[16.70, 31.82]			
Columns (unadj)	[18.00, 7.40]	[3, 3]	[6.75, 4.12]			
Treatments (adj)	[86.25, 98.35]	[3, 3]	[28.75, 32.78]	[10.05, 9.59]	$10.05 - 9.59 I_{F_N}$; $I_{F_N} \in [0, 0.048]$	[0.003, 0.004]
Error	[25.75, 30.75]	[9, 9]	[2.86, 3.42]			
Total	[196.80, 263.80]	[19, 19]				

Example 4.2. Suppose that a researcher conducts an experiment to examine the effects of neutrosophic treatments on a particular experiment. The 6×3 neutrosophic row-column design is used. Table 5 illustrates the distribution of data.

Table 5. Data for the neutrosophic row-column design

	Column		
Row	1	2	3
1	B[10.71, 11]	C[12.11, 12.18]	A[8.79, 9.75]
2	C[11.24, 12.2]	A[11.34, 11.75]	B[6.34, 7.08]
3	C[12.09, 12.86]	B[10.05, 10.2]	A[10.84, 11.17]
4	A[8.1, 8.79]	B[9.65, 9.83]	C[10.07, 10.33]
5	B[8.34, 8.56]	A[10.41, 10.46]	C[10.77, 11.74]
6	A[6.36, 6.94]	C[11.42, 11.73]	B[11.9, 12.08]

Table 6. ANOVA table for the neutrosophic row-column design

Source	NSS	ndf	NMS	F_N	Neutrosophic form F_N	p_N -value
Rows (unadj)	[5.89, 5.77]	[5, 5]	[1.18, 1.15]			
Columns (unadj)	[6.06, 2.94]	[2, 2]	[3.03, 1.47]			
Treatments (adj)	[14.26, 16.63]	[2, 2]	[7.13, 8.32]	[2.03, 2.57]	$2.03 + 2.57 I_{F_N}$; $I_{F_N} \in [0, 0.210]$	[0.194, 0.138]
Error	[28.13, 25.93]	[8, 8]	[3.52, 3.24]			
Total	[54.34, 51.27]	[17, 17]				

In order to conduct the proposed F_N-test for neutrosophic row-column design, the following steps will need to be taken:

Step 1. We test the following statistical hypothesis:

$$H_{N0} : \tau_{N1} = \tau_{N2} = \cdots = \tau_{Nt} = 0 \text{ vs } H_{N1} : \text{at least one } \tau_{Ni} \neq 0.$$

Step 2. We organize the NANOVA table for the proposed design.

Step 3. At the level of significance $\alpha = 0.05$, we calculate the p_N-value.

From the NANOVA Table 4 in Example 4.1: p_N-value $= [0.003, 0.004]$ and the NANOVA Table 6 in Example 4.2: p_N-value $= [0.194, 0.138]$.

Step 4. We accept the null hypothesis H_{N0} if p_N-values ≥ 0.05, and reject it otherwise.

In Example 4.1: We reject the null hypothesis H_{N0} because p_N-value $= [0.003, 0.004] < 0.05$, i.e., there is a difference in mean between the three treatments.

In Example 4.2: We accept the null hypothesis H_{N0} because p_N-value $= [0.194, 0.138] \geq 0.05$, i.e., the treatments have the same mean.

5. Discussion and Comparative Study

The aim of this section is to define the advantages of the proposed design in the presence of uncertainty in which, the neutrosophic logic literature has indicated that a method based on data in an indeterminate interval is more effective and suitable for use in uncertainty than determined values under classical statistics. This paper proposes the row-column design under NS as a generalization of the existing row-column design under classical statistics. As long as uncertainty does not exist, the proposed design reduces to the existing row-column design. In order to determine the effectiveness of the proposed F_N-test, we assess its measure of indeterminacy, adequacy, information, and flexibility. For example, in Table 6, the neutrosophic form of the F_N-test is $F_N = 2.03 + 2.57 I_{F_N}$; $I_{F_N} \in [0, 0.210]$. There are two parts to this neutrosophic form: an F-test of classical statistics and an indeterminate part. The neutrosophic form of the neutrosophic F_N-test reduces to the F-test when $I_{F_N} = 0$. In other words, the value 2.03 represents the F-test value under classical statistics for the existing row-column design. As for the second part, $2.57 I_N$, it contains an indeterminate part that has a measure of indeterminacy of 0.210.

According to Table 6, the proposed F_N-test has a range of values between 2.03 and 2.57. On the other hand, the existing F-test only considers a single value that is adequate when dealing with uncertainty. At α significance level, the p_N-value is $[0.194, 0.138] \geq 0.05$. In light of this, the neutrosophic null hypothesis is accepted while the neutrosophic alternative hypothesis is rejected. This indicates that there are no significant differences between the means of the assumed treatments. Additionally, 0.210 is the measure of indeterminacy associated with the proposed F_N-test. The existing F-tests cannot provide information regarding measure of indeterminacy. In the light of the results of the study, it can be concluded that the proposed F_N-test is more informative and flexible than the existing F-test.

6. Conclusion

In this paper, we presented a row-column design under neutrosophic statistics that is suitable for analyzing indeterminate, uncertain, and imprecise data. The statistical model and NANOVA table for the proposed design have been discussed. Furthermore, we examined the effectiveness of the proposed F_N-test for neutrosophic row-column design compared with the existing row-column design test. A numerical example of the application of the proposed row-column design has been presented. The results demonstrate that the proposed F_N-test provides greater flexibility, applicability, and information than the existing F-test.

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