

Rank tests for Comparing several treatments with a control in a Randomized Block experiment

Sang-Gue Park *,Jeong-il kim **,Eun-Koo Lee **

ABSTRACT

Propose three rank tests based on different kinds of ranking methods for comparing several treatments with a control in a randomized block experiment. Monte Carlo power simulation study is examined in some small sample sizes and configurations to recommend a better test for applications.

I . Introduction

In order to secure the advantages of increased homogeneity and the resultant increased precision in detecting some of treatment effects, it has been well-known to stratify the populations or to divide the experimental subjects into blocks, using a randomized block design. The present investigation is concerned with three kinds of rank tests of comparing several treatments with a control in randomized block design. As in the literatures (Lehmann (1975)), we can adopt

* Dept. of Applied Statistics, Hannam Univ., Dajeon, Korea

** Dept. of Statistics, Dajeon Univ., Dajeon, Korea

three approaches to this problem; the first is the most popular on which is “within blocks” ranking approach used by many authors since Friedman(1937) did. The second, suggested by Hollander(1966) is based on “between blocks” rankings. The third is based on “aligned” ranking scheme considered by Hodges and Lehmann(1962) and Mehra and sarangi(1967) among others.

Many parametric or rank tests based on these three approaches has been proposed in different forms for the omnibus or ordered alternatives. Here we propose three tests in three approaches for comparing several treatments with a control in randomized block experiments. Further this study also investigates the small sample approximate powers of three tests assuming various population models.

II. Test statistics

Let us consider a two factor experiment comprising $n(\geq 2)$ blocks, each block containing $(k+1)(\geq 2)$ plots receiving k different treatments and a control(standard). Like the usual randomized block design model, we express the responses X_{ij} of the plot receiving the j -th treatment in the i -th block as

$$(2.1) \quad X_{ij} = \mu + \beta_i + \tau_j + \varepsilon_{ij}, \quad i=1,2,\dots,n; j=0,1,\dots,k;$$

where μ stands for the mean effect, $\beta_1, \beta_2, \dots, \beta_n$ for the block effects(may or may not be stochastic), $\tau_0, \tau_1, \dots, \tau_k$ for the treatment effects(assumed to be nonstochastic), and ε_{ij} 's are the independent random variables with a common distribution function F and the corresponding density f ; $P(X_{ij} \leq x) = F_j(x - \beta_i)$. Without any loss of generality, we may set $\sum_{0 \leq j \leq k} \tau_j = 0$ and $\sum_{i \geq 1 \leq n} \beta_i = 0$. We consider β_i 's as nuisance parameters.

The problem of interest under this setting is to test

$$(2.2) \quad H_0: \tau_0 = \tau_1 = \dots = \tau_k = 0$$

against

$$(2.3) \quad H_1: \tau_0 \leq \tau_1, \tau_2, \dots, \tau_k, \text{ at least one strict inequality.}$$

Under this situation, we consider three kinds of tests based on different ranking schemes.

Remark 1: The alternative hypothesis can be formulated as

$$H_2: \tau_0 \geq \tau_1, \tau_2, \dots, \tau_k, \text{ at least one strict inequality.}$$

2.1 “Within-blocks” rank statistics

When we consider the model(2.1), it is meaningless the ranks based on joint ranking because of the block effects. Thus Friedman(1937) first proposed a test based on independent rankings of observations within each block. Since then, many researches have been done for various alternatives. We can adopt this idea and propose a test statistic based on this ranking scheme. Let $R_{ij}(j=0,1,\dots,k)$ be the ranks of X_{ij} among i -th block’s observations($X_{i0},X_{i1},\dots,X_{ik}$). Then we can form a statistic for detecting differences between treatments and a control in each block as

$$D_i = \sum_{j=1}^K (R_{ij} - R_{i0}).$$

Now a test statistic for (2.2) against (2.3) can be

$$(2.4) \quad T_1 = \sum_{i=1}^n D_i.$$

The test based on (2.4) rejects H_0 for large values of T_1 . From the well-known asymptotic results of rank statistic, we may use a normal approximation of T_1 with

$$(2.5) \quad E(T_1) = 0,$$

$$(2.6) \quad \text{Var}(T_1) = nk(k+1)^2(k+2)/12.$$

Remark 2: Similarly Fligner and Wolfe(1982) proposed a test based on “within blocks” ranking with Mann-Whitney statistics for H_0 against H_1 .

2.2 “Between blocks” rank statistics

Let $Y_{ij} = |X_{i0} - X_{ij}|$ and S_{ij} =rank of Y_{ij} in the ranking from least to greatest of $Y_{ij}; 1 = 1, 2, \dots, n$. Furthermore, let

$$(2.7) \quad V_j = \sum_{i=1}^n S_{ij} \psi_{ij},$$

where $\psi_{ij}=1$ if $X_{i0} < X_{ij}$ and 0 otherwise. Following the works of Hollander (1966), we adopt his lemma 2 here.

Theorem 1: Assume $0 < \int F_0 dF_j < 1$ for $j=1,2,\dots,k$ and let $Q_j = F_j * F_j$,

$W_j = V_j / \binom{n}{2}$ Then $\sqrt{n}(W_j - \int Q_0 dQ_0)$ have an asymptotic k-variate normal distribution.

Hollander proposed an asymptotically distribution-free multiple comparison procedure. We propose a test statistics T_2 for testing H_0 against H_1 by modifying his works;

$$(2.8) \quad T_2 = \sum_{j=1}^n W_j.$$

The test based on (2.8) rejects H_0 for large values of T_2 . Hollander showed that the distribution of $V_j(j=1,2,\dots,k)$ was asymptotically normally distributed with

$$(2.9) \quad E(V_j) = n(n+1)/4,$$

$$(2.10) \quad \text{Cov}(V_i, V_j) = A_1 + 2A_2 + A_3 - n^2(n+1)^2/16,$$

where $A_1 = n(n-1)/6 + n(n-1)(n-2)\lambda(F) + n(n-1)(n-2)(n-3)/16$,

$A_2 = n(n-1)\mu(F) + n(n-1)(n-2)/8$, $A_3 = n/3 + n(n-1)/4$ and

$$\lambda(F) = \Pr(X_1 < X_2; X_1 < X_3 + X_6 - X_7),$$

$$\mu(F) = \Pr(X_1 < X_2 + X_3 - X_4; X_1 < X_5 + X_6 - X_7)$$

when X_1, X_2, \dots, X_7 are iid according to F . Since the test based on T_2 is not distribution-free, we need to estimate $\lambda(F)$ and $\mu(F)$ to obtain an asymptotically distribution-free test. However, estimating these are not an easy job, so we can have a conservative version of T_2 by plugging in maximum possible values of $\lambda(F)$ and $\mu(F)$. Lehmann(1964) showed the inequality $6/24 < \lambda(F) \leq 7/24$ and Hollander(1967) showed that $\mu(F) \leq ((\sqrt{2} + 6)/24) = .3089$. Thus we can have a conservative test based on T_2^* by setting $\lambda(F) = 7/24$ and $U(F) = 0.3089$.

2.3. "aligned" rank statistics

Hodge and Lehmann(1962) suggested a conditional ranking procedure after alignment. This procedure seems to be combinations of the above two procedures; the first step is to bring the observations in the various blocks into alignment with one another. This is done by subtracting from each observation the mean observation in its block, but some cases other methods for alignment might be better, such as subtracting median or trimmed mean. Once the observations

are aligned, then they are pooled and ranked without regard to their blocks. Let \hat{R}_{ij} be the rank of X_{ij} after alignment and \hat{R}_j be the rank sum of \hat{R}_{ij} from $\hat{R}_{1j}, \hat{R}_{2j}, \dots, \hat{R}_{nj}$, then we propose the test statistic for H_0 against H_1 as followed;

$$(2.13) \quad T_3 = \sum_{j=1}^k (\hat{R}_j - \hat{R}_{\cdot 0}).$$

The test based on T_3 rejects H_0 for large values of T_3 . The test based on T_3 is the conditional test, which modifies the test proposed by Hodge and Lehmann(1962) for the omnibus alternatives to the one-sided alternatives(2.3). From Mehra and Sarange(1967) we may have the following theorem.

Theorem 2: Let $E_c(\cdot)$, $Var_c(\cdot)$ stand for the conditional expectation, variance and covariance respectively, under H_0 , given a configuration. Then for $j=0, 1, \dots, k$,

$$(2.14) \quad E_c(\hat{R}_{\cdot j}) = \sum_{i=1}^n \bar{R}_i$$

$$(2.15) \quad Var_c(\hat{R}_{\cdot j}) = \sum_{i=1}^n \sigma_{\alpha_i}^2;$$

$$(2.16) \quad Cov_c(\hat{R}_{\cdot j}, \hat{R}_{\cdot j'}) = \sum_{i=1}^n [\sigma_{\alpha_i}^2/k];$$

where $\bar{R}_i = \sum_{j=0}^k R_{ij}/(k+1), \sigma_{\alpha_i}^2 = \sum_{j=0}^k (\hat{R}_{ij} - \bar{R}_i)^2/(k+1)$.

From theorem 2, we can easily have $E_c(T_3) = 0, Var_c(T_3) = (K^2 + 3) \sum_{i=1}^n \sigma_{\alpha_i}^2$.

Let T_m stands for the vectors $(T_{n0}, T_{n1}, \dots, T_{nk})'$ respectively, where

$$(2.17) \quad T_{nj} = \frac{\sqrt{k} \{R_j - n(n(k+1) + 1).2\}}{\{(k+1) (\sum_{i=1}^n \delta_{\alpha_i}^2)\}^{1/2}}$$

and Δ stands for the covariance matrix $\|\delta_{ij} - 1/(k+1)\|$, where δ_{ij} is the kronecker's delta. By using some discussion of Mehra and Sarangi on p.97, we can have the following theorem easily.

Theorem 3: Under H_0 the random vector T_n converges in distribution, as $n \rightarrow \infty$, to a

multivariate normal vector $N(0, \Delta)$.

Following the asymptotic results of theorem 3, we may have the asymptotic normality of test statistics T_3 , given a configuration as $n \rightarrow \infty$ and complete a testing procedures of H_0 against H_1 .

III. Simulation

A simulation study is undertaken to compare the approximate power performance of the tests considered here. We assume that one observation is in each cell and sizes of block are 10 and 15.

The distributions, used to generate the samples, are uniform, normal, Cauchy and exponential. The scale parameters for all these distributions are given as 1. SAS IML is used to generate the samples.

The study includes 3 values for the number of treatments, namely 3, 4 and 5. The approximate 0.05 and 0.01 critical values of discussed tests are used. The sizes and powers of each test are estimated using 1000 repetitions.

Three types of τ_i 's configurations under H_1 are used as

Type 1: $\tau_0 < \tau_1 = \dots = \tau_k$;
 $\tau_0 = -0.k, \tau_i = 0.1$;

Type 2: $\tau_0 < \tau_1 < \dots < \tau_k$;
 $\tau_0 = -0.1, \tau_i = 0.0, \tau_k = 0.1$

Type 3: $\tau_0 = \tau_1 = \dots < \tau_k$;
 $\tau_0 = -0.1, \tau_i = -0.1, \tau_k = 0.k$

B_i 's configurations are given by

$n=10, (\beta_1; \beta_5) = (-5; -1(1)); (\beta_6; \beta_{10}) = (1; 5(1))$,

$n=15, (\beta_1; \beta_7) = (-7; -1(1)); \beta_8 = 0; (\beta_9; \beta_{15}) = (1; 7(1))$. Further let $u=0$.

The values in the parenthesis are the approximate powers at $\alpha=0.01$.

(i) Approximate power estimates for the case of $k=3, n=10$

Distributions	T ₁	T ₂	T ₃
Normal			
H ₀	0.05(0.003)	0.04(0.004)	0.04(0.006)
Type 1	0.27(0.06)	0.244(0.07)	0.3(0.08)
Type 2	0.168(0.035)	0.163(0.046)	0.17(0.047)
Type 3	0.1(0.12)	0.087(0.018)	0.092(0.023)
Uniform			
H ₀	0.074(0.014)	0.06(0.018)	0.064(0.016)
Type 1	0.93(0.67)	0.95(0.84)	0.96(0.85)
Type 2	0.65(0.27)	0.71(0.33)	0.73(0.40)
Type 3	0.23(0.05)	0.17(0.038)	0.22(0.044)
Cauchy			
H ₀	0.064(0.008)	0.064(0.006)	0.056(0.014)
Type 1	0.16(0.034)	0.12(0.034)	0.13(0.04)
Type 2	0.10(0.008)	0.068(0.008)	0.075(0.01)
Type 3	0.122(0.012)	0.08(0.014)	0.08(0.024)
Exponential			
H ₀	0.04(0.006)	0.05(0.007)	0.05(0.01)
Type 1	0.43(0.16)	0.37(0.15)	0.39(0.14)
Type 2	0.28(0.074)	0.22(0.063)	0.24(0.065)
Type 3	0.15(0.023)	0.1(0.03)	0.12(0.026)

(ii) Approximate power estimates for the case of k=4, n=10

Distributions	T ₁	T ₂	T ₃
Normal			
H ₀	0.045(0.005)	0.04(0.007)	0.042(0.008)
Type 1	0.346(0.132)	0.364(0.125)	0.396(0.173)
Type 2	0.16(0.04)	0.18(0.04)	0.195(0.05)
Type 3	0.094(0.016)	0.09(0.016)	0.092(0.016)
Uniform			
H ₀	0.038(0.01)	0.038(0.006)	0.038(0.004)
Type 1	0.988(0.93)	0.996(0.984)	0.998(0.982)
Type 2	0.636(0.33)	0.73(0.336)	0.74(0.392)

Type 3	0.174(0.04)	0.14(0.028)	0.2(0.044)
Cauchy			
H ₀	0.048(0.01)	0.054(0.014)	0.062(0.016)
Type 1	0.194(0.07)	0.16(0.048)	0.142(0.056)
Type 2	0.068(0.016)	0.064(0.01)	0.07(0.018)
Type 3	0.072(0.012)	0.054(0.008)	0.064(0.016)
Exponential			
H ₀	0.042(0.009)	0.035(0.006)	0.037(0.004)
Type 1	0.56(0.326)	0.5(0.256)	0.55(0.3)
Type 2	0.22(0.08)	0.2(0.07)	0.213(0.07)
Type 3	0.114(0.02)	0.108(0.017)	0.12(0.017)

(iii) Approximate power estimates for the case of $k=5, n=10$

Distributions	T ₁	T ₂	T ₃
Normal			
H ₀	0.066(0.01)	0.059(0.012)	0.06(0.014)
Type 1	0.5(0.2)	0.5(0.21)	0.515(0.23)
Type 2	0.26(0.08)	0.266(0.08)	0.28(0.085)
Type 3	0.11(0.022)	0.105(0.02)	0.11(0.027)
Uniform			
H ₀	0.04(0.008)	0.045(0.009)	0.052(0.012)
Type 1	1.0(0.996)	1.0(1.0)	1.0(1.0)
Type 2	0.94(0.69)	0.944(0.65)	0.95(0.76)
Type 3	0.196(0.046)	0.118(0.03)	0.156(0.042)
Cauchy			
H ₀	0.048(0.01)	0.04(0.008)	0.058(0.01)
Type 1	0.23(0.06)	0.18(0.038)	0.148(0.05)
Type 2	0.13(0.038)	0.106(0.030)	0.11(0.022)
Type 3	0.076(0.01)	0.054(0.008)	0.06(0.02)
Exponential			
H ₀	0.058(0.009)	0.056(0.007)	0.052(0.005)
Type 1	0.69(0.42)	0.59(0.33)	0.65(0.4)
Type 2	0.42(0.18)	0.34(0.13)	0.38(0.14)
Type 3	0.117(0.028)	0.087(0.02)	0.09(0.02)

(iv) Approximate power estimates for the case of $k=3, n=15$

Distributions	T_1	T_2	T_3
Normal			
H_0	0.053(0.006)	0.04(0.005)	0.04(0.004)
Type 1	0.315(0.11)	0.36(0.115)	0.36(0.13)
Type 2	0.215(0.056)	0.227(0.058)	0.233(0.064)
Type 3	0.104(0.022)	0.093(0.017)	0.103(0.02)
Uniform			
H_0	0.054(0.02)	0.052(0.012)	0.056(0.016)
Type 1	0.978(0.898)	0.998(0.96)	0.998(0.96)
Type 2	0.79(0.504)	0.87(0.58)	0.87(0.612)
Type 3	0.286(0.108)	0.276(0.078)	0.324(0.106)
Cauchy			
H_0	0.062(0.012)	0.054(0.014)	0.058(0.014)
Type 1	0.14(0.026)	0.12(0.016)	0.11(0.02)
Type 2	0.12(0.028)	0.11(0.018)	0.1(0.02)
Type 3	0.064(0.01)	0.054(0.01)	0.064(0.014)
Exponential			
H_0	0.05(0.013)	0.05(0.011)	0.053(0.01)
Type 1	0.535(0.277)	0.46(0.21)	0.5(0.23)
Type 2	0.336(0.122)	0.274(0.087)	0.3(0.1)
Type 3	0.142(0.024)	0.114(0.021)	0.12(0.002)

(v) Approximate power estimates for the case of $k=4, n=15$

Distributions	T_1	T_2	T_3
Normal			
H_0	0.04(0.007)	0.05(0.008)	0.055(0.01)
Type 1	0.08(0.009)	0.09(0.01)	0.11(0.026)
Type 2	0.07(0.01)	0.09(0.015)	0.09(0.017)
Type 3	0.075(0.012)	0.105(0.018)	0.101(0.026)
Uniform			
H_0	0.046(0.014)	0.05(0.008)	0.044(0.008)
Type 1	1.0(1.0)	1.0(1.0)	1.0(1.0)

Type 2	0.76(0.54)	0.86(0.6)	0.86(0.63)
Type 3	0.24(0.076)	0.23(0.044)	0.3(0.074)
Cauchy			
H ₀	0.042(0.01)	0.054(0.012)	0.05(0.01)
Type 1	0.19(0.08)	0.16(0.04)	0.14(0.044)
Type 2	0.11(0.04)	0.11(0.026)	0.1(0.026)
Type 3	0.06(0.02)	0.06(0.01)	0.064(0.012)
Exponential			
H ₀	0.043(0.005)	0.058(0.009)	0.053(0.009)
Type 1	0.23(0.066)	0.237(0.062)	0.23(0.068)
Type 2	0.1(0.017)	0.118(0.017)	0.1(0.016)
Type 3	0.115(0.02)	0.13(0.025)	0.116(0.02)

(vi) Approximate power estimates for the case of $k=5, n=15$

Distributions	T ₁	T ₂	T ₃
Normal			
H ₀	0.052(0.01)	0.048(0.006)	0.054(0.01)
Type 1	0.61(0.343)	0.656(0.35)	0.66(0.37)
Type 2	0.295(0.118)	0.343(0.1)	0.344(0.11)
Type 3	0.094(0.027)	0.1(0.019)	0.102(0.026)
Uniform			
H ₀	0.054(0.008)	0.052(0.006)	0.048(0.006)
Type 1	1.0(1.0)	1.0(1.0)	1.0(1.0)
Type 2	0.98(0.87)	0.988(0.886)	0.992(0.914)
Type 3	0.21(0.07)	0.17(0.038)	0.22(0.06)
Cauchy			
H ₀	0.058(0.01)	0.05(0.008)	0.056(0.014)
Type 1	0.31(0.13)	0.24(0.07)	0.2(0.05)
Type 2	0.15(0.04)	0.14(0.03)	0.12(0.03)
Type 3	0.098(0.01)	0.08(0.012)	0.084(0.022)
Exponential			
H ₀	0.57(0.013)	0.048(0.008)	0.045(0.011)
Type 1	0.817(0.64)	0.769(0.51)	0.822(0.59)
Type 2	0.5(0.291)	0.435(0.194)	0.47(0.234)
Type 3	0.129(0.043)	0.117(0.029)	0.128(0.034)

IV. Discussion & Conclusion

we considered three rank tests based on different ranking methods for comparing several treatments with a control in randomized block experiments. Three methods themselves have own benefits and shortcomings; that is,

- 1) the test based on “within blocks ranking” is easy to use and good powers in the case of Cauchy or exponential distributions, but it shows lower powers comparing with the others when the probability models are normal and uniform.
- 2) The test based on “between blocks ranking” utilizes more information and has a reasonable power (most cases lie between T_1 and T_3) under three types of H_1 configurations, but it is very complex to evaluate test statistic,
- 3) the test based on “aligned ranking” looks good when the probability models are normal and uniform but it also needs two-step calculations.

Unfortunately we could not find the test which dominates other tests. However, we can suggest the followings in view of this simulation results; the test based on “within blocks” ranking when the probability models are exponential, Cauchy, lognormal and weibull (did partially). Further if the probability models are normal, uniform, contaminated normal (did partially), we found the test based on “aligned” ranking shows superior to other tests. But these two approximate power differences are not much, so we would recommend to use the test based on T_1 (“within blocks” rank statistic) if experimenters do not have any idea about the probability models.

References

- Fligner, M. A. and Wolfe, D.A. (1982) : Distribution-free tests for comparing several treatments with a control. *Statistica Neerlandica*. 36, 119–127.
- Friedman, M. (1937) : The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *J. Amer. Statist. Assoc.* 32, 675–701.
- Hodges, J. L., Jr. and Lehmann, E. L. (1962) : Rank methods for combination of independent experiments in analysis of variance. *Ann. Math. Statist.* 33, 482–497.
- Hollander, M. (1966) : An asymptotically distribution-free multiple comparison procedure: treatments vs control. *Ann. Math. Statist.* 37, 735–738.

Lehmann, E. L. (1975) : Nonparametrics. Holden-Day, Inc. San Francisco.

Mehra, L. L. and Sarange, J. (1967) : Asymptotic efficiency of certain rank tests for comparative experiments. Ann. Math. Statist. 38, 90-107.

Sen, P. K. (1968) : On a class of aligned order tests in two-way layouts. Ann. Math. Statist. 38, 1115-1124.