Adaptive Scheme for ANOVA Models

Gilbert Biney\textsuperscript{1*}, Gabriel Asare Okyere\textsuperscript{2} and Abukari Alhassan\textsuperscript{1}

\textsuperscript{1}Department of Statistics, Faculty of Mathematical Sciences, University for Development Studies, Tamale, Navrongo Campus, Ghana.

\textsuperscript{2}Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.

**Authors’ contributions**

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

**Article Information**

DOI: 10.9734/JAMCS/2020/v35i430266

Editor(s):

(1) Dr. Leo Willyanto Santoso, Petra Christian University, Indonesia.

Reviewer(s):

(1) Sarita Gajbhiye Meshram, Ton Duc Thang University, Vietnam.

(2) Jewel Kumar Roy, Jatiya Kabi Kazi Nazrul Islam University, Bangladesh.

Complete Peer review History: http://www.sdiarticle4.com/review-history/57574

---

**Abstract**

This paper deals with the concept of adaptive scheme and with an application to the One-way ANOVA model under uncorrelated errors. One way ANOVA model is sensitive to non-normality as well as variance heterogeneity. To overcome these problems, an adaptive scheme is proposed. The adaptive test is a two step procedure. The given data is first examined and classified based on measures of skewness and tailweight. Secondly, a selector statistic is used for selecting a test to be conducted. A 10,000 simulations were conducted to compare the performance of the two models from different continuous distributions. Analysis of real data sets on equal and unequal sample sizes were performed to evaluate the efficiency of the two models. The findings showed that our adaptive scheme outperformed the parametric $F$-test in symmetric or skewed distributions with varying tailweights except for symmetric and medium-tailed distributions.

**Keywords:** Uncorrelated errors; adaptive test; selector statistic; skewness; tailweight; simulation; asymptotic relative efficiency (ARE).

*Corresponding author: E-mail: gillypee63@gmail.com;*
1 Introduction

In this paper, we propose an adaptive scheme for Oneway ANOVA Models under uncorrelated errors. In practice, often the underlying distribution of a statistical model is not known so a procedure which will maximise power and efficiency should be selected. For example, if the distribution of errors is known to be normal in a linear model then inference based on least squares which maximises power and efficiency should be chosen. On the other hand, when the assumption of normality of the error distribution is violated as a result of outliers, then a more robust method can be used to analyse the problem. The rank-based method is robust to outliers and has high efficiency and power for both normal and non-normal distributions, see [1] for details. Robustness signifies insensitivity to small deviations from the assumptions of normality [2].

ANOVA model which could be reduced to Gauss Markov model relies mostly on normality, homogeneity of variance and large sample size for it to be modelled. ANOVA models are very sensitive to nonnormality and departures from normality may originate from either skewness or outliers. Furthermore, ANOVA model which are mostly used in clinical trials may have very low enrolment at centres and hence a small sample size. This will inhibit the efficiency of the statistical procedure used.

One particular problem in which normality assumptions become inappropriate is small sample size. In most statistical modelling or techniques, sample size must be large enough for such procedure to be statistically admissible or valid. For small samples, some nonparametric methods have been developed. The advocacy of distribution-free (nonparametric) tests for differences in location problems between samples has been emphasized over the past seven decades [3].

In this paper, the nine winsorised scores proposed by [4] are considered in the adaptive test of [5]. The adaptive two-sample location problem is extended to the Gauss Markov model (GMM). The Oneway Analysis of Variance (ANOVA) model which is a special case of GMM and the adaptive test are the focus of this paper.

An adaptive test for equality of means in a Oneway layout is described by [6] though he used weighted method. A robust procedure to fit Oneway ANOVA model under adaption on the observed samples was extensively done by [7]. The adaptation in this present study is based on residuals after an initial fit on the observed sample.

1.1 Literature review

In this subsection, the Oneway Analysis of Variance (ANOVA) model which is a special case of Gauss Markov model was briefly reviewed.

1.1.1 Gauss Markov model (GMM)

The Gauss Markov model is given by

\[ Y = X\beta + \epsilon \]  \hspace{1cm} (1.1)

where \( Y \) is an \( n \times 1 \) vector of observed responses, \( X \) is an \( n \times p \) (design) matrix of fixed constants, \( \beta \) is a \( p \times 1 \) vector of fixed but unknown parameters, and \( \epsilon \) is an \( n \times 1 \) vector of unobserved random errors. Both \( Y \) and \( \epsilon \) are random vectors. It is assumed that \( E(\epsilon) = 0 \) and \( \text{Cov}(\epsilon) = \sigma^2 I \) where \( \sigma^2 \) is some unknown parameter and \( \epsilon \sim N(0, \sigma^2 I) \), see [8] and [9].

1.1.2 Oneway analysis of Variance (ANOVA) model

Consider an experiment that is performed to compare \( k \geq 3 \) treatments. For the \( i^{th} \) treatment level, suppose that \( n_i \) experimental units are selected at random and assigned to the \( i^{th} \) treatment.
The Oneway ANOVA model is given by

\[ Y_{ij} = \mu + \alpha_i + \epsilon_{ij}, \]
\[ \{ i = 1, 2, 3, \ldots, k \} \]
\[ \{ j = 1, 2, 3, \ldots, n_i \} \]

(1.2)

where the \( Y_{ij} \) is the \((ij)\)th observation, \( \mu \) is a parameter common to all treatments called the overall mean, \( \alpha_i \) is the \(i\)th treatment effect and random errors \( \epsilon_{ij} \) are uncorrelated random variables with zero mean and common variance \( \sigma^2 > 0 \). If the \( \alpha \) treatment effects \( \alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_k \) are best regarded as fixed constants, then model (1.2) is a special case of model (1.1).

Thus,

\[
Y_{n \times 1} = \begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{kn} \end{bmatrix}, \quad X_{n \times p} = \begin{bmatrix} 1_{n_1} & 1_{n_1} & 0_{n_1} & 0_{n_1} & \cdots & 0_{n_1} \\ 1_{n_2} & 0_{n_2} & 1_{n_2} & 0_{n_2} & \cdots & 0_{n_2} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1_{n_k} & 0_{n_k} & 0_{n_k} & \cdots & \cdots & 1_{n_k} \end{bmatrix}, \quad \beta_{p \times 1} = \begin{bmatrix} \mu \\ \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_k \end{bmatrix}, \quad \epsilon_{n \times 1} = \begin{bmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{13} \\ \vdots \\ \epsilon_{kn} \end{bmatrix},
\]

where \( p = k + 1 \), \( 1_{n_i} \) is an \( n_i \times 1 \) vector of ones and \( 0_n \) is an \( n \times 1 \) vector of zeros, \( E(\epsilon) = 0 \), \( Cov(\epsilon) = \sigma^2 I \) and

\[ n = \sum_{i=1}^{k} n_i \]

see [9].

In Oneway ANOVA model, the test of hypothesis of interest is

\[ H_0: \mu_1 = \mu_2 = \cdots = \mu_k \]
\[ H_1: \mu_r \neq \mu_s \]

for at least one pair \((r, s)\), \( r \neq s \).

Our motivation for the study is to find robust adaptive procedures for parametric tests which are most often used by statisticians and researchers but which are inefficient for nonnormal distributions. In addition, the asymptotic properties of statistical estimates and tests solely rely on the Central Limit Theorem (CLT), however, sample sizes are often not large as in clinical trials.

Real data sets are used to perform a test of hypothesis for Oneway ANOVA models with uncorrelated errors and our proposed scheme in order to ascertain the efficiecies of the two models.

The Introduction of the paper in Section 1 presents the background, the problem and proposed solution, and a brief literature review. The rest of the paper is organised as follows: Section 2 is focused on materials and methods used for the development of the adaptive test. The third section presents the results and discussion of simulation and numerical examples. Section 4 presents the conclusions of the paper highlighting the major findings.

2 Materials and Methods

In this section, the methods and theorem for the development of the adaptive procedures are discussed.
2.1 Rank Test

The rank test considered in this paper is of the form

\[ T_\varphi = \sum_{i=1}^{n} \varphi \left( \frac{R(Z_i)}{n+1} \right) I(Z_i = Y_i) \]  

(2.1)

where \( Y_i \) and \( Z_i \) are the combined ordered residuals respectively, \( a_\varphi(i) = \varphi \left( \frac{i}{n+1} \right) \), \( a_\varphi(1), a_\varphi(2), \cdots, a_\varphi(n) \) are scores and \( \varphi \) satisfies the following conditions

- \( \varphi \) nondecreasing function and square-integrable on \((0, 1)\)
- \( \varphi \) is differentiable on \((0, 1)\)

Thus,

\[ \int_0^1 \varphi(u) du = 0 \]

and

\[ \int_0^1 \varphi^2(u) du = 1, \]

see [10].

2.2 Adaptive test

[11] and [12] distinguished between two different concepts of adaptive procedures; nonrestrictive and restrictive ones. The restrictive procedures are applied in this paper. The Adaptive test of [13] is a two-step procedure. The data is first examined and classified based on measures of skewness and tailweight from a class of continuous distributions. After that a selector statistic is then used for selecting a score for a test to be conducted. This two-staged adaptive procedure maintains the level of significance \( \alpha \) for all continuous distribution functions. See [14] for the main theorem behind adaptation.

In this paper, we adapt on residuals, so the combined ordered residuals from an initial fit is used. The measures of skewness and tailweight of the residuals are obtained by using \( Q^*_1 \) and \( Q^*_2 \) respectively.

2.3 Selector statistic

The selector statistic \( S = (Q^*_1, Q^*_2) \), aids in selecting a score function, where \( Q^*_1 \) and \( Q^*_2 \) are the respective measures of skewness and tailweight are defined respectively by

\[ Q^*_1 = \frac{(m(0.95,0) - m(0.25,0.25))}{(m(0.25,0.25) - m(0,0.95))} \]  

(2.2)

\[ Q^*_2 = \frac{(m(0.95,0) - m(0,0.95))}{(m(0.5,0) - m(0,0.5))} \]  

(2.3)

where \( m(\alpha_1, \alpha_2) = \frac{1}{n} \sum_{i=t_1+1}^{n-t_2} Z(i) \) and

- \( Z(i) \) are ordered residuals from an initial fit
- \( t_1 = [n\alpha_1] \)
- \( t_2 = [n\alpha_2] \)
- \([x]\) denotes the smallest integer greater than \( x\)
- \( h = n - t_1 - t_2\).

The benchmarks proposed by [15] for the cut off values are used. These benchmarks depend on the sample size \( n \) but as \( n \to \infty \), the measures converge to those proposed by [5].
For $Q_1^*$,

\[
\text{Lower cut off} = 0.36 + \frac{0.68}{n}
\]

\[
\text{Upper cut off} = 2.73 - \frac{3.72}{n}
\]  

(2.4)

For $Q_2^*$,

if $n < 25$,

\[
\text{Lower cut-off} = 2.17 - \frac{3.01}{n}
\]

\[
\text{Upper cut-off} = 2.63 - \frac{3.94}{n}
\]  

(2.5)

if $n \geq 25$,

then

\[
\text{Lower cut off} = 2.24 - \frac{4.68}{n}
\]

\[
\text{Upper cut off} = 2.95 - \frac{9.37}{n}
\]  

(2.6)

The cut off points are used to select a rank test which is based on a rank score function corresponding to an unknown distribution. In this paper, the nine Winsorised scores proposed by [4] were considered the most appropriate set of rank scores for testing hypothesis are used. These are classified into four generic scores.

\[
\varphi_I(u) = \begin{cases} 
  s_3, & u > s_1 \\
  s_3 + \frac{s_3 - s_2}{s_1 - s_2}(u - s_1), & \text{otherwise} 
\end{cases}
\]

\[
\varphi_{II}(u) = \begin{cases} 
  -\frac{s_1}{s_1 - s_2}(u - s_1), & u < s_1 \\
  -\frac{s_1}{s_2 - s_1}(u - 1) + s_4, & u > s_2 \\
  0, & \text{otherwise} 
\end{cases}
\]

\[
\varphi_{III}(u) = \begin{cases} 
  s_2, & u < s_1 \\
  s_3 + \frac{s_3 - s_2}{s_1 - s_2}(u - 1), & \text{otherwise} 
\end{cases}
\]

\[
\varphi_{IV}(u) = \begin{cases} 
  s_3, & u < s_1 \\
  s_4, & u > s_2 \\
  s_3 + \frac{s_3 - s_2}{s_2 - s_1}(u - s_1), & \text{otherwise} 
\end{cases}
\]

where $s_1, s_2, s_3, s_4$ and $s_5$ are parameters and $a_i(j) = \varphi_i\left(\frac{j}{n+1}\right)$

2.4 Adaptive test and test statistics

Let $D_k$ and $\varphi_k$ be a region and score selected respectively as in Fig. 1, with $k = 1, 2, \ldots, 9$, then the adaptive test, $AD(S, \varphi)$, is

\[
AD(S, \varphi) = T_{\varphi_k}, S \in D_k
\]  

(2.7)

where

\[
T_{\varphi_k}(\Delta) = \sum_{i=1}^{n_2} a_{\varphi_k}(R(y_i - \Delta))
\]  

(2.8)
is a test statistic based on the ranks and score $\varphi_k$ associated with region $D_k$ and hence distribution-free. Under $H_0$, the mean of $T_{\varphi_k}(\Delta)$ is zero.

The nine regions which depend on the selector statistics $S = (Q_1^*, Q_2^*)$ are defined by:

\[ D_1 = LH = Q_1^* < \hat{Q}_1^* < Q_2^* > \hat{Q}_2^* \]
\[ D_2 = SH = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_3 = RH = Q_1^* > \hat{Q}_1^* < Q_2^* > \hat{Q}_2^* \]
\[ D_4 = LM = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_5 = SM = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_6 = RM = Q_1^* > \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_7 = LL = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_8 = SL = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]
\[ D_9 = RL = Q_1^* < \hat{Q}_1^* < Q_2^* < \hat{Q}_2^* \]

where $\hat{Q}_1^*$, $\hat{Q}_2^*$ are benchmarks from the ordered residuals, see [15].

![Fig. 1. Plot of scores with n = 50](image)

### 2.5 Proposed adaptive scheme

The procedure for the proposed adaptive scheme is as follows:

1. Let $Y_{(1)}, Y_{(2)}, \ldots, Y_{(n)}$ be the combined ordered residuals of $Y_{11}, Y_{12}, \ldots, Y_{1n_1}, Y_{21}, Y_{22}, \ldots, Y_{2n_2}, Y_{n_1}, Y_{n_2}, \ldots, Y_{nn}$ from continuous distribution function $f(t)$ with some amount of variations denoted by $\Delta$ among the residuals, that is $f(t - \Delta)$.
2. The unknown distribution of the residuals will be classified using both the selector statistic $S = (Q_1^*, Q_2^*)$ and the cut-off values.
3. Once the distribution of these residuals is classified, a corresponding score of the unknown distribution is selected.
4. After the selection of the score function, the test is then conducted.

**Hypothesis Testing**

We wish to test

\[ H_0 : \Delta = 0 \]
\[ H_1 : \Delta \neq 0 \]

### 3 Results and Discussion

This section presents the findings of the study of a 10,000 simulations and numerical examples.
3.1 Simulation results

A 10,000 simulations were conducted for Normal (Norm), Contaminated Normal (CNorm), Logistic (Logis), Laplace (Lap), Lognormal (LNorm), Exponential (Exp), Cauchy (Cau), Weibull (Wei), Mixture (Mixt) and Pareto (Par) distributions.

3.1.1 Classification Table

Table 1 displays the classification of performance of $S = (Q_1^*, Q_2^*)$ for sample size $n_1 = n_2 = n_3 = 100$ for each of the distributions.

| Sel Stats | Norm | CNorm | Logis | Lap | LNorm | Exp | Cau | Wei | Mixt | Par |
|-----------|------|-------|-------|-----|-------|-----|-----|-----|------|-----|
| LH        | 0    | 0     | 0     | 0   | 0     | 0   | 1702| 0   | 1507 | 0   |
| LL        | 0    | 0     | 0     | 0   | 0     | 0   | 0   | 0   | 0    | 0   |
| LM        | 0    | 0     | 0     | 0   | 0     | 0   | 0   | 0   | 0    | 0   |
| RH        | 0    | 0     | 0     | 0   | 9939  | 2958| 1508| 2939| 1409 | 10000|
| RL        | 0    | 0     | 0     | 0   | 0     | 0   | 0   | 0   | 0    | 0   |
| RM        | 0    | 0     | 0     | 0   | 61    | 7042| 0   | 7058| 0    | 0   |
| SH        | 5    | 9     | 2548  | 9898| 0     | 0   | 6790| 0   | 7083 | 0   |
| SL        | 1    | 1     | 0     | 0   | 0     | 0   | 0   | 0   | 0    | 0   |
| SM        | 9994 | 9990  | 7452  | 102 | 0     | 0   | 3   | 1   | 0    | 0   |

Source: Simulation study

The Normal, Contaminated Normal, Logistic, Laplace, Cauchy and Mixture of distributions were all symmetric but have different tailweights. The Lognormal and Pareto distributions were classified as right-skewed and heavy-tailed. The Exponential and Weibull distributions were also identified as right-skewed and medium-tailed distributions.

The normal and contaminated normal distributions were correctly classified to be symmetric and medium-tailed by 99.94% and 99.90% respectively. The Laplace distribution is correctly classified as a symmetric and heavy-tailed by 98.98% and Lognormal distribution as a right-skewed and heavy-tailed by 99.39%. The Pareto distribution on the other hand was 100% classified as a right-skewed and heavy-tailed distribution.

A simulation was conducted to compare the parametric $F$-test and the adaptive test. For the parametric, $F$ test statistic (Value) and the residual standard error ($\sigma$) were obtained. In the case of the adaptive test, the underlying error distribution (score), test statistic (value), scale parameters for the sample and residual ($\tau_s$) and ($\tau_r$) respectively were obtained. The comparison is presented on Tables 2, 3, 4, 5 and 6.

3.1.2 Normal distribution

Using the normal distribution with the location parameter $\mu = 0$ and scale parameter $\sigma = 1$, under $H_0$, 10,000 simulations were run for the various sample sizes.

Table 2 displays the simulation results for the Normal distribution. The selector statistic for the adaptive test identified the normal distribution as a symmetric and medium-tailed distribution. The parametric $F$-test performed better than the adaptive test at all the sample sizes considered. However, at 5% or 1% significance level, the two models failed to reject the null hypothesis of no difference in level means.
Table 2. Normal distribution

| Sample Size | F-Test Value | F-Test Score | Adaptive Test Value | Adaptive Test Score |
|-------------|--------------|--------------|---------------------|---------------------|
| (5, 10, 15) | 1.1716       | 0.9831       | SH 2.2919           | 1.0601              |
| (10, 10, 20)| 1.0788       | 0.9901       | SM 2.1401           | 1.0297              |
| (15, 15, 25)| 1.0507       | 0.9935       | SM 2.1022           | 1.0274              |
| (20, 20, 30)| 1.0367       | 0.9943       | SM 2.0485           | 1.0302              |
| (25, 25, 35)| 1.0237       | 0.9957       | SM 2.0286           | 1.0307              |
| (30, 30, 40)| 1.0138       | 0.9974       | SM 2.0024           | 1.0292              |
| (40, 40, 50)| 1.0049       | 0.9981       | SM 2.0023           | 1.0293              |
| (50, 50, 60)| 1.0000       | 0.9999       | SM 2.0000           | 1.0299              |

Source: Simulation study

3.1.3 Laplace distribution

The results for 10,000 simulations carried out for Laplace distribution with the location parameter \( \mu = 0 \) and a scale parameter \( \lambda = 1 \) is displayed on Table 3.

| Sample Size | F-Test Value | F-Test Score | Adaptive Test Value | Adaptive Test Score |
|-------------|--------------|--------------|---------------------|---------------------|
| (5, 5, 5)   | 1.1641       | 1.3535       | SH 2.3088           | 1.2634              |
| (10, 10, 10)| 1.0680       | 1.3856       | SH 2.1494           | 1.1955              |
| (15, 15, 15)| 1.0593       | 1.3958       | SH 2.1568           | 1.1501              |
| (20, 20, 20)| 1.0445       | 1.3988       | SH 2.1604           | 1.1276              |
| (25, 25, 25)| 1.0177       | 1.4048       | SH 2.0619           | 1.1308              |
| (30, 30, 30)| 1.0383       | 1.4050       | SH 2.0784           | 1.1300              |
| (40, 40, 40)| 1.0250       | 1.4063       | SH 2.0568           | 1.1121              |
| (50, 50, 50)| 1.0112       | 1.4112       | SH 2.0220           | 1.0956              |

Source: Simulation study

The selector statistic for the adaptive test classified the Laplace distribution as a symmetric and heavy-tailed distribution. The adaptive test outperformed the \( F \)-test as the variance returned for the adaptive test is smaller than the \( F \)-test. At 5% or 1% level of significance, the two tests failed to reject the null hypothesis.

3.1.4 Cauchy distribution

The Cauchy distribution with the location parameter \( \mu = 0 \) and a scale parameter \( \gamma = 1 \) is simulated under \( H_0 \). The results of the simulation is shown on Table 4.

The Cauchy distribution is identified by the selector statistic as a symmetric and heavy-tailed distribution. The adaptive test outperformed the traditional \( F \)-test as the variance returned by the adaptive test is smaller than the \( F \)-test. Both tests however, failed to reject the null hypothesis of no difference in level means at 5% or 1% significance level.

3.1.5 Weibull distribution

Simulation Results for Weibull distribution with the shape parameter \( k > 0 \) and a scale parameter \( \lambda = 1 \) is shown on Table 5.
The Weibull distribution was identified by the selector statistic as a right-skewed and medium-tailed distribution. The adaptive test outperformed the F-test. It is worth noting that as the sample size increases the residual standard error ($\sigma$) increases but the estimated scale parameters ($\tau_s$) and ($\tau_r$) decrease. Notwithstanding, both tests failed to reject the null hypothesis at 5% or 1% level of significance.

### 3.1.6 Mixture of distributions

A 10,000 simulations of mixture of distributions for three samples were generated from the Normal $N(0,1)$, Laplace ($\mu = 0, \lambda = 1$) and Cauchy ($\mu = 0, \gamma = 1$) distributions respectively and is shown on Table 6.

| Sample Size | Value | $\sigma$ | Score | Value | $\tau_s$ | $\tau_r$ |
|-------------|-------|----------|-------|-------|----------|----------|
| (5, 5, 5)   | 1.1740 | 10.6971  | SH    | 2.6740 | 1.6893   | 1.7001   |
| (10, 10, 10)| 1.0934 | 10.0139  | LH    | 2.6780 | 1.6295   | 1.6261   |
| (15, 15, 15)| 1.0369 | 88.1010  | SH    | 2.6322 | 1.5095   | 1.5088   |
| (20, 20, 20)| 1.0345 | 14.2196  | SH    | 2.6094 | 1.4928   | 1.4922   |
| (25, 25, 25)| 1.0229 | 14.5802  | SH    | 2.6327 | 1.5079   | 1.5082   |
| (30, 30, 30)| 1.0280 | 16.3163  | SH    | 2.5979 | 1.5414   | 1.5415   |
| (50, 50, 50)| 1.0151 | 32.4284  | SH    | 2.7024 | 1.5213   | 1.5211   |
| (100, 100, 100)| 0.9995 | 39.4103 | SH    | 3.0333 | 1.4866   | 1.4865   |

*Source: Simulation study*
The mixture of distributions was classified by the selector statistic as a symmetric and heavy-tailed distribution. The variance returned suggest that the adaptive test outperformed the $F$-test at all levels of the sample sizes. However, the two tests failed to reject the null hypothesis of no difference in level means at 5% or 1% significance level.

### 3.2 Numerical examples

#### 3.2.1 Example for equal sample size

Three different pain relief drugs were administered on 27 patients suffering from migraine headache. Table 7 shows time in minutes of relief from the migraine headache. This is an extract from [16].

**Table 7. Time of relief for migraine headache sufferers**

| Drug A | 4 5 4 3 2 4 3 4 4 |
|--------|--------------------|
| Drug B | 6 8 4 5 4 6 5 8 6 |
| Drug C | 6 7 6 6 7 5 6 5 5 |

From Fig. 2, the assumption of normality to the data on Table 7 is not appropriate. An outlier in Drug B is obvious. The result of the analysis is displayed on Table 8.

![Fig. 2. Time of relief for migraine headache sufferers](image)

**Table 8. Time of relief for migraine headache sufferers**

| Sample Size $(n_1, n_2, n_3)$ | $F$-Test | Adaptive Test |
|-------------------------------|----------|---------------|
| Value | p-value | $\sigma$ | Score | Value | p-value | $\tau$ |
| (9, 9, 9) | 11.91 | 0.0003 | 1.089 | SH | 13.6881 | 0.0001 | 0.8788 |

*Source: Table 7*

The selector statistic classified the underlying error distribution of the data as a symmetric and heavy-tailed distribution. The adaptive test reported the least variance, that is, the adaptive test is more efficient than the $F$-test. However, both models rejected the null hypothesis, $H_0$ at 5% or 1% significance level. Thus, there are differences in mean time for the pain relief. The asymptotic relative efficiency (ARE) of the adaptive test over the $F$-test is about 65.1%.
3.2.2 Example for unequal sample sizes

Four catalysts that may affect the concentration of one component in a three-component liquid mixture are being investigated. The data as shown on Table 9 is extracted from [17].

Table 9. Catalyst

|      | 1   | 2    | 3   | 4   |
|------|-----|------|-----|-----|
| 1    | 58.2| 56.3 | 50.1| 52.9|
| 2    | 65.2| 54.5 | 54.2| 49.9|
| 3    | 58.4| 57.0 | 55.4| 50.0|
| 4    | 55.8| 55.3 | 51.7| 54.9|

The results of the analysis is presented on Table 10.

Table 10. Catalyst

|                  | Sample Size | F-Test | Adaptive Test |
|------------------|-------------|--------|---------------|
|                  | (n₁, n₂, n₃, n₄) | Value   | p-value | σ     | Value   | p-value | τ     |
| n₁ = 5, n₂ = 4, n₃ = 3, n₄ = 4 | 5.8778 | 0.0104 | 2.7472 | SL    | 7.9989 | 0.0056 | 1.9989 |

Source: Table 9

The selector statistic classified the underlying error distribution of the data as a symmetric and light-tailed distribution. The adaptive test performed better than the F-test because the variance returned ($\sigma = 2.7472$) is greater than the scale parameter ($\tau = 1.9989$). At 5% or 1% significance level, both tests rejected the null hypothesis. As a consequence, the four catalysts do not have the same mean effect on the concentration of the three-component liquid mixture. The asymptotic relative efficiency of the adaptive test over the F-test is about 52.95%.

4 Conclusions

In this paper, the Oneway Analysis of Variance (ANOVA) model was compared with the adaptive test. We used the two dimensional selector statistic $S = (Q₁^*, Q₂^*)$, where $Q₁^*$ and $Q₂^*$ are respective measures of skewness and tailweight of the unknown distribution function. The usage of the nine winsorised scores accommodated a wide range of distributions which are either symmetric or asymmetric with varying tailweights as shown on Table 1.

The performance of these tests at small sample sizes was of much interest in this study because most sensitive areas of the application of ANOVA models such as cinical trials often has low enrolment. The adaptive test was more efficient than the traditional ANOVA F-test at very small sample sizes, in the presence of outliers and nonnormal distributions. As a consequence, the adaptive test should be taken note of in statistical modelling.

Competing Interests

Authors have declared that no competing interests exist.

References

[1] Hájek J, Sidák ZS. Theory of rank tests. New York. Academic Press; 1967.
[2] Huber JP, Ronchetti EM. Robust statistics. John Wiley & Sons Inc., Hoboken, New Jersey; 2009.
[3] Hao L, Houser D. Adaptive procedures for nonparametric test: Seven decades of advances. Communications in Statistics-Theory and Methods; 2012.

[4] Hettmansperger TP. Statistical inference based on ranks. John Wiley and Sons, Inc., New York; 1984.

[5] Hogg RV, Fisher DM, Randles RH. A two-sample adaptive distribution-free test. Journal of the American Statistical Association. 1975;70:656-661.

[6] O’Gorman TW. Adaptive tests of significance using permutations of residuals with R and SAS ®. John Wiley and Sons, Inc., Hoboken, New Jersey; 2012.

[7] Afrifa-Yamoah E, Okyere GA, Asare-Bediako M, Bashiru IIS. A robust procedure for the fit of oneway ANOVA model under adaptation on the observed samples. Journal of Mathematics and Statistical Science. 2016;534-553.

[8] Christensen R. Plane answers to complex questions: The theory of linear models. Albuquerque, New Mexico; 2001.

[9] Monahan JF. A primer on linear models. Chapman and Hall CRC, Taylor and Francis Group, Boca Raton; 2008.

[10] Okyere GA. Robust adaptive scheme for linear mixed models. PhD Thesis, Western Michigan University; 2011.

[11] Husková M. Partial review of adaptive procedures. In: Sequential Methods in Statistics, 16, Banach Center Publicatons, Warschau; 1985.

[12] Hájek J, Sidák ZS, Sen PK. Theory of rank tests. Academic, New York; 1999.

[13] Hogg RV. Adaptive robust procedures: A partial review and some suggestions for future applications and theory. Journal of the american statistical association. 1974;69:909-923.

[14] Bünning H. Adaptive test for the c-sample location problem. In Statistical Inference, Econometric Analysis and Matrix Algebra. 2009;I:3-17.

[15] Al-Shomrani AA. A comparison of different schemes for selecting and estimating score functions based on residuals. PhD thesis, Western Michigan University; 2003.

[16] Oehlert GW. A first course in design and analysis of experiments. Library of Congress Cataloging-in-Publication Data. University of Minnesota; 2010.

[17] Montgomery DC. Design and analysis of experiments. 8th Edition. John Wiley & Sons, New York; 2013.

© 2020 Biney et al.; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
http://www.sdiarticle4.com/review-history/57574