

# A note on risk efficiency and regret of sequential procedure of mean

Sumit Koul

Department of Statistics, University of Jammu, Jammu-180006, INDIA.

Email: [sumit.koul8@gmail.com](mailto:sumit.koul8@gmail.com)

## Abstract

The Problem of minimum risk point estimation of the mean of the two parameter exponentiated inverted Weibull distribution is taken up. Consideration is given to the squared-error loss function and linear cost of sampling. The failure of fixed sample size procedure is established and a sequential procedure is developed. Some asymptotic properties are obtained for the sequential procedure.

**Key Words:** Sequential procedure, loss function, Risk efficiency and Regret.

## \*Address for Correspondence:

Dr. Sumit Koul, Department of Statistics, University of Jammu, Jammu-180006, INDIA.

Email: [sumit.koul8@gmail.com](mailto:sumit.koul8@gmail.com)

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## INTRODUCTION

Flaih *et al* (2012) proposed the two parameter exponentiated inverted Weibull distribution (EIWD). This distribution is a generalization to the inverted Weibull distribution through adding a new shape parameter  $\theta \in \mathbb{R}^+$  by exponentiation to distribution function  $F$ . Let us consider a sequence  $\{X_i\}; i = 1, 2, 3, \dots$  of independently distributed random variable then from two parameter exponentiated inverted Weibull distribution with the p.d.f given as

$$f(x; \theta, \beta) = \theta \beta x^{-(\beta+1)} \exp(-\theta x^{-\beta}); x > 0, \theta > 0, \beta > 0. \quad (1.1)$$

For  $\theta=1$ , it represents the standard inverted Weibull distribution and for  $\beta=1$ , it represents the exponentiated inverted exponential distribution.

From equation(1.1), the mean of the distribution is given by  $\phi = E(X_i) = \theta^{\frac{1}{\beta}} \Gamma\left(1 - \frac{1}{\beta}\right)$  and  $Var(X_i) = \theta^{\frac{2}{\beta}} \Gamma\left(1 - \frac{2}{\beta}\right) - \theta^{\frac{2}{\beta}} \left[\Gamma\left(1 - \frac{1}{\beta}\right)\right]^2$ .

This distribution is really used in literature and has its applications in estimating the parameters so this sequential Procedure is considered instead of fixed sample size in this paper. The pioneer work of sequential test is proposed by Wald (1947), he developed sequential probability ratio test (SPRT) for testing hypothesis against a simple alternative. Further, in recent decades many authors has developed sequential procedure for point and interval estimation. For some citation, one may refers to Anscombe (1952), Woodroffe (1977), Zacks (1971), Nagao (1980), Chaturvedi (1987), Chaturvedi, Pandey and Gupta (1991), Chaturvedi and Shukla (1990), Mukhopadhyay and Pepe (2006), Uno, Isogai and Lim (2004), Roughani and Mohmoudi (2015) and others. The purpose of this note is two-fold. The problem of minimum risk point estimation of the mean( $\phi$ ) of exponentiated inverted Weibull distribution under the square error loss function and linear cost of sampling is considered. It has been proved that the failure of the fixed sample size procedures to handle the estimation problem. purely sequential procedure are developed to tackle the situations. In section 2, the set-up of the estimation problem has been described and proved the failure of fixed sample size procedure to deal with them. In section 3, the sequential procedure for the point estimation of the mean of two parameter exponentiated inverted Weibull

distribution has been proposed and the asymptotic Risk efficiency and regret for the given sequential procedure is achieved in the paper.

**SET-UP OF THE ESTIMATION PROBLEM**

Having record a sample  $X_1, X_2, \dots, X_n$  of size n, let us define  $\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$ , as the estimator for  $\phi$ . Let the Loss-

incurred in estimating  $\phi$  by  $\bar{X}_n$  is of the form

$$L_n(C) = A(\bar{X}_n - \phi)^2 + nC, \quad (2.1)$$

where  $A(>0)$  is known weight,  $C(>0)$  is the cost function.

Form the loss(2.1), the risk comes out to be

$$R_n(C) = \frac{A}{n} \theta^{\frac{2}{\beta}} \left[ \Gamma\left(1 - \frac{2}{\beta}\right) - \left[ \Gamma\left(1 - \frac{1}{\beta}\right) \right]^2 \right] + nC. \quad (2.2)$$

Treating n as a continuous variable, the value  $n^*$  of n, which minimize the risk is

$$n^* = \left(\frac{A}{C}\right)^{\frac{1}{2}} \phi \left[ \frac{\Gamma\left(1 - \frac{2}{\beta}\right)}{\left[\Gamma\left(1 - \frac{1}{\beta}\right)\right]^2} - 1 \right]^{\frac{1}{2}}. \quad (2.3)$$

and the corresponding risk when  $n=n^*$ , we get,

$$R_{n^*}(C) = 2n^*C. \quad (2.4)$$

Once again, since  $n^*$  depends on  $\theta$ , in the absence of any knowledge about  $\theta$ , no fixed sample size procedure minimizes the risk simultaneously for all values of  $\theta$ . So, to handle this problem in the following section we adopt sequential procedure.

**SEQUENTIAL PROCEDURE FOR THE POINT ESTIMATION OF MEAN**

Without loss of generality, we assume  $\beta$  is known i.e.  $\beta=4$ , we rewrite ( $n^*$ ) and  $R_{n^*}(C)$  as,

$$n^* = K \left(\frac{A}{C}\right)^{\frac{1}{2}} \phi_0, \quad (2.5)$$

where,  $\phi_0$  is the value of mean at  $\beta=4$  and  $K = \frac{\Gamma\left(1 - \frac{2}{\beta}\right)}{\left[\Gamma\left(1 - \frac{1}{\beta}\right)\right]^2} -$

$$1 \Big]^{\frac{1}{2}}.$$

$$R_{n^*}(C) = 2K\sqrt{AC}\phi_0. \quad (2.6)$$

The stopping time  $N \equiv N(C)$  is the first positive integer  $n \geq m(\geq 2)$  defined by

$$N = \inf \left[ n \geq m; n \geq \left(\frac{A}{C}\right)^{\frac{1}{2}} \left[ \theta^{\frac{2}{\beta}} \Gamma\left(1 - \frac{2}{\beta}\right) -$$

$$\left[ \Gamma\left(1 - \frac{1}{\beta}\right) \right]^2 \right]^{\frac{1}{2}} \Big] \quad (2.7)$$

$$N = \inf \left[ n \geq m; n \geq \left(\frac{A}{C}\right)^{\frac{1}{2}} \phi_0 K \right] \quad (2.8)$$

where, m being the starting sample size. Use  $\bar{X}_N$  to estimate  $\phi_0$ .

Following Starr (1966a,1996b), we define the Risk-efficiency of the sequential procedure is given by

$$R_e(C) = \frac{R_N(C)}{R_{n^*}(C)} \quad (2.9)$$

Also we define Regret as,

$$R_g(C) = R_N(C) - R_{n^*}(C), \quad (2.10)$$

where,  $R_N(C)$  is Risk associated with the sequential procedure, i.e.

$$R_N(C) = E(L(\phi_0, \bar{X}_N)) = A[E((\bar{X}_N - \phi_0)^2)] + C E(N). \quad (2.11)$$

The following theorem based on Risk efficiency and Regret as follows is proved.

**Theorem 1.** For the stopping rule define in (2.8) and all  $\phi_0$ ,

$$\lim_{C \rightarrow 0} R_e(C) = 1. \quad (2.12)$$

**Proof.** Rewrite the (2.8) and using  $S_n = \sum_{i=1}^n X_i$ ,

$$N = \inf \left[ n \geq 1; n \geq \left(\frac{A}{C}\right)^{\frac{1}{2}} \phi_0 K \right]$$

$$N = \inf \left[ n \geq 1; n \geq \left(\frac{A}{C}\right)^{\frac{1}{2}} \bar{X}_n K \right]$$

$$N = \inf \left[ n \geq 1; n^2 \geq K \left(\frac{A}{C}\right)^{\frac{1}{2}} \sum_{i=1}^n X_i \right]$$

$$N = \inf \left[ n \geq 1; n^2 \geq K \left(\frac{A}{C}\right)^{\frac{1}{2}} S_n \right]$$

$$N = \inf \left[ n \geq 1; S_n \leq \frac{n^2}{K \left(\frac{A}{C}\right)^{\frac{1}{2}}} \right]. \quad (2.13)$$

From Wald's Lemma for cumulative sum,

$$E[(S_N - N\phi_0)^2] = K^2 \phi_0^2 E(CN).$$

From (2.11), we get,

$$\begin{aligned} R_N(C) &= A[E((\bar{X}_N - \phi_0)^2)] - C E(N) + 2C E(N) \\ &= A \left[ E \left( \left( \frac{S_N}{N} - \phi_0 \right)^2 \right) \right] - C E(N) + 2C E(N); \bar{X}_N = \frac{S_N}{N} \\ &= E \left( (S_N - N\phi_0)^2 \frac{A}{N^2} \right) - C E(N) + 2C E(N) \\ &= E \left( (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2} \phi_0^{-2} \right) \right) + 2CE(N). \end{aligned} \quad (2.14)$$

Substitute (2.6), (2.11) in (2.9), we get,

$$\begin{aligned} R_e(C) &= \frac{E \left( (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2} \phi_0^{-2} \right) \right) + 2CE(N)}{2K\sqrt{AC}\phi_0} \\ &= E \left( (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2} \phi_0^{-2} \right) \right) (2K\sqrt{AC}\phi_0)^{-1} + E \left( \frac{N}{\left(\frac{A}{C}\right)^{\frac{1}{2}} \phi_0 K} \right). \end{aligned} \quad (2.15)$$

It can be seen that  $\frac{N}{\left(\frac{A}{C}\right)^{\frac{1}{2}}} \rightarrow \phi_0 K$  almost surely(a.s) as

$C \rightarrow 0$ .

The result follows from Gut(1974) that

$$\left[ \left( \left( \frac{A}{C} \right)^{\frac{1}{2}} N \right)^4 : A \geq 1 \right], \text{ is uniformly integrable. (2.16)}$$

Using (2.16) and Domianted Convergence theorem,

$$\lim_{C \rightarrow 0} E \left( \frac{N}{\left( \frac{A}{C} \right)^{\frac{1}{2}} \phi_0 K} \right) = 1. \text{ (2.17)}$$

From (2.15) and (2.17), we conclude that the result follows if we can prove that

$$E \left( \left( \frac{A}{C} \right)^{\frac{1}{2}} (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right) = o(1) \quad \text{as}$$

$$C \rightarrow 0. \text{ (2.18)}$$

Using Holder's Inequality,

$$E \left| \left( \frac{A}{C} \right)^{\frac{1}{2}} (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right| \leq E^{\frac{1}{2}} \left| \left( \frac{A}{C} \right)^{\frac{1}{4}} (S_N - N\phi_0) \right|^4 E^{\frac{1}{2}} \left| \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right|^2. \text{ (2.19)}$$

From (2.16) and Lemma 5 of Chow and Yu (1981),

$$\left[ \left| \left( \frac{A}{C} \right)^{\frac{1}{4}} (S_N - N\phi_0) \right|^4 : A \geq 1 \right] \text{ is uniformly integrable. (2.20)}$$

From the definition of N at (9),  $N^{-2} \left( \frac{A}{C} \right) \leq (S_N K)^{-1} \left( \frac{A}{C} \right)^{\frac{1}{2}}$ . Hence, using the dominated ergodic theorem of Marcinkiewicz and Zygmund[see Chow and Teicher(1978, p.35)],

$$\left[ \left( \left( \frac{A}{C} \right)^{\frac{1}{2}} N^{-4} \right) : A \geq 1 \right] \text{ is uniformly integrable. (2.21)}$$

Since  $\left( \frac{A}{C} \right) N^{-2} \rightarrow \phi_0 K^{-1}$  (a.s.) as  $C \rightarrow 0$ , using (2.20) and (2.21), we obtained from (2.19) that

$$\left( \frac{A}{C} \right)^{\frac{1}{2}} E \left| (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right| \leq o(1) E^{\frac{1}{2}} \left| \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right|^2 = o(1) \text{ as } C \rightarrow 0.$$

In the next theorem, we prove the bounded nature of the 'Regret'.

**Theorem 2:** For the Sequential Procedure (2.8),

$$\lim_{C \rightarrow 0} R_g(C) = o \left( \left( \frac{A}{C} \right)^{\frac{1}{2}} \right).$$

**Proof:**  $R_g(C) = R_N(C) - R_n^*(C)$ ,

From (2.14) and (2.6), we obtain as,

$$R_g(C) = E \left( (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right) + 2CE(N) - 2K\sqrt{AC}\phi_0$$

=

$$E \left[ (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right] + 2 \left( \frac{A}{C} \right)^{\frac{1}{2}} E \left[ N \left( \frac{A}{C} \right)^{\frac{1}{2}} - K\phi_0 \right]. \text{ (2.22)}$$

On using Holder's inequality, we get

$$E \left| (S_N - N\phi_0)^2 \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right| \leq \left( \frac{A}{C} \right)^{\frac{1}{2}} E^{\frac{1}{2}} \left| \left( \frac{A}{C} \right)^{\frac{1}{4}} (S_N - N\phi_0) \right|^4 E^{\frac{1}{2}} \left| \left( \frac{A}{N^2} - K^{-2}\phi_0^{-2} \right) \right|^2. \text{ (2.23)}$$

Utilizing (2.20), (2.21) and (24), we obtained from (2.22) as  $C \rightarrow 0$ .

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