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# On Bayesian prediction of future median generalized order statistics using doubly censored data from type-I generalized logistic model

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#### Abstract

This paper is concerned with the problem of deriving expressions for the Bayesian predictive survival functions for the median of future sample of generalized order statistics having odd and even sizes. Both of the informative and future samples are drawn from a population whose distribution is truncated type-I generalized logistic distribution TTIGL  $(\beta, \alpha, \tau)$ . Doubly type II censored data and two sample technique have been used here. Bayesian prediction intervals using two independent samples, based on informative prior is obtained. Bayesian prediction intervals for: upper order statistics and upper records are considered as special cases. Numerical computations based on simulation study are given to illustrate the performance of the procedures.

**Keywords:** Bayesian prediction; Double censoring; Logistic distribution; Twosample prediction; Order statistics; Records; Generalized order statistics

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# 1 Introduction

In Kamps (1995) generalized order statistics (GOS) have been introduced as a unified approach to several models of ordered random variables. Such models are ordinary order statistics (OOS) [David and Nagaraja (2003), Arnold, Balakrishnan and Nagaraja (1992), records [Ahsanullah (1994) and Arnold, Balakrishnan and Nagaraja (1998)], sequential order statistics [Cramer and Kamps (1996)] and ordering via truncated distributions and censoring schemes [Kamps (1995)]. Kamps's book (1995) gave several applications such as a variety of disciplines, recurrence relation for moments of order statistics and characterizations. Several authors utilized the GOS in their work, such authors, among others, are Ahsanullah (2000), Habibullah and Ahsanullah (2000), Kamps and Gather (1997), Keseling (1999), Cramer and Kamps (2000), Pawlas and Szynal (2001), Ahmad and Fawzy (2003), AL-Hussaini and Ahmad (2003a,b), AL-Hussaini (2004), Ahmad (2007, 2010) and Jaheen (2002, 2005). Several authors have predicted future order statistics and records from homogeneous and heterogeneous populations that can be represented by single or finite mixtures of distributions. For a good survey see, AL-Hussaini and Jaheen (1995, 1996, 1999), AL-Hussaini and Ahmad (2003b), Ali Mousa (2003) and AL-Hussaini (1999, 2001). The logistic distribution is one of the oldest growth models. The truncated logistic distribution plays a role in a variety of applications, also, the type I generalized logistic distribution has applications in the theoretical and practical fields. For more details on the logistic and half-logistic distributions, see Balakrishnan (1985, 1992), Balakrishnan and Wang (1991) and Balakrishnan and Chan (1992). AL-Angary (1997) introduced the truncated type I generalized logistic distribution which was denoted by  $TTIGL(\beta, \gamma, \alpha)$  and described some of its properties. Some studies have discussed the truncated type I generalized logistic distributions such as, AL-Hussaini and Ateya (2003, 2005) and AL-Hussaini et al. (2006). A random variable X is said to have a truncated type I generalized logistic distribution with vector of parameters  $\Theta = (\beta, \alpha, \tau)$  if it's probability density function (PDF) is given by

$$f(x;\theta) = \frac{\alpha}{\tau(1-2^{-\alpha})} \exp[-(x-\beta)/\tau] [1 + \exp[-(x-\beta)/\tau]]^{-(\alpha+1)},$$
(1)  
$$x \ge \beta, (\beta \ge 0, \tau > 0, \alpha > 0).$$

The reliability and hazard rate functions are given by

$$R(x) = \frac{1 - \omega^{-\alpha}}{1 - 2^{-\alpha}},$$
(2)

$$r_{\theta}(x) = \frac{\alpha(\omega - 1)\omega^{-\alpha - 1}}{\tau(1 - \omega^{-\alpha})},\tag{3}$$

where  $\omega = 1 + e^{-(x-\beta)/\tau}$ ,  $x \ge \beta$ . In our study we will take  $\beta = 0$ , then the vector of parameters will be  $\theta = (\alpha, \tau)$ . For a value  $x_i$  of the random variable X, let

$$\omega_{i} = 1 + \exp^{-\frac{x_{i}}{r}},$$

$$\varepsilon_{i}(\alpha, \tau) = 1 - \omega_{i}^{-\alpha},$$

$$\eta_{i}(\alpha, \tau) = \frac{(\omega_{i} - 1)\omega_{i}^{-\alpha - 1}}{\varepsilon_{i}(\alpha, \tau)}.$$

$$(4)$$

So, (1), (2) and (3) can be written in the following forms (with  $\beta = 0$ ) as

$$f(x_i;\alpha,\tau) = \frac{\alpha}{\tau} (1-2^{-\alpha})^{-1} \varepsilon_i(\alpha,\tau) \eta_i(\alpha,\tau), x_i > 0, (\tau > 0, \alpha > 0).$$
(5)

The reliability and hazard rate functions are given, respectively, by (6) and (7)

$$R(x_i) = (1 - 2^{-\alpha})^{-1} \varepsilon_i(\alpha, \tau),$$
(6)

and

$$r_{\theta}(x_i) = \frac{\alpha}{\tau} \eta_i(\alpha, \tau).$$
(7)

We will write  $\varepsilon_i, \eta_i$  instead of  $\varepsilon_i(\alpha, \tau), \eta_i(\alpha, \tau)$ . Suppose that  $X_1, X_2, \ldots, X_n$ is a random sample (rs) of size n drawn from a population whose cdf is F(x)and pdf is f(x). Let  $X_{1;n,m,k}, \ldots, X_{n;n,m,k}$  be the corresponding GOS, where  $m \ge 1, k \ge 1$ , see Kamps (1995). It was shown by Ahmad and Abu-Shal (2008) that the joint PDF of the  $GOS X_{r_1;n,m,k}, \ldots, X_{r_\ell;n,m,k}$ , can be written, for  $0 < r_1 < \cdots < r_\ell < 1, r_0 = 0, r_{\ell+1} = n + 1, x_0 = -\infty, x_{r_\ell+1} = \infty$ , as

$$f_{r_1,\dots,r_{\ell}}(x_{r_1},\dots,x_{r_{\ell}}) = C(i;r_{\ell})[h_m(F_{\theta}(x_{r_1})) - h_m(0)]^{r_1-1}[\overline{F}_{\theta}(x_{r_{\ell}})]^{\gamma_{r_{\ell}}-1}$$
$$\times [\prod_{i=1}^{\ell-1} [\overline{F}_{\theta}(x_{r_i})]^m f_{\theta}(x_{r_i})][h_m(F_{\theta}(x_{r_{i+1}})) - h_m(F_{\theta}(x_{r_i}))]^{r_{i+1}-r_i-1}]f_{\theta}(x_{r_{\ell}}), \quad (8)$$

for  $F_{\theta}^{-1}(0+) < x_{r_1} \leq \cdots \leq x_{r_{\ell}} < F_{\theta}^{-1}(1)$ , where

$$C(i; r_{\ell}) = C_{r_{\ell}-1} / \prod_{i=0}^{\ell-1} (r_{i+1} - r_i - 1)!$$

$$C_{r_{\ell}-1} = \prod_{i=1}^{r_{\ell}} \gamma_i, \quad \gamma_i = k + (n-i)(m+1)$$

$$h_m(z) = -(1-z)^{m+1} / (m+1), \quad m \neq -1$$

$$-\ln(1-z), \quad m = -1$$
(9)

The joint *PDF* of the first r GOS  $X_{1;n,m,k}, \ldots, X_{r;n,m,k}$ , for  $1 \le r \le n$  can be obtained if we choose  $r_1 = 1, r_2 = 2, \ldots, r_{\ell} = r$  in (8), see Kamps (1995). If we choose, in (8) and (9),  $r_1 = s, r_2 = s + 1, \ldots, r_{\ell} = s + \ell - 1 \equiv r$ , we can easily show that

$$f_{s,\dots,r}(x_s,\dots,x_r) = \frac{C_{r-1}}{(s-1)!} [h_m(F_{\theta}(x_s)) - h_m(0)]^{s-1} [\prod_{i=s}^{r-1} [\overline{F}_{\theta}(x_i)]^m f_{\theta}(x_i)] [\overline{F}_{\theta}(x_r)]^{\gamma_r - 1} f_{\theta}(x_r),$$

$$= \frac{(-1)^{s-1} C_{r-1}}{(m+1)^{s-1} (s-1)!} [\prod_{i=s}^{r-1} [\overline{F}_{\theta}(x_i)]^m f_{\theta}(x_i)] f_{\theta}(x_r) [\overline{F}_{\theta}(x_r)]^{\gamma_r - 1}$$

$$\times \sum_{\ell=0}^{s-1} \omega_{\ell}^{(s)} [\overline{F}_{\theta}(x_s)]^{(s-\ell-1)(m+1)}, \quad m \neq -1,$$

$$\frac{(-1)^{s-1} k^r}{(s-1)!} [\ln(\overline{F}_{\theta}(x_s))]^{s-1} [\overline{F}_{\theta}(x_r)]^{k-1} \times f_{\theta}(x_r) \prod_{i=s}^{r-1} r_{\theta}(x_i), \quad m = -1,$$
(10)

where  $\omega_{\ell}^{(s)} = (-1)^{\ell} {\binom{s-1}{\ell}}$  and  $\gamma_r = k + (m+1)(n-r)$ .

Suppose that n items are simultaneously put on a life test and that for some reasons, the first s - 1 failure times were not observed. The observed failure times are start only from the *sth* to the *rth* failure time, 1 < s < r < n. These ordered observations are referred to as a doubly type II censored data. Type II censoring is obtained when s = 1 and the complete sample is obtained when s = 1 and r = n. For more about doubly censored sample, reader is referred to Khen et al. (2011, 2010), among others. Suppose that  $X_s < X_{s+1} < \cdots < X_r$ , where 1 < s < r < n, where  $X_i \equiv X_{i;n,m,k}$ , i = 1, 2, ..., n be a doubly type-II censored random sample (informative). Let  $Y_1 < Y_2 < \cdots < Y_N$ , where  $Y_i \equiv Y_{i;N,M,K}$ , i = 1, 2, ..., N, M > 0, K > 0 be a second independent generalized

ordered random sample (of size N) of future observations drawn from the same distribution. Based on such a doubly type II censored observations, we want to predict the future median (unobserved)  $Y_N \equiv Y_N^*$ . Then for  $\xi$  being a positive integer  $\geq 1$  we have:

$$Y_N^{\star} = \begin{cases} Y_{\xi;N,M,K}, & N = 2\xi - 1\\ \frac{Y_{\xi;N,M,K} + Y_{\xi+1;N,M,K}}{2}, & N = 2\xi. \end{cases}$$
(11)

# 2 Density functions of future median

## 2.1 The case of odd N

In the case of the odd future sample size where  $N = 2\xi - 1, \xi = 1, 2, 3, ..., N$ , let  $Y_N^{\star}$  donete the median of future generalized order statistics. For a given  $\theta$ , the *PDF* of  $Y_N^{\star}$  is given, see Kamps (1995), by

$$f_{Y_N^{\star}}(y|\theta) = \frac{C_{\xi-1}^{\star}}{(\xi-1)!(M+1)!} [\overline{F}_{\theta}(y)]^{\gamma_{\xi}^{\star}-1} f_{\theta}(y) g_M^{\xi-1} [F_{\theta}(y)],$$
(12)

where

$$C_{\xi-1}^{\star} = \prod_{j=1}^{\xi} \gamma_{j}^{\star}, \quad \gamma_{j}^{\star} = K + (N-j)(M+1)$$

$$g_{M}(y) = h_{M}(y) - h_{M}(0), \quad y \in (0,1)$$

$$h_{M}(y) = -(1-y)^{M+1}/(M+1), \quad M \neq -1$$

$$-\ln(1-y), \qquad M = -1$$

$$\left. \right\}$$

$$(13)$$

By substituting Eqn.(13) in Eq.(12), yields

$$f_{Y_N^{\star}}(y|\theta) = \frac{C_{\xi-1}^{\star}}{(\xi-1)!(M+1)!} [\overline{F}_{\theta}(y)]^{\gamma_{\xi}^{\star}-1} f_{\theta}(y) [h_M(F_{\theta}(y)) - h_M(F_{\theta}(0))]^{\xi-1}.$$
(14)

By expanding  $[h_M(F_{\theta}(y)) - h_M(F_{\theta}(0))]^{\xi-1}$  binomially,  $f_{Y_N^{\star}}(y|\theta)$  can be written as

$$f_{Y_N^{\star}}(y|\theta) \propto [\overline{F}_{\theta}(y)]^{\gamma_{\xi}^{\star}-1} f_{\theta}(y) \Sigma_{j=0}^{\xi-1} w_{\xi}^{(j)} [h_M(F_{\theta}(y))]^j,$$
(15)

By making use of Eq.(13) and (15), we obtain

$$f_{Y_N^{\star}}(y|\theta) \propto \begin{cases} [\overline{F}_{\theta}(y)]^{\gamma_{\xi}^{\star}-1} f_{\theta}(y) \Sigma_{j=0}^{\xi-1} \omega_{\xi}^{(j)} [\overline{F}_{\theta}(y)]^{j(M+1)}, & M \neq -1\\ [\overline{F}_{\theta}(y)]^{K-1} f_{\theta}(y) [\ln(\overline{F}_{\theta}(y))]^{\xi-1}, & M = -1. \end{cases}$$
(16)

By substituting Eqn.(5),(6) and (7) in Eq.(16), we obtain.

$$f_{Y_{N}^{\star}(y|\theta)} \propto \begin{cases} \frac{\alpha}{\tau} \eta_{y} [(1-2^{-\alpha})^{-1} \varepsilon_{y}]^{\gamma_{\xi}^{\star}} \times \sum_{j=0}^{\xi-1} \omega_{\xi}^{(j)} [(1-2^{-\alpha})^{-1} \varepsilon_{y}]^{j(M+1)}, & M \neq -1 \\ \frac{\alpha}{\tau} \eta_{y} [(1-2^{-\alpha})^{-1} \varepsilon_{y}]^{K} \\ \times [ln[(1-2^{-\alpha})^{-1} \varepsilon_{y}]]^{\xi-1}, & M = -1. \end{cases}$$
(17)

where  $\gamma_{\xi}^{\star} = K + (N - \xi)(M + 1)$  and  $\omega_{\xi}^{(j)} = (-1)^{j} {\binom{\xi - 1}{j}}.$ 

# 2.2 The case of even N

It can be shown when N is even, that the PDF of the median  $Y_N^\star$  for a given  $\theta,$  is given by

$$f_{Y_N^{\star}}(y|\theta) \propto \begin{cases} \sum_{j=0}^{\xi} \omega_j(\xi) \psi_j(y \mid \theta), & M \neq -1, \\ \varpi(y \mid \theta), & M = -1, \end{cases}$$
(18)

where

$$\psi_{j}(y|\theta) = \int_{0}^{y} [\overline{F}_{\theta}(z)]^{j(M+1)+M} [1 - F_{\theta}(2y - z)]^{\gamma_{\xi+1}^{\star} - 1} \\ \times f_{\theta}(2y - z) f_{\theta}(Z) dz, \quad M \neq -1, \\ \varpi(y|\theta) = \int_{0}^{y} H_{\theta}(z) H_{\theta}(2y - z) [S(z)]^{\xi - 1} \\ \times [1 - F_{\theta}(2y - z)]^{K} dz, \quad M = -1.$$
(19)

By substituting Eqn.(4),(5) and (6) in Eq.(19), we obtain

$$\psi_{j}(y \mid \theta) = \int_{0}^{y} \frac{\alpha^{2}}{\tau^{2}} [(1 - 2^{-\alpha})^{-1} \varepsilon_{z}]^{(M+1)(j+1)} \\
\times [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y-z}]^{\gamma_{\xi+1}^{\star}} \eta_{z} \eta_{2y-z} dz, \quad M \neq -1, \\
\varpi(y \mid \theta) = \int_{0}^{y} \frac{\alpha^{2}}{\tau^{2}} [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y-z}]^{K} \\
\times [\ln[(1 - 2^{-\alpha})^{-1} \varepsilon_{z}(\alpha, \tau)]]^{\xi-1} \eta_{z} \eta_{2y-z} dz, \quad M = -1. \\
\end{cases} .$$
(20)

Based on the GOS  $X_{s;n,m,k}, X_{s+1;n,m,k}, \ldots, X_{r;n,m,k}$ , for  $0 \le s \le \cdots \le r \le n$ , the likelihood function can be written, see Ahmad and Abu-Shal (2008), as

$$L(\theta \mid \underline{\mathbf{x}}) \propto [h_m(F_{\theta}(x_s)) - h_m(0)]^{s-1} [\prod_{i=s}^{r-1} [\overline{F}_{\theta}(x_i)]^m f_{\theta}(x_i)] [\overline{F}_{\theta}(x_r)]^{\gamma_r - 1} f_{\theta}(x_r)$$
$$= \begin{cases} [\prod_{i=s}^{r-1} [\overline{F}_{\theta}(x_i)]^m f_{\theta}(x_i)] [\overline{F}_{\theta}(x_r)]^{\gamma_r - 1} f_{\theta}(x_r) \\ \times \sum_{\ell=0}^{s-1} \omega_{\ell}^{(s)} [\overline{F}_{\theta}(x_s)]^{(s-\ell-1)(m+1)}, & m \neq -1, \\ [\ln(\overline{F}_{\theta}(x_s))]^{s-1} [\overline{F}_{\theta}(x_r)]^{k-1} \\ \times f_{\theta}(x_r) \prod_{i=s}^{r-1} r_{\theta}(x_i), & m = -1, \end{cases}$$
(21)

where  $\Theta = (\alpha, \tau)$  and  $\underline{x} = (x_{s;n,m,k}, x_{s+1;n,m,k}, \dots, x_{r;n,m,k}) = (x_s, \dots, x_r)$ . Using Eqs.(4),(5),(6) and (7) in Eq.(21), we get

$$L(\alpha, \tau \mid \underline{\mathbf{x}}) \propto \begin{cases} \frac{(\frac{\alpha}{\tau})^{r-s+1}}{(1-2^{-\alpha})^{\gamma_1}} [\varepsilon_r]^{\gamma_{r+1}} [\prod_{i=s}^r \varepsilon_i^{m+1} \eta_i] \sum_{\ell=0}^{s-1} \omega_\ell^{(s)} \\ \times (1-2^{-\alpha})^{\ell(m+1)} \varepsilon_s^{(m+1)(s-\ell-1)}, & m \neq -1, \\ \frac{(\frac{\alpha}{\tau})^{r-s+1}}{(1-2^{-\alpha})^k} [ln_{\frac{\varepsilon_s}{1-2^{-\alpha}}}]^{s-1} \varepsilon_r^k [\prod_{i=s}^r \eta_i], & m = -1. \end{cases}$$
(22)

Suppose that the conjugate prior density, which is measured by a function  $\pi(\alpha, \tau)$  given by

$$\pi(\alpha, \tau) = \pi_1(\tau | \alpha) \pi_2(\alpha).$$
(23)

Suppose that  $\pi_1(\tau | \alpha)$  is Gamma  $(c_1, \alpha), \pi_2(\alpha)$  is Gamma  $(c_2, c_3)$  with respective densities

$$\pi_1(\tau \mid \alpha) \propto \alpha^{c_1} \tau^{c_1 - 1} \exp(-\tau \alpha), \quad \alpha, \tau > 0, \quad (c_1 > 0), \quad (24)$$

$$\pi_2(\alpha) \propto \alpha^{c_2 - 1} \exp(-c_3 \alpha), \alpha > 0, (c_2, c_3 > 0).$$
 (25)

It then follows, by substituting (24) and (25) in (23), that the prior PDF of  $\alpha$  and  $\tau$  is given by

$$\pi(\alpha,\tau) \propto \alpha^{c_1+c_2-1} \tau^{c_1-1} \exp[-\alpha(\tau+c_3)], \alpha,\tau > 0, (c_1,c_2,c_3>0),$$
(26)

where  $c_1$ ,  $c_2$  and  $c_3$  are the prior parameters (or hyper-parameters).

Using the likelihood function (22) and the prior (26) the posterior probability density function of  $\alpha$  and  $\tau$  for given informative data, say,  $\pi^*(\alpha, \tau \mid \underline{x})$  is given by

$$\pi^{\star}(\alpha, \tau \mid \underline{\mathbf{x}}) \propto L(\alpha, \tau; \underline{\mathbf{x}}) \pi(\alpha, \tau).$$
(27)

Using the likelihood function (22) and the prior (26) the posterior pdf of  $\alpha$  and  $\tau$  can be written using (27) as

$$\pi^{\star}(\alpha, \tau \mid \underline{\mathbf{x}}) \propto \begin{cases} \alpha^{\Im} \tau^{\wp}[\varepsilon_{r}]^{\gamma_{r+1}} (1 - 2^{-\alpha})^{-\gamma_{1}} \exp[-\alpha(\tau + c_{3})] [\prod_{i=s}^{r} \varepsilon_{i}^{m+1} \eta_{i}] \\ \times \sum_{\ell=0}^{s-1} \omega_{\ell}^{(s)} (1 - 2^{-\alpha})^{\ell(m+1)} \varepsilon_{s}^{(m+1)(s-\ell-1)}, & m \neq -1 \\ \alpha^{\Im} \tau^{\wp} (1 - 2^{-\alpha})^{-k} \exp[-\alpha(\tau + c_{3})] [\ln \frac{\varepsilon_{s}}{1 - 2^{-\alpha}}]^{s-1} \\ \times \varepsilon_{r}^{k} [\prod_{i=s}^{r} \eta_{i}], & m = -1, \end{cases}$$

$$(28)$$

where  $\Im = c_1 + c_2 + r - s$  and  $\wp = c_1 - r + s - 2$ .

# **3** Bayesian prediction

## 3.1 The case of odd future sample size

By making use of Eqn.(28) and (17), yields the Bayes predictive density function of the future median  $Y_N^{\star}$ ,  $N = 2\xi - 1, \xi = 1, 2, 3, ..., N$ , given the (r - s + 1) gos's, denoted by  $h_{Y_N^{\star}}(y|\theta)$  as

$$h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) = \int_{\Theta} f_{Y_N^{\star}}(y|\theta) \pi^{\star}(\theta \mid \underline{\mathbf{x}}) d\theta, \quad y > x_r.$$
(29)

By making use of Eqs.(28) and (17)in (29), we obtain

$$f_{Y_{N}^{\star}}(y|\theta)\pi^{\star}(\theta \mid \underline{\mathbf{x}}) \propto \begin{cases} \alpha^{\Im+1}\tau^{\wp-1}\varepsilon_{r}^{\gamma_{r+1}}\eta_{y}\exp[-\alpha(\tau+c_{3})][\Pi_{i=s}^{r}\varepsilon_{i}^{m+1}\eta_{i}]](1-2^{-\alpha})^{-1}\varepsilon_{y}]^{\gamma_{\xi}\star} \\ \times \sum_{j=0}^{\xi-1}\sum_{\ell=0}^{s-1}\zeta_{\ell,j}^{(\xi,s)}(1-2^{-\alpha})^{-\gamma_{\ell}+1}[(1-2^{-\alpha})^{-1}\varepsilon_{y}]^{j(M+1)} \\ \times \varepsilon_{s}^{(m+1)(s-\ell-1)}, \quad m \neq -1, M \neq -1, \\ \alpha^{\Im+1}\tau^{\wp-1}\eta_{y}(1-2^{-\alpha})^{-k}\exp[-\alpha(\tau+c_{3})][(1-2^{-\alpha})^{-1}\varepsilon_{y}]^{K} \\ \times [ln\frac{\varepsilon_{s}}{(1-2^{-\alpha})}]^{s-1}\varepsilon_{r}^{k}[\Pi_{i=s}^{r}\eta_{i}][ln[(1-2^{-\alpha})^{-1}\varepsilon_{y}]]^{\xi-1}, \quad m = -1, M = -1, \end{cases}$$

$$(30)$$

where

$$\zeta_{\ell,j}^{(\xi,s)} = (-1)^{\ell+j} \binom{s-1}{\ell} \binom{\xi-1}{j}.$$
(31)

To obtain  $(1 - \tau)100$  Bayesian prediction interval BPI for a future generalized order statistic  $Y_N^{\star}$ , say (L, U), we solve simultaneously the following two nonlinear equations, numerically,

$$P[Y_N^{\star} > L|\underline{\mathbf{x}}] = \int_L^\infty h_{Y_N^{\star}}(y|\theta) dy = 1 - \frac{\tau}{2}, \qquad (32)$$

$$P[Y_N^{\star} > U | \underline{\mathbf{x}}] = \int_U^\infty h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) dy = \frac{\tau}{2}.$$
(33)

Equation (32) and (33), can be solved by using Newton-Raphson iteration form as follows:

$$L_{j+1} = L_j - \frac{\int_{L_j}^{\infty} h_{Y_N^{\star}}(y \mid \underline{x}) dy - (1 - \frac{\tau}{2})}{-h_{Y_N^{\star}}(L_j \mid \underline{x})},$$
(34)

$$U_{j+1} = U_j - \frac{\int_{U_j}^{\infty} h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) dy - \frac{\tau}{2}}{-h_{Y_N^{\star}}(U_j \mid \underline{\mathbf{x}})},$$
(35)

where the initial values  $L_o, U_o$  can be taken equal to  $x_r$ . The integrals in (34) and (35) can be obtained using the routine QDAGI in IMSL.

### 3.1.1 Order statistics case

The Bayes prediction density function of the future median  $Y_N^*$ ,  $N = 2\xi - 1, \xi = 1, 2, 3, ..., N$ , given the informative sample  $x_s, \ldots, x_r$ , can be written from (29) and (30), when m = 0, k = 1, M = 0 and K = 1 for as  $Y_N^*$  as

$$h_{Y_{N}^{*}(y|\theta)} = A_{1} \int_{0}^{\infty} \int_{0}^{\infty} \alpha^{\Im+1} \tau^{\wp-1} \varepsilon_{r}^{n-r} \eta_{y} \exp^{-\alpha(\tau+c_{3})} [\Pi_{i=s}^{r} \varepsilon_{i} \eta_{i}] \\ \times [(1-2^{-\alpha})^{-1} \varepsilon_{y}]^{N-\xi+1} \sum_{j=0}^{\xi-1} \sum_{\ell=0}^{s-1} \zeta_{j,\ell}^{(\xi,s)} (1-2^{-\alpha})^{-(n-\ell)} \\ \times [(1-2^{-\alpha})^{-1} \varepsilon_{y}]^{j} \varepsilon_{s}^{s-\ell-1} d\alpha d\tau,$$
(36)

where  $A_1$  is a normalizing constant. Using the iteration forms (34) and (35), the routine QDAGI in IMSL to compute the double and triple integrals we obtain the prediction bounds of  $Y_N^{\star}$ .

#### 3.1.2 Record values case

Making use of Eq.(30), yields the Bayes predictive density function of the future median  $Y_N^{\star}$ ,  $N = 2\xi - 1, \xi = 1, 2, 3, ..., N$  when m = -1, k = 1, M = -1 and K = 1 for  $Y_N^{\star}$  as

$$h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) = A_1 \int_0^\infty \int_0^\infty \alpha^{\Im + 1} \tau^{\wp - 1} \eta_y \varepsilon_y \varepsilon_r (1 - 2^{-\alpha})^{-2} \exp[-\alpha(\tau + c_3)] \\ \times [\Pi_{i=s}^r \eta_i] [\ln[(1 - 2^{-\alpha})^{-1} \varepsilon_y]]^{\xi - 1} [\ln \frac{\varepsilon_s}{(1 - 2^{-\alpha})}]^{s - 1} d\alpha d\tau,$$
(37)

Using the iteration forms (34) and (35), the routine QDAGI in IMSL to compute the double and triple integrals we obtain the prediction bounds of  $Y_N^{\star}$ .

## 3.2 The case of even future sample size

Substituting Eqs.(18) and (28) in the integrand of (29), with  $N = 2\xi, \xi = 1, 2, ..., N$ , we obtain

$$h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) = \int_{\Theta} f_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) \pi^{\star}(\theta \mid \underline{\mathbf{x}}) d\theta, \quad y > 0,$$
(38)

Where

$$f_{Y_{N}^{\star}}(y \mid \underline{\mathbf{x}}) \pi^{\star}(\theta \mid \underline{\mathbf{x}}) \propto \begin{cases} \int_{0}^{y} \alpha^{\Im + 2} \tau^{\wp - 2} \eta_{z} \eta_{2y - z} [\varepsilon_{r}]^{\gamma_{r+1}} (1 - 2^{-\alpha})^{-\gamma_{1}} \exp^{-\alpha(\tau + c_{3})} \\ \times [\Pi_{i=s}^{r} \varepsilon_{i}^{m+1} \eta_{i}] [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y - z}]^{\gamma_{\epsilon}^{\star}} \sum_{\ell=0}^{s-1} \sum_{j=0}^{\xi} \zeta_{j,\ell}^{(\xi,s)} \\ \times [(1 - 2^{-\alpha})^{-1} \varepsilon_{z}]^{(M+1)(j+1)} (1 - 2^{-\alpha})^{\ell(m+1)} \\ \varepsilon_{s}^{(m+1)(s-\ell-1)} dz, m \neq -1, M \neq -1 \\ \int_{0}^{y} \alpha^{\Im + 2} \tau^{\wp - 2} \eta_{z} \eta_{2y - z} \varepsilon_{r}^{k} (1 - 2^{-\alpha})^{-k} \exp^{-\alpha(\tau + c_{3})} \\ \times [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y - z}]^{K} [\ln[(1 - 2^{-\alpha})^{-1} \varepsilon_{z}]]^{\xi - 1} \\ \times [\Pi_{i=s}^{r} \eta_{i}] [\ln \frac{\varepsilon_{s}}{1 - 2^{-\alpha}}]^{s-1} dz, m = -1, M = -1 \end{cases}$$

$$(39)$$

### 3.2.1 Order statistics case

Making use of Eq.(39), the Bayes predictive density function of the future median  $Y_N^{\star}$ ,  $N = 2\xi$ ,  $\xi = 1, 2, 3, ..., N$  when m = 0, k = 1, M = 0, K = 1, for  $Y_N^{\star}$  is

$$h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) = A_1 \int_0^\infty \int_0^\infty \alpha^{\Im + 2} \tau^{\wp - 2} \eta_z \eta_{2y - z} (1 - 2^{-\alpha})^{-(n-1)} \exp^{-\alpha(\tau + c_3)} \\ \times \varepsilon_r^{n - r + 2} [\Pi_{i=s}^r \varepsilon_i \eta_i] [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y - z}]^{N - \xi + 1} \\ \times \sum_{\ell=0}^{s-1} \sum_{j=0}^{\xi} \omega_j(\xi) \omega_\ell(s) \times [(1 - 2^{-\alpha})^{-1} \varepsilon_z]^{j+1} (1 - 2^{-\alpha})^\ell \varepsilon_s^{s-\ell - 1} d\alpha d\tau.$$
(40)

The Baysian prediction bounds of future order statistics in case is case of s = 1

$$h_{Y_N^{\star}}(y \mid \underline{\mathbf{x}}) = A_1 \int_0^\infty \int_0^\infty [\alpha^{\Im+2} \tau^{\wp-2} \eta_z \eta_{2y-z} \varepsilon_r^{n-r+2} (1-2^{-\alpha})^{-(n-1)} \exp^{-\alpha(\tau+c_3)} \\ \times [\Pi_{i=s}^r \varepsilon_i \eta_i] [(1-2^{-\alpha})^{-1} \varepsilon_{2y-z}]^{N-\xi+1} \sum_{j=0}^{\xi} \omega_j(\xi) [(1-2^{-\alpha})^{-1} \varepsilon_Z]^{j+1}] d\alpha d\tau, \quad (41)$$

Using the iteration forms (34) and (35), the routine QDAGI in IMSL to compute the double and triple integrals we obtain the prediction bounds of  $Y_N^{\star}$ .

#### 3.2.2 Record values case

Making use of Eq.(39), yields the Bayes predictive density function of the future median  $Y_N^{\star}$ ,  $N = 2\xi - 1$ ,  $\xi = 1, 2, 3, ..., N$  when m = -1, k = 1, M = -1, K = 1 is

$$h_{Y_{N}^{\star}}(y \mid \underline{\mathbf{x}}) = A_{2} \int_{0}^{\infty} \int_{0}^{\infty} \alpha^{\Im + 2\tau \wp - 2} \eta_{z} \eta_{2y-z} \varepsilon_{r} (1 - 2^{-\alpha})^{-1} \exp^{-\alpha(\tau + c_{3})} [\Pi_{i=s}^{r} \eta_{i}] \\ \times [(1 - 2^{-\alpha})^{-1} \varepsilon_{2y-z}] [ln[(1 - 2^{-\alpha})^{-1} \varepsilon_{z}]]^{\xi - 1} [ln \frac{\varepsilon_{s}}{1 - 2^{-\alpha}}]^{s - 1} d\alpha d\tau, \quad (42)$$

where

$$A_{2}^{-1} = \int_{0}^{y} \int_{0}^{\infty} \int_{0}^{\infty} \alpha^{\Im+2} \tau^{\wp-2} \eta_{z} \eta_{2y-z} \varepsilon_{r} (1-2^{-\alpha})^{-1} \exp^{-\alpha(\tau+c_{3})} [\Pi_{i=s}^{r} \eta_{i}] \\ \times [(1-2^{-\alpha})^{-1} \varepsilon_{2y-z}] [\ln[(1-2^{-\alpha})^{-1} \varepsilon_{z}]]^{\xi-1} [\ln\frac{\varepsilon_{s}}{1-2^{-\alpha}}]^{s-1} d\alpha d\tau dz.$$
(43)

Using the iteration forms (34) and (35), the routine QDAGI in IMSL Library to compute the double and triple integrals we obtain the prediction bounds of  $Y_N^{\star}$ .

**Remark 3.1.** (1) It may be noted that if s = 1, we obtain a type II censored sample technique and if we choose s = 1 and r = n, our results reduce to the complete sample case.

(2) In some situations one can not observe some initial values of any sample, so he must be chosen the doubly type II censoring scheme.

## 4 Numerical computations

In this section, we obtain the interval predictors of future median OOS and ordinary upper record when the underlying population has TTIGL distribution according to the following steps.

# **4.1 OOS** (m = 0, k = 1)

Based on a given doubly Type-II censored sample, We will consider here the case which represents the OOS. The 95% Bayesian prediction bounds for the future median, and their actual (simulated) prediction levels, are obtained according to the following steps:

(1) A random sample of sizes (10, 30, 50) are generated from TTIGL distribution. The sample is ordered and the upper 10%, 20%, 25%, 30%, 40% and 50% are censored where the future sample size N is fixed and set to 5, 8. The computation are carried out for the hyper-parameters cases (c1, c2, c3) are set to (0.7, 1.3, 0.85), the data generated from TTIGL (0, 0.977, 1.25) and (0, 0.8, 2.239).

(2) Based on these doubly Type-II censored data, the 95% Bayesian prediction bounds for the future (unobserved) are then calculated by solving Eqs.(34) and (35) for the lower and upper bounds with  $\tau = 95\%$  for different values of N, when  $N = 2\xi - 1$  is odd and  $N = 2\xi$  is even.

(3) For 10,000 generated future ordered samples each of size N, from TTIGL density, the simulated prediction levels of  $Y_N^{\star}$  are then calculated. The prediction are conducted on the basis of a doubly type II censored samples and type II censored samples. The results are presented in Tables 1-2.

Case	$V^{\star}$	s = 1		s = 2		s = 3	
Cuor	N	(LL, UL)	%	(LL, UL)	%	(LL, UL)	%
		Length		Length		Length	
n = 10	$Y_3^{\star}$	(0.0115, 1.5640)	91.7	(0.0059, 1.7099)	88.5	(0.00342, 1.8180)	85.7
r = 5		1.5525		1.7040		1.8146	
	$Y_4^{\star}$	(0.01203, 1.4843)	85.7	(0.0095, 1.8716)	86.5	(0.01203, 1.9940)	84.5
		1.4843		1.8673		1.9820	
n = 10	$Y_3^{\star}$	(0.02450, 1.4091)	91.8	(0.0115, 1.5916)	92.8	(0.00368, 1.7085)	90.7
r = 8		1.3846		1.5801		1.7048	
	$Y_4^{\star}$	(0.01004, 1.3105)	89.5	(0.01281, 1.63011)	92.3	(0.0125, 1.8145)	87.3
		1.30054		1.6173		1.7420	
n = 30	$Y_5^{\star}$	(0.9042, 1.9700)	88.7	(0.7163, 1.8803)	87.4	(0.7542, 1.9650)	89.3
r = 18		1.06583		1.1640		1.2108	
	$Y_6^{\star}$	(0.08505, 0.88645)	84.4	(0.0963, 0.94552)	85.5	(0.08501, 0.9885)	86.4
		0.80340		0.84927		0.90342	
n = 30	$Y_5^{\star}$	(0.0421, 0.9848)	92.7	(0.0050, 1.0096)	92.5	(1.003, 2.0093)	84.5
r = 22		0.9424		1.0046		1.0063	
	$Y_6^{\star}$	(0.0904, 0.8765)	89.5	(0.0800, 0.8614)	88.2	(0.0904, 0.9165)	87.2
		0.7861		0.7814		0.8761	
n = 30	$Y_5^{\star}$	(0.0082, 0.7944)	94.7	(0.0065, 0.8570)	93.5	(1.0042, 1.9199)	86.5
r = 27		0.8026		0.8505		0.9157	
	$Y_6^{\star}$	(0.08014, 0.76142)	95.5	(0.07404, 0.8302)	97.2	(0.08605, 0.8940)	97.2
		0.6810		0.7562		0.8079	
n = 50	$Y_5^{\star}$	(0.0641, 1.0930)	92.7	(0.0441, 1.2135)	92.5	(0.0613, 1.2187)	91.5
r = 25		1.0866		1.1694		1.2800	
	$Y_6^{\star}$	(0.08001, 0.86142)	84.5	(0.07114, 0.9103)	88.2	(0.0850, 0.9885)	84.2
		0.7814		0.8392		0.9035	
n = 50	$Y_5^{\star}$	(0.0416, 0.9289)	92.7	(1.0041, 2.1350)	86.5	(1.0041, 2.0408)	84.5
r=35		0.9705		1.1309		1.0367	
	$Y_6^{\star}$	(0.06499, 0.7723)	93.5	(0.0963, 0.94552)	96.2	(0.07114, 0.9103)	92.2
		0.7073		0.8442		0.8392	
n = 50	$Y_5^{\star}$	(0.0910, 0.8485)	95.7	(0.0631, 1.0237)	96.5	(1.0043, 2.0064)	87.5
r=40		0.7575		0.9606		1.0021	
	$Y_6^{\star}$	(0.09625, 0.7455)	92.5	(0.0800, 0.7614)	92.2	(0.0672, 0.7863)	84.2
		0.6493		0.6814		0.7191	

**Table 1:** The lower limit (LL), the upper limit (UL), the length of the BPI and the percentage coverage of the 95% BPI for the future median  $Y_N^*$  when  $N = 2\xi - 1$  is odd or  $N = 2\xi$  from TTIGL( $\beta = 0, \alpha = 0.977, \tau = 1.25$ ).

Case	V*	s = 1		s = 2		s = 3	
Cuse	N	(LL, UL)	%	(LL, UL)	%	(LL, UL)	%
		Length		Length		Length	
n = 10	$Y_3^{\star}$	(1.7371, 5.0102)	90.7	(1.6711, 5.8874)	91.5	(2.5870, 6.5371)	84.11
r = 5		4.2730		4.2163		3.9501	
	$Y_4^{\star}$	(1.4135, 5.5819)	91.7	(1.5289, 5.1217)	91.5	(2.0009, 6.7622)	85.5
		3.1684		3.5928		4.7613	
n = 10	$Y_3^{\star}$	(2.6371, 5.6468)	88.3	(1.9007, 5.0090)	85.8	(3.7371, 6.4809)	96.7
r = 8		3.0097		3.1083		3.1438	
	$Y_4^{\star}$	(2.10621, 5.4787)	90.5	(2.5581, 6.0617)	86.3	(3.0618, 6.5305)	83.7
		3.3725		3.5036		3.4732	
n = 30	$Y_5^{\star}$	(1.7986, 5.3097)	86.7	(1.9800, 6.0062)	89.4	(3.7986, 8.6071)	87.7
r = 18		3.5111		4.0262		4.8085	
	$Y_6^{\star}$	(1.01074, 5.9458)	88.3	(0.01075, 4.14680)	90.5	(3.0309, 7.0049)	84.1
		4.9351		4.1361		3.9740	
n = 30	$Y_5^{\star}$	(2.0905, 6.0007)	87.2	(2.7987, 6.3096)	92.5	(2.7301, 7.1700)	81.5
r = 22		3.9102		3.5109		4.3714	
	$Y_6^{\star}$	(1.6902, 4.6411)	93.5	(1.0102, 4.1037)	92.2	(2.0131, 6.7056)	97.2
		2.9509		3.0936		4.6925	
n = 30	$Y_5^{\star}$	(1.8960, 4.0076)	92.7	(1.0780, 3.5090)	92.5	(2.7180, 5.2182)	92.5
r = 27		2.1116		2.4310		2.5002	
	$Y_6^{\star}$	(1.0183, 3.0450)	94.5	(1.1709, 3.6460)	93.2	(2.0160, 5.0060)	93.2
		2.0267		2.4751		2.9900	
n = 50	$Y_5^{\star}$	(1.7006, 5.0096)	96.7	(2.7987, 6.4007)	96.5	(4.0310, 10.3098)	96.5
r = 25		3.3090		3.6020		4.2788	
	$Y_6^{\star}$	(2.01043, 5.1247)	94.5	(2.02075, 5.1068)	95.2	(5.01107, 9.3580)	94.2
		3.11414		3.08605		4.3469	
n = 50	$Y_5^{\star}$	(1.9003, 3.9093)	96.7	(2.8087, 6.0076)	96.5	(2.9007, 6.2969)	96.5
r = 35		2.009		3.1989		3.3962	
	$Y_6^{\star}$	(1.01178, 3.2128)	94.5	(2.01074, 5.1458)	96.2	(2.09572, 6.9641)	97.2
		2.2010		2.1351		4.8684	
n = 50	$Y_5^{\star}$	(1.7987, 3.3096)	96.7	(1.1008, 4.3607)	95.5	(2.8087, 5.5666)	96.5
r = 40		1.5109		2.5620		2.7579	
	$Y_6^{\star}$	(1.01074, 3.1458)	96.5	(1.01142, 3.1899)	97.2	(2.01075, 4.1458)	83.2
		2.1351		2.1785		2.4405	

**Table 2:** The lower limit (LL), the upper limit (UL), the length of the BPI and the percentage coverage of the 95% BPI for the future median  $Y_N^*$  when  $N = 2\xi - 1$  is odd or  $N = 2\xi$  from TTIGL ( $\beta = 0, \alpha = 0.8, \tau = 2.239$ ).

## **4.2 OURV** (m = -1, k = 1)

Our interest is in the median future recored, because generating of record sample takes a relatively longer time than the OOS, we use n = 10, 15 from TTIGL ( $\alpha = 0.8, \tau = 2.239$ ) distribution and apply 20% and 50% censoring. The future sample size N is fixed. The vector of hyperparameters ( $c_1, c_2, c_3$ ) are same as in OOS example (0.7, 1.3, 0.85). Based on these doubly Type-II censored data, the 95% Bayesian prediction bounds for the future (unobserved) are then calculated by solving Eqs.(3.6) and (3.7) for the lower and upper bounds.

For 100,000 generated future recored samples each of size N = 4, 5, from TTIGL density, the percentage coverage for the simulated prediction levels of  $Y_N^{\star}$  are then calculated. The results are presented in Table 3.

**Table 3:** The lower limit (LL), the upper limit (UL), the length of BPI and the percentage coverage of the 95% BPI for the future median  $Y_N^*$  of ordinary upper record values when  $N = 2\xi - 1$  is odd or  $N = 2\xi$  from TTIGL ( $\beta = 0, \alpha = 0.8, \tau = 2.239$ ).

		s = 1	s = 2			
Case	$Y_N^{\star}$					
		(LL, UL)	%	(LL, UL)	%	
		Length		Length		
n = 10	$Y_3^{\star}$	(3.6035, 7.5723)	88.7	(3.1134, 7.1229)	89.1	
r = 5		3.9688		4.0095		
	$Y_2^{\star}$	(2.914889, 7.09231)	92.5	(2.15007, 6.4831)	90.4	
		4.1774		4.3330		
n = 10	$Y_3^{\star}$	(2.9617, 6.7875)	93.6	(2.4493, 6.1373)	89.7	
r=8		3.8258		3.6880		
	$Y_2^{\star}$	(3.9838, 7.6229)	93.1	(3.1440, 6.6493)	89.4	
		3.6391		3.5053		
n = 15	$Y_3^{\star}$	(1.2967, 4.2712)	84.7	(2.2593, 5.4408)	92.5	
r = 7		2.9745		3.1815		
	$Y_2^{\star}$	(1.3983, 4.5923)	85.6	(2.8332, 5.1774)	92.4	
		3.1940		3.3442		
n = 15	$Y_3^{\star}$	(2.1489, 4.8712)	92.6	(2.6580, 5.6841)	92.7	
r=12		2.7223		3.0261		
	$Y_2^{\star}$	(3.2004, 5.3824)	94.1	(2.9058, 5.7516)	93.5	
		2.1820		2.8458		

## 4.3 Concluding remarks

Based on the numerical results in Tables (1-3), it may be observed that: (1) The generalized results obtained for the prediction of GOS enable us to specialize to any of the other cases which are included in the GOS by appropriate choice of m and k.

(2) As  $\tau$  increases the lengths of the intervals increase.

(3) Whether n is odd or even, shorter predictive intervals BPI and its percentage coverage could be obtained by increasing r, since more information is introduced to the informative sample.

(4) from the tables we realize that for fixed value of n the percentage coverage probability improve by using a large number of observed values.

IMSL Reference manual, institute of mathematical statistics library, IMSL, Inc; Houston, TX, 1984.

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