

# MODELING RELIABILITY IN $k$ -OUT-OF- $m$ SYSTEMS WITH UNEQUAL LOAD SHARING USING PROPORTIONAL CONDITIONAL REVERSE HAZARD RATE

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## Abstract

*This paper explores a load-sharing model within a  $k$ -out-of- $m$  system, where multiple components work together to handle a shared load. Such systems are prevalent in various engineering and industrial applications. While previous studies have focused on equal load-sharing rules, this research emphasizes systems operating under an unequal load-sharing rule, which has a significant impact on the system's reliability and performance. Specifically, the paper examines a  $k$ -out-of- $m$  load-sharing system modeled using the proportional conditional reverse hazard rate model, incorporating unequal load sharing. We have derived expressions for the probability density function and cumulative distribution function of system failure. To illustrate the model, they use a 2-out-of-4 configuration with Weibull baseline distributions. The maximum likelihood estimation method is employed to estimate the model parameters, and the performance of these estimates is evaluated through a simulation study, assessing both bias and mean square errors. Additionally, the practical applicability of the model is demonstrated through the analysis of two real datasets.*

**Keywords:**  $k$ -out-of- $m$  system, Load sharing phenomenon, Order statistics, Proportional hazard rate, Reverse hazard rate, Unequal load share rule.

## 1. INTRODUCTION

A  $k$ -out-of- $m$  system with  $m$  components fails when  $(m - k + 1)$  or more of its components fail. This setup includes series systems (where  $k = m$ ) and parallel systems (where  $k = 1$ ) as specific instances. Generally, the failure times of the first  $(m - k + 1)$  components are modeled as the first  $(m - k + 1)$  order statistics from a set of  $m$  independent and identically distributed (i.i.d.) random variables. In  $k$ -out-of- $m$  load-sharing systems, when one component fails, the load of the failed component is distributed on the remaining components. This creates a dependency among the lifetimes of the components, making these systems dynamic in terms of reliability. Failure of component may increase or release the load of remaining components. Examples of  $k$ -out-of- $m$  load-sharing systems include fibrous composite materials, power plants, automobiles, and the two jet engines of an airplane. A similar pattern is observed in the human body, where the failure of one organ (e.g., a kidney) typically increases the failure rate of the surviving organ [1]. Conversely, in scenarios like food scarcity within a litter, the death of some offspring can improve the survival and growth of the remaining ones by increasing their food supply [10]. Similarly, in software development, detecting one bug can help in finding others, thereby reducing the detection time.

[12] and Kvam and Pena [13] have emphasized the importance of modeling the load-sharing phenomenon in various contexts. Besides these works, load-sharing systems have been explored extensively, beginning with Daniels [1], and continuing through the studies of Birnbaum and Saunders [2], Coleman [3], Rosen [4], [5], Singpurwalla [6], Hollander and Pena [7], Cramer and Kamps [8, 12], Lynch [11], Durham and Lynch [12], McCool [13], Pena [16], and Deshpande et al. [17], among others. A comprehensive review can be found in Dewan and Naik-Nimbalkar [18]. Then after Deshpande et al. [17], Jain and Gupta [19], Sutar and Naik-Nimbalkar [20], Sutar and Naik-Nimbalkar [21], Wang et al. [22], Zhao et al. [23], Xu et al. [24], Zhang et al. [25], Sutar and Naik-Nimbalkar [26], Choudhary et al. [27], Park et al. [28], Sutar [29], Zhang et al. [30], Rykov et al. [31], Pesch et al. [32], Sutar et al. [33], Biswas et al. [34], and Pesch et al. [35] all contributed to the study of load-sharing systems.

Sutar and Naik-Nimbalkar [21] explored load-sharing systems within the framework of a  $k$ -out-of- $m$  system using a proportional conditional reverse hazard rate model. They concentrated on equal load sharing, particularly examining a two-component parallel system where the components' initial lifetimes followed Weibull and linear failure rate distributions as baseline models. Their research also extended to developing and applying inference techniques for analyzing this system. However, the assumption of equal load sharing does not always hold true, making it essential to create models that account for unequal load distribution. In these situations, it is necessary to develop models that accurately represent the varying loads each component bears to more effectively predict system reliability. An example of this is as follows.

Consider a power grid with multiple generators providing electricity to a city. If one generator fails, the remaining generators must absorb the additional load, but they may not equally distribute this increased demand due to differences in capacity and efficiency. In such a scenario, modeling the system with an unequal load-sharing approach is vital for accurately predicting the grid's reliability and preventing potential outages.

In this article, we present a model for the load-sharing phenomenon in a  $k$ -out-of- $m$  system, utilizing proportional conditional reverse hazard rate (PCRHR) with an unequal load-sharing rule. We aim to capture the complexities of real-world systems where components do not equally share the load after failures occur. The structure of this article is as follows:

Section 2 introduces the model for a  $k$ -out-of- $m$  unequal load-sharing system. Illustration of the model is given in Section 3. In Section 4, we examine parameter estimation for  $k$ -out-of- $m$  and in particular 2-out-of-4, 2-out-of-3, and 1-out-of-4 load sharing systems, assuming that lifetimes are independently distributed according to a Weibull distribution. Section 5 reports a simulation study that assesses the proposed estimation method's performance based on bias and mean square error. Section 6 applies the model to a real dataset, and the final section summarizes the conclusions.

## 2. PROPOSED PCRHR BASED LOAD SHARING MODEL FOR $k$ -OUT-OF- $m$ SYSTEM

Let  $U_1, U_2, \dots, U_m$  are the components of a  $k$ -out-of- $m$  system ( $1 \leq k \leq m$ ). Let us assume that the lifetimes of components are independent and identical distributed (i.i.d.) with baseline probability density function (pdf)  $f(\cdot)$ , Cumulative distribution function (cdf)  $F(\cdot)$  and survival function (sf)  $\bar{F}(\cdot)$  and reverse hazard rate function  $r(\cdot)$ . The system is to be functioning as long as  $(m - k + 1)$  components is not failed. Let  $X_{(j)}$  be the time of  $j^{\text{th}}$  failure in the system,  $j = 1, 2, \dots, (m - k + 1)$ . That is  $X_{(j)}$  is minimum of the failure times of remaining  $(m - j + 1)$  surviving components and system failure is occurs at time point  $X_{(m-k+1)}$ . In the i.i.d. set up, the failure of a component does not affect the lifetime of the surviving component and the joint density of  $X_{(j)}$  and  $X_{(j+1)}$  can be written as

$$g_{X_{(j)}, X_{(j+1)}}(x_j, x_{j+1}) = \frac{m!}{(j-1)!(m-j-1)!} (F(x_j))^{j-1} (\bar{F}(x_{j+1}))^{m-j-1} f(x_j)f(x_{j+1}), \quad j = 1, 2, \dots, (m - k). \quad (1)$$

The conditional density function of  $X_{(j+1)}$  given  $X_{(j)} = x_j$  is given by

$$g_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) = (m-j) \left\{ \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right\}^{m-j} \frac{f(x_{j+1})}{\bar{F}(x_{j+1})}, \quad j = 1, 2, \dots, (m-k). \quad (2)$$

Thus the conditional distribution function of  $X_{(j+1)}$  given  $X_{(j)} = x_j$  is given by

$$G_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) = 1 - \left( \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right)^{m-j}, \quad j = 1, 2, \dots, (m-k). \quad (3)$$

Assuming that there exists load sharing effect in model, then conditional distribution function with load sharing effect is given by

$$\begin{aligned} H_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) &= \left\{ G_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) \right\}^{\beta_j} \\ &= \left\{ 1 - \left( \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right)^{m-j} \right\}^{\beta_j}, \end{aligned} \quad (4)$$

$$\beta_j > 0, \quad x_{j+1} \geq x_j, \quad j = 1, 2, \dots, (m-k).$$

**Remark (1):** From the above equation (4), we observe that if  $\beta_j < 1$  then  $H_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) > G_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1})$ ,  $\forall j = 1, 2, \dots, (m-k)$ , The lifetime of the surviving component under the distribution  $H$  is stochastically smaller than under the i.i.d. setup  $G$ . and if  $\beta_j > 1$  then the residual life is stochastically larger. For  $\beta_j = 1, \forall j = 1, 2, \dots, (m-k)$  means residual lifetimes are same as that under i.i.d. setup.

We also assume that the conditional distribution of the residual lifetime of a surviving component depends only on the last failure time, that is the failure epochs form a Markov process.

**Theorem 1.** If the conditional distribution of  $X_{(j+1)}$  given  $X_{(j)} = x_j$  is as given in equation (4), then we have the following

(i) The joint p.d.f. of  $(X_{(1)}, X_{(2)}, \dots, X_{(m-k+1)})$  is given by,

$$\begin{aligned} h(x_1, x_2, \dots, x_{m-k+1}) &= \frac{m!}{(k-1)!} \prod_{j=1}^{(m-k)} \beta_j \left\{ 1 - \left( \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right)^{m-j} \right\}^{\beta_j-1} \\ &\quad (\bar{F}(x_{m-k+1}))^{k-1} \prod_{j=1}^{m-k+1} f(x_j). \end{aligned} \quad (5)$$

$$0 < x_1 < x_2 < \dots < x_{m-k+1}, \quad \beta_j > 0.$$

(ii) The marginal density of the system failure time  $X_{m-k+1}$ , is given by

$$\begin{aligned} h_{X_{(m-k+1)}}(x_{m-k+1}) &= m \prod_{j=1}^{m-k} \beta_j (\bar{F}(x_{m-k+1}))^{(m-1)} f(x_{m-k+1}) \\ &\quad \int_{x_{m-k}=0}^{1-a_{m-k}} u_{m-k}^{\beta_{m-k}-1} (1-u_{m-k})^{\frac{-m}{k}} \dots \int_{x_j=0}^{1-a_j} u_j^{\beta_j-1} (1-u_j)^{\frac{-m}{m-j}} \\ &\quad \dots \int_{x_1=0}^{1-a_1} u_1^{\beta_1-1} (1-u_1)^{\frac{-m}{m-1}} du_1 du_2 \dots du_{(m-k)}. \end{aligned} \quad (6)$$

$0 < x_{m-k+1} < \infty, \beta_j > 0, \forall j = 1, 2, \dots, (m-k)$ , where,  $a_{m-k} = (\bar{F}(x_{m-k+1}))^k$  and

$$a_j = \frac{(\bar{F}(x_{m-k+1}))^{m-j}}{(1-u_{j+1})^{\frac{m-j}{m-j-1}}(1-u_{j+2})^{\frac{m-j}{m-j-2}} \dots (1-u_{m-k})^{\frac{m-j}{m-(m-k)}}}, \quad 1 \leq j \leq (m-k-1).$$

**Proof. (a)** Using (4), the conditional density of  $X_{(j+1)}$  given  $X_{(j)} = x_j$ , is given by

$$h_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) = (m-j)\beta_j \left\{ 1 - \left( \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right)^{m-j} \right\}^{\beta_j-1} \frac{f(x_{j+1}) (\bar{F}(x_{j+1}))^{m-j-1}}{(\bar{F}(x_j))^{m-j}}, \quad (7)$$

$$\beta_j > 0, \quad x_{j+1} \geq x_j, \quad j = 1, 2, \dots, (m-k).$$

Using the Markov assumption, the joint density of  $(X_{(1)}, X_{(2)}, \dots, X_{(m-k+1)})$  can be written

$$h(x_1, x_2, \dots, x_{m-k+1}) = \prod_{j=1}^{(m-k)} h_{X_{(j+1)}|X_{(j)}=x_j}(x_{j+1}) h(x_1), \quad 0 < x_1 < x_2 < \dots < x_{m-k+1}, \quad \beta_j > 0.$$

Using expression (7) and the fact that  $h(x_1) = m(\bar{F}(x_1))^{m-1} f(x_1)$ ,  $x_1 > 0$ , we get (5).

**Proof. (b)** The marginal density function of  $X_{(m-k+1)}$  is obtained by integrating equation (5) with respect to  $x_1, x_2, \dots, x_{m-k}$  over the region defined by  $0 \leq x_1 \leq x_2 \leq \dots \leq x_{m-k+1}$ .

That is,

$$\begin{aligned} h_{X_{(m-k+1)}}(x_{m-k+1}) &= \int_{x_{m-k}=0}^{x_{m-k+1}} \int_{x_{m-k-1}=0}^{x_{m-k}} \dots \int_{x_1=0}^{x_2} h(x_1, x_2, \dots, x_{m-k+1}) dx_1 dx_2 \dots dx_{(m-k)} \\ &= \frac{m!}{(k-1)!} (\bar{F}(x_{m-k+1}))^{k-1} f(x_{m-k+1}) \int_{x_{m-k}=0}^{x_{m-k+1}} \int_{x_{m-k-1}=0}^{x_{m-k}} \dots \\ &\quad \int_{x_1=0}^{x_2} \prod_{j=1}^{(m-k)} \left\{ 1 - \left( \frac{\bar{F}(x_{j+1})}{\bar{F}(x_j)} \right)^{m-j} \right\}^{\beta_j-1} f(x_j) dx_1 dx_2 \dots dx_{(m-k)}. \end{aligned}$$

Let

$$I_1 = \int_{x_1=0}^{x_2} \left\{ 1 - \left( \frac{\bar{F}(x_2)}{\bar{F}(x_1)} \right)^{m-1} \right\}^{\beta_1-1} f(x_1) dx_1.$$

Putting  $u_1 = 1 - \left( \frac{\bar{F}(x_2)}{\bar{F}(x_1)} \right)^{m-1}$  in above expression and simplifying, we get

$$I_1 = \frac{\bar{F}(x_2)}{m-1} \int_{u_1=0}^{1-(\bar{F}(x_2))^{(m-1)}} u_1^{\beta_1-1} (1-u_1)^{\frac{-m}{m-1}} du_1.$$

Similarly, let

$$\begin{aligned} I_2 &= \frac{1}{m-1} \int_{x_2=0}^{x_3} \left\{ 1 - \left( \frac{\bar{F}(x_3)}{\bar{F}(x_2)} \right)^{m-2} \right\}^{\beta_2-1} \bar{F}(x_2) f(x_2) \\ &\quad \int_{u_1=0}^{1-(\bar{F}(x_2))^{(m-1)}} u_1^{\beta_1-1} (1-u_1)^{\frac{-m}{m-1}} du_1 dx_2. \end{aligned}$$

After putting  $u_2 = 1 - \left( \frac{\bar{F}(x_3)}{\bar{F}(x_2)} \right)^{m-2}$  and simplifying we get

$$\begin{aligned} I_2 &= \frac{(\bar{F}(x_2))^2}{(m-1)(m-2)} \int_{u_1=0}^{1-(\bar{F}(x_3))^{(m-2)}} u_2^{\beta_2-1} (1-u_2)^{\frac{-m}{m-2}} \\ &\quad \int_{u_1=0}^{1-(\bar{F}(x_3))^{(m-1)}(1-u_2)^{\frac{-(m-1)}{(m-2)}}} u_1^{\beta_1-1} (1-u_1)^{\frac{-m}{m-1}} du_1 du_2. \end{aligned}$$

Proceeding in the same manner and by letting  $I_3, I_4, \dots, I_{(m-k)}$ , we get (6).

**Remark 2.** Under the model defined by (4), the conditional reversed hazard rate (CRHR)  $r_{X_{(j+1)}|X_{(j)}=s}^*(t)$  of  $X_{(j+1)}$  given  $X_{(j)} = s$  is proportional to the CRHR  $r_{X_{(j+1)}|X_{(j)}=s}(t)$  under the i.i.d. setup. That is,

$$r_{X_{(j+1)}|X_{(j)}=s}^*(t) = \beta_j r_{X_{(j+1)}|X_{(j)}=s}(t), \quad \beta_j > 0, \quad t \geq s, \quad j = 1, 2, \dots, (m - k). \quad (8)$$

Thus we refer to the model given in (5) as proportional conditional reversed hazard rate (PCRHR) model.

### 3. ILLUSTRATION

#### 3.1. The PCRHR based Load Sharing Model for 2-out-of-4 System

Let us consider the system involve four components with component lifetimes  $U_1, U_2, U_3, U_4$  and are being iid with common lifetime distribution  $f_{\underline{\theta}}(\cdot)$ ,  $\underline{\theta}$  may be scale or vector valued parameter.  $f_{\underline{\theta}}(\cdot)$  is called the baseline distribution and  $\underline{\theta}$  is known as baseline parameter. Let  $F_{\underline{\theta}}(\cdot)$  and  $\bar{F}_{\underline{\theta}}(\cdot)$  are the distribution function (d.f.) and survival function (s.f.).

The 2-out-of-4 system will work until 3 components work and system fails after the third failure. Let  $X_{(1)}, X_{(2)}$  and  $X_{(3)}$  be the first, second and third failure times. Therefore the *p.d.f.* of  $X_{(1)}$  is given by

$$h_{X_{(1)}}(x_1) = 4f_{\underline{\theta}}(x_1) (\bar{F}_{\underline{\theta}}(x_1))^3, \quad x_1 > 0.$$

From equation (7) the conditional density of  $X_{(2)}$  given  $X_{(1)} = x_1$  is given by

$$h_{X_{(2)}|X_{(1)}=x_1}(x_2) = 3\beta_1 \left\{ 1 - \left( \frac{\bar{F}_{\underline{\theta}}(x_2)}{\bar{F}_{\underline{\theta}}(x_1)} \right)^3 \right\}^{\beta_1 - 1} \frac{f_{\underline{\theta}}(x_2) (\bar{F}_{\underline{\theta}}(x_2))^2}{(\bar{F}_{\underline{\theta}}(x_1))^3},$$

$$0 \leq x_1 \leq x_2 \leq \infty, \quad \beta_1 > 0,$$

and the conditional density of  $X_{(3)}$  given  $X_{(2)} = x_2$  is given by

$$h_{X_{(3)}|X_{(2)}=x_2}(x_3) = 2\beta_2 \left\{ 1 - \left( \frac{\bar{F}_{\underline{\theta}}(x_3)}{\bar{F}_{\underline{\theta}}(x_2)} \right)^2 \right\}^{\beta_2 - 1} \frac{f_{\underline{\theta}}(x_3) \bar{F}_{\underline{\theta}}(x_3)}{(\bar{F}_{\underline{\theta}}(x_2))^2},$$

$$0 \leq x_2 \leq x_3 \leq \infty, \quad \beta_2 > 0,$$

Therefore the joint distribution of  $(X_{(1)}, X_{(2)}, X_{(3)})$  is given by

$$h(x_1, x_2, x_3) = 4! \beta_1 \beta_2 \bar{F}_{\underline{\theta}}(x_3) \left\{ 1 - \left( \frac{\bar{F}_{\underline{\theta}}(x_2)}{\bar{F}_{\underline{\theta}}(x_1)} \right)^3 \right\}^{\beta_1 - 1} \left\{ 1 - \left( \frac{\bar{F}_{\underline{\theta}}(x_3)}{\bar{F}_{\underline{\theta}}(x_2)} \right)^2 \right\}^{\beta_2 - 1} \prod_{j=1}^3 f_{\underline{\theta}}(x_j). \quad (9)$$

$$0 \leq x_1 \leq x_2 \leq x_3 \leq \infty, \quad \beta_1, \beta_2 > 0$$

The marginal distribution of system failure, i.e. distribution of  $X_{(3)}$  is given by

$$h_{X_{(3)}}(x_3) = 4\beta_1 \beta_2 f_{\underline{\theta}}(x_3) (\bar{F}_{\underline{\theta}}(x_3))^3 \int_{u_1=0}^{1 - (\bar{F}(x_3))^2} u_2^{\beta_2 - 1} (1 - u_2)^{-2} \int_{u_1=0}^{1 - (\bar{F}(x_3))^3 (1 - u_2)^{\frac{3}{2}}} u_1^{\beta_1 - 1} (1 - u_1)^{\frac{-4}{3}} du_1 du_2. \quad (10)$$

$$0 \leq x_3 \leq \infty, \quad \beta_1, \beta_2 > 0.$$

In the following subsection, we demonstrate the 2-out-of-4 load-sharing system using a Weibull baseline distribution.

### 3.2. The PCRHR based Load Sharing Model for 2-out-of-4 System with Weibull Baseline Distribution

Let us consider a 2-out-of-4 load sharing system, with the component lifetimes  $U_1, U_2, U_3$  and  $U_4$  being i.i.d. Weibull random variables. The p.d.f. of Weibull with shape parameter  $a$  and scale parameter  $b$  is

$$f(u_i) = \left(\frac{a}{b}\right) \left(\frac{u_i}{b}\right)^{a-1} \exp\left\{-\left(\frac{u_i}{b}\right)^a\right\}, \quad u_i > 0, \quad a, b > 0, \quad i = 1, 2, 3, 4.$$

Therefore the p.d.f of first failure  $X_{(1)}$  is given by

$$h_{X_{(1)}}(x_1) = 4 \left(\frac{a}{b}\right) \left(\frac{x_1}{b}\right)^{a-1} \exp\left\{-4\left(\frac{x_1}{b}\right)^a\right\}, \quad x_1 > 0, \quad a, b > 0, \quad i = 1, 2, 3, 4.$$

The conditional p.d.f of  $X_{(2)}$  given  $X_{(1)} = x_1$  is given by

$$h_{X_{(2)}|X_{(1)}=x_1}(x_2) = 3\beta_1 \left(\frac{a}{b}\right) \left(\frac{x_2}{b}\right)^{a-1} \exp\left\{-3\left[\left(\frac{x_2}{b}\right)^a - \left(\frac{x_1}{b}\right)^a\right]\right\} \\ \left[1 - \exp\left\{-3\left[\left(\frac{x_2}{b}\right)^a - \left(\frac{x_1}{b}\right)^a\right]\right\}\right]^{\beta_1-1}, \quad (11)$$

$$0 \leq x_1 \leq x_2 \leq \infty, \quad \beta_1 > 0, \quad a, b > 0.$$

and conditional p.d.f of  $X_{(3)}$  given  $X_{(2)} = x_2$  is given by

$$h_{X_{(3)}|X_{(2)}=x_2}(x_3) = 2\beta_2 \left(\frac{a}{b}\right) \left(\frac{x_3}{b}\right)^{a-1} \exp\left\{-2\left[\left(\frac{x_3}{b}\right)^a - \left(\frac{x_2}{b}\right)^a\right]\right\} \\ \left[1 - \exp\left\{-2\left[\left(\frac{x_3}{b}\right)^a - \left(\frac{x_2}{b}\right)^a\right]\right\}\right]^{\beta_2-1},$$

$$0 \leq x_2 \leq x_3 \leq \infty, \quad \beta_2 > 0, \quad a, b > 0.$$

From (9) the joint density function of  $(X_{(1)}, X_{(2)}, X_{(3)})$  is given by

$$h(x_1, x_2, x_3) = 4! \beta_1 \beta_2 \left(\frac{a}{b}\right)^3 \left(\frac{x_1}{b}\right)^{a-1} \left(\frac{x_2}{b}\right)^{a-1} \left(\frac{x_3}{b}\right)^{a-1} \exp\left\{-4\left(\frac{x_1}{b}\right)^a - 3\left[\left(\frac{x_2}{b}\right)^a - \left(\frac{x_1}{b}\right)^a\right] \right. \\ \left. - 2\left[\left(\frac{x_3}{b}\right)^a - \left(\frac{x_2}{b}\right)^a\right]\right\} \left[1 - \exp\left\{-2\left[\left(\frac{x_3}{b}\right)^a - \left(\frac{x_2}{b}\right)^a\right]\right\}\right]^{\beta_2-1} \\ \left[1 - \exp\left\{-3\left[\left(\frac{x_2}{b}\right)^a - \left(\frac{x_1}{b}\right)^a\right]\right\}\right]^{\beta_1-1}, \quad (12)$$

$$0 \leq x_1 \leq x_2 \leq x_3 \leq \infty, \quad \beta_1, \beta_2 > 0, \quad a, b > 0.$$

In the next subsequent section we discuss the parameter estimation procedures for the proposed model.

## 4. PARAMETER ESTIMATION

Let  $\underline{\theta} = (\theta_1, \theta_2, \dots, \theta_p)$  be the baseline parameters and  $\underline{\beta} = (\beta_1, \beta_2, \dots, \beta_{(m-k)})$  be the load sharing parameters involved in the proposed PCRHR based load sharing model. The maximum likelihood estimation procedure is used to estimate the parameters.

### 4.1. For $k$ -out-of- $m$ Load Sharing System

Let  $r = m - k + 1$ ,  $x_{ij}$  be the  $j^{\text{th}}$  failure  $X_{(j)}$  of  $i^{\text{th}}$   $k$ -out-of- $m$  load sharing system and  $x_{ij+1}$  is the  $(j + 1)^{\text{th}}$  failure  $X_{(j+1)}$  of  $i^{\text{th}}$   $k$ -out-of- $m$  load sharing system with  $i = 1, 2, \dots, n$ ,  $j = 1, 2, \dots, m - k$ .

The likelihood function of  $(\underline{\theta}, \underline{\beta})$  based on  $n$  independent  $k$ -out-of- $m$  load sharing systems is given by

$$L(\underline{\theta}, \underline{\beta}) = \left(\frac{m!}{(k-1)!}\right)^n \left(\prod_{j=1}^{(m-k)} \beta_j\right)^n \prod_{i=1}^n \bar{F}_{\underline{\theta}}(x_{ir})^{k-1} \prod_{i=1}^n \prod_{j=1}^r f_{\underline{\theta}}(x_{ij}) \prod_{i=1}^n \prod_{j=1}^{(m-k)} \left[1 - \left\{\frac{\bar{F}_{\underline{\theta}}(x_{ij+1})}{\bar{F}_{\underline{\theta}}(x_{ij})}\right\}^{m-j}\right]^{\beta_j-1}.$$

The corresponding log-likelihood function can be written as,

$$\log L = n \log \left(\frac{m!}{(k-1)!}\right) + n \sum_{j=1}^r \log \beta_j + (k-1) \sum_{i=1}^n \log \bar{F}_{\underline{\theta}}(x_{ir}) + \sum_{i=1}^n \sum_{j=1}^r \log f_{\underline{\theta}}(x_{ij}) + \sum_{i=1}^n \sum_{j=1}^{m-k} (\beta_j - 1) \log \left[1 - \left\{\frac{\bar{F}_{\underline{\theta}}(x_{ij+1})}{\bar{F}_{\underline{\theta}}(x_{ij})}\right\}^{m-j}\right].$$

To obtain maximum likelihood estimates (MLEs) of unknowns parameters  $\underline{\theta}$  and  $\underline{\beta}$  differentiate the above log-likelihood partially w.r.t. unknown parameters and equate to zero, we have likelihood equations to estimate as

$$\frac{\partial \log L}{\partial \theta_l} = 0, \quad l = 1, 2, 3, \dots, p, \tag{13}$$

$$\frac{\partial \log L}{\partial \beta_j} = 0, \quad j = 1, 2, \dots, (m-k). \tag{14}$$

The above  $p + (m - k)$  equations are not in closed form so are solved by iterative procedures. We could use the ‘optim’ function in R software to solve these equations.

#### 4.2. For $k$ -out-of- $m$ Load Sharing System with Weibull Baseline

The likelihood function based on  $n$  i.i.d.  $k$ -out-of- $m$  load systems with component lifetimes as Weibull  $(a, b)$  is given by

$$L(a, b, \underline{\beta}) = \left(\frac{m!}{(k-1)!}\right)^n \left(\frac{a}{b}\right)^{nr} \left(\prod_{j=1}^{(m-k)} \beta_j\right)^n \prod_{i=1}^n \prod_{j=1}^r \left(\frac{x_{ij}}{b}\right)^{a-1} \exp \left[-k \sum_{i=1}^n \left(\frac{x_{ir}}{b}\right)^a\right] \exp \left[-\sum_{i=1}^n \sum_{j=1}^{(m-k)} \left(\frac{x_{ij}}{b}\right)^a\right] \prod_{i=1}^n \prod_{j=1}^{m-k} \left\{1 - \exp \left(-\frac{(m-j)}{b^a} [(x_{ij+1})^a - (x_{ij})^a]\right)\right\}^{\beta_j-1}.$$

Hence, the log-likelihood function is given by

$$\log L(a, b, \underline{\beta}) = n \log \left(\frac{m!}{(k-1)!}\right) + nr \log \left(\frac{a}{b}\right) + n \sum_{j=1}^{(m-k)} \log \beta_j + (a-1) \sum_{i=1}^n \sum_{j=1}^r \log \left(\frac{x_{ij}}{b}\right) - k \sum_{i=1}^n \left(\frac{x_{ir}}{b}\right)^a - \sum_{i=1}^n \sum_{j=1}^{(m-k)} \left(\frac{x_{ij}}{b}\right)^a + \sum_{i=1}^n \sum_{j=1}^{m-k} (\beta_j - 1) \log \left\{1 - \exp \left(-\frac{(m-j)}{b^a} [(x_{ij+1})^a - (x_{ij})^a]\right)\right\}.$$

The MLEs of  $a, b$  and  $\beta_j, j = 1, 2, \dots, (m - k)$  are obtained by maximizing above log-likelihood function. The likelihood or log-likelihood function is maximized by differentiating it partially with respect to unknown parameters and equating to zero. The likelihood equations are

$$\frac{\partial \log L}{\partial a} = 0, \quad \frac{\partial \log L}{\partial b} = 0, \quad \frac{\partial \log L}{\partial \beta_j} = 0, \quad j = 1, 2, \dots, (m - k).$$

We observed that likelihood equations are not in closed form, so iterative procedures are used to estimate the unknown parameters.

### 4.3. For 2-out-of-4 Load Sharing System with Weibull Baseline

The likelihood function for the 2-out-of-4 load sharing system with Weibull  $(a, b)$  baseline distribution is given by

$$L(a, b, \beta_1, \beta_2) = (4!)^n \left(\frac{a}{b}\right)^{3n} (\beta_1 \beta_2)^n \prod_{i=1}^n \left(\frac{x_{i1}}{b} \frac{x_{i2}}{b} \frac{x_{i3}}{b}\right)^{(a-1)} \exp \left[ -2 \sum_{i=1}^n \left(\frac{x_{i3}}{b}\right)^a \right] \\ \exp \left[ - \sum_{i=1}^n \left\{ \left(\frac{x_{i1}}{b}\right)^a + \left(\frac{x_{i2}}{b}\right)^a \right\} \right] \prod_{i=1}^n \left\{ 1 - \exp \left( -\frac{3}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\}^{\beta_1-1} \\ \prod_{i=1}^n \left\{ 1 - \exp \left( -\frac{2}{b^a} [(x_{i3})^a - (x_{i2})^a] \right) \right\}^{\beta_2-1}.$$

Thus the log-likelihood function is given by

$$\log L(a, b, \beta_1, \beta_2) = n \log(4!) + 3n \log \left(\frac{a}{b}\right) + n \log \beta_1 + n \log \beta_2 + (a-1) \sum_{i=1}^n \left( \log \left(\frac{x_{i1}}{b}\right) \right. \\ \left. + \log \left(\frac{x_{i2}}{b}\right) + \log \left(\frac{x_{i3}}{b}\right) \right) - \sum_{i=1}^n \left\{ 2 \left(\frac{x_{i3}}{b}\right)^a + \left(\frac{x_{i2}}{b}\right)^a + \left(\frac{x_{i1}}{b}\right)^a \right\} \\ + (\beta_1 - 1) \sum_{i=1}^n \log \left\{ 1 - \exp \left( -\frac{3}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\} \\ + (\beta_2 - 1) \sum_{i=1}^n \log \left\{ 1 - \exp \left( -\frac{2}{b^a} [(x_{i3})^a - (x_{i2})^a] \right) \right\},$$

and the likelihood equations are

$$\frac{\partial \log L}{\partial a} = 0, \quad \frac{\partial \log L}{\partial b} = 0, \quad \frac{\partial \log L}{\partial \beta_1} = 0, \quad \frac{\partial \log L}{\partial \beta_2} = 0.$$

These equation solved simultaneously to get MLEs of  $a, b, \beta_1$  and  $\beta_2$ . It is seen that the likelihood equations not in closed form, iterative procedures are used.

### 4.4. For 2-out-of-3 Load Sharing System with Weibull Baseline

The likelihood function for the 2-out-of-3 load sharing model with Weibull  $(a, b)$  baseline distribution is given by

$$L(a, b, \beta_1) = (3!)^n \left(\frac{a}{b}\right)^{2n} \beta_1^n \prod_{i=1}^n \left(\frac{x_{i1}}{b} \frac{x_{i2}}{b}\right)^{(a-1)} \exp \left[ - \sum_{i=1}^n \left\{ \left(2 \frac{x_{i2}}{b}\right)^a + \left(\frac{x_{i1}}{b}\right)^a \right\} \right] \\ \prod_{i=1}^n \left\{ 1 - \exp \left( -\frac{2}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\}^{\beta_1-1}.$$

Hence, the log-likelihood function is given by

$$\log L(a, b, \beta_1) = n \log(3!) + 2n \log \left(\frac{a}{b}\right) + n \log \beta_1 + (a-1) \sum_{i=1}^n \left\{ \log \left(\frac{x_{i1}}{b}\right) + \log \left(\frac{x_{i2}}{b}\right) \right\} \\ - \sum_{i=1}^n \left\{ 2 \left(\frac{x_{i2}}{b}\right)^a + \left(\frac{x_{i1}}{b}\right)^a \right\} + (\beta_1 - 1) \sum_{i=1}^n \log \left\{ 1 - \exp \left( -\frac{2}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\}.$$



The likelihood equations are

$$\frac{\partial \log L}{\partial a} = 0, \quad \frac{\partial \log L}{\partial b} = 0, \quad \frac{\partial \log L}{\partial \beta_1} = 0.$$

These equations are solved simultaneously to obtain the MLEs of  $a, b$ , and  $\beta_1$ . Since the likelihood equations do not have a closed-form solution, iterative procedures are required to solve them.

#### 4.5. For 1-out-of-3 Parallel Load Sharing System with Weibull Baseline

Under the 1-out-of-3 load sharing model with Weibull  $(a, b)$  baseline Distribution the likelihood function is given by

$$L(a, b, \beta_1, \beta_2) = (3!)^n \left(\frac{a}{b}\right)^{3n} (\beta_1 \beta_2)^n \prod_{i=1}^n \left(\frac{x_{i1}}{b} \frac{x_{i2}}{b} \frac{x_{i3}}{b}\right)^{(a-1)} \exp \left[ - \sum_{i=1}^n \left\{ \left(\frac{x_{i3}}{b}\right)^a + \left(\frac{x_{i1}}{b}\right)^a + \left(\frac{x_{i2}}{b}\right)^a \right\} \right] \\ \prod_{i=1}^n \left\{ 1 - \exp \left( - \frac{2}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\}^{\beta_1 - 1} \prod_{i=1}^n \left\{ 1 - \exp \left( - \frac{1}{b^a} [(x_{i3})^a - (x_{i2})^a] \right) \right\}^{\beta_2 - 1}.$$

The log-likelihood function is given by

$$\log L(a, b, \beta_1, \beta_2) = n \log(3!) + 3n \log \left(\frac{a}{b}\right) + n \log \beta_1 + n \log \beta_2 + (a-1) \sum_{i=1}^n \left\{ \log \left(\frac{x_{i1}}{b}\right) \right. \\ \left. + \log \left(\frac{x_{i2}}{b}\right) + \log \left(\frac{x_{i3}}{b}\right) \right\} - \sum_{i=1}^n \left\{ \left(\frac{x_{i3}}{b}\right)^a + \left(\frac{x_{i2}}{b}\right)^a + \left(\frac{x_{i1}}{b}\right)^a \right\} \\ + (\beta_1 - 1) \sum_{i=1}^n \log \left\{ 1 - \exp \left( - \frac{2}{b^a} [(x_{i2})^a - (x_{i1})^a] \right) \right\} \\ + (\beta_2 - 1) \sum_{i=1}^n \log \left\{ 1 - \exp \left( - \frac{1}{b^a} [(x_{i3})^a - (x_{i2})^a] \right) \right\}$$

The likelihood equations are

$$\frac{\partial \log L}{\partial a} = 0, \quad \frac{\partial \log L}{\partial b} = 0, \quad \frac{\partial \log L}{\partial \beta_1} = 0, \quad \frac{\partial \log L}{\partial \beta_2} = 0.$$

These equation solved simultaneously to get MLEs of  $a, b, \beta_1$  and  $\beta_2$ . It is seen that the likelihood equations not in closed form, iterative procedures are used.

### 5. SIMULATION STUDY

In this section, we carry out the simulation study for 2-out-of-4 load sharing model with Weibull  $(a, b)$  baseline distribution. The MLEs, Bias and Mean Square Estimates (MSE) are obtained for various combination of sample size, baseline parameters and load sharing parameters. The performance of estimates are accessed to bias and MSE. We consider sample sizes 30, 50, 100 and 200, the baseline parameters are considered to be  $a = 1, 1.5, 2$  and  $b = 0.5, 0.7, 1, 2$ , and load share parameters  $\beta_j = 1, 1.5, 2, j = 1, 2$ . The parameters are estimated using 1000 samples for each sample size and parameter combinations. The results, including the MLEs, bias, and MSE, are detailed in Tables 1 to 4 and illustrated in Figures 1 to 4. These tables and figures provide a comprehensive overview of the estimation accuracy and performance metrics associated with the model.









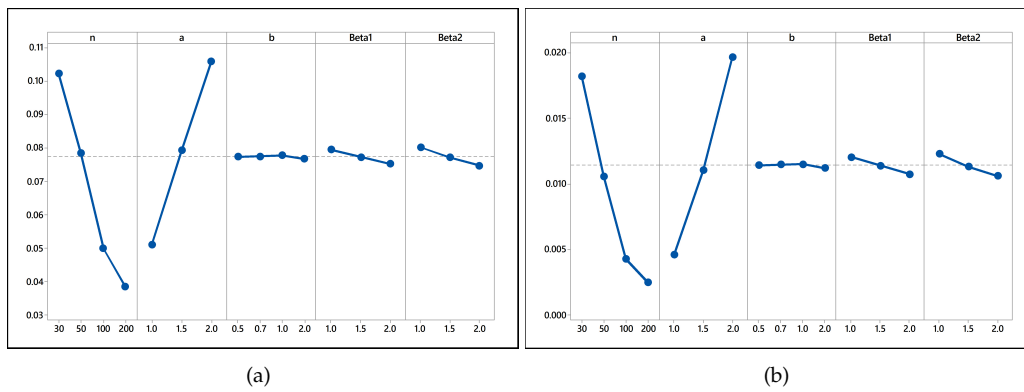


Figure 1: Main Effect Plots of and MSE of shape parameter : (a) Bias( $\hat{a}$ ) (b) MSE( $\hat{a}$ )

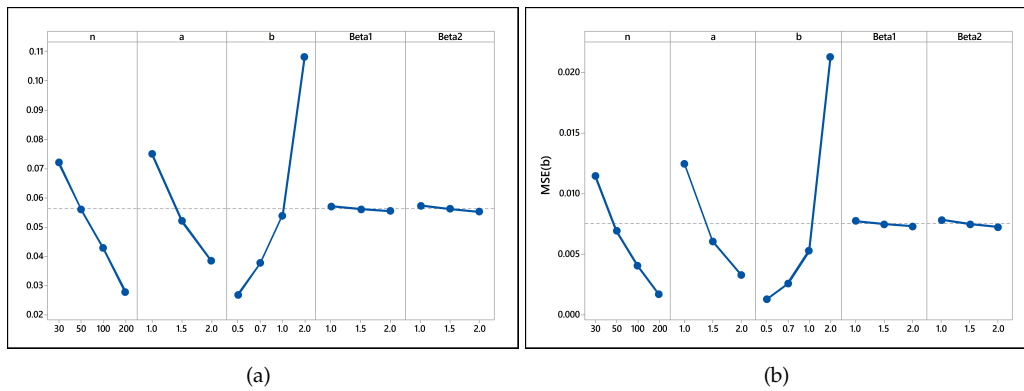


Figure 2: Main Effect Plots of and MSE of scale parameter: (a) Bias( $\hat{b}$ ) (b) MSE( $\hat{b}$ )

Figure 1 is the main effect plot for the bias and MSE of shape parameter  $a$  for various sample sizes ( $n$ ), shape parameters( $a$ ), scale parameters ( $b$ ), and load share parameters ( $\beta_1$  and  $\beta_2$ ). It is observed that as  $n$  increases both the bias and MSE decreases. Bias and MSE increase as its own value is increases. Scale parameter ( $b$ ) is not affecting on the bias and MSE of shape parameter ( $a$ ). Bias in ( $a$ ) slightly decreases as load share parameters  $\beta_1$  and  $\beta_2$  increases. Figure 2 is the main effect plot for the bias and MSE of scale parameter  $b$  for various values of different parameters. From figure 2 observed that bias as well as MSE is decreases as  $a$  and  $n$  increases and it increases as its own value increases while is not affected by changes in load share parameters.

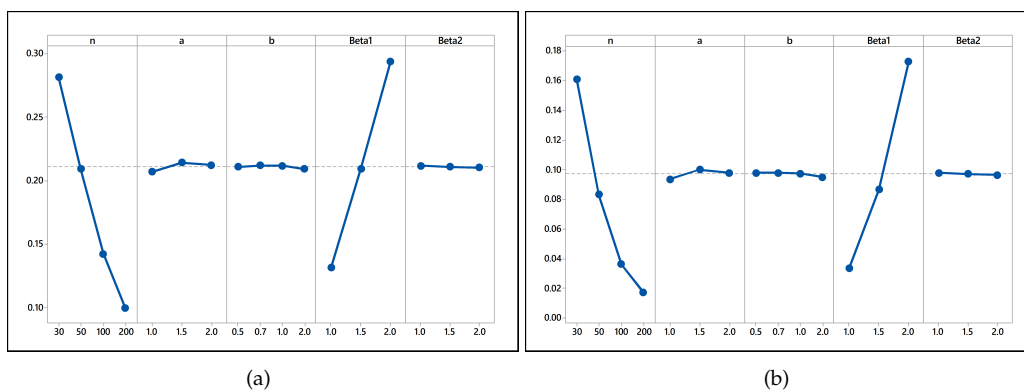


Figure 3: Main Effect Plots of bias of different parameters: (a) Bias( $\hat{\beta}_1$ ) (b) MSE( $\hat{\beta}_1$ )

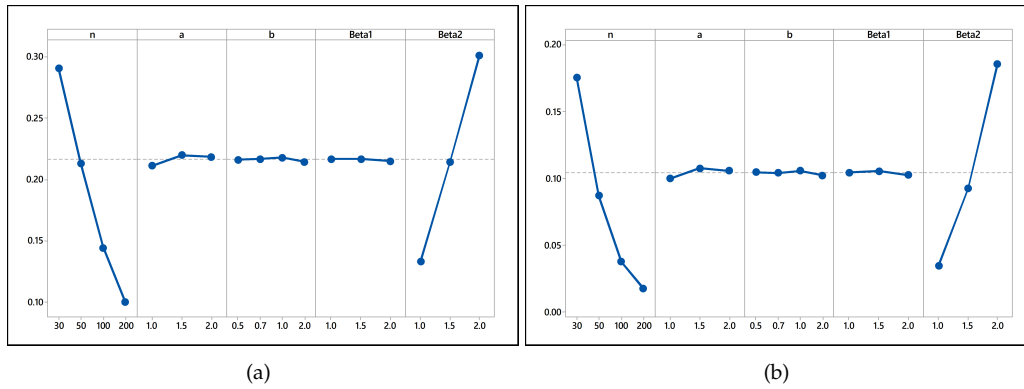


Figure 4: Main Effect Plots of MSE of different parameters: (a) Bias( $\beta_2$ ) (b) MSE( $\beta_2$ )

Figure 3 and 4 is the main effect plot for the bias and MSE of load share parameters  $\beta_1$  and  $\beta_2$  for various sample sizes ( $n$ ), shape parameters( $a$ ), scale parameters ( $b$ ), and load share parameters ( $\beta_1$  and  $\beta_2$ ). It is observed that as  $n$  increases both the bias and MSE decreases. Bias and MSE increase as its own value is increases. Changes in scale parameter ( $b$ ) is not affecting on the bias as well as MSE. Also, the bias and MSE of load share parameter in not affected by the changes in other load share parameter.

## 6. DATA ANALYSIS

To illustrate the practical application of the proposed method, we have analyzed two datasets taken from Kim and Kvam [13]. Each datasets consists of 20 observations, specifically capturing the first three failure times of the systems under consideration. We interpret these datasets in the context of two load-sharing configurations: a three-component parallel (1-out-of-3) load-sharing system and a 2-out-of-3 load-sharing system. In our analysis, we utilize Weibull distributions as the baseline distributions for modeling

The failure time data for both datasets are summarized in Table 5, showing the values of the first three failure times ( $x_1, x_2, x_3$ ) for each dataset.

Table 5: Failure Time Data

Data Set 1			Data Set 2		
$x_1$	$x_2$	$x_3$	$x_1$	$x_2$	$x_3$
0.37	1.94	6.93	0.36	3.85	6.49
0.06	2.42	7.44	0.14	0.32	7.57
0.14	0.2	0.2	0.12	5.98	8.29
1.62	2.14	2.34	0.86	3.43	6.12
1.91	1.96	5.7	1.19	2.42	6
2.25	4.6	8.23	0.2	1.53	6.26
0.09	1.4	2.5	1.01	1.18	2.5
0.79	2.44	7.27	1.19	1.3	9.13
0.06	0.12	0.92	2.08	3.62	4.32
0.73	0.79	8.61	0.49	2.89	6.28
1.38	2.78	7.22	3.25	3.88	6.22
0.85	2.81	5.05	0.03	4.18	17.87
0.52	4.13	8.5	0.46	8.99	27.63
1.11	5.67	12.93	2.17	4.08	15.02
0.96	3.54	4.46	1.93	6.81	10.18
2.38	3.5	7.16	0.37	2.7	5.04
0.32	1.89	19.59	0.34	0.97	2.47
1.54	4.98	7.32	2.64	5.16	5.43
2.58	8.61	10.29	0.1	2.38	4.03
1.22	1.73	2.22	0.16	2.26	3.98

The Table 6 summarizes the estimated parameters, along with the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for the models applied to the given datasets.

**Table 6:** Estimates of Parameters, AIC, and BIC for Different Load Sharing Models

Data	Model	Estimate				AIC	BIC
		$\hat{a}$	$\hat{b}$	$\hat{\beta}_1$	$\hat{\beta}_2$		
Dataset 1	1 out of 3	0.948	3.597	0.915	0.931	-194.09	-191.1
	2 out of 3	1.001	3.484	0.926	-	-100.227	-97.25
Dataset 2	1 out of 3	0.978	3.419	1.41	1.35	-209.04	-206.05
	2 out of 3	0.928	3.492	1.395	-	-108.72	-105.74

The table above presents the estimated parameters, along with the AIC and BIC values, for different load-sharing models applied to two datasets. The analysis compares the performance of "1-out-of-3" and "2-out-of-3" load-sharing systems, with parameters  $\hat{a}$ ,  $\hat{b}$ ,  $\hat{\beta}_1$ , and  $\hat{\beta}_2$  estimated for each model. Notably, the "2-out-of-3" model is simpler, as it omits the  $\hat{\beta}_2$  parameter.

The comparison of AIC and BIC values reveals that the "1-out-of-3" model consistently outperforms the "2-out-of-3" model in both datasets, as indicated by its lower AIC and BIC values. This suggests that the "1-out-of-3" model provides a better fit, despite its increased complexity. The variability in the estimates of  $\hat{\beta}_1$  and  $\hat{\beta}_2$  across the models further highlights the different behaviors of the systems under the respective load-sharing rules.

Overall, these findings suggest that while the "2-out-of-3" model is simpler, the "1-out-of-3" model may more accurately represent the underlying load-sharing systems in these datasets. This makes it potentially more effective and practical for engineering and industrial applications where precise modeling is crucial.

## 7. CONCLUSIONS

In this paper, we developed a load-sharing model for  $k$ -out-of- $m$  systems using the Proportional Conditional Reverse Hazard Rate approach with an unequal load-sharing rule. Our model addresses the complexities of real-world systems where components share the load unevenly after failures occur. To illustrate the model, a 2-out-of-4 configuration with Weibull baseline distributions is employed. Maximum likelihood estimation is used to estimate the model parameters, and the accuracy of these estimates is assessed through a simulation study that evaluates bias and mean square error. Furthermore, the model's practical applicability is demonstrated by analyzing two real datasets.

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## REFERENCES

- [1] Daniels, H. E. (1945). The statistical theory of the strength of bundles of threads. I. *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, 183(995):405-435.
- [2] Birnbaum, Z. W., and Saunders, S. C. (1958). A statistical model for life-length of materials. *Journal of the American Statistical Association*, 53(281):151-160.
- [3] Coleman, B. D. (1958). Statistics and time dependence of mechanical breakdown in fibers. *Journal of Applied Physics*, 29(6):968-983.
- [4] Rosen, B. W. (1964). Tensile failure of fibrous composites. *AIAA Journal*, 2(11):1985-1991.
- [5] Phoenix, S. L. (1978). The asymptotic time to failure of a mechanical system of parallel members. *SIAM Journal on Applied Mathematics*, 34(2):227-246.
- [6] Singpurwalla, N. D. (1995). Survival in dynamic environments. *Statistical Science*, 10(1):86-103.



- [7] Hollander, M., and Pe?a, E. A. (1995). Dynamic reliability models with conditional proportional hazards. *Lifetime Data Analysis*, 1:377-401.
- [8] Cramer, E., and Kamps, U. (1996). Sequential order statistics and k-out-of-n systems with sequentially adjusted failure rates. *Annals of the Institute of Statistical Mathematics*, 48:535-549.
- [9] Lynch, J. D. (1999). On the joint distribution of component failures for monotone load-sharing systems. *Journal of Statistical Planning and Inference*, 78, 13-21.
- [10] Drummond, H., Vazquez, E., Sanchez-Colon, S., Martinez-Gomez, M., Hudson, R. (2000). Competition for milk in the domestic rabbit: survivors benefit from littermate deaths. *Ethology*, 106:511-526.
- [11] Durham, S. D., and Lynch, J. D. (2000). A threshold representation for the strength distribution of a complex load sharing system. *Journal of Statistical Planning and Inference*, 83, 25-46.
- [12] Cramer, E., and Kamps, U. (2003). Marginal distributions of sequential and generalized order statistics. *Metrika*, 58:293-310.
- [13] Kim, H., and Kvam, P. H. (2004). Reliability estimation based on system data with an unknown load share rule. *Lifetime Data Analysis*, 10:83-94.
- [14] Kvam, P. H., and Pena, E. A. (2005). Estimating load-sharing properties in a dynamic reliability system. *Journal of the American Statistical Association*, 100(469), 262-272.
- [15] McCool, J. I. (2006). Testing for dependency of failure times in life testing. *Technometrics*, 48(1), 41-48.
- [16] Pena, E. A. (2006). Dynamic modelling and statistical analysis of event times. *Statistical Science: A Review Journal of the Institute of Mathematical Statistics*, 21(4), 1.
- [17] Deshpande, J. V., Dewan, I., and Naik-Nimbalkar, U. V. (2010). A family of distributions to model load sharing systems. *Journal of Statistical Planning and Inference*, 140(6):1441-1451.
- [18] Dewan, I., and Naik-Nimbalkar, U. V. (2010). Load-sharing systems. *Wiley Encyclopedia of Operations Research and Management Science*.
- [19] Jain, M., and Gupta, R. (2012). Load sharing M-out of-N: G system with non-identical components subject to common cause failure. *International Journal of Mathematics in Operational Research*, 4(5):586-605.
- [20] Sutar, S. S., and Naik-Nimbalkar, U. V. (2014). Accelerated failure time models for load sharing systems. *IEEE Transactions on Reliability*, 63(3):706-714.
- [21] Sutar, S. S., and Naik-Nimbalkar, U. V. (2016). A model for k-out-of-m load-sharing systems. *Communications in Statistics-Theory and Methods*, 45(20):5946-5960.
- [22] Wang, D., Jiang, C., and Park, C. (2019). Reliability analysis of load-sharing systems with memory. *Lifetime Data Analysis*, 25:341-360.
- [23] Zhao, X., Liu, B., and Liu, Y. (2018). Reliability modeling and analysis of load-sharing systems with continuously degrading components. *IEEE Transactions on Reliability*, 67(3):1096-1110.
- [24] Xu, H., Fang, Y., and Fard, N. (2018). Reliability Assessment of Repairable Load-Sharing k-out-of-n: G System with Flowgraph Model. In *2018 Annual Reliability and Maintainability Symposium (RAMS)*, 1-6, IEEE.
- [25] Zhang, Z., Yang, Y., and Guo, Z. (2019). Reliability Analysis for a Repairable Load-Sharing Parallel System. In *2019 2nd International Conference on Mathematics, Modeling and Simulation Technologies and Applications (MMSTA 2019)*, 93:128-132, Atlantis Press.
- [26] Sutar S. S. and Naik-Nimbalkar, U. V. (2019). A load share model for non-identical components of a k-out-of-m system. *Applied Mathematical Modelling*, 72:486-498.
- [27] Choudhary, N., Tyagi, A., and Singh, B. (2020). Analysing load-sharing system model with type-I and type-II failure censored data from Weibull distribution. *Annals of Data Science*, 9:645-674.
- [28] Park, C., Wang, M., Alotaibi, R. M., and Rezk, H. (2020). Load-Sharing Model under Lindley Distribution and Its Parameter Estimation Using the Expectation-Maximization Algorithm. *Entropy*, 22(11):13-29.
- [29] Sutar, S. S. (2021). Likelihood Ratio Test and Non-parametric Test for Load Sharing. *Austrian Journal of Statistics*, 50(1):41-58.

- [30] Zhang, Z., Yang, Y., and Li, D. (2022). Estimation of parameters for load-sharing parallel systems under exponential Pareto distribution. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 236(2):248-255.
- [31] Rykov, V., Ivanova, N., and Kochetkova, I. (2022). Reliability Analysis of a Load-Sharing k-out-of-n System Due to Its Components' Failure. *Mathematics*, 10(14):24-57.
- [32] Pesch, T., Polpo, A., Cripps, E., and Cramer, E. (2023). Reliability inference with extended sequential order statistics. *Applied Stochastic Models in Business and Industry*, 39(4):520-535.
- [33] Sutar, S. S., Gardi, C. G., and Pawar, S. D. (2023). Analyzing load sharing system reliability: A modified Weibull distribution approach. *Reliability: Theory & Applications*, 18(3), 708-724.
- [34] Biswas, S., Ganguly, A., and Mitra, D. (2023). Reliability Analysis of Load-sharing Systems using a Flexible Model with Piecewise Linear Functions. *arXiv preprint arXiv:2301.01477*.
- [35] Pesch, T., Cramer, E., Polpo, A., and Cripps, E. (2024). Estimation with extended sequential order statistics: A link function approach. *Applied Stochastic Models in Business and Industry*, 40(1):1-24.