Research Article

Estimation of Sine Inverse Exponential Model under Censored Schemes

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In this article, we introduce a new one-parameter model, which is named sine inverted exponential (SIE) distribution. The SIE distribution is a new extension of the inverse exponential (IE) distribution. The SIE distribution aims to provide the SIE model for data-fitting purposes. The SIE distribution is more flexible than the inverted exponential (IE) model, and it has many applications in physics, medicine, engineering, nanophysics, and nanoscience. The density function (PDF) of SIE distribution can be unimodal shape and right skewed shape. The hazard rate function (HRF) of SIE distribution can be J-shaped and increasing shaped. We investigated some fundamental statistical properties such as quantile function (QF), moments (Mo), moment generating function (MGFu), incomplete moments (ICMo), conditional moments (CMo), and the SIE distribution parameters were estimated using the maximum likelihood (ML) method for estimation under censored samples (CS). Finally, the numerical results were investigated to evaluate the flexibility of the new model. The SIE distribution and the IE distribution are compared using two real datasets. The numerical results show the superiority of the SIE distribution.

1. Introduction

In the recent years, inverse and half-inverse problems are studied in general operator theory [1–3], numerous authors have attracted the attention of generated families of distributions such as Kumaraswamy-G by [4], sine generated (S-G) by [5], Kumaraswamy Type-I half-logistic-G [6], Weibull-G [7], odd Fréchet -G by [8], the Burr type X-G by [9], Kumaraswamy Kumaraswamy-G [10], truncated Cauchy power-G by [11], generalized odd half-Cauchy-G by [12], and among others.

The cumulative distribution function (CDFu) and PDFu of S-G are

\[ F(x; \xi) = \sin \left( \frac{\pi}{2} G(x; \xi) \right), \quad x \in R, \quad (1) \]

\[ f(x; \xi) = \frac{\pi}{2} g(x; \xi) \cos \left( \frac{\pi}{2} G(x; \xi) \right), \quad x \in R. \quad (2) \]

Letting \( g(x; \xi) \) and \( G(x; \xi) \), the PDFu and CDFu of IE distribution, it has the following form:

\[ g(x) = \theta x^{-2} e^{-(\theta x)}, \quad \theta > 0, \quad x > 0, \quad (3) \]

\[ G(x) = e^{-(\theta x)}, \quad \theta > 0, \quad x > 0. \quad (4) \]

The main idea for this paper was to introduce a new one-parameter model that is more flexible than the IE model by using the S-G family. The new model is called the SIE model. The SIE model is more flexible than the IE model and it has
many applications in physics, medicine, nanophysics, and nanoscience [13–16]. This manuscript is arranged as follows. Section 2 presents materials and methods. In Section 3, statistical inference of the SIE model under the censored scheme is studied. Section 4 presents results and discussion. At the end of article, conclusions are discussed.

2. Materials and Methods

2.1. The New SIE Model. Letting random variable \( X \) to have SIE distribution, then the CDF \( u \), PDF \( f \), survival function \( S(u) \), and survival function \( S(u)/(1-u) \) of the SIE model can be increasing or J-shaped.

The SIE distribution is computed as follows:

\[
F(x) = \sin \left[ \frac{\pi}{2} e^{-(\theta/\pi)} x \right], \quad x > 0, \quad \theta > 0, \tag{5}
\]

\[
f(x) = \frac{\pi \theta}{2x^2} e^{-(\theta/\pi)} \cos \left[ \frac{\pi}{2} e^{-(\theta/\pi)} x \right], \quad x > 0, \quad \theta > 0, \tag{6}
\]

\[
R(x) = 1 - \sin \left[ \frac{\pi}{2} e^{-(\theta/\pi)} x \right], \tag{7}
\]

\[
h(x) = \frac{\left( \frac{\pi \theta}{2x^2} \right) e^{-(\theta/\pi)} \cos \left[ \frac{\pi}{2} e^{-(\theta/\pi)} x \right]}{1 - \sin \left[ \frac{\pi}{2} e^{-(\theta/\pi)} x \right]}, \tag{8}
\]

where \( \theta \) is a scale parameter.

Figures 1–3 show the plots of PDF, CDF, and HR of the SIE model. The PDF of the SIE model can be right skewed and unimodal shaped, while the HR of the SIE model can be increasing or J-shaped.

2.2. Quantile and Median. If \( X \sim \text{SIE} \) then the QF of SIE is as follows:

\[
Q(u) = \theta \left[ \ln \left( \frac{\pi}{2 \arcsin(u)} \right) \right]^{-1}, \tag{9}
\]

and by taking \( u = 0.5 \), we get the median (M) as

\[
M = \theta [\ln(3)]^{-1}. \tag{10}
\]

MacGillivray’s skewness function is defined in [17] as

\[
\text{MGS} = \frac{Q(u) + Q(1-u) - 2M}{Q(u) - Q(1-u)}. \tag{11}
\]

Figure 4 plots MGS for all values of the parameter \( \theta \).

2.3. Moments

Theorem 1. Letting \( X \) be a r.v. from the SIE model, then its \( r^{th} \) Mo is

\[
\theta_r' = \sum_{i=0}^{\infty} \theta_i^{-1} \Gamma (1-r) \left( \frac{2i+1}{2i+1} \right). \tag{12}
\]

By inserting the expansion \( \cos[G(x)] = \sum_{i=0}^{\infty} ((-1)^{i}/(2i!))G(x)^{2i}, \) to the previous equation, then

\[
\theta_r' = \sum_{i=0}^{\infty} \theta_i^{-1} \Gamma (1-r) \left( \frac{2i+1}{2i!} \right) \int_0^\infty x^{-\delta} e^{-(2i+1)/2i+1} x \, dx. \tag{13}
\]

The last equation can be rewritten as follows:

\[
\theta_r' = \sum_{i=0}^{\infty} \theta_i^{-1} \Lambda \int_0^\infty y^{-\tau} e^{-(2i+1)/2i+1} y \, dy. \tag{14}
\]

Then,

\[
\theta_r' = \sum_{i=0}^{\infty} \theta_i^{-1} \Lambda \Gamma (1-r) \left( \frac{2i+1}{2i+1} \right). \tag{15}
\]

The MGF of \( X \) is

\[
M_X(t) = \sum_{r=0}^{\infty} \theta_r' \Lambda \Gamma (1-r) \left( \frac{2i+1}{2i+1} \right). \tag{16}
\]

The ICM of \( \Lambda \), denoted by \( \phi_\Lambda(t) \), of the SIE distribution is

\[
\phi_\Lambda(t) = \int_0^t x^r f(x) \, dx = \frac{\pi \theta}{2} \int_0^t x^{-\delta} e^{-(\theta/\pi)} x \, dx. \tag{17}
\]

By using equation (18), \( \phi_\Lambda(t) \) will be as

\[
\phi_\Lambda(t) = \sum_{i=0}^{\infty} \theta_i^{-1} \Gamma (1-r) \left( \frac{2i+1}{2i+1} \right). \tag{18}
\]

By using equation (20), \( \tau_i(t) \) will be given

\[
\tau_i(t) = \sum_{i=0}^{\infty} \theta_i^{-1} \Gamma (1-r) \left( \frac{2i+1}{2i+1} \right). \tag{19}
\]

2.4. Order Statistics. Let \( X_1, X_2, \ldots, X_n \) be random sample from the SIE distribution with order statistics (OS) \( X_{(1)}, X_{(2)}, \ldots, X_{(n)} \). The pdf of \( T_{(n)} \) of OS is
The pdf of $X_{(m)}$ can be expressed as

$$f_{X_{(m)}}(x) = \frac{n!}{(m-1)!(n-m)!} x^{m-1} f(x) (1 - F(x))^{n-m}.$$  

(22)

$$f_{X_{(m)}}(x) = \frac{n!\pi\theta}{2(m-1)!(n-m)!} x^{m-1} e^{-\theta x} \sin^{-1} \left[ \frac{\pi e^{-\theta x}}{2} \right] \cos \left[ \frac{\pi e^{-\theta x}}{2} \right] \left( 1 - \sin \left[ \frac{\pi e^{-\theta x}}{2} \right] \right)^{n-m}. \quad \quad \quad \quad (23)$$
Specially, the pdfs of the lowest and greatest OS can be computed as

\[
f_{X_{(1)}}(x) = \frac{n \pi \theta}{2} x^{-2} e^{-(\theta / x)} \cos \left[ \frac{\pi}{2} e^{-(\theta / x)} \right] \left( 1 - \sin \left[ \frac{\pi}{2} e^{-(\theta / x)} \right] \right)^{n-1},
\]

\[
f_{X_{(n)}}(x) = \frac{n \pi \theta}{2} x^{-2} e^{-(\theta / x)} \sin^{-1} \left[ \frac{\pi}{2} e^{-(\theta / x)} \right] \cos \left[ \frac{\pi}{2} e^{-(\theta / x)} \right].
\]

3. Statistical Inference under Censored Samples

For different reasons, such as time constraints, money, or other resources, reliability or lifespan testing trials are typically censored. Generally speaking, there are two types of censorship schemes: Type-I and Type-II CS. Estimation using these two censoring techniques will be discussed in this section of the paper. If we use type-I censoring, we have a set time, say \( X \), but the amount of things that fail during the trial is completely random. Type-II censoring, on the contrary, is a process that continues until the stated number of failures is reached.
3.1. ML Estimation under Type-I Censor. Assume that \( X_1, X_2, \ldots, X_r \) be a type-I CS of size \( r \) obtained from lifetime testing experiment on \( k \) items whose lifetime follows the PDF \( F \) for SIE. The likelihood function \( (LLFu) \) of type-I CS is given as

\[
L = \frac{n!}{(n-r)!} \left[ 1 - F(x_r) \right]^{n-r} \left\{ \prod_{i=1}^{r} f(x_i) \right\}.
\]

The log-LLF corresponding to equation (26) is given by

\[
\ln L = \ln \left( \frac{n!}{(n-r)!} \right) + (n-r) \ln \left[ 1 - F(x_r) \right] + r \ln \frac{\pi e^{-(\theta x_r)}}{2} + r \ln \theta - 2 \sum_{i=1}^{r} \ln(x_i) - \sum_{i=1}^{r} \frac{\theta}{x_i} + \sum_{i=1}^{r} \ln \left( \cos \frac{\pi e^{-(\theta x_i)}}{2} \right).
\]

The ML equations for the SIE distribution are as follows:

\[
\frac{\partial \ln L}{\partial \theta} = \frac{(n-r)ne^{-(\theta x_r)} \cos \left( \frac{\pi}{2} e^{-(\theta x_r)} \right)}{2x_r \left[ 1 - \sin \left( \frac{\pi}{2} e^{-(\theta x_r)} \right) \right]} + \frac{r}{\theta} \sum_{i=1}^{r} \frac{\theta}{x_i} + \frac{\delta \pi}{2 \theta} \sum_{i=1}^{r} \left( \tan \frac{\pi e^{-(\theta x_i)}}{2} \right).
\]

Then, the ML estimators for the parameter \( \theta \) are computed by putting \( (\partial \ln L/\partial \theta) = 0 \) and solving.

3.2. ML Estimation under Type-II Censor. Let \( X_1, X_2, \ldots, X_r \) be a type-II CS of size \( r \) observed from lifetime testing experiment on \( k \) items whose lifetime has the PDF \( F \) for SIE.

\[
L = \frac{n!}{(n-r)!} \left[ 1 - F(x_r) \right]^{n-r} \left\{ \prod_{i=1}^{r} f(x_i) \right\}.
\]

The log-LLF corresponding to equation (29) is given by

\[
\ln L = \ln \left( \frac{n!}{(n-r)!} \right) + (n-r) \ln \left[ 1 - F(x_r) \right] + r \ln \frac{\pi e^{-(\theta x_r)}}{2} + r \ln \theta - 2 \sum_{i=1}^{r} \ln(x_i) - \sum_{i=1}^{r} \frac{\theta}{x_i} + \sum_{i=1}^{r} \ln \left( \cos \frac{\pi e^{-(\theta x_i)}}{2} \right).
\]

The ML equations for the SIE distribution are as follows:

\[
\frac{\partial \ln L}{\partial \theta} = \frac{(n-r)ne^{-(\theta x_r)} \cos \left( \frac{\pi}{2} e^{-(\theta x_r)} \right)}{2x_r \left[ 1 - \sin \left( \frac{\pi}{2} e^{-(\theta x_r)} \right) \right]} + \frac{r}{\theta} \sum_{i=1}^{r} \frac{\theta}{x_i} + \frac{\delta \pi}{2 \theta} \sum_{i=1}^{r} \left( \tan \frac{\pi e^{-(\theta x_i)}}{2} \right).
\]

Then, the ML estimators for the parameter \( \theta \) is calculated by putting \( (\partial \ln L/\partial \theta) = 0 \) and solving.

3.3. Simulation Outcomes. Numerical outcomes are given in this section to examine how the estimators behave in cases of full, TIC, and TIIC estimations. With the help of Mathematica 9, you can compute the mean square errors (A1) as well as the lower limit (L1) and upper bound (U1) of the confidence interval, as well as the average length (AvLe) for 90 percent and 95 percent. The following is a description of how the following algorithm works:

(i) SIE distribution generates 5000 random samples with size \( n = 30, 50, 100, 200, 300, 500, 1000, \) and 2000.

(ii) True parameter \( \theta \) values are taken.

(iii) The termination time is set to \( T = 1.5 \) in the event of TIC and 3 in the absence of TIC. Three levels of censorship are chosen: \( r = 80\% \), \( r = 90\% \) (TIIC), and \( r = 100\% \) (complete sample).

(iv) The ML estimates, A1, L1, U1, and AvLe for various parameter values are computed.

(v) Tables 1–6 include numerical outputs based on completeness and TIIC, while Tables 7–10 contain TIC-based simulation findings.

From Tables 1–10, we can note that when \( n \) increases, the MLE and AvLe are decreased.
4. Results and Discussion

4.1. Application. In this section, two real datasets are analyzed to explain the benefit of the SIEm model compared to the IE model. To compare the competitive models, we suggested some information criterion (ICr) as minus two log-LLFu ($D_1$), Akaike ICr ($D_2$), the correct Akaike ICr ($D_3$), Bayesian ICr ($D_4$), and Hannan–Quinn ICr ($D_5$).

The first data are known as ball bearing data, and it represents the number of rotations before ball bearing failure obtained [18]. The second data set consists of 100 observations of breaking stress of carbon fibres (in Gba) given by

| n  | MLE  | A1  | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|----|------|-----|-------|-------|------|-------|-------|------|
| 30 | 0.6394 | 0.0336 | 0.4777 | 0.8010 | 0.3233 | 0.4467 | 0.8320 | 0.3853 |
| 50 | 0.6410 | 0.0327 | 0.5152 | 0.7667 | 0.2515 | 0.4911 | 0.7908 | 0.2997 |
| 100 | 0.6454 | 0.0295 | 0.5474 | 0.7235 | 0.1761 | 0.5305 | 0.7403 | 0.2098 |
| 200 | 0.6519 | 0.0294 | 0.5700 | 0.6939 | 0.1238 | 0.5582 | 0.7057 | 0.1476 |
| 300 | 0.6530 | 0.0286 | 0.5824 | 0.6836 | 0.1013 | 0.5727 | 0.6933 | 0.1207 |
| 500 | 0.6630 | 0.0284 | 0.5938 | 0.6722 | 0.0785 | 0.5863 | 0.6797 | 0.0935 |
| 1000 | 0.6720 | 0.0282 | 0.6043 | 0.6597 | 0.0554 | 0.5990 | 0.6650 | 0.0660 |
| 2000 | 0.6813 | 0.0276 | 0.6118 | 0.6509 | 0.0391 | 0.6080 | 0.6546 | 0.0466 |

| n  | MLE  | A1  | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|----|------|-----|-------|-------|------|-------|-------|------|
| 30 | 0.7151 | 0.0161 | 0.5501 | 0.9000 | 0.3500 | 0.5165 | 0.9336 | 0.4170 |
| 50 | 0.7203 | 0.0125 | 0.5856 | 0.8550 | 0.2694 | 0.5598 | 0.8808 | 0.3210 |
| 100 | 0.7270 | 0.0099 | 0.6222 | 0.8119 | 0.1897 | 0.6040 | 0.8301 | 0.2260 |
| 200 | 0.7344 | 0.0090 | 0.6476 | 0.7813 | 0.1337 | 0.6348 | 0.7941 | 0.1592 |
| 300 | 0.7359 | 0.0085 | 0.6594 | 0.7685 | 0.1090 | 0.6490 | 0.7789 | 0.1299 |
| 500 | 0.7446 | 0.0079 | 0.6723 | 0.7569 | 0.0845 | 0.6642 | 0.7650 | 0.1007 |
| 1000 | 0.7448 | 0.0076 | 0.6849 | 0.7447 | 0.0598 | 0.6791 | 0.7504 | 0.0713 |
| 2000 | 0.7536 | 0.0056 | 0.6925 | 0.7347 | 0.0422 | 0.6885 | 0.7388 | 0.0503 |

| n  | MLE  | A1  | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|----|------|-----|-------|-------|------|-------|-------|------|
| 30 | 0.8200 | 0.0129 | 0.6229 | 0.9972 | 0.3743 | 0.5871 | 1.0330 | 0.4459 |
| 50 | 0.8157 | 0.0073 | 0.6616 | 0.9498 | 0.2882 | 0.6341 | 0.9774 | 0.3434 |
| 100 | 0.7893 | 0.0040 | 0.6983 | 0.9003 | 0.2021 | 0.6789 | 0.9197 | 0.2408 |
| 200 | 0.7965 | 0.0017 | 0.7271 | 0.8699 | 0.1428 | 0.7134 | 0.8835 | 0.1701 |
| 300 | 0.8024 | 0.0013 | 0.7438 | 0.8610 | 0.1171 | 0.7326 | 0.8722 | 0.1396 |
| 500 | 0.7986 | 0.0008 | 0.7544 | 0.8448 | 0.0904 | 0.7457 | 0.8535 | 0.1077 |
| 1000 | 0.8011 | 0.0004 | 0.7690 | 0.8331 | 0.0641 | 0.7629 | 0.8392 | 0.0763 |
| 2000 | 0.8005 | 0.0002 | 0.7778 | 0.8231 | 0.0453 | 0.7735 | 0.8274 | 0.0539 |

| n  | MLE  | A1  | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|----|------|-----|-------|-------|------|-------|-------|------|
| 30 | 0.6394 | 0.0336 | 0.4777 | 0.8010 | 0.3233 | 0.4467 | 0.8320 | 0.3853 |
| 50 | 0.6410 | 0.0327 | 0.5152 | 0.7667 | 0.2515 | 0.4911 | 0.7908 | 0.2997 |
| 100 | 0.6454 | 0.0295 | 0.5474 | 0.7235 | 0.1761 | 0.5305 | 0.7403 | 0.2098 |
| 200 | 0.6519 | 0.0294 | 0.5700 | 0.6939 | 0.1238 | 0.5582 | 0.7057 | 0.1476 |
| 300 | 0.6530 | 0.0286 | 0.5824 | 0.6836 | 0.1013 | 0.5727 | 0.6933 | 0.1207 |
| 500 | 0.6630 | 0.0284 | 0.5938 | 0.6722 | 0.0785 | 0.5863 | 0.6797 | 0.0935 |
| 1000 | 0.6720 | 0.0282 | 0.6043 | 0.6597 | 0.0554 | 0.5990 | 0.6650 | 0.0660 |
| 2000 | 0.6813 | 0.0276 | 0.6118 | 0.6509 | 0.0391 | 0.6080 | 0.6546 | 0.0466 |
Table 5: MLEs, estimates, $A_1$, $L_1$, $U_1$, and AvLe of the SIE model under THIC for $x_r = 0.9$ and $\theta = 1.5$.

| $n$ | MLE   | $A_1$ | $90\%$ | $95\%$ | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|-----|-------|-------|--------|--------|-------|-------|------|-------|-------|------|
| 30  | 0.7151 | 0.0161 | 0.5501 | 0.9000 | 0.3500 | 0.5165 | 0.9336 | 0.4170 |
| 50  | 0.7203 | 0.0125 | 0.5856 | 0.8550 | 0.2694 | 0.5398 | 0.8808 | 0.3210 |
| 100 | 0.7270 | 0.0099 | 0.6222 | 0.8119 | 0.1897 | 0.6040 | 0.8301 | 0.2260 |
| 200 | 0.7344 | 0.0090 | 0.6476 | 0.7813 | 0.1337 | 0.6348 | 0.7941 | 0.1592 |
| 300 | 0.7359 | 0.0085 | 0.6594 | 0.7685 | 0.1090 | 0.6490 | 0.7789 | 0.1299 |
| 500 | 0.7446 | 0.0079 | 0.6723 | 0.7569 | 0.0845 | 0.6642 | 0.7650 | 0.1007 |
| 1000| 0.7448 | 0.0076 | 0.6849 | 0.7447 | 0.0598 | 0.6791 | 0.7504 | 0.0713 |
| 2000| 0.7536 | 0.0056 | 0.6925 | 0.7347 | 0.0422 | 0.6885 | 0.7388 | 0.0503 |

Table 6: MLEs, estimates, $A_1$, $L_1$, $U_1$, and AvLe of the SIE model under THIC for $x_r = 1$ and $\theta = 1.5$.

| $n$ | MLE   | $A_1$ | $90\%$ | $95\%$ | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|-----|-------|-------|--------|--------|-------|-------|------|-------|-------|------|
| 30  | 0.8200 | 0.0129 | 0.6229 | 0.9972 | 0.3743 | 0.5871 | 1.0330 | 0.4459 |
| 50  | 0.8157 | 0.0073 | 0.6616 | 0.9498 | 0.2882 | 0.6341 | 0.9774 | 0.3434 |
| 100 | 0.7893 | 0.0040 | 0.6983 | 0.9003 | 0.2021 | 0.6789 | 0.9197 | 0.2408 |
| 200 | 0.7965 | 0.0017 | 0.7271 | 0.8699 | 0.1428 | 0.7134 | 0.8835 | 0.1701 |
| 300 | 0.8024 | 0.0013 | 0.7438 | 0.8610 | 0.1171 | 0.7326 | 0.8722 | 0.1396 |
| 500 | 0.7986 | 0.0008 | 0.7544 | 0.8448 | 0.0904 | 0.7457 | 0.8535 | 0.1077 |
| 1000| 0.8011 | 0.0004 | 0.7690 | 0.8331 | 0.0641 | 0.7629 | 0.8392 | 0.0763 |
| 2000| 0.8005 | 0.0002 | 0.7778 | 0.8231 | 0.0453 | 0.7735 | 0.8274 | 0.0539 |

Table 7: MLEs, estimates, $A_1$, $L_1$, $U_1$, and AvLe of the SIE model under TIC for $T = 1.5$ and $\theta = 0.2$.

| $n$ | MLE   | $A_1$ | $90\%$ | $95\%$ | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|-----|-------|-------|--------|--------|-------|-------|------|-------|-------|------|
| 30  | 0.1671 | 0.0040 | 0.1252 | 0.2090 | 0.0838 | 0.1172 | 0.2170 | 0.0998 |
| 50  | 0.1672 | 0.0033 | 0.1350 | 0.1995 | 0.0645 | 0.1288 | 0.2056 | 0.0769 |
| 100 | 0.1674 | 0.0027 | 0.1444 | 0.1898 | 0.0455 | 0.1400 | 0.1942 | 0.0542 |
| 200 | 0.1685 | 0.0018 | 0.1533 | 0.1857 | 0.0324 | 0.1502 | 0.1888 | 0.0386 |
| 300 | 0.1688 | 0.0017 | 0.1557 | 0.1820 | 0.0263 | 0.1531 | 0.1845 | 0.0314 |
| 500 | 0.1696 | 0.0012 | 0.1575 | 0.1778 | 0.0203 | 0.1555 | 0.1797 | 0.0242 |
| 1000| 0.1714 | 0.0010 | 0.1641 | 0.1787 | 0.0146 | 0.1627 | 0.1801 | 0.0174 |
| 2000| 0.1719 | 0.0008 | 0.1667 | 0.1771 | 0.0103 | 0.1658 | 0.1781 | 0.0123 |

Table 8: MLEs, estimates, $A_1$, $L_1$, $U_1$, and AvLe of the SIE model under TIC for $T = 3$ and $\theta = 0.2$.

| $n$ | MLE   | $A_1$ | $90\%$ | $95\%$ | $L_1$ | $U_1$ | AvLe | $L_1$ | $U_1$ | AvLe |
|-----|-------|-------|--------|--------|-------|-------|------|-------|-------|------|
| 30  | 0.1898 | 0.0051 | 0.1447 | 0.2349 | 0.0902 | 0.1360 | 0.2435 | 0.1075 |
| 50  | 0.1913 | 0.0032 | 0.1591 | 0.2295 | 0.0704 | 0.1523 | 0.2362 | 0.0839 |
| 100 | 0.1923 | 0.0024 | 0.1668 | 0.2159 | 0.0491 | 0.1621 | 0.2206 | 0.0585 |
| 200 | 0.1925 | 0.0021 | 0.1760 | 0.2110 | 0.0350 | 0.1727 | 0.2143 | 0.0417 |
| 300 | 0.1931 | 0.0019 | 0.1878 | 0.2073 | 0.0285 | 0.1761 | 0.2100 | 0.0340 |
| 500 | 0.1939 | 0.0016 | 0.1828 | 0.2050 | 0.0222 | 0.1807 | 0.2071 | 0.0264 |
| 1000| 0.1940 | 0.0016 | 0.1828 | 0.2050 | 0.0222 | 0.1807 | 0.2071 | 0.0264 |
| 2000| 0.1942 | 0.0012 | 0.1864 | 0.2020 | 0.0157 | 0.1849 | 0.2035 | 0.0186 |
According to Tables 11 and 12, our new model is better suited than the IE model and has the lowest values for all statistics.

4.2. Discussion. From the modelling to ball bearing and carbon fibres datasets, we see that the SIE model provides the greatest fit for the both datasets. IY_he numerical values in Tables 11 and 12 are proposed; the both datasets supported the superiority of the SIE model.

5. Conclusion

In this study, we proposed a new one-parameter model, which is called the SIE model. Some basic statistical properties of the SIE model are also proposed. Estimation of the SIE parameter was assessed by using the ML method of estimation censored and complete samples. Application to carbon fibres datasets were used to explain the importance of SIE model against the IE model. The SIE model as we see is very flexible and simple model, so many authors can use it in the future articles. The authors can use Bayesian estimation under complete and various censored schemes to estimate its parameters. Also, ranked set sampling papers can apply the new model. Also, the authors which are interested in distribution theory can generalize more extensions of this model by many different ways.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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