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Estimating the Survival Function of Mixture Inverse Rayleigh and Inverse Gompertz Using a New Hybrid Meta Heuristic Algorithm

Shahad K. Taher[1] and **Bayda Atiya Kalaf** [2*]
[1,2]Department of Mathematics, College of Education for Pure Sciences (Ibn Al-Haitham), University of Baghdad, Baghdad, Iraq
*Corresponding Author.

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Abstract:

This paper proposes a new compound model involving the inverse Rayleigh and inverse Gompertz distributions with four versatile parameters. Some of the statistical measures of the newly suggested distribution are derived, including the survival function, hazard function, cumulative distribution function, moments about the origin, mode, and median. To estimate the survival function from the distribution parameters, a new hybrid optimization algorithm (PSOMA) is introduced. The robust algorithm combines the strengths of Particle Swarm Optimization (PSO) and Monkey Optimization (MO). A simulated experiment following the mean square error (MSE) metric is conducted to compare the performance of PSOMA with the standard PSO and MO algorithms. The results are that the new hybrid algorithm can accurately estimate the survival function with virtually perfect precision under simulated conditions. Besides, PSOMA consistently produces lower mean square errors than competing methods, confirming its improved predictive capability, robustness, and reliability for a broad variety of survival analysis tasks.

Keywords: Mixture distribution, Particle Swarm Optimization, Monkey algorithm, survival function.

1. Introduction

The survival analysis refers to an analysis that is done to determine the likelihood that events related to failure or death would occur after treatment[1]. Estimating survival functions has long piqued the curiosity of statisticians[2]. Furthermore, survival analysis has long used statistical distributions[3]. Many academics have recently concentrated on ideas for more adaptable probability distributions, employing various methods to characterize a set of data. Distribution characteristics are a great way to show how capable a distribution[4].

Hassan[5] used an exponential Weibull distribution for the model of maximum and significant wave heights. presented the Kumaraswamy-Weibull distribution. Vigas[6] presented the Poisson-Weibull distribution. Sarhan and Apaloo[7] proposed an extension of the Weibull distribution. Weibull-Rayleigh distribution with three parameters was defined parameters[8]. Bayesian was used to estimate the Weibull mixture distribution[9]. Sharba[10] developed a new generalized class of distributions, the Burr-Weibull Power Series. One-parameter Lindley and Weibull distributions introduced[11]. studied reliability analysis for mixed Weibull distribution. With data's increasing complexity and models' nonlinearity, estimating distributions' parameters has become a major challenge[12]. For this reason, researchers have turned to using metaheuristic algorithms that have proven effective in improving parameter estimation. Shin[13] estimated the parameters of the mixture's normal distribution was estimated its parameters by maximizing the log-likelihood outcome using a meta-heuristic technique. The Jackknife algorithm is suggested for predicting Gumbel distribution parameters[14]. Meta-heuristic algorithms encompass various methods that enhance the survival function's estimation by refining the input parameters' accuracy[15].

Additionally, the hybrid approach has several advantages in estimating the survival function. Hybrid algorithms effectively balance exploration and exploitation, enhancing survival function estimation accuracy. Experimental studies have demonstrated that the hybrid approach often outperforms traditional methods and even single algorithms, particularly with complex and variable data[16,17]. Therefore, in this study, a new hybrid algorithm was adopted to estimate the parameters of a new mixture distribution based on survival functions.

2. Materials and Methods

2.1 Mixture Inverse Rayleigh Inverse Gompertz Distribution (IRIGD)

The inverse Rayleigh (IR) distribution was presented[18]. The PDF and CDF of the IR distribution with one parameter α are given by:

$$f_{IR}(x,\lambda) = \frac{2\lambda^2}{x^3}\, \mathrm{e}^{-\frac{\lambda^2}{x^2}} \qquad x, \alpha > 0 \tag{1}$$

$$F_{IR}(x,\lambda) = e^{\left(\frac{-\lambda^2}{x^2}\right)} \quad , for\ x \geq 0\ and\ \eta > 0 \tag{2}$$

On the other hand, the Inverse Gompertz Distribution (IGD) was introduced by Eliwa et al.[19]. and the PDF and CDF of IGD with shape parameter δ, and scale parameter ϑ, as:

$$f_{IG}(x) = \frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}} \qquad \mathrm{x} > 0, \beta, \eta > 0 \tag{3}$$

$$F_{IG}(x;\eta,\beta) = e^{-\frac{\eta}{\beta}(e^{\frac{\beta}{x}}-1)}, x > 0, \eta, \beta > 0 \tag{4}$$

The Mixture Inverse Rayleigh Inverse Gompertz Distribution (IRIGD).

$$\mathrm{f}_{IRIGD}(\mathrm{x}) = \alpha \frac{2\lambda^2}{x^3}\, \mathrm{e}^{-\frac{\lambda^2}{x^2}} + (1-\alpha)\frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}$$

$$f_{IRIGD}(x) = \alpha\left(\frac{2\lambda^2}{x^3}\, \mathrm{e}^{-\frac{\lambda^2}{x^2}} - \frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}\right) + \frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}} \tag{5}$$

The CDF of IRIGD will be:

$$F_{IRIGD}(x) = \alpha\left(e^{\left(\frac{-\lambda^2}{x^2}\right)} - e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)}\right) + e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)} \tag{6}$$

The survival and hazard functions of the IRIGD are given as:

$$S(x) = 1 - \alpha\left(e^{\left(\frac{-\lambda^2}{x^2}\right)} - e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)}\right) + e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)} \tag{7}$$

$$h(x) = \frac{\alpha\left(\frac{2\lambda^2}{x^3}\, \mathrm{e}^{-\frac{\lambda^2}{x^2}} - \frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}\right) + \frac{\eta}{x^2}\, e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}}{1-\alpha\left(e^{\left(\frac{-\lambda^2}{x^2}\right)} - e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)}\right) + e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)}} \tag{8}$$

Figures 1- 4 illustrate the plots of the probability density function, cumulative distribution function, survival function, and hazard function of the proposed distribution, respectively.

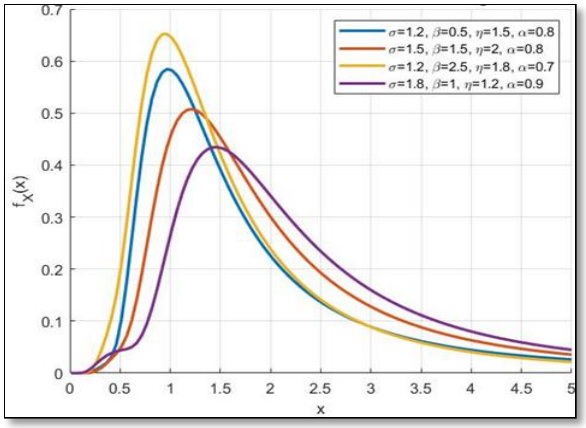


Figure 1. PDF for the mixture IRIGD

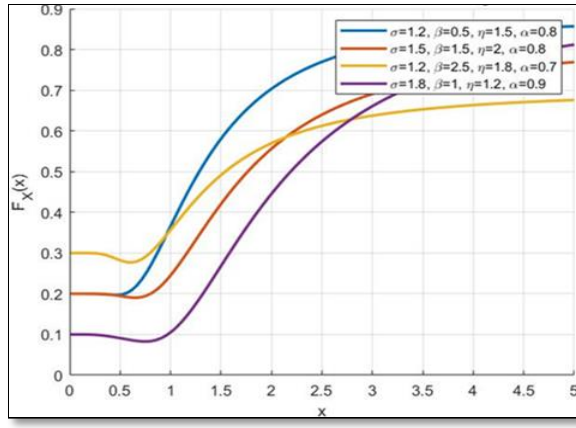


Figure 2. CDF for the mixture IRIGD

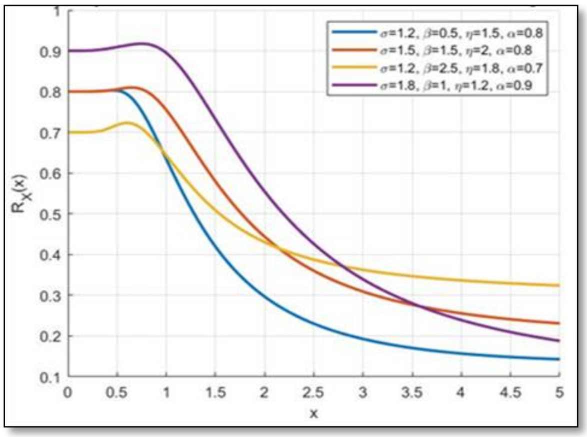


Figure 3. Survival function for the mixture IRIGD

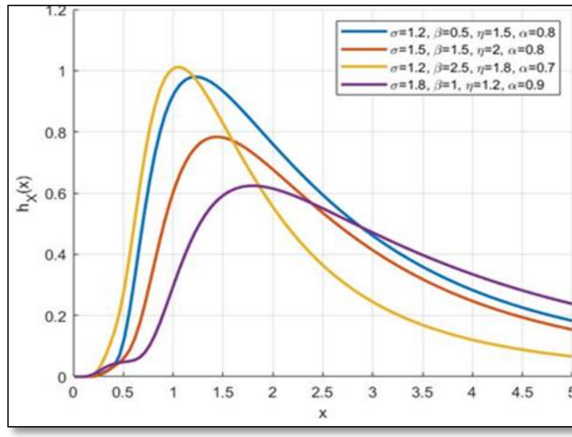


Figure 4. Hazard function for the mixture IRIGD

2.2. Statistical properties of Mixture Inverse Rayleigh Inverse Gompertz distribution

- **Moments about the Origin**

$$E[x^K] = \alpha\left(\lambda^{\frac{\kappa}{2}}\Gamma(1-\kappa/2)\right) + \left(\frac{k-1}{2}\right)2\sigma^{k+1}\Gamma.\alpha \quad \textbf{(9)}$$

Where K=1

$$E[x] = \alpha\left(\lambda^{\frac{1}{2}}\Gamma_0\right) = \alpha\lambda^{\frac{1}{2}}$$

K=2

$$E[x^2] = \alpha(\lambda\,\Gamma(-1/2)) + \left(\frac{1}{2}\right)2\sigma^3\Gamma.\alpha \text{Then}$$

$$var(x) = E(x^2) - \left(E(x)\right)^2 = \alpha(\lambda\,\Gamma(-1/2)) + \left(\frac{1}{2}\right)2\sigma^3\Gamma.\alpha - \alpha^2\lambda \quad \textbf{(10)}$$

- **Median**

The Median of Mixture IRIGD can be found as follows:

$$F_{RTIGD}(x) = \frac{1}{2}$$

$$x_{med} = \alpha\left(\frac{\lambda}{\sqrt{ln2}} - \frac{\beta}{\ln\left(1+\frac{\beta ln2}{\eta}\right)}\right) + \frac{\beta}{\ln\left(1+\frac{\beta ln2}{\eta}\right)} \quad \textbf{(11)}$$

- **Mode**

The Mode of Mixture IRIGD can be found as follows:

$$\frac{\mathrm{D}f_{\mathrm{RTIGD}}(\mathrm{x})}{\mathrm{dx}} = 0$$

$$\alpha\sqrt{\frac{2}{3}}\lambda + (1-\alpha)\eta e^{\frac{\beta}{x}} - 2x - \beta = 0$$

$$\alpha\left(\sqrt{\frac{2}{3}}\lambda-\eta e^{\frac{\beta}{x}}+2x+\beta\right)+\eta e^{\frac{\beta}{x}}-2x-\beta=0$$

It has to be obtained numerically. Further, it can be seen that it always exists and **is** unique.

2.4 Hybrid Meta-Heuristic Algorithm.

Many algorithms are used in optimization processes, and each algorithm has advantages and disadvantages that affect its performance in solving different problems. While some algorithms perform highly in a particular class of issues, they may be less effective when applied to other problems. This difference is not limited to problem classes but extends to specific cases within a single problem. In light of this, modern heuristics focus on two main components: exploration and exploitation. Exploration aims to search for new solutions in the solution space, while exploitation focuses on improving the discovered solutions to reach the optimal one[20-24]. A new hybrid algorithm (PSOMO) has been developed to balance these two components, combining the Particle Swarm Optimization Algorithm and the Monkey Algorithm (**Figure 5**).

- Monkey algorithm in Hybrid Meta-Heuristics:

Spider Monkey Optimization (MO) is based on spider monkeys' foraging as well as social conduct to obtain dynamic equilibrium between exploration and exploitation. Its hybrid variants (e.g., combining SMO with k-means clustering or integrating SMO in Artificial Neural Networks) have improved performance in clustering and prediction tasks. Modern hybridizations like weighted-estimated SMO (w‑SMNO) and ANN-SMO models. Also, show its versatility in data-driven and engineering optimization domains[25-27].

- Particle Swarm Optimization (PSO) in Hybrid Meta-heuristics:

Particle Swarm Optimization takes inspiration from bird flocking to guide particles to personal and global optima, exchanging exploration with exploitation. Novel hybrids complement PSO's versatility with dynamic approaches from Differential Evolution, chaotic mapping, or smooth integration with Genetic Algorithms. These enhance accuracy, velocity, and search depth without causing premature convergence[28-30]

- Hybrid Meta-heuristics:

The PSOMO algorithm is designed to estimate the parameters of a mixture of inverse Rayleigh and inverse Gompertz distributions based on the survival function. This approach improves computational efficiency, as diversity in the search is essential to avoid falling into local solutions, especially when the algorithm converges towards optimal solutions. Steps of the PSOMO algorithm:

- Generate initial solutions: A random set of solutions is generated as an initial step.

- Implement the MO algorithm: It improves exploration by moving solutions towards the best solutions based on light intensity.

- **Implement the PSO:** It expands the search by replacing some solutions with new ones according to the nesting strategy.

- Evaluate solutions: The updated solutions are evaluated using the objective function associated with the likelihood function $\alpha\left(2nln2\lambda-ln(\prod_{i=1}^{n}x_i^3)-\alpha\sum_{i=1}^{n}\frac{1}{x_i^2}-nln\eta+\beta\sum_{i=1}^{n}\frac{1}{x_i}-\frac{\eta}{\beta}\sum_{i=1}^{n}(e^{\frac{\beta}{x_{i-1}}}-2\sum_{i=1}^{n}lnx_i\right)+nln\eta+\beta\sum_{i=1}^{n}\frac{1}{x_i}-\frac{\eta}{\beta}\sum_{i=1}^{n}(e^{\frac{\beta}{x_{i-1}}}-2\sum_{i=1}^{n}lnx_i$

- Update parameters: The solutions are updated, based on the performance of the two algorithms to achieve a balance between exploration and exploitation.

Verify stopping criterion: The steps are repeated until convergence is achieved or the maximum number of iterations is reached.

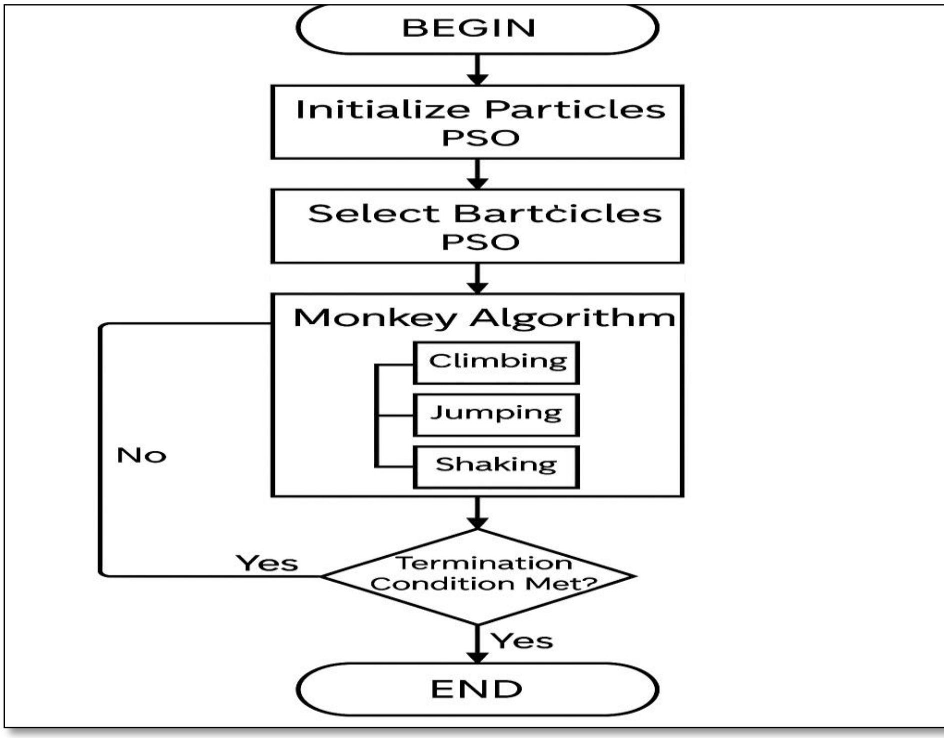


Figure 5. Flowchart of the Proposed Hybrid Algorithm (PSOMO)

3.Simulation study

The simulation process was carried out according to the Mean Squared Error criterion. Each case was generated using 1,000 iterations to ensure the accuracy of the results. Different sample sizes were tested to evaluate the method's performance, including 10, 20, 30, 40, 50, 75, 100, and 120. This variation in sample size aims to determine how estimation accuracy is affected by data overload.

Step 1: Initializing the parameters of the Algorithms (MO, PSO, and the hybrid algorithm (PSMOA)).

Step 2: Generate random samples as, which can be defined by the continuous uniform distribution of the interval (0,1). After that, using CDF, transform it to random samples that followed the IRIGD:

$$F_{IRIGD} = \alpha\left(e^{\left(\frac{-\lambda^2}{x^2}\right)} - \frac{\eta}{x^2}\ e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}\right) + \frac{\eta}{x^2}\ e^{-\frac{\eta}{\beta}\left(e^{\frac{\beta}{x}}-1\right)+\frac{\beta}{x}}$$

Then, defined a vector that is used for all required parameters, such as Ӽ = $[\alpha, \beta, \sigma, \eta]$, and generates N solutions for Ӽ.

Step 3: Recall the $S$from equations [3].

Step 4: The optimal value of $\hat{s}$ is determined using the PSO, MO, and PSOMO algorithms.

Step 5: Calculate the mean squared error (MSE) Based on L=1000 trials, the MSE is calculated as follows.

Step 6: Based on L=1000 trials, MSE will be calculated as follows**:**

$$\text{MSE} = \left(\frac{1}{L}\sum_{i=1}^{n}(\hat{s}_i - s)^2\right)$$

4. Results and Discussion

To determine the best method for the proposed estimation methods of the mixture Inverse Rayleigh Inverse Gompertz Distribution, six sample sets (15, 25, 40, 75, 100, 120) were used to estimate the survival function based on the four parameters $(\beta, \eta, \lambda, \sigma)$ of the new distribution (**Figure 6**). A simulation study was used to compare the proposed algorithms (PSMOA) with the standard algorithms (PSO and MOA). In addition, the simulation results for all algorithms were shown in **Tables 1-3**, depending on survival analyses and MSE values. **Tables 1** and **2** show the PSMOA algorithm gave the best results in all sample sizes. While in **Table 3**, the PSO algorithm gave a lower value of MSE except in the sample size when n=100 (0.01386). The hybrid algorithm[30] consistently provides lower values than MA and PSO, suggesting better optimization performance, especially at higher iterations. MA shows relatively stable values but lacks the precision of PSO or Hybrid methods. Hybrid tends to outperform MO and PSO in some cases. This result suggests the hybrid approach leverages the strengths of both methods effectively. Scalability: As n increases, the differences between the methods diminish slightly, but PSOMO still shows superior performance, particularly for n=75. PSO's performance increases with n, indicating potential robustness for more significant problems. **Figures 6-8** display a graphical comparison of the estimated survival function performance generated by the three algorithms (PSO, MA, and PSMOA) against the actual baseline curve across various sample sizes, demonstrating the superior efficiency and precision of the proposed hybrid meta-heuristic algorithm

Table 1.MSR values of $\widehat{S}$ When $\beta = 1\ ,\lambda = 0.7, \sigma = 2.5\ and\ \eta = 0.5$

n	PSO	MA	PSMOA
15	0.0014993	0.0034547	0.0013877
25	0.0078814	0.028079	0.0011465
40	0.0054823	0.012152	0.0022779
75	0.0099957	0.0076832	0.0010448
100	0.014372	0.022461	0.00051
120	0.018217	0.0073964	0.00010665

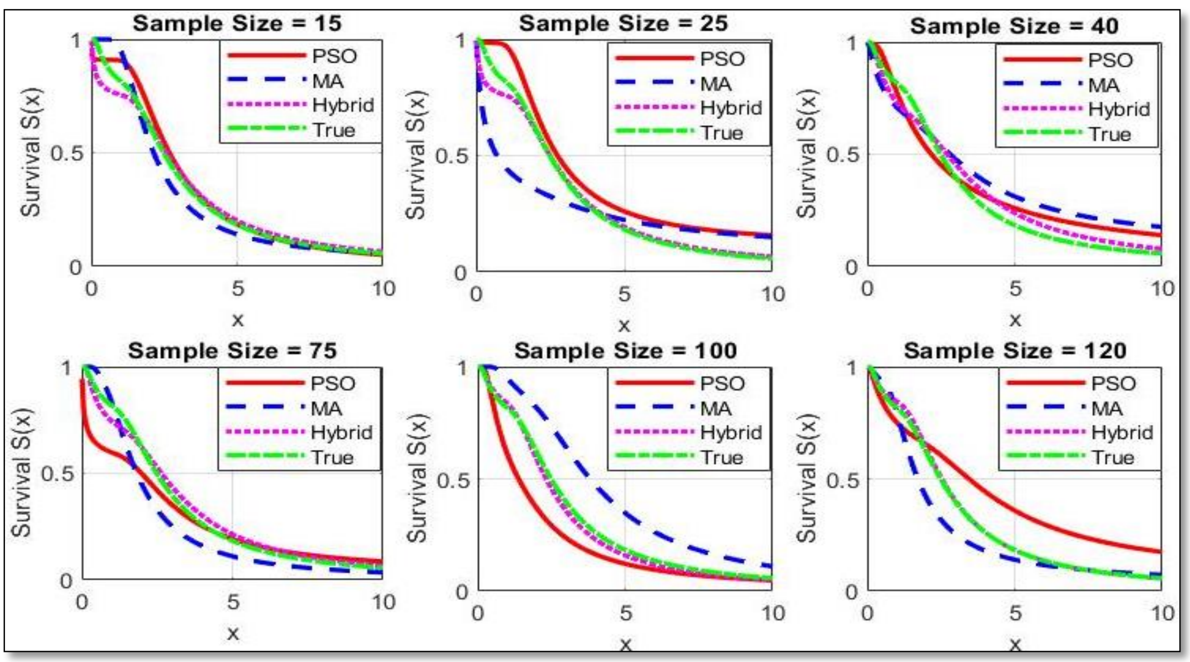
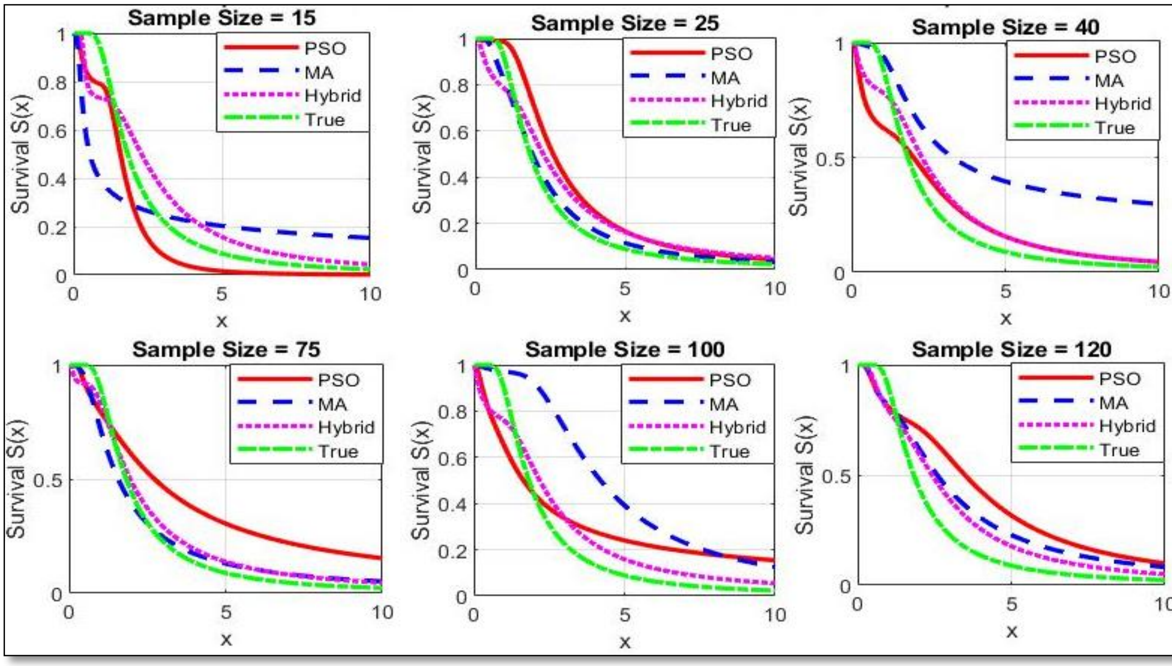


Figure 6. Comparison of Survival Function for Different sample size

Table 2 .MSR values of $\widehat{S}$ When$\beta = 2\ ,\lambda = 0.9, \sigma = 1.5\ and\ \eta = 3$

n	PSO	MA	Hybrid
15	0.0086727	0.040227	0.0086388
25	0.013306	0.0011002	0.0070884
40	0.011007	0.072378	0.0070884
75	0.031639	0.0034599	0.0022624
100	0.020258	0.087036	0.0072647
120	0.041119	0.016158	0.0087847



Figures 7. Comparison of Survival Function for Different sample size

Table 3 .MSR values of $\widehat{S}$ When$\beta = 2 , \lambda = 3, \sigma = 1.5$ *and* $\eta = 2.5$

n	PSO	MA	Hybrid
15	0.063219	0.045906	0.034928
25	0.039445	0.038413	0.004552
40	0.048263	0.08984	0.018891
75	0.017099	0.010554	0.0018506
100	0.010049	0.044438	0.01386
120	0.017905	0.027029	0.013075

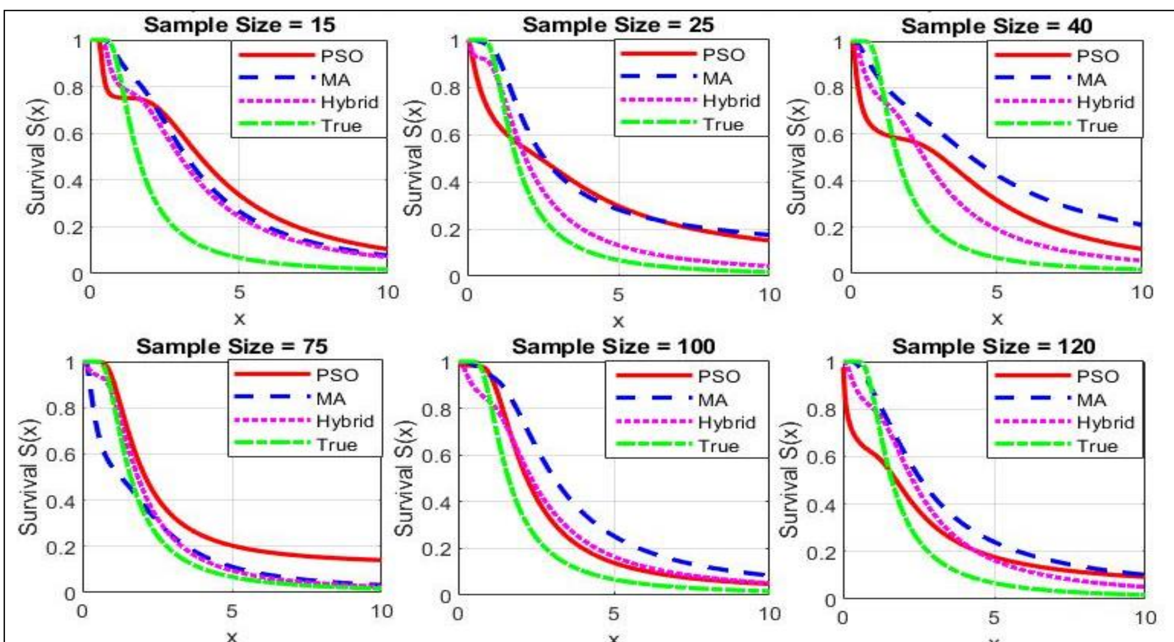


Figure 8. Comparison of Survival Function for different sample size

5. Conclusion

This study presented a new mixture distribution by combining the Inverse Rayleigh and Inverse Gompertz distributions; some statistical properties of the distribution are obtained. In addition, the study suggested a new hybrid algorithm (PSMOA), which was developed by integrating the particle swarm optimization algorithm and the monkey optimization algorithm. This algorithm is meant to improve the survival function estimation based on the distribution parameters. It improves estimating accuracy over conventional techniques. The hybrid method (PSOMO) is a more effective and efficient choice for estimating these functions since it is accurate and greatly lowers the mean square error, according to the simulation findings.

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Conflict of Interest

There are no conflicts of interest.

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