Neutrosophic inverse power Lindley distribution: A modeling and application for bladder cancer patients

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Abstract

The inverse power Lindley distribution is employed in the realm of survival analysis to imitate human lifetime data practices. The neutrosophic inverse power Lindley distribution (NIPLD) is intended to characterize a variety of survival data with indeterminacies. The established distribution is particularly useful for modeling uncertain data that is roughly positively skewed. This work discusses the key statistical properties of the developed NIPLD, including the neutrosophic survival function, neutrosophic hazard rate, and neutrosophic moments. In addition, the neutrosophic parameters are estimated using the well-known maximum likelihood estimation approach. To find out if the predicted neutrosophic parameters were reached, a simulation study is done. Not to mention, actual data has been utilized to discuss potential NIPLD real-world applications. Real data were used to illustrate how well the proposed model performed in compared to the current distributions.

Keywords: Neutrosophic statistics; inverse power Lindley distribution; survival analysis; hazard function; bladder cancer.

1. Introduction

Neutosophic statistics is a branch of statistics that deals with handling uncertainty and incompleteness in data by applying neutrosophic logic. The use of fuzzy logic was expanded by [1] to create neutrosophy, which enables the depiction of uncertainty, ambiguity, and contradiction. Traditional statistics often makes the assumption that the data is unambiguous, in which case each observation is assigned a certain value. However, information in real-world circumstances occasionally contains unclear or insufficient details. Neutosophic statistics gives a paradigm for handling unclear, inadequate, and inconsistent data in order to get over these limitations [2-4].
Neutosophic statistics considers three factors: truth membership, indeterminacy membership, and falsity membership. Each component is a representation of the degree of truth, ambiguity, or untruth associated with an observation or a hypothesis. Membership functions are used to represent these degrees in a manner similar to fuzzy sets. [2, 3].
Numerous industries, such as decision-making, pattern identification, data mining, and image processing, use neutrosophic statistics [4-7]. It offers a versatile mathematical tool for modeling and analyzing complicated systems with a high degree of uncertainty and imprecision.
The examination of survival statistics is one of the crucial uses of neutrosophic information. A statistical method called survival analysis looks at how long it will be until an event occurs [8]. The probability distributions of the temporal data provide the basis of the survival analysis in its entirety. The idea of a neutrosophic survival probability distribution combines neutrosophic logic and survival analysis. The likelihood of an event happening at different times is represented by the survival probability distribution in the context of neutrosophic. Neutosophic logic is employed to account for the ambiguity and uncertainty in the survival statistics. It makes it

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possible to depict having only partial or fragmentary understanding of events. The degree of truth, falsity, and uncertainty associated with the survival probability at different time points must be reflected by neutrosophic factors as well as the survival data that are currently accessible. This can be done using mathematical models and techniques specific to neutrosophic logic. Numerous articles discuss neutrosophic probability distribution [8-20]. The inverse power Lindley distribution has applications in various fields, such as survival analysis. In this paper, we expanded the uses of the inverse power Lindley distribution when the data is in interval form and has some degree of indeterminacy in the form of neutrosophy. With the aid of simulated and real data application based on bladder cancer, a number of properties are examined under the newly proposed distribution and their applications are discussed.

2. Neutrosophic inverse power Lindley distribution

The inverse Lindley distribution, proposed by [21], considers the inverse of a random variable with a Lindley distribution. More specifically, if a random variable Y has a Lindley distribution, then the random variable X=1 / Y follows an inverse Lindley distribution with density and cumulative distribution functions defined, respectively, by:

$$f\left(x|\ \beta\right)=\frac{\beta^2}{1+\beta}\left(\frac{1+x}{x^3}\right)e^{-\frac{\beta}{x}}, \qquad (1)$$

$$F\left(x\mid\beta\right)=\left(1+\frac{\beta}{1+\beta}\frac{1}{x}\right)e^{-\frac{\beta}{x}}, \qquad (2)$$

where $x>0$ and $\beta>0$

Another generalization is the power Lindley distribution, which considers the power of a random variable with a Lindley distribution, proposed by [22].

In other words, if a random variable Y has a Lindley distribution, then the random variable $X=Y^{\frac{1}{\alpha}}$ follows a power Lindley distribution.

The power Lindley distribution can be obtained by mixing two distributions, namely, the Weibull distribution with shape parameter α and scale parameter β and the generalized gamma distribution with shape parameters 2 and α and scale parameter β Thus, its probability density function is given by:

$$f\left(x\mid\alpha,\beta\right)=\frac{\alpha\beta^2}{1+\beta}\left(1+x^{\alpha}\right)x^{\alpha-1}e^{-\beta x^{\alpha}}, \qquad (3)$$

where $x>0,\alpha>0$ and $\beta>0$

The cumulative distribution function is given by:

$$F\left(x\mid\alpha,\beta\right)=1-\left(1+\frac{\beta x^{\alpha}}{1+\beta}\right)e^{-\beta x^{\alpha}}. \qquad (4)$$

It can be noticed that the Lindley distribution is a special case of the power Lindley distribution when $\alpha=1$. Starting from the inverse Lindley distribution, the inverse power Lindley distribution (IPLD) is considered in this article. The probability density function is given by [23]:

$$\mathrm{f}\left(\mathrm{x}|\ \alpha,\beta\right)=\frac{\alpha\beta^2}{1+\beta}\left(\frac{1+\mathrm{x}^{\alpha}}{\mathrm{x}^{2\alpha+1}}\right)\mathrm{e}^{-\frac{\beta}{\mathrm{x}^{\alpha}}}, \qquad (5)$$

where $x>0,\alpha>0$ and $\beta>0$

The cumulative distribution and, survival, hazard functions of the IPLD are defined, respectively, by:

$$F\left(x\mid\alpha,\beta\right)=\left(1+\frac{\beta}{1+\beta}\frac{1}{x^{\alpha}}\right)e^{-\frac{\beta}{x^{\alpha}}}, \qquad (6)$$

$$S\left(x\mid\alpha,\beta\right)=1-\left(1+\frac{\beta}{1+\beta}\frac{1}{x^{\alpha}}\right)e^{-\frac{\beta}{x^{\alpha}}}, \qquad (7)$$

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$$h(x \mid \alpha,\beta)=\frac{\alpha\beta^{2}\left(1+x^{-\alpha}\right)}{x\left[-\beta+x^{\alpha}(1+\beta)\left(e^{\frac{\beta}{x^{\alpha}}}-1\right)\right]} \qquad (8)$$

The concept of neutrosophic probability as a function $NP:\rightarrow [0,\ 1]^{3}$ was originally presented by [2], where U is a neutrosophic sample space and defined the probability mapping to take the form

$NP(S) = (ch(S),\ ch(neut\ S),\ ch(anti\ S)) = (\eta,\ \beta,\ \tau)$

where $0 \le \eta,\ \beta,\ \tau \le 1$ *and* $0 \le \eta + \beta + \tau \le 3$. The term Ψ represents the set of sample space, R represents the set of real numbers, and Υ denotes a sample space event, X_N and Y_N denote neutrosophic r.v. Furthermore, we demonstrate certain renowned definitions and characteristics of neutrosophic probability and logic that will be important in creating this neutrosophic probability model.

Definition 1:

Consider the real-valued crisp r.v. X which has the following definition:

$X : \Psi \rightarrow R$

Where Ψ is the event space and X_N neutrosophic r.v. as follows:

$X_N : \Psi \rightarrow R(I)$

and

$X_N = X + I$

The term I represents indeterminacy.

Theorem 1:

Let the neutrosophic r.v. $X_N = X + I$ and the *CDF* of X is $F_X(x) = P(X \le x)$ [13]. The following assertions are correct:

$FX_N(x) = F_X(x - I)$,

$f_{X_N}(x) = f_X(x - I)$,

where F_{X_N} and f_{X_N} are the *CDF* and *PDF* of a neutrosophic r.v. X_N, respectively.

Theorem 2 :

Let $X_N = X + I$, is the neutrosophic r.v., then the expected value and variance can be derived as follows: $E(X_N) = E(X) + I$ and $V(X_N) = V(X)$ [13].

Suppose the neutrosophic variable could be expressed as: $x_N = x_L + x_U I_N$ where $I_N \in \{I_L, I_U\}$ and x_L and $x_U I_N$ denote the determined and indeterminate parts, respectively. Assume that the neutrosophic random variable $x_N \in \{x_L, x_U\}$ follows the IPLD having neutrosophic scale parameter $\beta_N \in \{\beta_L, \beta_U\}$ and neutrosophic shape parameter $\alpha_N \in \{\alpha_L, \alpha_U\}$ where the letters L and U are the lower values and the upper values, respectively. Then, the neutrosophic probability density function (NPDF) of of neutrosophic IPLD (NIPLD) is given by:

$$f(x_N \mid \alpha_N, \beta_N)=\frac{\alpha_N \beta_N^{2}}{1+\beta_N}\left(\frac{1+x_N^{\alpha_N}}{x_N^{2\alpha_N+1}}\right)e^{-\frac{\beta_N}{x_N^{\alpha_N}}},\ x_N>0, \alpha_N>0, \beta_N>0 \qquad (9)$$

Figures 1 shows the NPDF for different values of β and α. The neutrosophic cumulative density function (NCDF), the neutrosophic survival, and neutrosophic hazard functions are given below, respectively:

$$F(x_N \mid \alpha_N, \beta_N)=\left(1+\frac{\beta_N}{1+\beta_N}\frac{1}{x_N^{\alpha_N}}\right)e^{-\frac{\beta_N}{x_N^{\alpha_N}}}, \qquad (10)$$

$$S(x_N \mid \alpha_N, \beta_N)=1-\left(1+\frac{\beta_N}{1+\beta_N}\frac{1}{x_N^{\alpha_N}}\right)e^{-\frac{\beta_N}{x_N^{\alpha_N}}}, \qquad (11)$$

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$$h\left(x_N \mid \alpha_N, \beta_N\right) = \frac{\alpha_N \beta_N^2 \left(1 + x_N^{-\alpha_N}\right)}{x_N \left[-\beta_N + x_N^{\alpha_N}\left(1+\beta_N\right)\left(e^{\frac{\beta_N}{x_N^{\alpha_N}}} - 1\right)\right]} \tag{12}$$

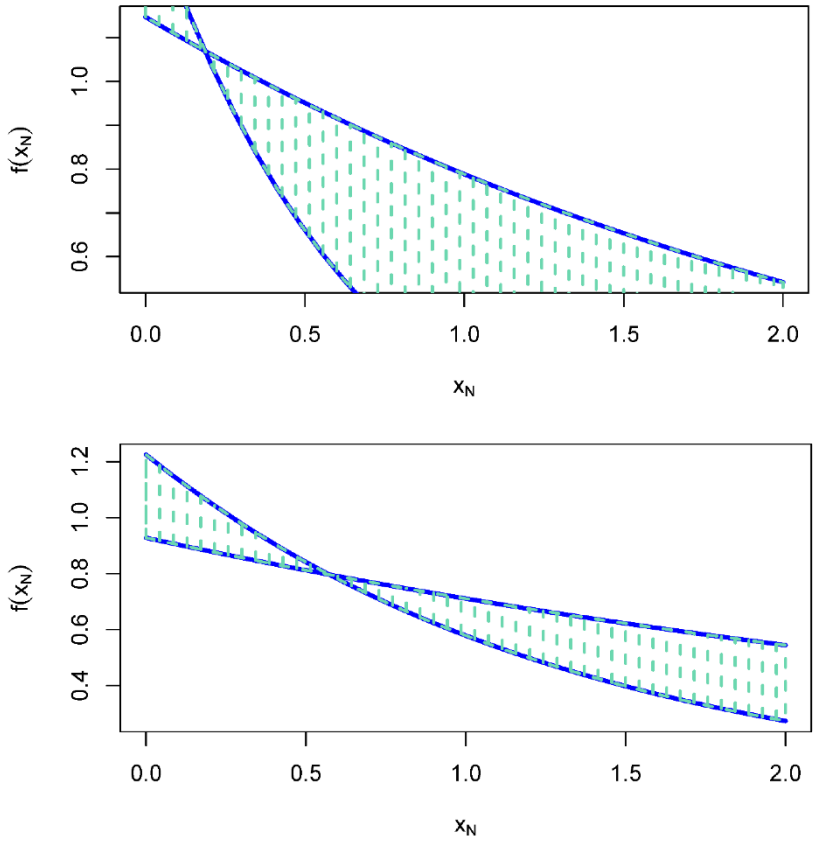

Figure 1: (Top) The pdf of NIPLD when $\beta_N \in [2, 2.5]$ and $\alpha_N \in [3, 4.5]$, (bottom) The pdf of NIPLD when $\beta_N \in [1.5, 3]$ and $\alpha_N \in [0.5, 2.5]$.

3. Statistical Properties of IPLD

In this section, statistical properties of the IPLD are covered.

Moments: The r^{th} moment about origin is given by

$$E\left(X_N^{\,r}\right) = \frac{\left(\alpha_N \beta_N^{\frac{r}{\alpha_N}} - r\beta_N^{\frac{r}{\alpha_N}} + \alpha_N \beta_N^{\frac{r+\alpha_N}{\alpha_N}}\right)\Gamma\left(\frac{\alpha_N - r}{\alpha_N}\right)}{\alpha_N\left(1+\beta_N\right)}. \tag{13}$$

It is worth of note that, for the r^{th} raw moment to exist, the constraint $\alpha_N > r$ must be satisfied. From (13), the mean and the variance of the inverse power Lindley distribution can be defined, respectively, as

$$E\left(X_N\right) = \frac{\left(\alpha_N \beta_N^{\frac{1}{\alpha_N}} - \beta_N^{\frac{1}{\alpha_N}} + \alpha_N \beta_N^{\frac{1+\alpha_N}{\alpha_N}}\right)\Gamma\left(\frac{\alpha_N - 1}{\alpha_N}\right)}{\alpha_N\left(1+\beta_N\right)}, \tag{14}$$

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$$V\left(X_N\right)=\frac{\left(\alpha_N\beta_N^{\frac{2}{\alpha_N}}-2\beta_N^{\frac{2}{\alpha_N}}+\alpha_N\beta_N^{\frac{2+\alpha_N}{\alpha_N}}\right)\Gamma\left(\frac{\alpha_N-2}{\alpha_N}\right)\alpha_N\left(1+\beta_N\right)-\left(\alpha_N\beta_N^{\frac{1}{\alpha_N}}-\beta_N^{\frac{1}{\alpha_N}}+\alpha_N\beta_N^{\frac{1+\alpha_N}{\alpha_N}}\right)^2\left[\Gamma\left(\frac{\alpha_N-1}{\alpha_N}\right)\right]^2}{{\alpha_N}^2(1+\beta_N)^2}$$

(15)

4. Parameter Estimation of IPLD

Maximum likelihood estimation (MLE) method is mostly used in estimating IPLD parameters. Let $x_{N1},x_{N2},...,x_{Nn}$ be random sample of size n drawn from IPLD .The log-likelihood function is then given by:

$$L\left(\alpha_N,\beta_N\mid x_N\right)=n\left[\log\alpha_N+2\log\beta_N-\log\left(1+\beta_N\right)\right]+\sum_{i=1}^{n}\log\left(1+x_{Ni}^{\alpha}\right)-\left(2\alpha_N+1\right)\sum_{i=1}^{n}\log x_{Ni}-\beta_N\sum_{i=1}^{n}x_{Ni}^{-\alpha_N}. \quad (15)$$

Thus, the maximum likelihood estimates $\hat{\alpha}_N,\hat{\beta}_N$ for α_N,β_N are the solutions to the nonlinear equations:

$$\frac{\partial}{\partial\alpha_N}L\left(\alpha_N,\beta_N\mid x_N\right)=\frac{n}{\alpha_N}+\sum_{i=1}^{n}\frac{x_{Ni}^{\alpha_N}\log x_{Ni}}{1+x_{Ni}^{\alpha_N}}-2\sum_{i=1}^{n}\log x_{Ni}+\beta_N\sum_{i=1}^{n}x_{Ni}^{-\alpha_N}\log x_{Ni}=0, \quad (16)$$

$$\frac{\partial}{\partial\beta_N}L\left(\alpha_N,\beta_N\mid x_N\right)=\frac{n\left(2+\beta_N\right)}{\beta_N\left(1+\beta_N\right)}-\sum_{i=1}^{n}x_{Ni}^{-\alpha}=0. \quad (17)$$

On the other hand, Eq. (16) can be rewritten as:

$$\left(\sum_{i=1}^{n}x_{Ni}^{-\alpha_N}\right)\beta_N^2+\left(\sum_{i=1}^{n}x_{Ni}^{-\alpha_N}-n\right)\beta_N-2n=0, \quad (18)$$

and therefore, the maximum likelihood estimate $\hat{\beta}_N$ is the only solution to the equation above, given by

$$\hat{\beta}_N\left(\hat{\alpha}_N\right)=\frac{-\left(\sum_{i=1}^{n}x_{Ni}^{-\hat{\alpha}_N}-n\right)+\sqrt{\left(\sum_{i=1}^{n}x_{Ni}^{-\hat{\alpha}_N}-n\right)^2+8n\sum_{i=1}^{n}x_{Ni}^{-\hat{\alpha}_N}}}{2\sum_{i=1}^{n}x_{Ni}^{-\hat{\alpha}_N}}, \quad (19)$$

and $\hat{\alpha}_N$ is obtained by the solution to the nonlinear equation:

$$G\left(\alpha_N\right)=\frac{n}{\alpha_N}+\sum_{i=1}^{n}\frac{x_{Ni}^{\alpha_N}\log x_{Ni}}{1+x_{Ni}^{\alpha_N}}-2\sum_{i=1}^{n}\log x_{Ni}+\hat{\beta}_N\left(\alpha_N\right)\sum_{i=1}^{n}x_{Ni}^{-\alpha_N}\log x_{Ni}=0. \quad (20)$$

5. Simulation results

A Monte Carlo simulation is run in R software with several sample sizes, $n=30,50,150,250$ and neutrosophic parameters in two cases: (1) $\beta_N\in[1,2.5]$ and $\alpha_N\in[1.5,3]$ and (2) $\beta_N\in[1.5,2]$ and $\alpha_N\in[2.5,4]$. The simulation is replicated for 1000 times. Performance measures, such as the neutrosophic average of the estimators, the neutrosophic average bias (NAB) and neutrosophic Mean Square Error (NMSE) are attained for all values of n. The results are given in Tables 1 and 2. From Tables 1 and 2, It is seen that, as expected, the NAB and NMSE fall for both neutrosophic parameters as sample sizes rise. Furthermore, according to the study's findings, the neutrosophic MLE for the NIPLD offers accurate estimation with a higher sample size.

Table 1: Average NAB and NMSE for case 1

n	NAB	NMSE

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	β_N	α_N	β_N	α_N
30	[0.0183, 0.0191]	[0.0201, 0.0210]	[0.0373, 0.0381]	[0.0414, 0.0422]
50	[0.0121, 0.0134]	[0.0144, 0.0152]	[0.0331, 0.0342]	[0.0364, 0.0372]
150	[0.0110, 0.0119]	[0.0149, 0.0151]	[0.0321, 0.0329]	[0.0349, 0.0351]
250	[0.0044, 0.0057]	[0.0075, 0.0084]	[0.0254, 0.0268]	[0.0273, 0.0288]

Table 2: Average NAB and NMSE for case 2

n	NAB		NMSE	
	β_N	α_N	β_N	α_N
30	[0.0244, 0.0257]	[0.0275, 0.0283]	[0.0454, 0.0463]	[0.0485, 0.0501]
50	[0.0201, 0.0210]	[0.0225, 0.0243]	[0.0411, 0.0422]	[0.0443, 0.0463]
150	[0.0182, 0.0198]	[0.0212, 0.0225]	[0.0401, 0.0413]	[0.0328, 0.0310]
250	[0.0136, 0.0148]	[0.0147, 0.0159]	[0.0335, 0.0349]	[0.0264, 0.0271]

6. Applications

In order to gauge interest in the NIPLD distribution, a real-world dataset was employed in a practical application in this section. The information being considered consists of a collection of remission times from 128 cancer patients, expressed in months. The remission times presented here are primarily for descriptive purposes and are based on a subset of data from bladder cancer studies that [24,25] published. The inverse power Lindley distribution is one of the likely distributions for the remission times, according to the results of the goodness of fit test based on Kolmogorov–Smirnov (KS) test. According to [12], this data shows that remission times for certain cancer patients, such as [7.26, 8.2], [12, 14.77], [15, 17.2], [5.3, 7.1], [75.02, 81], and [1.5, 3.2], are not precisely reported but are provided in intervals.

The neutrosophic exponential distribution (NED) applications for complex data processing investigated by [12] are compared to the model suitability of the proposed NIPLD. The methods used to choose which model best fits the data are the log-likelihood value (LogL), Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Kolmogorov-Smirnov (KS) test. The highest LogL values and the lowest AIC, BIC, and KS statistic values determine which model is the best match. Furthermore, a higher p-value denotes that the model fits the neutrosophic data the best. The neutrosophic maximum likelihood estimators and model sufficiency indicators are listed in Table 3. The results demonstrate that the NIPLD is superior to the NED for data. The bold values in the table show how well the suggested model works.

Table 3: The criteria selection neutrosophic distributions for cancer patients data

	NED	NIPLD
Parameter	$\alpha_N = [0.1081, 0.10822]$	$\beta_N = [1.202, 1.213]$ $\alpha_N = [0.1532,\ 0.1578]$
Log	[10.352, 13.241]	**[80.3025, 81.1497]**
AIC	[63.508, 65.334]	**[156.605, 158.2994]**
BIC	[60.218, 61.229]	**[154.8234, 156.5187]**
KS-value	[0.752, 0.774]	**[0.124, 0.132]**
KS- p-value	$[1.135\times10^{-6}, 1.188\times10^{-6}]$	**[0.955, 0.987]**

7. Conclusions

A neutrosophic inverse power Lindley distribution (NIPLD) has been proposed in this article. This well-established distribution can be applied to a wide range of application data for survival and dependability uncertainties. As the primary statistical features of the evolved NIPLD, the neutrosophic survival function,

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neutrosophic hazard rate, and neutrosophic moments have all been investigated. The neutrosophic MLEs have been constructed and have demonstrated neutrosophic average bias and MSEs for various sample sizes. To determine whether the computed neutrosophic parameters were met, a simulation study was conducted. The sample size and neutrosophic parametric value are significant factors in precisely predicting an unknown parameter, according to simulation data. The employment of the NIPLD under neutrosophic circumstances is further supported by the collection of remission times from 128 cancer patients used.

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